NEAR EAST UNIVERSITY
INSTITUTE OF GRADUATE STUDIES
DEPARTMENT OF COMPUTER INFORMATION SYSTEMS

FACIAL RECOGNITION SYSTEM FOR DISTANCE LEARNING TO MONITOR AND DETECT STUDENTS' CHEATING BEHAVIOR IN REAL-TIME

Ph.D. THESIS

Aayat Al-JARRAH

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Aayat Al-JARRAH

Supervisor
Prof. Dr. Fezile Özdamlı

Co-Supervisor
Assoc. Prof. Dr. Damla Karagozlu

Nicosia

February 2023

Approval

The Thesis defence was held online. The Jury members declared their acceptance verbally, which is recorded.

Examining Committee	Name-Surname	Signature
Head of Committee:	Assist. Prof. Dr. Selin UZELALTİNBULAT	
Committee Member:	Assist. Prof. Dr. Mustafa BABAGIL	
Committee Member:	Assoc. Prof. Dr. Boran SEKEROGLU	
Committee Member:	Prof. Dr. Hüseyin BİCEN	
Supervisor:	Prof. Dr. Fezile ÖZDAMLI	
Co-Supervisor:	Assoc. Prof. Dr. Damla KARAGOZLU	

Approved by the Head of the Department

20/3/2023

Prof. Dr. Nadire Çavuş
Head of the Department

Approved by the Institute of Graduate Studies

/ /2023

Prof. Dr. Kemal Hüsnü Can Başer
Head of the Institute

NEAR EAST UNIVERSITY INSTITUTE OF GRADUATE STUDIES

Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Aayat Al-JARRAH
9/2/2023

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Aayat Al-JARRAH

Abstract

Facial Recognition System for Distance Learning to Monitor and Detect Students' Cheating Behaviour in Real-Time

Aayat Al-JARRAH

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Online invigilating or supervising of students' examinations has been a subject of debate following its sudden rise in usage during COVID-19. This is coupled with the dearth of a method to recognize and capture student efforts to cheat during examination in distance learning as well as the dearth of a system to identify and validate students' personalities online. The key objective of this research is to develop a facial recognition system using an Agile approach to monitor and detect students' cheating behaviour in distance learning. To achieve this objective, this study utilizes techniques such as computer vision convolution neural network algorithms. The system was improved with the help of the semi-structural interviews. According to the results, the facial identification system has demonstrated great performance and accuracy in identifying students' expressed behaviors as well as deviant behaviors, as well as in tracking their gaze and their facial movements. The findings of students' identification, follow-up during class, and follow-up during the exam were found to be effectively predicted by the developed facial recognition system. This system was developed using a number of deep learning algorithms, and the goal was successfully attained. The technology was designed for distance learning invigilation reasons. The system has a student verification system and was designed to be employed by university instructors to supervise students taking online examinations. Real-time data for cheating recognition was one of the difficulties we encountered during the development process. As a result, we used input from the lecturers in our systems to improve distance learning. This study concluded that combining several models to enhance student monitoring in remote learning systems has imaginarily, architecturally, and statistically improved motion picture data in online learning using deep learning algorithms and an agile methodology.

Key words: cheating behaviour, computer vision algorithm, convolution neural network, distance learning, face recognition system.

Öz

Öğrencilerin Kopya Davranışlarını Gerçek Zamanlı Olarak İzlemek ve Tespit Etmek İçin Uzaktan Eğitime Yönelik Yüz Tanıma Sistemi

Aayat Al-JARRAH
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Öğrencilerin Öğrencilerin sınavlarının çevrimiçi gözetlenmesi veya denetlenmesi, COVID-19 sırasında kullanımındaki ani artışın ardından tartışma konusu oldu. Bu, öğrencilerin uzaktan eğitimde sınav sırasında kopya çekme çabalarını tanıyacak ve yakalayacak bir yöntemin yanı sıra öğrencilerin çevrimiçi kimliklerini saptayacak ve doğrulayacak bir sistemin eksikliğini ortaya çıkarmıştır. Bu çalışmanın temel amacı, çevrimiçi eğitimde öğrencilerin kopya çekme davranışlarını izlemek ve tespit etmek için Çevik bir yaklaşım kullanarak bir yüz tanıma sistemi geliştirmektir. Bu amaca ulaşmak için, bilgisayarla görme evrişimi sinir ağı algoritmaları gibi yöntemler kullanılmıştır. Sistemin geliştirilme sürecinde yar yapılandırmacı görümelerden elde edilen sonuçlardan faydalanılmıştır. Elde edilen sonuçlara göre, geliştirilen system aracılığıyla yüz tanıma sistemi, öğrencilerin ifade edilen davranışlarının yanı sıra sapkın davranışları belirlemede ve ayrıca bakışlarını ve yüz hareketlerini takip etmede büyük performans ve doğruluk göstermiştir. Geliştirilen yüz tanıma sistemi ile öğrencilerin kimlik tespiti, ders içi takip ve sınav esnasında takip bulgularının etkili bir şekilde tahmin edilebildiği görülmüştür. Bu sistem, bir dizi derin öğrenme algoritması kullanılarak geliştirildi ve hedefe başarıyla ulaşıldı. Teknoloji, uzaktan eğitim gözetleme nedenleriyle tasarlanmıştır. Sistem, öğrenci doğrulama sistemine sahiptir ve üniversite öğretim elemanları tarafından çevrimiçi sınava giren öğrencilerin takibi için tasarlanmıştır. Sonuç olarak, bu çalışma, derin öğrenme algoritmaları ve çevik bir metodoloji kullanarak hareketli görüntü verilerini hayali, mimari ve istatistiksel olarak analiz ederek uzaktan öğrenme sistemlerinde öğrenci izlemeyi geliştirmek için çeşitli modelleri birleştirme hakkında bilgi sunar.

Anahtar kelimeler: kopya çekme davranışı, bilgisayarlı görme algoritması, evrişimli sinir ağı, çevrimiçi öğrenme, yüz tanıma sistemi.

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List of Abbreviations

3WPCA	Three Level Wavelet Decomposition-Principal Component Analysis
ADFES	Amsterdam Dynamic Facial Expression Set
ADFES-BIV	Amsterdam Dynamic Facial Expression Set Bath Intensity Variations
AI	Artificial intelligence
ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
AUs	Action Units
BU_3DFE	Binghamton University 3D facial expression
BU_4DFE	Bingthman University 4D facial expression
CK+	Extended Cohn_kanada
CNN	Convolution Neural Network
CNN	Convolutional Neural Networks
COCO	Common Objects in Context
DL	Deep Learning
DNN	Deep Neural Networks
DWT	Discrete Wavelet Transform
FACS	Facial Action Coding System
FDA	Fisher Discriminant Analysis
FER	Facial expression recognition
GD	Gradient Descent
GMM	Gaussian Mixture Model
GQT	Goldfeld-Quandt Test
HMM	Hidden Markov Model

IMT	Institute of Management Technology
JAFFE	Japanese female fashion expression
LDA	Linear Discriminant Analysis
LPCC	Linear Predictive Cepstral Coefficient
LRC	Linear Regression Classification
MFCC	Mel-Frequency Cepstral Coefficient
ML	Machine Learning
MLP	Multilayer Perceptron
MOUE	Model of User's Emotions
MSFs	Modulation Spectral Features
MUG	Multimedia Understanding Group
NEU	Near East University
OpenCV	Embedded Vision Processors
PCA	Principal Component Analysis
PLP	Perceptual Linear Prediction
RBM	Restricted Boltzmann Machine
RNN	Recurrent Neural Networks
SVM	Support Vector Machine
VCA	Virtual Classmate Agent
VTA	Virtual Instructor Agent
WSEFEP	Warsaw set of emotional facial expression pictures

CHAPTER I

INTRODUCTION

1.1. Introduction

This section discusses the setting of this study. It discusses the study's background, the research problem, the research objectives, the research questions, significance of this study, and the scope covered by this study. It also presents the contribution made by this study and, last but not least, the key limitations of the study.

1.2. Background of the study

A facial identification system is a technology with the ability to harmonize human faces in digital images or a video clip over a database of faces (Salama AbdELminaam et al., 2020). It is commonly utilized to authenticate users via identity authentication services. It does this by recognizing and quantifying facial features from a collection of images (Khosravy et al., 2021). Face detection and recognition are active research fields with several applications that are generated from still and moving pictures (Khosravy et al., 2022). Face identification, face tracking, location estimation, and expression recognition are all topics of face processing study. Pictures containing faces are necessary for modern vision-based human computer interactions. However, many methods have been reported about identification and arrangement of image or set of pictures for facial recognition using deep learning and machine learning algorithms for different purposes, such as education, banking, security, etc (Talahua, et al., 2021). Face detection algorithms are reliable and efficient if systems that analyse the information in face pictures are fully automated (Ali et al., 2022).

In addition to facial features and structure, emotion recognition also makes it feasible to identify faces. Professor Picard proposed emotion recognition in 1994 along with classifying emotions in computing (Picard, Vyzas, & Healey, 2001). The physical display of emotions and the modeling of expressive behavior are just two of the many factors that need to be judged in the artificial model of social communications under the function of emotions. Besides creating a system to identify the seven primary emotions (surprise, fear, disgust, anger, happiness, sorrow, and neutral), Picard divided emotions into four categories: fear, anger, sadness, and happiness. These emotional expressions have help researchers over the decades in identifying the faces and its emotions (Boekaerts, 2010; Boekaerts, & Pekrun, 2015; Arriaga, Valdenegro-Toro, & Plöger, 2017; Beher et al., 2021). The facial recognitions have made life in easy across all work of life, including educational contexts. Facial recognition is challenging across all educational levels, particularly in online exams, invigilation, quiz, lessons, and so on.

As a result, unlike face-to-face learning, where the instructor can perceive the emotional and psychological changes with the aid of the instructor's experience, knowledge, and observation, which the system does not accurately comprehend the true of these emotions (Devi, & Preetha, 2020). The inability to perceive learners' emotions and appropriately evaluate them in digital assessments are the two key issues that universities may encounter with distance learning systems. That might take place as a result of how difficult it is to adequately supervise students and evaluate emotions in the classroom, particularly in distance learning situations.

Online tools for distance learning are a technique that continues to aid instructors and students alike in teaching and learning throughout the globe. Technology and online learning materials can help students develop successful self-directed learning techniques. They might determine what they must study, find and utilize resources online, use the information to perform activities in the classroom, take exams, and even evaluate the feedback that results (Tibingana-Ahimbisibwe et al., 2022). After passing an exam procedure using online resources and technology, students can achieve a degree via remote learning (Bashitialshaaer, Alhendawi, & Lassoued, 2021). One of the tools used in online education to identify students who cheat on exams and engage in other misconduct is facial recognition technology (Masud, Hayawi, Mathew, Michael, & El Barachi, 2022). Users of ID verification services are frequently verified using a facial recognition technology. It works by recognizing and quantifying the facial features in an image or video of a particular student. It examines a human face from an electronic photograph or video frame over a databank of faces (Masud et al., 2022).

When using distance learning technology, students are more involved than when using a more conventional method, which results in them spending more time on important learning activities (Ahmed et al., 2022). Lecturers have the opportunity to monitor students more closely through distance learning, enabling them to score well on exams without engaging in academic cheating. Although distance learning offers many benefits, it also has several drawbacks, including the inability to recognize students' emotions, which are crucial to their success (Lim et al., 2021). Due to their physical separation, lecturers cannot read their students' feelings or even anxieties during online classes. Additionally, they currently lack methods that increase the validity of online assessments (Coman et al., 2022).

Due to the importance of this subject, numerous approaches and tools have been developed to assist lecturers in precisely identifying their students' emotions and cheating behavior using algorithms, including face reader (Hadinejad, Moyle, Scott, & Kralj, 2019; LFW, 2022) and X press engine (Sun, Li, Huang, & Li, 2017). Convolutional neural networks (CNN) have helped a number of effective artificial intelligence algorithms, particularly deep learning algorithms, become well-known in the computer vision sector (Yang et al., 2020). It has often been used in picture classification and recognition. It should be mentioned that given the nature of face identification and recognition, extremely accurate image processing is required in order to create a system that is both effective and reliable.

To address these issues, a new system that integrates software techniques, computer vision algorithms, and artificial intelligence is being developed as part of this project. It provides significant methods for lecturers to be able to effectively control interaction with their students during lessons, along with ensuring cheating free in online or distance learning class. Also, a variety of techniques for extracting visual features for identification verification were used. Additionally, a system that uses facial identification and gaze tracking to detect cheating in a procedure. Moreover, this system includes a straightforward interface that makes it simple to access different functions.

In order to address these issues, the goal of this research is to create a novel system that uses computer vision and deep learning approaches to assist instructors in supervising and managing students during online learning meetings and examinations. The primary emphasis is on the learners' facial emotion recognition, classroom teamwork, face identification, and online exam cheating detection. The system analyses the students' facial features and produces the results. Lecturers evaluate the system's performance on students' ability to recognize facial expressions during exams through an interview. The system also helps students verify their identities (facial authentication). Additionally, it has a cheating detection system that made use of facial movement, gaze tracking, and face detection. The algorithm also looks for the appearance of many faces in the image or objects in use, such as a phone, book, or paper, or the motion of the hands and fingers, which can be a test-cheating strategies. Additionally, this system includes a straightforward user interface that makes it simple to access each of these functions. Based on semi-structured interviews with instructors to learn more about the difficulties and obstacles they face when instructing online or through distance learning, this system was developed. Their recommendations and opinions were used to advance the system up to the point of its most recent design, which was also taken into account. After the system had been finished and was in its final form, input from users was requested to determine how satisfied they were with it and whether they would support its use in distant learning.

1.3. Statement of the Problem

One of the most important issues that e-learning initiatives confront today is the use of technology in examinations, which universities use in a number of ways to administer exams and avoid instances of cheating (Chuang, Craig, & Femiani, 2017; Masud et al., 2022). This study provides highly important methodologies for distance learning, which has become more and more popular recently. Despite the fact that many universities use distance learning as an substitute to traditional learning, numerous have quizzed the usefulness and efficiency of the conventional system in overseeing students taking online tests (Bobyliev & Vihrova, 2021). As a result, some argue that as this method of monitoring students became more widely used, flaws and inadequacies became apparent.

Since its expanded use for student tests during the COVID-19, online proctoring or invigilation has been a hotly debated subject (Coghlan, Miller, & Paterson, 2021; Selwyn, O'Neill, Smith, Andrejevic, & Gu, 2021; Masud et al., 2022). However, due to increase number of distance learning programs and large number of students participating and subsequently partake in exams, invigilation has become increase challenging for lecturers in recognizing the students' cheating behaviours. In addition, identifying their precise faces in many instances where webcams become defaulted or issues is another challenge facing distance learning (Winarno, Hadikurniawati, Al Amin, & Sukur, 2017). For instance, there are issues with identification where the instructor's capacity to monitor students during the course, and how to set up a suitable testing system.

The main issues raised by this research are the absence of a way to recognize and confirm students' personalities during tests, online learning, and remote learning. Additionally, there is not a system in place to identify efforts by students to cheat during online quizzes and tests. These problems have already been identified in study as major barriers to distance learning (da Silva et al., 2022; Lee & Fanguy, 2022). Universities all over the world are investigating digital solutions as part of their strategic planning to prevent students from cheating on online tests. These solutions may be adopted, maintained, or upgraded.

1.4. Research Objectives

The key objective of this research is to develop a facial recognition system using the Agile approach to monitor and detect students' cheating behavior in distance learning.

1.4.1. Specific Objectives

1. To use wild data derived models to train face verification models in real time.

2. To train the gaze tracking model using the processed wild datasets for emotion recognition.

3. To develop a facial recognition system using convolutional neural networks and computer vision algorithms based on components of the Agile method to monitor students in real-time.

4. To use a convolutional neural network for image input and ranking of objects for feature differentiation.

5. To statistically predict facial emotions and behavior using Mini Xception convolutional neural network analysis.

6. To maximize pixel-level processing using OpenCV computer vision algorithms to improve the system efficiency and accuracy.

7. To evaluate the system's performance in recognizing students' facial expressions during e-exams and online classes through interviews.

1.5. Research Questions

1. How to use wild data derived models to train face verification models in real time?

2. How to train the gaze tracking model using the processed wild datasets for emotion recognition?

3. Can real-time student monitoring systems using convolutional neural networks and computer vision algorithms based on the Agile method be created?

4. How does a convolutional neural network for image input and object ranking differentiate diverse features?

5. How to predict facial emotions and behavior using Mini Xception convolutional neural network analysis?

6. How to maximize pixel-level processing using OpenCV computer vision algorithms in order to improve the system efficiency and accuracy?

7. How to determine the system's performance in recognizing students' facial expressions during e-exams and online classes?

1.6. Significance of the Study

The significance of this study span across many areas in the academic and society in general. Facial identification is a method for detecting or validating a student's identity utilizing their faces. Facial identification technology can identify students in still photos and videos as well as in real time. A subcategory of biometric security is facial recognition. The outcome of this can be useful to the general public outside the academic environment.

Application of combination of convolutional neural networks and computer vision algorithms to develop a system that can help to combat cheating may serve as a reference for colleges and universities as they develop and launch short- and long-term efforts to combat cheating. Any educational program must have exams as a vital component. Academic dishonesty is typically dealt with administratively in the classroom or at the institutional level. Humans are amazingly adept at deciphering information conveyed by other people by their movements, such as the gesture of a particular body part or the motion of the complete body.

Face recognition is an important ability that fosters quality of teaching and learning and emerges early and future in academic life of students. When it comes to facilitating attitudes and behavioral reasoning, emotion recognition may come in second only to face recognition. Facial expressions in academic, particularly in distance learning, provide lecturers with crucial cues about how students are responding to current events (i.e., e-exam or online test).

Convolutional neural networks and computer vision algorithms support future forecasting and pattern analysis of facial recognition system, facilitating swift and precise decision-making. The technique can be expanded upon and used in various disciplines. The suggested method is simple to integrate with the existing academic information systems.

Cheating in online distance learning exams is a severe issue that can destroy the equality and objectivity of the exam and further tarnish the reputation and reliability of education system. The sensitivity of university and course lecturers toward cheating behavior is negatively connected with cheating emotions, facial expression, and body language of students in distance education.

Face recognition technology can be used to track student attendance. Using this data, it is possible to identify the students who consistently miss class and provide them extra attention during interventions. This could increase overall student attendance, which could have a number of positive benefits, including improved academic performance. For a variety of purposes, including automating attendance verification and enhancing school security, schools may take advantage of using it to track students and visitors. Face recognition is frequently presented as being more effective and precise than other methods of identity verification and can be utilized to identify students in images, videos, even in real time in academic environment.

1.7. Contributions of the Study

In this thesis, on the one hand, a system has been proposed for identifying facial expressions in online lessons, identifying students, and keeping track of the students during online tests. This system will increase the likelihood of identifying students' faces and the opportunity to recognize their feelings during lessons, making it easier for the instructor to comprehend students' feelings and enhancing the instructor's abilities in addition to increasing the credibility of the instructor. However, the system contains a tool for detecting cheating that makes use of face recognition, gaze tracing, and facial movement. The system operates by searching for several faces in the image, items being used, such as a phone, book, or piece of paper, as well as hand and finger movements, which may be a test-cheating tactic. This system also features a simple user interface that makes it easy to access each of these features.

Additionally, this system operates in real-time and offers a graph of the emotional states of the students throughout the educational session. It also sends students' comments during the lesson and feedback about each student to the instructor afterward. This system seeks to protect students' privacy and makes sure that it will be convenient and easy to use even if the instructor changes the presentation and teaching methods later on.

To summarise, the fundamental contribution of this thesis is the connection made between online learning environments and CNN-style facial emotion recognition models. In addition to this approach, it will help raise the standard, effectiveness, and legitimacy of online distance learning.

1.8 Synopsis

A facial identification system is a piece of technology that can identify a human face in electronic photos or a video clip by comparing it to a database of faces. Through identity verification services, users are frequently verified. Face detection algorithms are reliable and efficient if systems that analyse the information in face pictures are fully automated. The inability to perceive students' emotions and the two main issues with distance learning practices that universities may run across are properly evaluating them in electronic evaluations. That might happen as a result of how difficult it is to adequately supervise students and evaluate emotions in the classroom, particularly in distance learning situations.

Technology and online learning tools can help students develop their self-guided learning abilities. One of the tools utilized in eLearning to monitor cheating and other irregularities on exams is the facial identification system. In comparison to more conventional methods, students who use distance learning technologies are more involved. Lecturers have the opportunity to monitor students more closely through remote learning, enabling them to perform well on tests and realize their full potential. Algorithms like face reader and the X press engine have been deployed to assist lecturers properly determine their students' emotional and cheating behavior. There is a need to further developed the facial recognition system for detecting student’s emotion and cheating behavior.

1.9 Limitations of the Study

Moreover, it's vital to note that there are no methods that are completely free from constraints, and the most significant constraint that this research faced is the real-time constraint based on recognizing facial emotions. This is the case for most automatic algorithms. The taking of images is greatly influenced by the location of cameras.

To produce something new and typical, some obstacles must be overcome at each stage of life. Here are some difficulties that were overcome. During the review of literature, numerous studies, particularly those that are directly linked to the topic under consideration, were examined, but information on the detection of cheating behavior patterns and characteristics of faces proved challenging. In addition to the selection of appropriate and reliable websites and other sources, there are other difficulties faced in this study.

The lighting conditions of the facial recognition process have an impact on optical flow, which analyses motion and approximates pixel density animation. Both a bright environment and a very dark environment have an impact on accounting for optical flow, which is unable to identify motions. Face rotation and head movement are both exceedingly challenging issues since they have an impact on the processes of detection, analysis, and classification. Detecting and correcting head movements is particularly challenging. Therefore, the main difficulty in this situation might be attributed to head movement.

With the aid of this developed system, it is possible to increase the validity of e-exams and the efficacy of distance learning, but there were a number of limitations, including the incapability to automatically identify full head movements, the incapability to take into account the different ways that a single student may express the same emotion to another, and the poor internet connection in countryside areas.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

This section presents and discusses the relevant literature about facial recognition systems to monitor students in distance learning. Many sectors have been controlled by technology because it is involved in development, particularly in teaching and learning. The growth of electronic education, which is becoming increasingly common in educational systems across the world, has improved teaching and learning. Despite its many benefits, it nevertheless has several flaws, such as a lack of tools to accurately recognize students' emotional changes and behavioral shifts toward negative attitudes in online classes, which represent a vital impact on their success (Lim et al., 2021). The section also provides background information necessary for comprehension and present some relevant earlier studies.

2.2 Face Identification

The process of determining the presence of human faces in an image or video is known as face identification (Carragher, Towler, Mileva, White, & Hancock, 2022). Face detection is regarded as a crucial first step that must be carried out before the recognition procedure. Because this system was previously trained to pinpoint the location of the face, face detection must find the face in the backdrop (Kumar et al., 2018). In the 1970s, face detection was invented for the first time. It continues to be enhanced, and in order to work in real-time, several contemporary tools are needed (Young, 1970).

There are numerous different kinds of software that may be used for all detections and recognitions, segmentation, sorting, and feature extraction to find the targeted faces and the number of persons present in the monitoring area. The capability of the program to be employed in biometric analysis systems and pattern matching, such as fingerprint matching, makes it helpful and advantageous (Li et al., 2015; Zhu et al., 2015). The image processing program, which is made simple by the use of MATLAB and Python, is the finest for such operations. The primary issues are how to identify faces using real-time recognition and its percentage (Sokolova, Savchenko, & Nikolenko, 2022). Face identification in digital is characterized as determining whether a user is legitimate or a fraud attempting to pose as one.

2.3. Concept of Emotions

One of the most challenging ideas in psychology to explain is emotion. In fact, the scientific literature has numerous definitions of emotions. A close, fleeting conscious experience branded as a high degree of both pleasure or discomfort and intensive mental activity characterizes emotion as a common term (Schacter, 2012). There are numerous definitions of emotion in scientific discourse, but there is no agreement on a single or widespread definition. They are connected to character, motivation, attitude, and character traits (Cherry & Snyder, 2019). Emotion is characterized psychologically as a complex condition of feelings that affects both the physical and psychological self. Such modifications impact behavior and thought (Cherry & Snyder, 2019). Emotions are collections of elements that include thoughts, feelings, actions, encouragement, and physiological modifications. This is not regarded as a cause based on another theory (LeDoux et al., 2015).

Positive or negative emotions, which are connected to a particular pattern of physiological processes, are defined by some researchers as either positive or negative emotions. Numerous behavioral, cognitive, and physiological changes are caused by emotions. Additionally, they play fundamental functions in encouraging adaptive behavior. These actions would have helped ensure human survival (Pace-Schott et al., 2019). Emotions were defined by theorists as reactions to important internal and external events. Therefore, it is believed that emotions have a short duration. They are made up of a coordinated series of actions, including neurological mechanisms as well as linguistic, behavioral, and physiological ones (Fox et al., 2008; Reisenzein, 2022).

According to Graham and others, who are psychotherapists, emotions can be understood as occurring on a spectrum of intensity (Graham et al., 2014). They demonstrate that the shame-related feelings can range from mild embarrassment to poisonous humiliation. Additionally, the emotions of dread can range from slight worry to terror (Graham et al., 2014). Therefore, emotions offer helpful remedies to the long-standing issues that our ancestors experienced in earlier times. They are therefore considered to be biologically innate and the product of evolution (Ekman, 1992). There are many important queries, such as: What is emotion? In addition to being scientific, this query is regarded as the ideal heading for the most well-known theoretical studies on emotions. For instance, the American psychologist and philosopher William James offered an influential theory of emotions in his essay titled "What is an emotion?" in 1884 (James, 1922). In light of this, his theory states that emotional intensity is correlated with the perception of specific body changes. Many contemporary theories take this stance, describing bodily responses as the cause rather than the effect of the emotion. The numerous disputes this hypothesis sparks serve as its yardstick. This demonstrates how challenging it is to come to terms with a precise definition of the complex and dynamic phenomenon known as emotions. The emotion can serve as a useful point of reference for a wide variety of effective activities, including emotions, feelings, wellbeing, and effects (Boekaerts, 2010). Another concept that was introduced in 2013 focused on an event and viewed emotions as a quick process. It consists of two steps: the first is a activate mechanism that is based on the event's applicability. The second one is the emotional reaction to numerous elements, such as behavior patterns and autonomic nervous system control reactions. the heartbeat, facial expressions, and feelings, for instance. Accordingly, the feeling is fleeting and brought on by a specific incident, but also, based on that description, it is a dynamic occurrence with a number of elements.

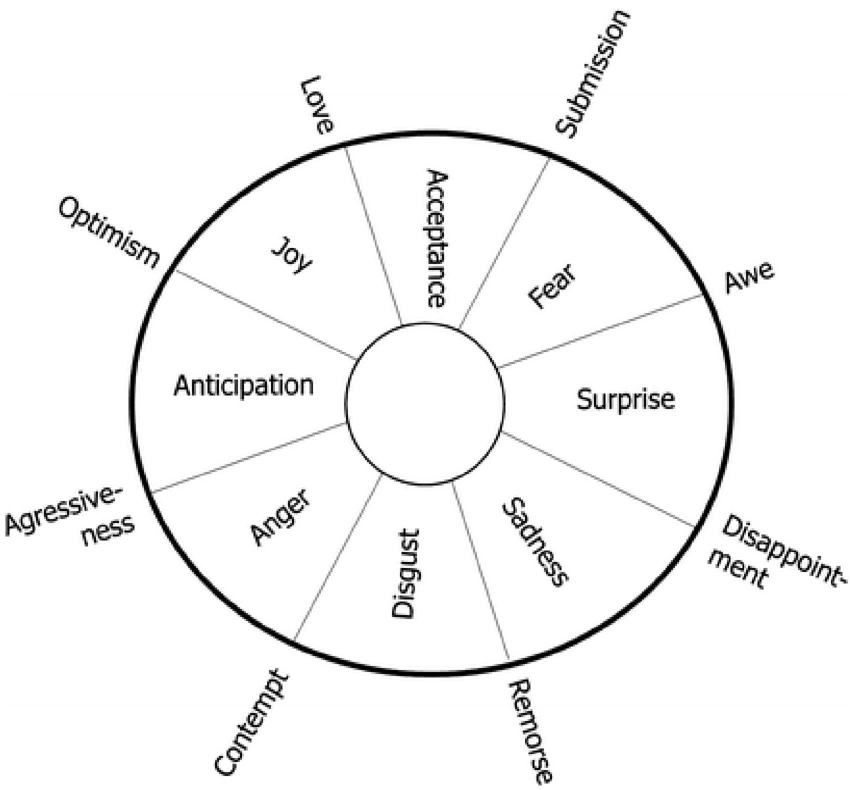
2.4. Emotion Classification

To better comprehend the notion of emotions, numerous studies have been written that recognize and categorize the different forms of emotions. As a result, we might draw the conclusion that Paul Ekman's classification from 1972 is important. He gives the example of the notion that there are six fundamental sorts of emotions that are present in all human societies. The various categories for them include disgust, fear, surprise, fury, happiness, and sadness (Ekman, 1992).

Paul Ekman attempted to include more main categories in 1999, including satisfaction, delight, excitement, disdain, embarrassment, and happiness (Ekman, 1999). Robert Plutchik, however, developed the wheel model in 1980 and provides additional emotion classifications (Handel, 2011). It was developed to explain how different emotions interact with one another. According to Robert Plutchik, a psychologist, there are eight main emotions: trust, joy, anger, contempt, fear, surprise, sadness, and anticipation. Figure 1 depicts this paradigm. In addition, he says there are eight fundamental bipolar emotions, including surprise and anticipation, rage and fear, acceptance and contempt, and happiness and despair. Most neuropsychologists and philosophers disagree with this categorisation because such emotions are blended in many different ways. However, Turner and Orton produced a vast array of studies to categorize the basic emotions in 1990. (Sander, 2013).

Figure 1

Plutchik's Model



2.5. Emotional Learning

2.5.1. Classroom Orchestration

It is described as the approach instructors use to manage a number of tasks in a situation with a variety of constraints (Roschelle et al., 2013). The function of instructors in schools is crucial. Through their instruction, they ought to consider the most recent paradigms. At this time, students are thought to experience both positive and negative emotions in the classroom. Therefore, it is crucial to address the issues of passivity and stress by fostering the right emotions in order to promote learning. In the classroom, feelings and knowledge coexist. Therefore, such blending creates safe, emotionally stimulating situations that both stimulate information acquisition and challenge and test students (Shuck et al., 2013).

2.5.2. The role of emotions in learning

Emotions are very vital since they are crucial to the learning process (MacIntyre & Vincze, 2017). They aid pupils in acquiring new knowledge and abilities. Additionally, they play a significant role in helping pupils succeed in school and commit to their studies. However, it is crucial that the way in which students are taught and the lecturers they work with take into account their emotional states. For instance, lecturers and instructors need to be able to control the emotional outbursts of their students. To give an example, they can lessen anxiety and stress. Additionally, they must be able to educate pupils how to regulate their emotions and provide a supportive learning environment for them. As a result, emotional control is crucial, which is why it is simple to recall, transfer, recover, and gather new information in addition to what we already know. As a result, emotions have a huge impact on our ability to learn, focus, solve problems, and think critically. Over time, students who experience negative emotions like anxiety or frustration will do worse on tests than those who approach them optimistically as challenges (MacIntyre & Vincze, 2017).

2.6. Face Emotion Recognition

Finding the emotions based on facial expressions is said to be a challenge inherent in human nature (Shahin, Hindawi, Nassif, Alhudhaif, & Polat, 2022). To be clear, there are many signs on a human face that provide dynamic information for a variety of subtle emotional indicators. Additionally, the development of the machines has the potential to produce the visual sense in face recognition, which has many advantages over computer science, cognitive science, arithmetic, physics, psychology, or even neuroscience. Physically speaking, it is essential and vital for robots to be able to recognize the emotions on a person's face as they become more widely available. It is obvious that the best body part for detecting human emotions is the face. The concept of face expression recognition is novel (Asokan, Kumar, Ragam, & Shylaja, 2022). Where an attempt has been made to automatically analyse face expressions by using motion spots on a picture stream. A link between all the voiced and experienced emotions was evident during that trial (Valente et al., 2018). For instance, the strength of the involuntary emotion that was not prepared purposely can be clearly seen in the facial expressions.

The secret to effective human communication must be the development of contemporary methods that enable machines to comprehend the defined meanings of gestures and place them in the context of sentiments. As a result, several techniques are used to identify emotions from the face. Such methods, which successfully address the major emotional groups, rely on relatively basic static models (Lennarz et al., 2019). These studies also focus on the mechanical action of the facial muscles that produce emotional facial emotions from various physical zones. As a result, it was discovered that dynamic information is important in identifying emotions. As a result, the wanted analysis depends on more authentic facial expression sequences rather than the isolated captures that are typically shown in the first databases (Fan & Tjahjadi, 2019). As a result, it is more challenging to establish emotional detection when it is applied to natural sequences as opposed to isolated emotions (Fang et al., 2014). Other approaches of categorizing data from facial expressions rely on precise coding systems that are close to dynamics, in which the activities of the face are coded in a collection of action units (AUs) with a muscular base known as the Facial Action Coding System (FACS) (Wibowo et al., 2019). Since automatic identification are screened by action components from facial motion systems, many authors worked by considering the dynamics of changing faces (Wetcho & Na-Songkhla, 2022).

Several face-based emotion identification systems and numerous methods, such as optical flow measurement, address the issue of face tracking (Zhang et al., 2018). Along with numerous other techniques, including active contour models (Lamba & Nain, 2020), face identifications, recovering the pose of the face apart from the facial expression (Siddiqi, 2018), a probabilistic approach to detecting and tracking human faces (Danelljan et al., 2020), active (Tzimiropoulos & Pantic, 2017), adaptive (Romanyuk et al., 2020), appearance models, multiple Eigen spaces-based techniques (Nanthini et al., 2021).

Many classifiers utilized in various facial expression detection tasks are made clear by the machine learning framework. Hidden Markov Models, Neural Networks, Linear Discriminant Analysis, Support Vector Machines, and Bayesian Network Classifiers are some of the techniques used to solve the recognition problem. For additional information, see (Ahmed, 2021; Li & Deng, 2020; Revina & Emmanuel, 2021). As a result, various methods for analyzing facial expressions of emotion, such as parametric models that extract the form along with the movement of the eyes and brows, the mouth also moves, can be highlighted (Rundo et al., 2017). Where the primary facial muscle directions are categorized in the emotion recognition system discussed in (Devi & Preetha, 2020). Lips, nasolabial furrows, and wrinkles are examples of permanent and ephemeral face features that are thought to be frequent indicators of emotions (Stöckli et al., 2018). Additionally, geometrical models that use strongly rectangular locations and include the appropriate facial muscles are useful for putting together facial expressions. The geometrical relationships and features are therefore the more important details (Singh et al., 2019). On the other hand, a common element in the detection of facial emotions is that it begins with the discovery of the face zone and extracts and tracks the pertinent facial data. The classification of facial expressions, which will be examined to determine activities associated to emotions, is among the final steps.

2.7. Face Recognition through E-Learning

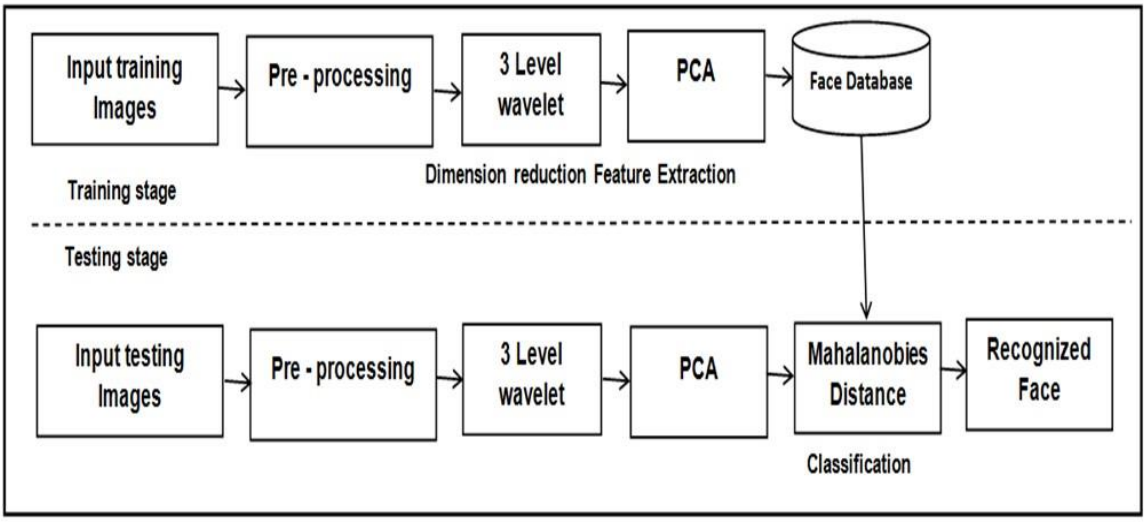
Face recognition is broken down into a number of categories, including AI and human-computer interface, to name a few (Jibrin & Muhammad, 2017). Face Recognition is used in e-learning as both a login system and a verification. As a result, the system is thought of as authenticating every account that is logged in as the original user or as someone imitating the original user. Figure 2 illustrates the stages of the facial recognition process, with the majority of portions dependent on 3WPCA-MD (Three-level Wavelet Decomposition Principal Component Analysis with Mahalonobis

Distance). It is a method that includes three stages of wavelet decomposition in the feature extraction that occurs between PCAs. However, Mahalonobis Distance is used in the classification features (Winarno et al., 2014).

As a result, the findings of such a tool are quite accurate in an experiment by Winarno et al. (Winarno et al., 2014), where the degree of dependability can reach 95.7 percent average and has swifter face identification calculation results, especially when than the traditional PCAs approaches. Because Mahalanobis Distances Classification is supported, the average computational velocity value using the 3WPCA-MD tool for each facial recognition procedure is approximately 5-7 milliseconds (ms). This Mahalanobis distance is a well-known method for creating classification results that take advantage of the data structure (Roth et al., 2014). Another work by Winarno et al. (2017) demonstrates how the 3WPCA is utilized to prevent face data falsification with identification accuracy that exceeds 98 percent and offers a good turnout system dependent on the face identification.

Figure 2

Pre-processing Face Recognition



2.8 Facial Emotion Dataset

Currently, social networking sites like Facebook, Instagram, Linkedin, and Twitter are the primary sources for text data mining, and the Internet serves as a convenient medium for people to voice their thoughts. As they do so in their regular activities to convey their thoughts, feelings, or responses, pupils use it (Tian et al., 2014; Xu et al., 2022). In a separate investigation, the researcher received feedback from students at the Institute of Management Technology (IMT) Nagpur, India. Facebook, Twitter, and MOODLE were utilized in order to do that (Jena, 2019). As a primary source of the vast amounts of data used by academics in their studies and tests, the Internet has become increasingly important. The following are the most important online databases for studying facial expressions:

1. ***Amsterdam Dynamic Facial Expression Set (ADFES)***

   There are numerous descriptions in the Amsterdam Dynamic Facial Expression Set (ADFES) data set. It has more than 620 different emotional emotions, for instance. These sets are precisely becoming understood throughout time to represent dynamic activities. Along with the other six primary emotions, disdain, glory, and astonishment are taken into account. About 22 people total 22 men and 10 women from Northern Europe and the Mediterranean regions are included in the collection. Additionally, it employs lively turning to show the expressions' orientation because researchers can also access it (Van Der Schalk et al., 2011).

2. ***Amsterdam Dynamic Facial Expression Set Bath Intensity Variations (ADFES-BIV):***

   The dataset group known as the Amsterdam dynamic facial expression set bath intensity variations, or ADFES BIV, is known for having a variety of properties. For example, it is viewed as a continuation of the earlier ADFES. More than 12 North European subjects, including ten performers from the Mediterranean region and five girls and seven males, use it. Through the expression of the six basic categories of emotions, including three complicated sentiments, they represent five girls and five males (Wingenbach et al., 2016). The dataset for ADFES BIV was created by Wingenbach et al. Editing 120 or so videos will accomplish this. Twelve actors from North Europe played these videos as they attempted to add three classes of intensities. So, using the identical feelings at three different intensities, low, medium, and high, three films were created. 360 movies in total make for a superb dataset because they are freely available to the majority of scientific researchers or for research purposes (Yang & Yin et al., 2017).

3. Binghamton University 3D facial expression (BU_3DFE)

It includes three-dimensional models for synthetic and human facial skin. Additionally, it has the feature that its size has an average of 2500 models for every 100 substances, 44 men, and more than 55 women. The ages that can be used range from 18 to over 70. The datasets' aimed expressions also include the emotions of happiness, fear, shyness, anger, surprise, and sadness. It also has posed expression for a further four distress degrees. To further exemplify, it is regarded as the first attempt to create a 3D face expression dataset that is accessible to the general public, or any research needs in communities (Hayat & Bennamoun, 2014).

4. Bingthman University 4D facial expression BU_4DFE

About three-dimensional videos used to identify face expressions are included in this dataset. There are more than 100 of them, with roughly 43 men and 58 women. They are between the ages of 18 and 45. They come from a variety of ethnic and ethical backgrounds as well. There are around 28 Asians, 8 Blacks, 3 Latinos, and 6 White people, for example. It contains the same 6 emotions as the previous one. Additionally, the facial expressions were recorded to produce a 4-second film. It features a 2-dimensional texture of various sequences and 3-dimensional shapes with approximately 25 frames per second. Finally, for it to benefit the social community, it must be accessible (Lucey et al., 2010).

5. The Cohn Kanade CK dataset

The Cohn Kanade CK dataset is the most used one. Out of 100 patients, 380 picture sequences are present. Every component and sequence have 12 to 16 frames. Additionally, the subjects' used ages range from 18 to 30 years old. 35 percent of them are male and 65 percent are female. The subjects used vary since they come from a wide range of sources. For instance, nearly 50% of the population has African American ancestry, and 3% has Asian or Latino American ancestry. Along with the neutral ones and the six fundamental emotions, it also offers staged expressions. The photographs must, however, contain sequences because some other subjects do not. There may be just one picture sequence for each expression. Finally, it is made accessible to the public with some restrictions (Jain et al., 2011).

6. Extended Cohn_kanada (CK+)

In addition to their duration level, which ranges from roughly 10 to 60 frames, the 593 sequences in the CK+ dataset that were produced from 123 participants are not considered to be fixed-length sequences. The neutral stance was the starting point for each sequence, which continued until the highest configuration for expressiveness was reached. The dataset included the locations over facial features, nevertheless. They are thus undeniably visible. Additionally, there must be both spontaneous and pose-based expressions. In addition to the neutral emotions, it also comprises the six primary emotions. Finally, roughly 309 out of 593 sequences in datasets are thought to represent the six fundamental emotions; as a result, it is freely accessible to research fields (Ebner et al., 2010).

7. The FACES dataset

About 171 real faces from all age groups, young, middle-aged, and elderly, are included in the FACES dataset. Both men and females are present. It is available to the public for free use in any scientific study and studies and contains over 2052 photos of individuals and almost 150 subjects of all ages (Goodfellow et al., 2013).

8. Facial expression recognition (FER_ 2013)

This particular dataset consists of more than 35887 photos, 28709 samples used for training, more than 3580 samples used for authentication, and 3589 samples used for testing. However, it also includes the key phrases that are offered for each sample. They must include a resolution of roughly 48 by 48 pixels for the Gray cycle photos. Such a dataset was created by using an API to search Google Photographs for images that may contain faces that fit a collection of 184 emotions that are related to the phrases, such as joyous and angered. Additionally, it's free to download (Jabid et al., 2010).

9. Japanese female fashion expression (JAFFE)

About 213 photos from the JAFFE dataset are specifically used for a few female facial expressions. Ten subjects are used to express them. The resolution of each image is 256 by 256 pixels, and there are an equal number of images for each type of expression. In order to highlight the emotive features of the chosen faces, all head shots must be taken in frontal perspective. However, the tungsten lights had to be set up in a way that would make it possible to clearly see the features of the face. Along with the neutral emotions, they must also include the six fundamental emotions. As a result, it can be utilized for free in only non-commercial research projects (Aifanti et al., 2010).

10. The multimedia understanding group (the MUG)

The type of data group includes a collection for the facial expressions that were employed in the image sequences, both posed and natural. Because of the great resolution and lack of occlusions, the entire sequences are captured in this instance in a controlled laboratory setting. The image collection consists of two parts and has a resolution of approximately 896 896 pixels. Nearly 86 subjects, 51 men and nearly 35 women, make up the first segment. Six fundamental emotions and the neutral one is performed. The second type also contains those subjects, but this time they are viewed as watching a film that simulates the desired emotions. About eighty points in the facial feature dataset have both the manual and the automatic explanations. Finally, the majority of the dataset's recordings are accessible to researchers (Olszanowski et al., 2015).

11. Warsaw set of emotional facial expression pictures (WSEFEP)

With 210 high-quality photographs, comprising 30 subjects, WSEFEP is able to have genuine expressions because to its incredibly high picture quality. It is freely accessible and can be downloaded for a variety of purposes, including requested scientific research (Rahulamathavan et al., 2012).

2.9. Facial Expression Recognition Methods

i. Architecture for Face Recognition Systems

Face identification systems may employ videos or images, therefore the output from all facial identification systems is used to verify or identify persons.

Other methods (Farokhi et al., 2016) perform it in three steps, with the possibility of combining face extraction and detection. Face Detection, on the other hand, is the technique of extracting faces from scenes. Consequently, the system's maps incorporate particular portions in a background as the face (s). Although the user appears to be moving, the system continues to follow the face, obtains, and crops the facial image to complete the detection process. A procedure known as feature extraction extracts the desired facial elements from a facial image. As features derived from the facial image, variations in the areas and angles of the face are taken into consideration. The Fisher Discriminant Analysis (FDA) is the feature extraction method employed in this study, and it is this method that allows the facial identification system to ultimately recognize and verify users by verifying for their existence in the database. The stage includes a test, an algorithm, and a comparison (Ghojogh et al., 2019).

ii. Feature Extraction

The process of dimensionality reduction, in which a basic group of the raw data is categorized and reduced into multiple groups to be managed, is considered as including feature extraction (Carragher et al., 2022). As a result, processing it will be made easier. The most important characteristic of this vast data group is that it contains a great deal of variables that demand a lot of computational power to handle. Therefore, by selecting and merging variables into features that decrease the amount of data, feature extraction aids in obtaining the optimal feature from massive data sets. The selection and extraction of pertinent elements is one of the most important steps in the recognition of sentiments (Dave, 2013). They are selected to deliver the desired information. Selecting the area is one of the difficulties in feature extraction. The signal is divided into frames using this tool. As a result, each frame is being used to extract features.

Linear Predictive Cepstral Coefficient (LPCC), Wavelet and RASTA PLP (Relative Spectral Transform), Mel-Frequency Cepstral Coefficient (MFCC), and Linear Discriminant Analysis (LDA), and others are all useful methods for feature extraction (Wen et al., 2018). Numerous examples include the discrete wavelet transform (DWT) (Wen et al., 2018), modulation spectral features (MSFs), and more. The most recent algorithms for categorizing speech emotions involve a mix of numerous variables. Quantitative involvement in the estimation of an emotion is part of the clever feature combination. Numerous studies on feature combinations showed an improvement in classification accuracy rate when compared to systems that still rely on personal features (Jain, Hu, & Aggarwal, 2017; Jain et al., 2020).

iii. Classification

Since a variety of classifiers were employed, none of them was able to categorize speech emotions in the most effective way. Both advantages and disadvantages apply to any classifier. Whose extracted features and database chosen will determine this. Among the classifiers, one may name the Gaussian Mixture Model (GMM), Support Vector Machine (SVM), and Hidden Markov Model (HMM) (Swain et al., 2018). Recurrent neural networks (RNN), restricted Boltzmann machine (RBM), multilayer perceptron (MLP) (Kwon, 2020), and convolution neural networks (CNN) are a few examples of the neural network models that have been used to recognize spoken emotions. Logistic regressions are used for classification (Dong, Zhu, & Gong, 2019; Ahmed, Jalal, & Kim, 2020).

For classification and regression tasks, logistic regression and linear regression are effective models. In particular, facial recognition, it obtains a high rate of recognition accuracy (Zhu et al., 2018). In modeling temporal information in the speech spectrum, the hidden Markov model, often known as the (HMM), is unmistakably recognized as a good classifier of moods. Artificial neural networks, or ANNs, are used in emotion recognition because they can identify nonlinear boundaries and linear states (Swain et al., 2018). The multilayer perceptron, often known as the (MLP), is another artificial neural network model. As soon as the ANN's architecture is established, it is fairly simple to construct and make changes to training algorithms.

Recent years have seen the application of numerous different types by scholars, such as the modified brain emotional learning model (BEL), which combines the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multilayer Perceptron (MLP) to recognize spoken emotions (Motamed et al., 2017).

Another method is the multiple kernel Gaussian process (GP) classification, which combines the principles of a linear kernel with a radial basis function (RBF) kernel (Sun et al., 2020). In order to approach the voiced signal segment as a textural image processing characteristic that differs from the conventional wisdom, the Voiced Segment Selection (VSS) technique is recommended (Amirgaliyev et al., 2017). The Log-Gabor filters are used to extract both voiced and unvoiced characteristics from the spectrogram. The emotional recognition of speech may make use of additional classifiers, such as decision trees (Sun et al., 2019) and K-nearest neighbor (KNN) (Mao et al., 2019). They require hand-crafted features that are very high resolution and empirically chosen.

iv. Facial Recognition Techniques

Based on their algorithms, face recognition is categorized or divided. For facial recognition, there are many different methods such as machine learning.

Where machine learning is a branch of artificial intelligence (AI). The definition Arthur Samuel gave of machine learning in 1959 is the simplest one to understand: "discipline of research that gives computers the ability to learn without being explicitly programmed." This definition offers a compelling understanding of the particular strategy used by this major. It is distinct from other majors in that every new feature must be manually added. For instance, in software enhancement, if a new requirement arises, the programmer must create a specific software to handle this new situation (Spiers, 2016). But in the ML, the situation is different. Models are created by its algorithms based on the given data. These models generate an output, which is often a group of forecasts or conclusions. The model may then be able to handle a new need or to provide a response without the need for further coding. Three broad categories can be used to categorize ML. Every area focuses on how a learning system carries out a learning process. They are reinforcement learning, unsupervised learning, and supervised learning (Kan, 2017).

Supervised learning occurs when a certain model accepts a set of categorized inputs together with the corresponding associated class. In an effort to translate each input to the proper output class, the model tries to change itself.

Unsupervised learning nevertheless receives a set of inputs that are not labeled. As a result, the model makes an effort to learn from the data by identifying patterns in it. Finally, reinforcement learning occurs when an agent is rewarded or penalized, leading to decisions being made to accomplish the aim (Kan, 2017; Spiers, 2016).

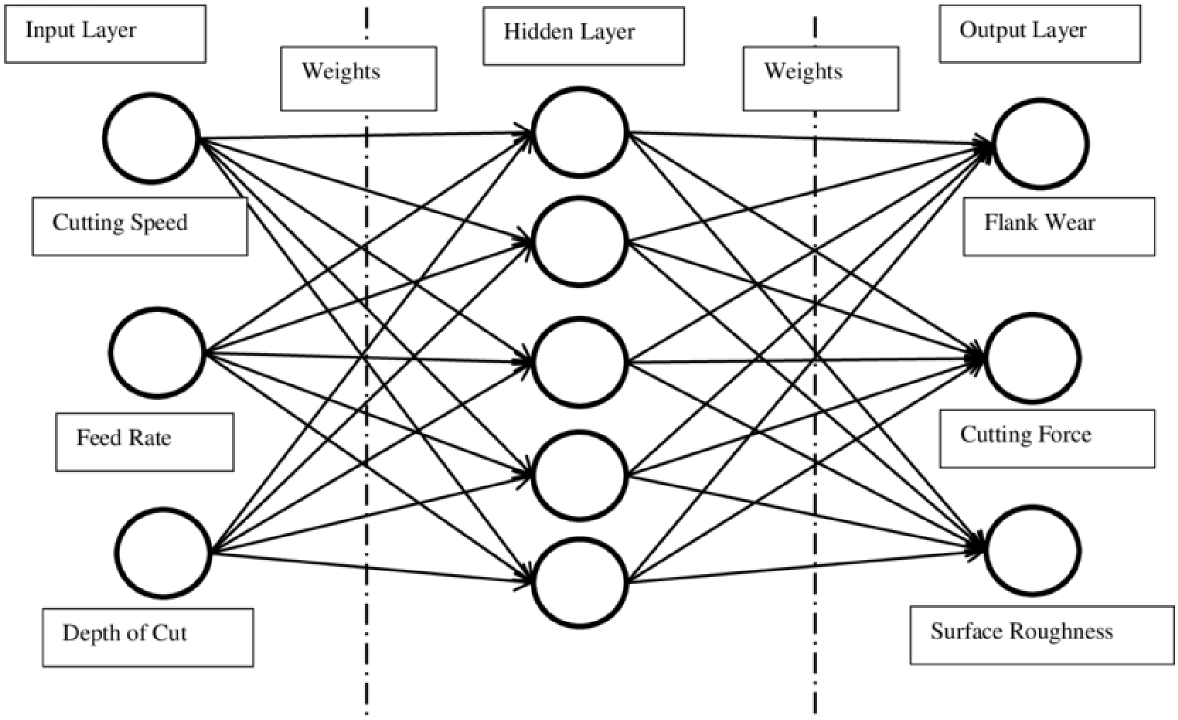
Unsupervised learning examines a collection of data that just consists of inputs and look for structure, such as grouping or data clustering. Thus, test information that has not been classed, or grouped is used by the systems to learn. Unsupervised learning recognizes patterns in the data and act based on the presence or absence of such patterns in each new piece of data rather than on feedback. The discipline of density approximation in data, which includes determining the probability density meaning, is a key area where unsupervised learning is applied (Prezelj et al., 2022). Unsupervised learning, however, also covers areas where data features need to be summarized and explained. When performing a cluster analysis, a set of data is divided into smaller groups, or "clusters," where data from the same cluster are similar based on one or more predetermined criteria, whereas data from other clusters are not. Diverse clustering methods base their expectations on different aspects of the data's structure, which is frequently determined by similarity metric and assessed, for instance, by internal density, or the comparation between cluster components, and partition, or the distance between clusters. Other approaches rely on graph connectedness and estimated densities. ML concentrates on prediction, according to known qualities learnt from the training data, this technique use analysis step of knowledge discovery. In contrast, ML also uses data mining techniques as "unsupervised learning" or as a preprocessing step to increase learning precision.

Artificial neural networks (ANNs), also known as neural networks (NNs) or neural nets, are computer architectures that draw inspiration from the biological neural networks seen in animal brains. Artificial neurons, which are a set of interconnected units or nodes that loosely resemble the neurons in a biological brain, are the foundation of an ANN. Like the synapses in a human brain, each link has the ability to send a signal to neighboring neurons. An artificial neuron can signal neurons that are connected to it after processing signals that are sent to it. The output of each neuron is calculated by certain non-linear function of the sum of its inputs, and the "signal" at a connection is a real number. Edges refer to the networks (Yang & Wang, 2020). The weight of neurons and edges often changes as learning progresses. The weight alters a connection's signal intensity by increasing or decreasing it. Neurons may have a limit, and only send a signal if the combined signal crosses it. Neurons frequently group together into layers. Separate layers may modify their inputs in different ways. Signals move through the layers, perhaps more than once, from the first layer (the input layer) to the last layer (the output layer) (Smys, Basar, & Wang, 2020).

ANNs were initially developed in an effort to use the human brain's structural design to carry out tasks that were difficult for traditional algorithms to successfully complete. Figure 3 displays artificial neural network topology. They soon abandoned efforts to remain true to their biological forebears and refocused on enhancing empirical findings. To enable the input of some neurons, develop into the output of others, neurons are linked to one another in a variety of ways. The system creates a weighted, targeted graph. A group of simulated neurons make up an artificial neural network. Every neuron function as a node that is linked to other nodes by networks that mimic biological neurite-synapse-dendrite links. The weight of each link controls how strongly one node influences another.

Figure 3

Artificial Neural Network Topology



Deep learning (DL) is a subset of a larger family of ML techniques that combine image learning and artificial neural networks. Several network layers are utilized when the term "deep learning" is used. A network with one hidden layer of unlimited width and a nonpolynomial initiation function has been shown to be more universally useful than a linear perceptron, according to early research. DL is a contemporary variant that focuses on an infinite number of layers with limited sizes, allowing for pragmatic function and optimized application while maintaining theoretical demand under benign requirements (Abu-Saqer, Abu-Naser, & Al-Shawwa, 2020). For the sake of effectiveness, trainability, and comprehensibility, DL also allows the layers to be diverse and deviate significantly from biologically inspired link models.

DL architectures have been used in a variety of domains, including deep neural networks (DNN), deep reinforcement learning, and deep belief networks. This includes computer vision, medical image analysis, natural language processing, machine translation, speech recognition, and material inspection. Where they have achieved outcomes on par with, and in some instances even better than, those of human experts (Cheng et al., 2020).

An ANN having more than two levels between the input and output levels is called a DNN. Although there are various kinds of neural networks, they all share very similar building blocks: neurons, synapses, loads, preferences, and tasks (Abu-Saqer, Abu-Naser, & Al-Shawwa, 2020. These elements can be trained similar to any other ML system and collectively perform comparably to the human brain. For instance, a DNN trained to identify cattle strains will examine the provided image and determine the likelihood that the cattle in the image belongs to a particular strain. When reviewing the outcomes, the user can choose which possibilities the network should show (those that are higher than a given limit, etc.) and return the suggested label. Each individual statistical operation is regarded as a layer, and complex DNN have several levels.

DNNs can simulate intricate non-linear interactions. The object is expressed as an overlaid structure of primitives in a model created by DNN designs. With the additional levels, information from lower levels can be combined to describe complex information with less elements than a surface network with equivalent performance. For example, it has been demonstrated that DNNs are exponentially simpler to estimate than surface networks (O'Mahony et al., 2020).

Convolutional neural networks (CNNs) are a type of ANN used most frequently in DL to interpret visual data. Multilayer perceptrons are modified into CNNs. Completely linked networks, or multilayer perceptrons, are those in which every neuron in one layer is linked to every neuron in the following layer. Due to their "complete connectedness," these networks are vulnerable to data overfitting (Zhou, 2020). Regularisation or overfitting prevention methods frequently involve punishing training parameters (e.g., weight deterioration) or cutting connectivity (bounced networks, regress, etc.). By utilizing the classified structure in the information and assembling designs of growing complexity utilizing lesser and easier models imprinted in their filters, CNNs adopt a novel strategy for regularisation. CNNs are thus at the lower end of the connectivity and convolution spectrum (Roy, Panda, & Roy, 2020).

Since the connecting arrangement between neurons mirrors how the animal visual brain is set up, convolutional nets were motivated by biological methods. The responsive area, a constrained area of the visual space, is the sole area where distinct cortical neurons react to inputs. The full visual space is covered by the limited overlap of the receptive areas of several neurons. Comparatively speaking to other image classification processes, CNNs employ a minimal amount of pre-processing. This implies that, unlike conventional methods where these filters are part-directed, the network learns to optimize the filters through automatic learning. This feature extraction's autonomy from preceding information and human interaction is a significant benefit (Zhou, 2020).

Layers using convolutions transmit their output to the following layer after convolutioning the input. This resembles how a visual cortex neuron would react to a particular stimulus. Every convolutional neuron only methods information for its specific receptive field. Even though completely linked feedforward neural networks can be utilized to learn features and categorize information, this design is typically unfeasible for higher inputs (for example, high-resolution images), where it would be necessary to use enormous numbers of neurons because each pixel is a significant input feature. Each neuron in the second level of a completely connected layer for an image of size 100 by100 has 10,000 weights. Convolution limits the amount of open parameters, enabling a deeper network. For instance, just 25 neurons are needed when employing a 5 5 tiling region with identical shared weights for each tile (Huang et al., 2020). The vanishing gradients and ballooning gradients issues encountered during backpropagation in older neural networks are avoided by using regularized weights across fewer parameters.

2.10. Applications of Facial Emotion Recognition

In order to boost vehicle safety, find depressed writers, provide emotion-sensitive interfaces, and provide distance learning settings, affect systems were developed (Quan and Ren, 2016). Since coexisting alongside humanoids (robots) is intended to be a vision of the future for humans, technological advancements in robotics and their capacity to recognize emotions in addition to comprehending and meeting human needs are seen as significant advances. For older individuals or those with disabilities, service robots that take into account human emotional state may appear to be of great assistance (Asokan et al., 2022). A humanoid robot makes an effort to mimic interpersonal interactions between people. Model of User's Emotions (MOUE) and Robot Kismet (Breazeal, 2003) are two examples of robots that can recognize and communicate with human emotions (Perez-Gaspar et al., 2016).

Robot Kismet is a social robot that can identify different speech inflections such as calm, grief, happiness, surprise, contempt, rage, scary, and exhaustion. Jibo is a Kismet extension that served as a companion robot for businesses (Alperstein). It can narrate stories, capture pictures, and recall important events, for instance. A smart interface called MOUE allows for patient monitoring at a distance. This technology uses a webcam and a wristband link to a computer to record physiological signs and emotional movements. The data is extracted and processed on a centralized computer. An animated character (avatar) that closely mimics the patient's facial expression can be used to interact with this artificial system by the patient. Frustration, grief, fear, rage, and neutrality can all be processed by it.

Due to the interest, it has received from both academics and businesspeople, face recognition has emerged as one of the most important areas of computer vision research. Commercial and law enforcement applications can be found in numerous fundamental domains where this technique was used.

- Law enforcement areas: Real-time matching using video picture sequences using surveillance cameras and so-called mugshot albums (static matching) (Tolba et al., 2006).

- Security access control: Face recognition is heavily used in environments where access is restricted to a small group of people and is extremely secure. Face-recognition technology is utilized to enter these locations. Chui, Trueface.ai is creating a facial-recognition doorbell using deep learning methods for fraud recognition and distinguishing a human face from an image (Kaur et al., 2020).

- Surveillance systems: A considerable number of CCTV cameras have recently been installed at key sites to aid in the identifying process. CCTV camera footage can be used to identify and identify people based just on their faces.

Due to the ability of technology like Face First to identify consumers' faces at a distance of up to 100 feet, theft rates in numerous superstores like Walmart have decreased by almost 30 percent (McClellan, 2019).

- General identity verification: Recent attempts to authenticate identity using facial photographs of individuals on major individual papers such national identification cards and passports (Ogochukwu, 2019).

- Image database investigations: When a person is lost, their identity is created by comparing their photo identification to databases already in existence (Tian et al., 2018).

- Mobile and laptop applications: Today, smartphones and laptops utilize face recognition technology instead of pin codes and passwords to protect user data. Arnautovski, 2019).

- Forensic science: In addition to being a fundamental research area in the field of forensic science, facial recognition is a very valuable technique. In the absence of technology, forensic scientists must do this important duty manually. For purposes of comparison, police enforcement may find it to be quite helpful (Zeinstra et al., 2018).

- Miscellaneous: It comprises names of people who have been identified as sources of evidence by police, hospitals, and courts (Zeinstra et al., 2018).

2.11. Online Learning Environment

The quick adoption of technology and the internet has changed how people live. In every aspect of our lives, everything goes online. There is also a role for the educational system. For instance, eLearning refers to online and computer-based learning. When compared to e-learning, traditional educational methods are less effective because e-learning offers many advantages like improving performance and cutting expenditures. It is possible to do asynchronous e-learning (Al-Shalchi, 2009). Both the advantages and disadvantages of this tool are present. When participating in asynchronous online learning, students can begin and end their courses whenever it is most convenient for them. Synchronous online learning, on the other hand, allows users and students to participate in real time. As a result, the following lists numerous common attributes of synchronous and asynchronous e-learning (Hrastinski, 2010).

Asynchronous online learning was pre-produced, available sporadically on demand, autonomous, self-managed, and cooperative. Live, real-time, planned, concurrent, and cooperative learning are all characteristics of synchronous e-learning. Self-learning courses, web coaching, broadcasting, computer-aided systems, discussion boards, and message boards are some of the intended e-learning methods (Amirgaliyev, Hahn, & Mussabayev, 2017). Audio and video conferences are used in these online classrooms. Along with the shared whiteboard, app sharing, and instant messaging, they are also using online conversations. In a virtual classroom, students share information in asynchronous online learning. various teaching methods that instructors use to communicate with their pupils, such as sharing a whiteboard, a video presentation, or applications. The Avatar is used to characterize virtual courses in synchronous online learning since it is comparable to a puppet. The Avatar has discovered a digital representation of users on their computers. Thus, a chosen Avatar's face employing the mirror method provides the real user facial expressions (Dharmawansa et al., 2013).

There are some similarities and contrasts between the learning environments seen in traditional (face-to-face) schools and those found online. Researchers (instructors) have made an effort to highlight the parallels between in-person and online learning (Ahmed et al., 2022). In addition to releasing the lecture notes, they used to offer similar syllabi, email and message access to the instructor. Additionally, video technologies offer a striking likeness to face-to-face classes. Based on these parallels, it is possible to observe how emotions are evoked in online environments that resemble traditional classroom settings. But because online has a certain quality, the pupils' assessments of control. As a result, the feelings felt may change. The concepts for the control-value theory are presented using various properties for both traditional and online learning environments (Heckel & Ringeisen, 2019). Some feelings are more intense in traditional, in-person classrooms than in virtual ones, and vice versa. For instance, the study reveals that in actual classrooms, happy feelings are approved more than unfavorable ones (Escadas, Jalali, & Farhangmehr, 2019). On the other hand, in the online learning environment, participants describe fundamental human emotions, including both positive and negative ones.

Pleasure-related emotions are therefore not just known to benefit students. Unpleasant emotions are not viewed as terrible, which is a paradox. For instance, the findings of several studies indicate that enjoyment is not usually the result of success (Imani & Montazer, 2019). In contrast, unpleasant feelings like boredom may really be highly beneficial for giving one time for reflection or relaxation (Boekaerts & Pekrun, 2015). The feeling of guilt might also motivate students to take action. According to earlier research, learning is made simpler by using simulations or the virtual world and learning performance has improved in comparison to more conventional learning methods (Pellas & Mystakidis, 2020). As a result, virtual learning environments facilitate learning and deepen understanding, particularly when they foster teamwork, empathy, self-assurance, and active problem-solving abilities (Mathew et al., 2019). These platforms aid in increasing belonging and trust. Such pleasant feelings improve people's capacity for learning and foster their capacity for original and imaginative problem-solving.

There are numerous effects of multimedia resources on students' feelings and performance that have been studied (Chen & Wang, 2011). The emWave technology is used to identify the learners' emotions. It becomes better The Institute of Heart Math uses physiological data from the human pulse to identify three emotional states: calm, both adverse and favorable. There is a link between student emotions and learning performance.as the three various forms of multimedia learning materials are provided to the students who are taking classes. Videos, animated interaction with text and images, static texts and images, and animated images with interactivity are the most often utilized multimedia learning resources in contemporary education (Heidig, Müller, & Reichelt, 2015). Thus, by evaluating three kinds of measured multimedia materials using video-based multimedia materials where men and women reflect significant emotional differences, the best performance and good feelings can be produced. Because of this, female students are more impacted by multimedia content than male students.

2.11.1. Effects of Emotions in Learning

According to the "attention-to-affect" concept, learning is viewed as a cognitive and emotional experience (Stojic et al., 2019). Emotions are recognized by their direct impact on human activities like learning. Therefore, it is important to understand how feelings may alter a student's approach to learning. This information may be significant because it seeks to develop learning by achieving goals and construct appropriate learning models. In accordance with Doulik et al. (2017), the style is broken down into five categories termed stimuli: physiological, which includes favourites for auditory, visual, tactile, and kinaesthetic stimuli; sociological, environmental; psychological; and emotional.

These variables influence how much a student learns, and in e-learning settings, human behavior, such as attitude, conduct, or emotion, must be replicated (Fatahi et al., 2016). Psychological research has shown that when it comes to problem-solving, decision-making, and learning processes, there are many fundamental and unique variances among people. In addition to understanding and evaluation, which are referred to as learning styles, the learning process differs because it also involves information processing (Labib et al., 2017). To give an example, the learning way has the physical, mental, and emotional characteristics that are used to understand how students engage with the learning materials and environments to learn the desired concepts (Moeller, 2021).

Many smart agents represent both emotions and personalities in order to supply a computerized agent that seeks to react to user communications. The findings have made it clear that user interfaces and educational settings are preferred that are created with their preferred learning styles in mind. For instance, the research of the intelligent agent-based learning environment (Cabada et al., 2018). As a result, the suggested learning environment has two main agents: the virtual classmate agent (VCA) and the virtual instructor agent (VTA). VTA employs the proper style and presents the student with a proper VCA based on the condition. The VCA is renowned for its unique approach to learning, and its findings indicate how the learner's level of pleasure, and its percentage are developed through encounters with intelligent agents that take into account human behavior. A novel emotional intelligent agent with three modules—perception, control, and action—is also introduced in (Chaffar & Frasson, 2004). Beginning today, agents relying on learner preference and color sequences are able to determine the learner's moods. The ideal emotional state for learning is then defined based on the learner's personality. As a result, the Bayes classifier that is used to maximize emotion expectations and the personality questionnaire are related to the identification of learners' personalities.

The instructor strives to make learning courses and being helpful for students easier for students in a classroom as a typical setting for learning. In order to be as near to the goals and needs of his students as possible, the instructor makes adjustments to the learning process. Lecturers do not, however, have a simple mechanism for analyzing the emotions and behavior of students in online learning environments. In order to address this issue, it is necessary to use computer programs that automatically detect students' emotions as well as modify the educational process to closely match their needs. In their work, Faria et al. (2017) developed a software prototype to demonstrate the emotional learning paradigm. Applying a change to the teaching process is critical when adopting efficient computing solutions. In addition to learning preferences and personality features, the emotion test platform considers the student's emotional condition. The enhanced emotion test platform is being used to replicate the complete learning process, from theoretical studying through practicing tests and assessment. Four key models are used to create it as a result: the student model, the application model, the emotional model, and the emotional educational model (Faria et al., 2015). a case study in emotional pedagogy. The emotional collaboration system is compelled to deal with the undesirable emotions and simplify the procedure of repression whenever a student experiences certain sensations that need to be suppressed (such as disgust, wrath, grief, and perplexity).

The broaden-and-develop idea states that some positive emotions, including love, pleasure, or delight, can make people more conscious and inspire innovative and exploratory thoughts, ideas, and behaviors (Tang, 2020). Positive emotions may also contribute to security and human growing, according to this notion. According to the hypothesis, experiencing happy feelings can broaden a student's range of cognition, activity, attention, or tendency. Additionally, it raises activity engagement. Positive emotions, on the other hand, increase activity support and decrease the learners' capacity for learning. The Broaden-and-Build theory's function is to enhance the acquisition of second languages, which is measured in (Rahimi & Bigdeli, 2014). The study so shows that motivation and learning are significantly impacted by happy emotions.

Many aspects and activities of human life are influenced by emotions. They significantly impact people's views, evaluations, judgments, and decision-making (Gardner & Dunkin, 2018). Currently, individual perceptions are formed with an emotional dimension (Stein et al., 2015). Researchers (Darban and Polites, 2016) made it clear that learners' perceptions of how radical new technologies are can be related to their views about their willingness to study that technology. Students have more and more opportunities to learn about new technology as educators' understandings grow. Radicalness opposes the connection between a person's true feelings and their willingness to learn. The four main emotions taken into account are avoidance, challenge, damage, and success. The results from the virtual learning setting demonstrate that while perceived radicalness is negatively associated with anger and excitement, it is positively correlated with fear. Happiness's beneficial effects are unimportant. Finally, negative emotions have greater consequences than good ones, particularly in terms of how radical people perceive things to be.

López & Cárdenas (2014) explains the impact of emotions on the acquisition of a second language. Emotional influences on learning include self-regulation, reliance on outcomes, encouragement levels, and the social environment in which learning occurs. It has been noted that some students have the capacity to transform unfavorable emotions into motivated force. In addition to the motivation and feelings of the students, the researchers in the study (Zhou, 2016) claim that the classroom learning orientation affects how well second language learners do. The findings show that language learners who suffer social anxiety have a dread of public speaking, are less independent, have less effective group learning, and are less successful in their verbal learning processes. The importance of feelings in learning a second language is also discussed in (Lockwood, 2015).

Self-regulated learning is one of the key elements in the success of online education. The primary precursors of self-regulated learning are the learners' intellectual sentiments (Yang et al., 2020). Since the mutual interaction between academic feelings and the perception of academic control in self-regulatory learning is examined, understanding the self-regulated learning process well is important because cognition and emotions are interrelated. In order to understand how Online learning involves interactions between self-controlled learning and perceived educational control, it is important to understand the significance of academic sentiments (You and Kang, 2014). Theoretically and computationally, the contributions of social interactions, in addition to emotions, to enhancing the learning process (Behera et al., 2021).

The presence of a instructor in a classroom is intended to facilitate learning as well as assist students in doing so (Rainey et al., 2018). As a result, they have a substantial impact on student performance. The instructor's nonverbal cues, such eye contact, facial expressions, postures, and gestures, communicate significant and serious communication or messages precisely if the voice is not accessible. There is a mention of the importance of emotive designs for the multimedia learning environment in (Heidig et al., 2015).

2.12 Detect Cheating in Online Exams

The majority of academic degrees awarded by higher education institutions are dependent on the performance of the students in a specified set of prerequisite courses. Exams are frequently used to judge student performance, and pertinent grades are given. Excellent marks are a requirement for advancement, so there might be a lot of pressure on students to cheat on exams in order to get higher exam scores (D'Souza & Siegfeldt, 2017). Academic dishonesty worries university administrators and staff because it compromises the validity of the degrees that universities grant their students (Drye et al., 2018). To guarantee that all students actually receive the mark that accurately represents their level of achievement, faculty members must conduct their exams under stringent oversight (D'Souza & Siegfeldt, 2017).

Many earlier studies used a variety of techniques, including the analysis of variance (ANOVA), correlation, regression analysis, the Goldfeld-Quandt Test (GQT) for heteroscedasticity, and exam results are compared between predicted and observed, starting with straightforward statistical models with illustrations and descriptions and progressing to more sophisticated inferential statistics (Harmon & Lambrinos, 2008). Application of two-dimensional graphs and descriptive statistics is the first step in the detection of cheating. These are essential for developing a conceptual knowledge of the term and spotting trends without making any assumptions, like in the other kind of statistical models. To arrange data in a form that may be utilized as inputs for statistical models, researchers use graphs. They were used to compare grades on proctored tests taken online and in-person, either separately or in conjunction with other statistical models. The test parameters' mean, and standard deviation are also calculated using it. Numerous academics employed the summaries of statistics to examine students' performing indicators and self-admitting responses for plagiarism (Hollister & Berenson 2009; Dobkin et al., 2010).

In order to figure out how to cheat on an online macroeconomics exam, Harmon and Lambrinos (2008) used correlation, regression, and variance analysis. Their final exam scores from the summers of 2004 and 2005 were predicted using a regression model using student-related explanatory factors. The courses "were essentially identical in structure and substance, despite being presented a year apart". The only significant measure that closely reflects a student's aptitude, according to Harmon and Lambrinos (2008), is GPA. In addition, absent days from class (excused or not) and the percentage of homework turned in prior to the exam day are viewed as independent variables that contribute to the learners' great grades on in-class tests (dependent variable) (Harmon & Lambrinos, 2008; Figueroa-Cañas, & Sancho-Vinuesa, 2020). These statistical models predicted whether there would be cheating on an objective exam or not. Based on statistical models, it is challenging to determine and demonstrate that particular learners have cheated (Marx & Longer, 1986; Dendir & Maxwell, 2020). Instructors who get notification may increase proctoring, increase student observation, and alter the format and timing of exams.

2.13. Existing Technologies

Numerous technological developments for the proctoring system have taken place online. The proctoring tools are highlighted by studies (Hussein et al., 2020; Masud et al., 2022). These systems and the review process were the subject of investigational research. The report makes suggestions for using the proctoring system in schools and universities based on the investigation. An intelligent online proctoring system is offered by (Prathish et al., 2016; Dendir & Maxwell, 2020). To provide an example, consider how the proctoring system is built using both audio and video characteristics.

However, the report lacks an evaluation of the research project. (Chua et al., 2019) that has a method that uses tab locking and random question banks to stop cheating. The e-Parakh, which is regarded as an online test invigilating system now utilized for mobile sets, was created by (Pandey et al., 2020). Online proctoring systems have a lot of cybersecurity, according to (Slusky, 2020). As a result, the paper covers the methods and tools for a number of different factors and authorisation. It makes use of biometrics (voice and face identification) and blockchain technology in addition to challenge-response authentication. There are a variety of working controls to catch cheaters, including lockdown browsers, webcam fraud detection, endpoint security, virtual private networks (VPNs) and screen sharing, keyboard hearing software, and technical measures to address the absence of physical space controls, compliance with regulations (GDPR), etc., which affects the students' achievement (Alessio et al., 2017; Coghlan, Miller, & Paterson, 2021; Slusky, 2020).

Multi-class Markov Chain Latent Dirichlet Allocation is one method used to categorize the anomalous behaviors in tests. Due to the fact that they are used as feature sensors to determine the movement of the arm joints, shoulders, and head or position, such models are quite beneficial (Khosravy et al., 2022). As a result, this model can divide the events into five different categories. Additionally, it may apply a hierarchical, dynamic, and supervised Bayesian model to the same problem (Hendryli & Fanany, 2016). As a result, several works have presented approaches or procedures to identify aberrant behaviors in the targeted movies, with the primary objective being the identification of abnormal behaviors and the definition of abnormality. The suggested approach is useful for identifying any aberrant activity by identifying the normal ones and labeling the others as abnormal (Tharwat et al., 2018).

Textual explanations of cheating are produced via gesture recognition. The main components of this gesture recognition model are 3DCNN and XGBoost. Additionally, the LSTM network, where the textual description captures such activities, is a component of the language generation model (Arinaldi & Fanany, 2017). Through the muttering of the cheaters, there are efforts to uncover test-taking cheating behavior. Energy, root mean square, time length, or spectral properties are the features that are utilised. When the whispering level exceeds a predetermined threshold, an alarm must sound (Asadullah & Nisar, 2016). There have been numerous attempts to catch cheaters taking advantage of online exams by analyzing their behavior using webcams. It functions by monitoring the time and the pupil's head movement while looking at the computer (Chuang et al., 2017). In order to analyze the data, methods like Support Vector Machine, depth sensors, and widely used wearable gear for archery are used. Consequently, it is evident that the depth sensor or Kinect sensor incorporated into a system for recognizing human activities produces reliable findings (Dhiman & Vishwakarma, 2019).

2.14. Previous Studies

One of the most well-known issues that e-Learning systems encounter is emotional illiteracy, or the lack of comprehension of learners' emotions. Researchers now place a greater emphasis on this issue because of the enormous growth of e-learning platforms immediately following the Covid-19 outbreak. Deep learning overtakes the usage of artificial intelligence and machine learning as the most well-known tool for creating educational systems. Smart emotional computing, which analyses student emotions to improve learning systems and raise the caliber of students' performance, is one of the most crucial strategies.

The analysis of textual emotions for students was a focus for many researchers (Tian et al., 2014), and the random forest method outperformed the support vector machine (SVM) and naive bayes in this task. Additionally, evaluating textual emotions intends to examine the outcomes of student opinion polls in a variety of sectors, in addition to improving students' performance (Chen et al., 2017; Nikoli et al., 2020). Deep learning, ANN, natural language processing, and ML are some of the methods are employed to get the best results while assessing textual feelings. The findings demonstrate a high degree of success in identifying the emotions, with 83 percent and 94 percent for good and adverse emotions, respectively. There is numerous research that use ML methods to identify students' emotions, either to examine their divergence or to model and forecast those emotions (Jena, 2019).

Additionally, a number of research analyzed notes and comments that were posted on social media sites and electronic websites that relate to students' perceptions of a particular scientific course or of the university (Chen et al., 2017; Balachandran & Kirupananda, 2017). Finding out whether the opinions are good or negative was the study's major goal. Since facial emotions are thought to be more expressive than textual ones, researchers are quite interested in studying them. In numerous studies, the researchers created systems that aid in assessing the activities of each student from the tapes of their sessions. Then, reports are sent that describe their actions (Ngoc Anh et al., 2019).

Additionally, one study created tools that track students enrolled in MOOCs to determine whether they are watching the instructional videos (Yang et al., 2018). Where it determines the iris center, this technique has had great success. The use of specialized face recognition techniques and learning to think arithmetically have also been used in numerous other studies to create systems that can support e-learning. Yueh et al (Rad et al., 2018), Additionally, some publications stress how social issues and obstacles surrounding face recognition in schools demand special consideration (Andrejevic & Selwyn, 2020). Additionally, some systems attempted to develop facial recognition technology to examine student attendance fraud and cheating by capturing numerous photos of the student in various poses and appearances and transmitting them to the administration. The technique was successful in accurately checking the ratio between 70% and 90%. This technology demonstrated that accuracy increased with the number of photographs in the database (Okokpujie et al., 2017). This comprehensive evaluation identified a gap in the body of literature on real-time emotion analysis. Thus, only five studies that assess how learners feel throughout a learning session have been found (Li & Wang, 2018; Mukhopadhyay et al., 2020; Wang et al., 2020; Sabri et al., 2020).

Conversely, they primarily focus on the learners' emotions, which leaves a significant vacuum because there isn't a system in place to fully identify and confirm the learner's identity, then understand their emotions in stages, and ultimately monitor students while they take tests. This was one of the main motivating factors for conducting this systematic study. The widespread use of e-learning programs at all academic levels is the second factor. Finally, the importance of real-time emotion analysis employing artificial intelligence methods like CNN, DNN, and SVM. In light of the lack of studies that have been supported in this area, a complete system is recommended to reinforce the e-learning platform, containing of three key aspects: confirming the student's identity, analysing their emotions in real-time while conveying information for their mental health, and supporting monitoring students during exams.

CHAPTER III

MATERIALS AND METHODS

3.1 Introduction

This section explains the general study method as well as how the Agile methodology was used from the outset to develop and analyse the system. The system was tested in an e-classroom environment, and feedback from experts was obtained to improve the system. This is done to evaluate the precision and potency of the system's recognition of the student's face and emotions, followed by the e-ability tests to identify cheating.

3.2 Research Design

The design of this research was based on the Agile development process (figure 4). Agile is an iterative program or system for software development that aids schools in providing top-notch instructional content and student monitoring. The Agile approach has been used in various software designs because it is characterized by easy use, allows modifications, and provides high reliability and precision (ben Othmane et al., 2014; Uluda et al., 2022). Additionally, it saves time and effort because developers are not required to totally rebuild code for any modifications (Farooq et al., 2022). An Agile approach was used in this study to support the deployment of facial recognition technology in manageable classrooms. Artificial intelligence (AI) tools such as computer vision are used for facial recognition development (Alsaadi & Saeedi, 2022). The four pillars of the Agile approach are (i) encourage better interactions between users, processes, and tools; (ii) accurate and thorough documentation; (iii) improved user collaboration; and (iv) improved response to change through predetermined actions. Figure 4 displays the Agile development process; each component of the process is explained in the following subheadings.

3.2.1 Planning component

Planning is the process of putting together the tasks required to achieve a goal. The foundational skill for Agile design and planning is foresight. Planning in accordance with accepted guidelines is an essential component of the Agile development process. The primary planning components of this study included establishing the goal of the facial recognition system; gathering sufficient data for the task; defining the system scope; finding interdependencies across activities; and projecting the facial recognition system's work effort. Along with creating the project budget, baseline plan, and overall timetable.

3.2.2 Design component

Agile has excelled as a method for software development. The user's demands were first determined through user needs identified, which was followed by the creation of a model that satisfies those needs. After the model was created, it was tested with actual users (i.e., the students and lecturers) to determine how well it functions. Following the user testing, the test findings were analysed, and the model design was adjusted in light of the findings (the experts' feedback). After that, a fresh round of user testing, evaluation, and improvement through expert feedback were used in the design process. The testing will continue until the design is satisfactory enough for classroom usage and the test findings are satisfactory.

3.2.3 Develop component

To facilitate the development of system for education application, various software development methods are used. These include convolutional neural networks and computer vision algorithms sourced from deep learning algorithms and artificial intelligence (Banerjee et al., 2019). Convolutional neural networks and computer vision algorithms were employed in the creation of the facial recognition system. Algorithms, interviews, and user experience testing were used to create the graphical user interface for the system. The algorithms for facial recognition and face detection use the faced library and Local Binary, for instance, OpenCV object detector.

3.2.4 Test component

Everything that the users (lecturers and students) experienced, displayed, and observed while testing the facial identification system in the classroom and online distance learning was obtained using an interview instrument. These comprise the actions, opinions, and emotions that users have when utilizing the recognition system. Using the system, the test was conducted by subjecting the students to particular activities and completing assigned tasks while the lecturers observed their behaviors and communicated with them through the system component.

Figure 4

Agile Development Process

3.2.5 Deploy and feedback track component

The system was improved using the feedback from the semi-structural interviews. Following the system's deployment, the feedback track step entails again seeking the experts' input on the system's tasks. Lecturers and professionals participated in a semi-structured interview (Brinkmann, 2014; David, 2017) to determine their satisfaction with and need for this system as well as to learn more about its efficacy and accuracy.

First, when analyzing the system needs, consider the thoughts of instructors and specialists to determine the issues and difficulties that they encounter in distance learning. Second, the material was designed and created, and the professionals' opinions will once more be sought regarding the goals and essence of the system. Third, it was developed in stages, with feedback and suggestions being gathered at each one to improve the system's design and development. Fourth, after the system's design and development were completed, all system phases were tested by the specialists. After the system is deployed, the feedback track step entails asking the experts for their updated opinions on the system's functions.

3.3. Computer Vision Algorithms

This system uses software techniques, computer vision algorithm (CVA) and deep learning algorithm (CNN) to create a novel system that enables instructors to effectively manage interaction with their students during the lesson, manage a classroom, and ensure their interest in addition to observing their behavioral condition in classes. Additionally, a method that uses facial identification and gaze tracking to find cheaters was demonstrated, along with other tools for employing facial feature extraction to authenticate identity. Furthermore, this system includes a straightforward interface that makes it easy to access any of these functions.

This study developed and applied a CVA on an advanced program created computer system. A reliable source of CVA is the OpenCV Library (Behera et al., 2021). OpenCV is free software that is currently open-source and written in C++. The OpenCV package consists of statistical ML library that includes deep neural networks (DNN), artificial neural networks (ANN), k-nearest neighbor algorithm (KNNA), expectation-maximization algorithm (EMA), boosting, naive bayes classifier (NBC), support vector machine (SVM), gradient boosting trees (GBT), decision tree learning (DTL), and random forest. From this package, this study used ANN. The investigation of the method in this work is concentrated on Agile to enhance systemic pixel-level processing because there are so many different embedded vision processors (OpenCV). This study implemented CVA in the Vision System Toolbox using Agile functions and Simulink blocks, and the present study were also able to create library of functions specifically for the Agile programming design.

Among the features used by computer vision systems are as follow:

Image acquisition: Digital images are produced by a number of image sensors from light-responsive cameras working together. An image series was created using the image data. The concentration of light in one or more spectral ranges is represented by the pixel values.

Pre-processing: Prior to the procedure could be used to image data to extract the necessary data, the data had to be processed to make sure that it complies with the rules established by the computer vision methodology. Resampling was done to make sure the image structure procedure is precise. Noise reduction was done to make sure that sensor noise didn't lead to inaccurate information. Contrast augmentation was carried out to make sure that crucial information can be recognized. The scale space representation was developed to enhance visual forms at nearby relevant scales.

Feature extraction: Image attributes with varied degrees of complexity were extracted from the data. Ridges, lines, and borders make up these. After that, we carried out confined interest locations, like blobs.

Detection/Segmentation: Which picture points or regions should undergo additional processing is decided during processing. by separating an image into sections, which each contains a distinct subject of concern. Image division into layered scene architecture with the focal point, target groups, specific objects, or visual salience. Then, we generate a focal point match for each setting of one or more videos while preserving the coherence of the temporal semantics of the films.

High-level processing: A collection of features or a portion of an image that is meant to contain a specific object are common examples of the input at this stage. In this part, the data's adherence to application- and model-based standards was examined. It was done to estimate the factors that are unique to a certain item size. Captured items are categorized into many groups via image recognition. Image process contrasts and integrates two different views of the same thing.

Decision making: Automated inspection algorithms that use a Pass/Fail system and matching or non-matching image identification are used to make the final judgment.

3.4. Convolutional Neural Network

In order to rank different features and objects inside an input image and make distinctions between them, CNN was employed as a deep learning system. In this study, face emotions were statistically predicted using the Mini Xception CNN analysis technique developed by He et al. (2016). The use of CNN to recognize emotional facial expressions is covered in one portion of the paper. In order to predict the probability of each of the seven basic emotional conditions occurring, CNN evaluates real-time video settings. The analysis model forecasts potential student emotions using instantaneous input from the output of the CNN model data. It is simpler to analyse human behavior and create feature predictions using the two-phase hierarchical approach. Following face detection and statistical analysis of the detected face's seven primary facial emotions were: The resulting data were fed into the real-time model in the second and most significant component of this research, which focuses on predicting emotions. The processed data was sent as an input as a csv file. The data obtained about a student throughout time and a different each emotion's set of inputs are used in the model to estimate the percentage of each emotion for the anticipated feature.

3.5. Data Collection and Tools

Various datasets were used in this investigation, including:

Images found on the Internet were utilized to create the first batch of tagged faces in the wild data utilized to train face authentication algorithms. This database has about 13,500 images (LFW, 2022).

The dataset utilized to train emotional identification algorithms is the second batch. This information was obtained from the approximately 32,300 photos of faces with various emotions in the FER dataset database on

Kaggle.com. The data simplifies seven primary emotions at a grayscale resolution of 48 x 48 pixels (Figure 5; Lu et al., 2015).

Our goal was to categorize every face according to its unique emotions. To encrypt the next: 0 indicates anger, 1=disgust, 2=fear, 3=happiness, 4=sadness, 5=surprise, and 6=neutral. There are roughly 35888 samples in the database, which are divided into two folders. The initial file is train.csv, which has two lines. One is for emotions; the other is for pixels.

The gaze tracking model was trained using the third dataset. This dataset, which includes 1380 photos with a size of 600 × 800 pixels, was obtained through gaze interaction for everyone (GI4E) (OpenCV, 2022). The eye movement model was trained using the fourth dataset. The dataset, which includes 2800 640x480 photos of 200 people, was taken from the FEI Face Database (Arriaga, Valdenegro-Toro, & Plöger, 2017). To find things captured by the camera, the fifth dataset was used. The dataset, which has 80 object categories, was gathered from Common Objects in Context (COCO) (George & Routray, A2016).

Figure 5

Sample Of FER Dataset

3.5.1 Initial processing of the data

The images are scaled to [-1,1] from the field [0,1] by dividing the data by 255, deducting 0.5, multiplying by 2, and this is thought to be the optimal field for the neural network to use as input in these forms of CVA challenges.

3.6. System Development by Combining the Models

The several models were combined using the Ploumpis et al. (2019) method in order to analyse the datasets. The procedure used the powerful statistical instruments of 3D morphable models to characterize the exteriors of the images in the category. It also combines two or more 3DMMs that were built using different datasets and unique templates, some of which may only partly overlap. The devices integrate two or more models by utilizing a regressor to fill in the data spaces in one model with data from the other model. Covariance matrices from different models are frequently combined using the Gaussian Process framework. By developing a new face model that incorporates the flexibility and facial features, this is accomplished.

3.7. System Structure

Python 3.3.8 was used to create this system on a computer operating Windows 10. Additionally, this system was created by splitting it into three structures in order to realize its objectives and satisfy the demands and recommendations of instructors. By doing this, we can more easily develop and alter any system while also lessening the processing load on the computer. This section will include system architecture, models that have been employed, and algorithms. The user interface and system phases are depicted in Figures 6 and 7, respectively.

Figure 6

The User Interface

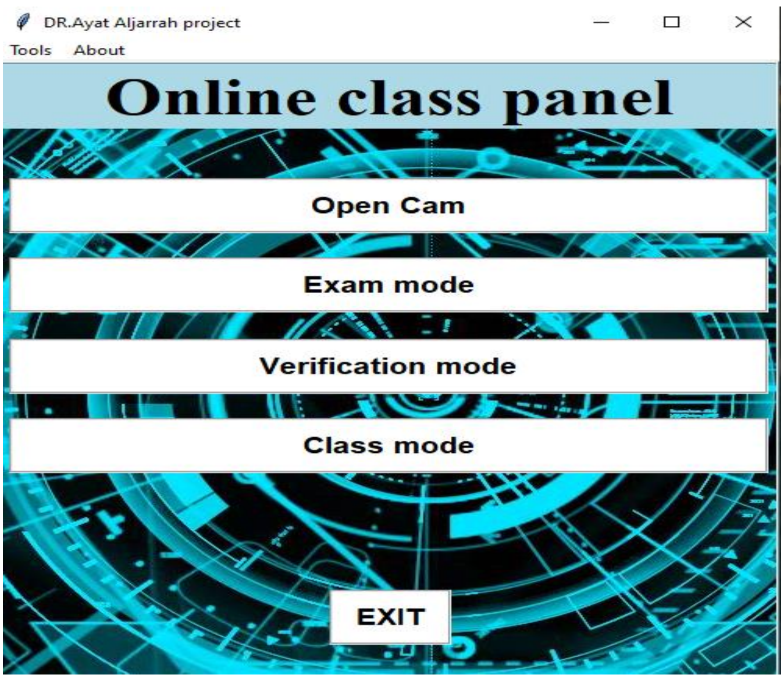
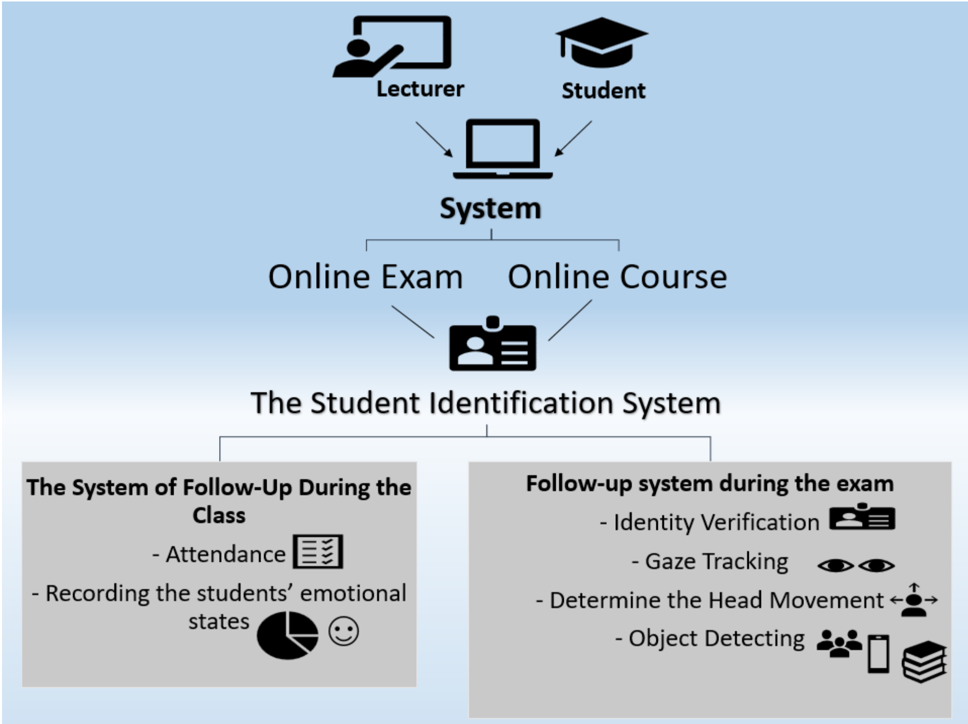


Figure 7

The Structure of the Developed System



3.7.1. The Student Identification System

With reference to this system, learners who join a lesson or an exam will be distantly recognized in order to confirm that the individual attending in order to prevent instances of cheating through identity stealing, the class or exam must be similar as the account owner. With the use of such a system, the web camera photos and the students' saved images must be evaluated. Consequently, it uses the ResNet-34 algorithm in two phases in addition to the deep metric learning algorithm (Guennouni, Ahaitouf & Mansouri, 2015; Redmon & Farhadi, 2018).

The initial step is to extract facial features from the database's images (figure 8). The faces obtained via the camera are compared to the faces stored or already present in the database in the second stage (figure 9). The images of the faces that must be recognized are entered first; these are the images of the class members. As a result, the face can be identified, for example, by identifying faces and determining where they are, whether they are there or not. Then, via an algorithm, approximately 128 facial traits are retrieved in the kind of numerical constants and kept in a beam. An algorithm known as "Deep Metric Learning" relies on using an output characterized by a beam of integer values rather than the customary tool.

Then, the vector produced by the 128 measurements is compared if no match is found with any vector, the face compared to the vectors contained in the database is regarded as unknown; however, if a match is found with an current vector in the database, the learner's image will be surrounded by a square, and the learner's name will be written as it is stored in the database. Application of the 34-ResNet algorithm is key to the facial identification network's design (Bashitialshaaer, Alhendawi, & Lassoued, 2021). Approximately 13250 photos from 5794 different persons make up the LFW dataset, which was used to train the network. Training data made up 70% of the dataset, while testing data made up the remaining 30% (LFW, 2022).

Figure 8

The Stage Of Facial Features Extraction

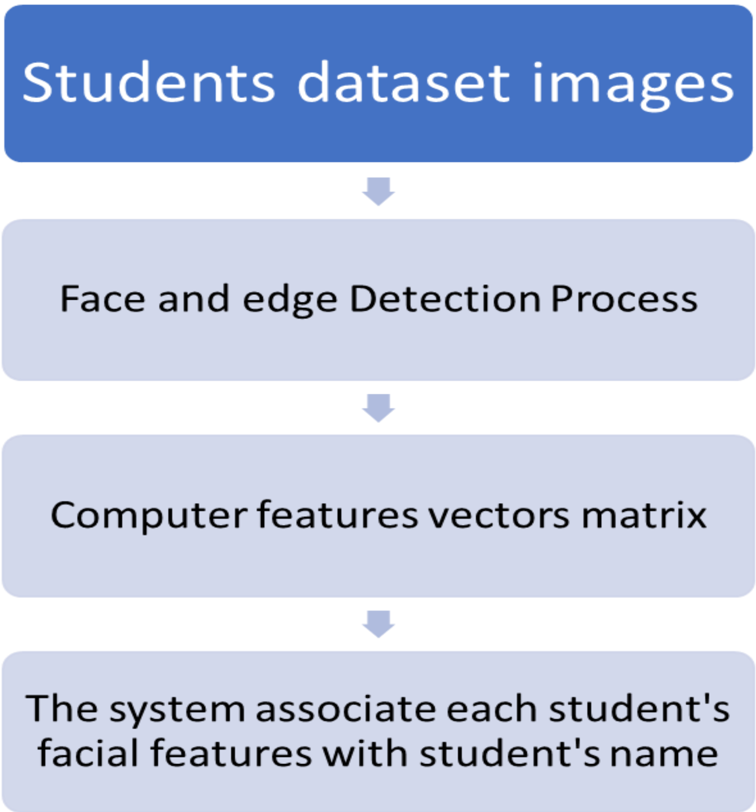


Figure 9

Comparison of faces captured by the webcam and those in the database

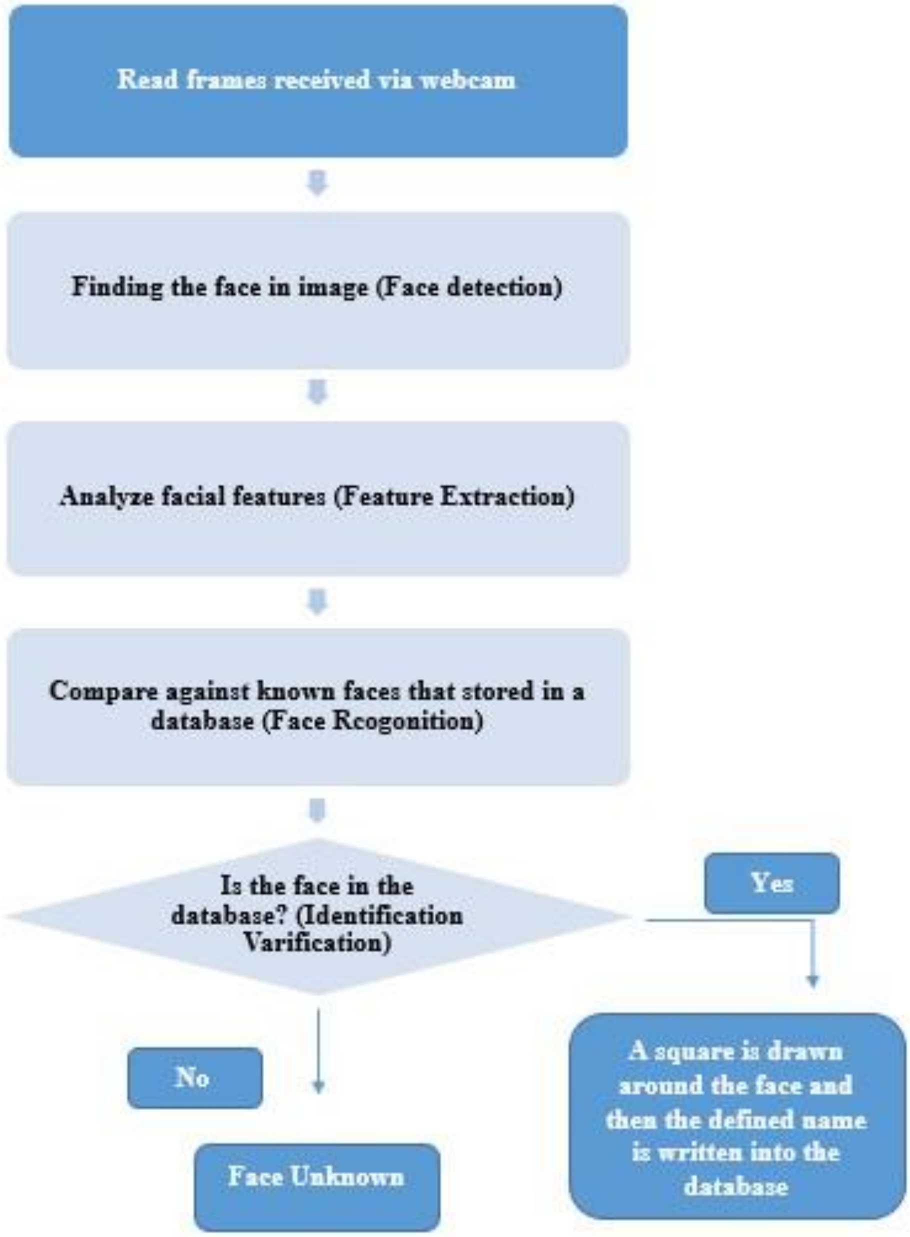
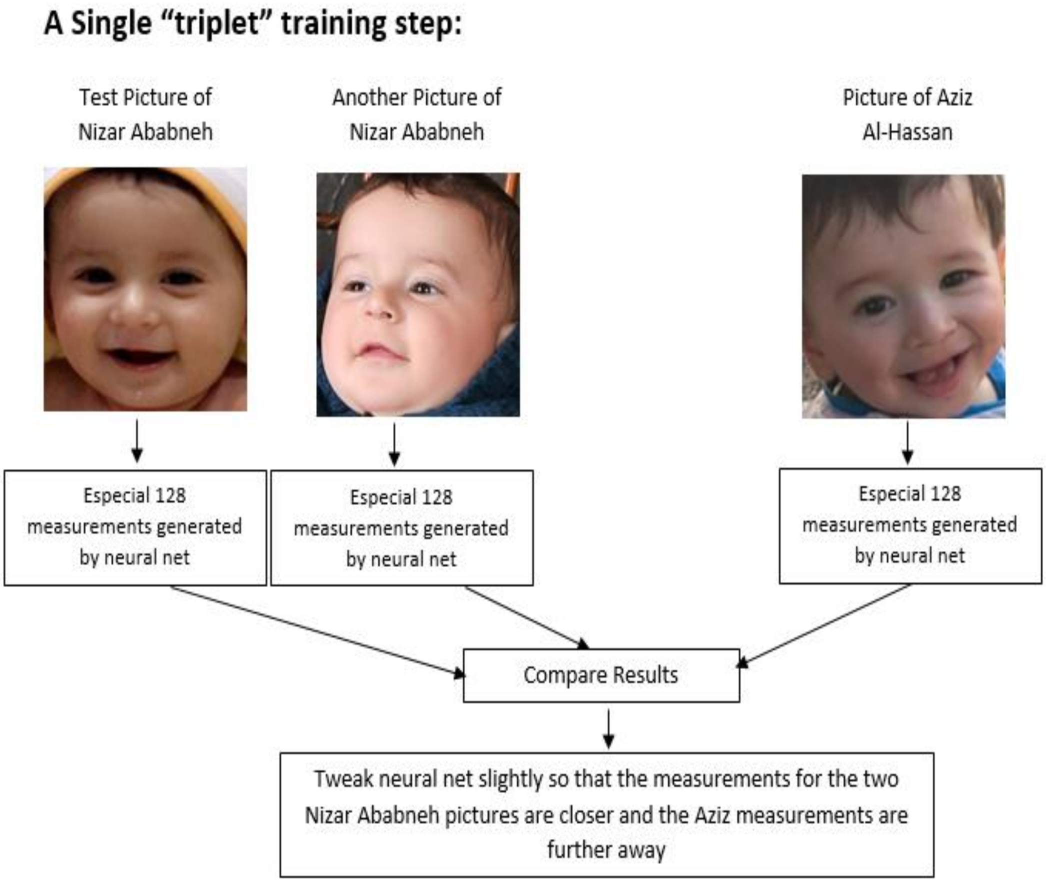


Figure 10

Facial recognition via deep metric learning



3.7.2 Interviews (Deploy and Feedback Track)

The most widely used techniques for collecting data in qualitative study is conducting interviews (Winarno et al., 2017). In order to find out more concerning the requirements for a facial identification method that will identify students cheating on exams, along with to gain more knowledge about the system's suitability for online invigilating and distance learning, this research employs semi-structured interviews.

Semi-structured interviews (Table 1) use a predetermined list of questions, but the interviewers (lecturers) are also asked to elaborate on certain issues and clarify certain points. Semi-structured interviews have the advantage of giving the researcher total control over the data gathering procedure. Interviews take place in a voluntary environment after obtaining the consent of the questioners and advising them that their participation would be kept private and anonymous. In this study, two different types of interviews were performed: for the lecturers and the students. The purpose of both interviews was to gauge how effectively the system worked for identifying faces, coordinating classroom activities, recognizing facial emotions, and catching cheaters on online examinations.

This method was developed as a result of interviews with professors on how they feel about using facial recognition technology in their instruction and examination processes, particularly for online or distance learning. The systems were developed using these responses and the challenges found. The responses cover the challenges and obstacles they face as well as the effectiveness of the system in identifying and catching the students' emotional outbursts and cheating conduct. Prior to the system reaches the last stage following a 14-week interval, at each stage of its development. The views of the professors were taken into account. Semi-structured interviews were conducted with a total of six university instructors at Cyprus International University. Additionally, to the 20 undergraduates who came from a group of 100 undergraduates who were chosen at random at Cyprus International University's Department of Management Information Systems in Nicosia. An easy sampling method was used. After the system was finished, input from the instructors was sought to ascertain how successful and pleased whether they were involved with it or ought to be incorporated into learning sessions conducted remotely or online.

Table 1

Interview Questions

Interview Questions

Lecturers	Students
Is facial recognition technology used in universities?	Is facial recognition technology used in universities?
What can you say about the facial recognition system?	Do you like the facial recognition system?
Are you using facial recognition technology in your teaching and learning process?	Does facial recognition system help your verification process?
Do you think the facial recognition system can help you effectively invigilate your students in online classes and exams?	Is the facial recognition system used in your online class and exam?
Does the use of facial recognition increase the risk of false detection of student cheating? What are your expectations of the facial recognition system in teaching and learning?	How easy is the face verification system?
Do you think facial recognition should be fast enough or moderate? How will the use of facial recognition affect students' privacy?	How fast is the face verification system?
Does the system accurately recognize students' faces in distance/online learning?	Is facial recognition accurate enough for exam use?
Does the detected student's face match the student's details?	Does facial recognition accurately register you?
What is the most common facial emotion exhibited by the students?	Does facial recognition affect your privacy?
Can the system differentiate similar images?	How is facial recognition different?
What is the common gaze you notice among the students?	What do you think about the efficiency of the system?
What is the most common type of attempt made by students? Eye movement or facial movement?	Are you satisfied with the facial recognition system?
How fast is the student's face detected using this system?	What is your level of satisfaction? High, moderate, or low?
What do you think about the efficiency of the system?	
Are you satisfied with the facial recognition system?	
Did the facial recognition perform as well as expected in detecting the students' cheating behavior during online exams?	
What is your level of satisfaction? High, moderate, or low?	

3.7.3. The System Follow-Up during the Class

This approach is important because it provides the instructor the opportunity to monitor the students' emotional state as they listen to material. In such a method, the learners' or students' emotional states are observed during the lesson. The instructor concentrates on the students and asks them questions in order to keep the highest level of student presence throughout the session and after the course is over. The technique thus gives a lecturer statistical feedback about a student's emotional conditions throughout the lesson, illustrative of how carefully instructors monitor students' development and the subject matter (figure 11). Face identification and emotion verification are the sentiment analysis system's two main operational phases.

Cascade classifiers based on Haar features for OpenCV are an advanced algorithm for real-time face detection that finds the frontal estimate of the face in the inbound pictures (Emami & Suciu, 2012). Additionally, the present approach employs a Haar cascade classifier in each area where detecting faces or eyes is required. The training and recognition phases of the sorting process are divided into two by the cascade classifier. The task of acquiring specimens that can be divided into positive and negative categories is completed during the training stage. The cascade classifier uses a few auxiliary procedures to create a training dataset and assess the strength of the classifiers. They require a collection of positive and negative specimens in order to train the cascade classifier. To generate the positive examples for an openCV-trained cascade in this study, we used the openCV generate specimens’ function. To train the recognized face, this function's output information is used as an input by an openCV-trained cascade. Negative specimens are gathered from random images that do not contain the target objects.

The last layer of the trained Mini_Xception CNN Model calculates the likelihood of every one of the seven emotions enumerated below for the detected face with 48 x 48 pixel input dimensions (Behera et al., 2021). Therefore, the aim was to categorize each face according to its emotions by determining the following: 0 = Angry, 1 = Disgust, 2 = Scare, 3 = Happy, 4 = Understand, 5 = Surprise, and 6 = Neutral. Image acquisition, pre-processing, feature extraction, detection/segmentation, high-level processing, and decision making are among the processes described in Section 3.3.

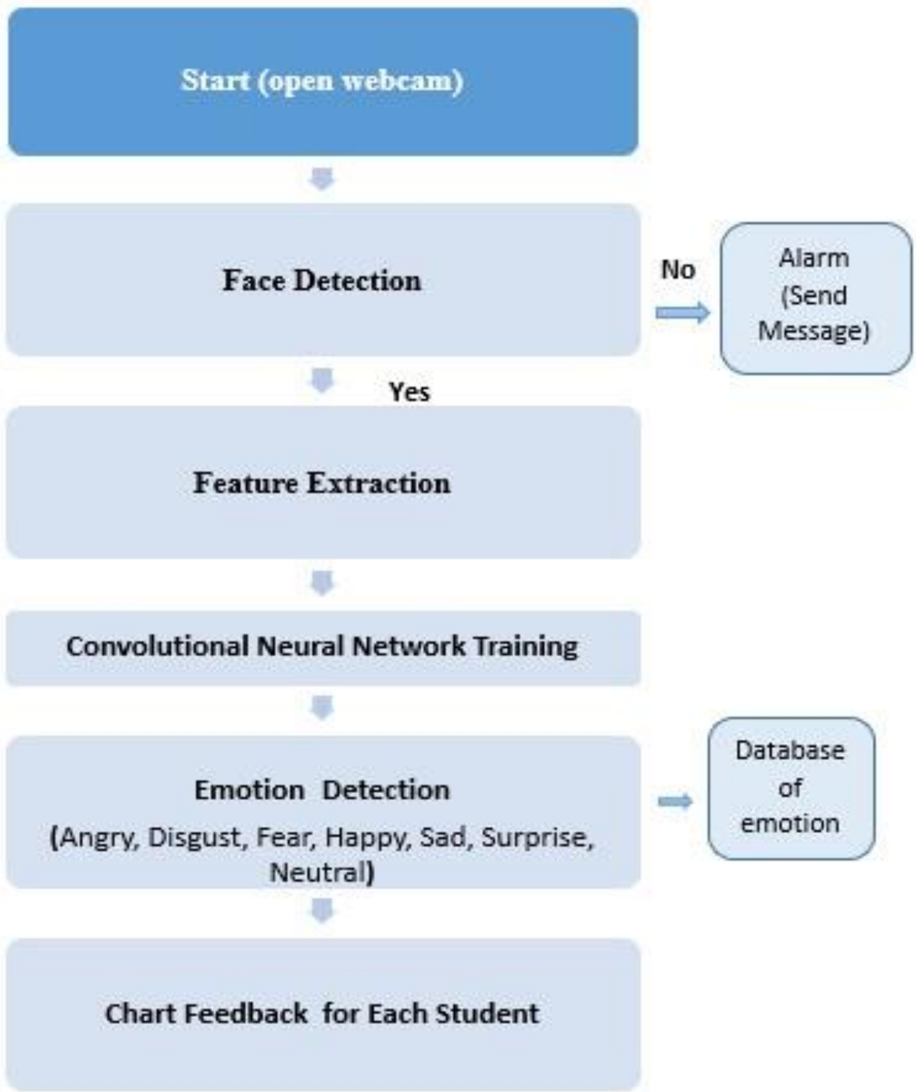
Train.csv is the first of two files that make up the database. There are two columns in this document: one for feelings and the other for pixels—and is divided into two halves. The images are transformed from the scale [0,1] field by multiplying by 2, multiplying by 255, and removing 0.5. This scales is from the field [1,1], which is thought to be the ideal field for the neural network's input in this particular type of CVA problem.

In summary, all of these processes were followed to gather and prepare data, use algorithms to pinpoint the face's location, and Convolutional neural networks can be trained to detect the emotions that students feel while participating in a lesson. Additionally, the Mini Xception CNN Model (Behera et al., 2021), which the architecture of the sentiment analysis system relies on it being trained using a FER dataset of approximately 35,600 pictures, split into 70% training data and 30% test data (Albastroiu et al., 2018).

The open webcam technique was then employed in class to identify students' faces (figure 11). This approach is important because it gives the instructor the chance to monitor the pupils' emotional state during each lesson. In such a method, the students' emotional state is monitored during the lesson. The instructor divides the questions among the students in an effort to maintain the highest level of attendance for the duration of the session and after the course is over. The method gives the lecturer plans for statistics regarding the emotional conditions suffered by the student through the session in order to indicate the depth of the student's involvement with the lecturers and the information presented.

Figure 11

The System Of Follow-Up During The Class



3.7.4. Follow-up system during the exam

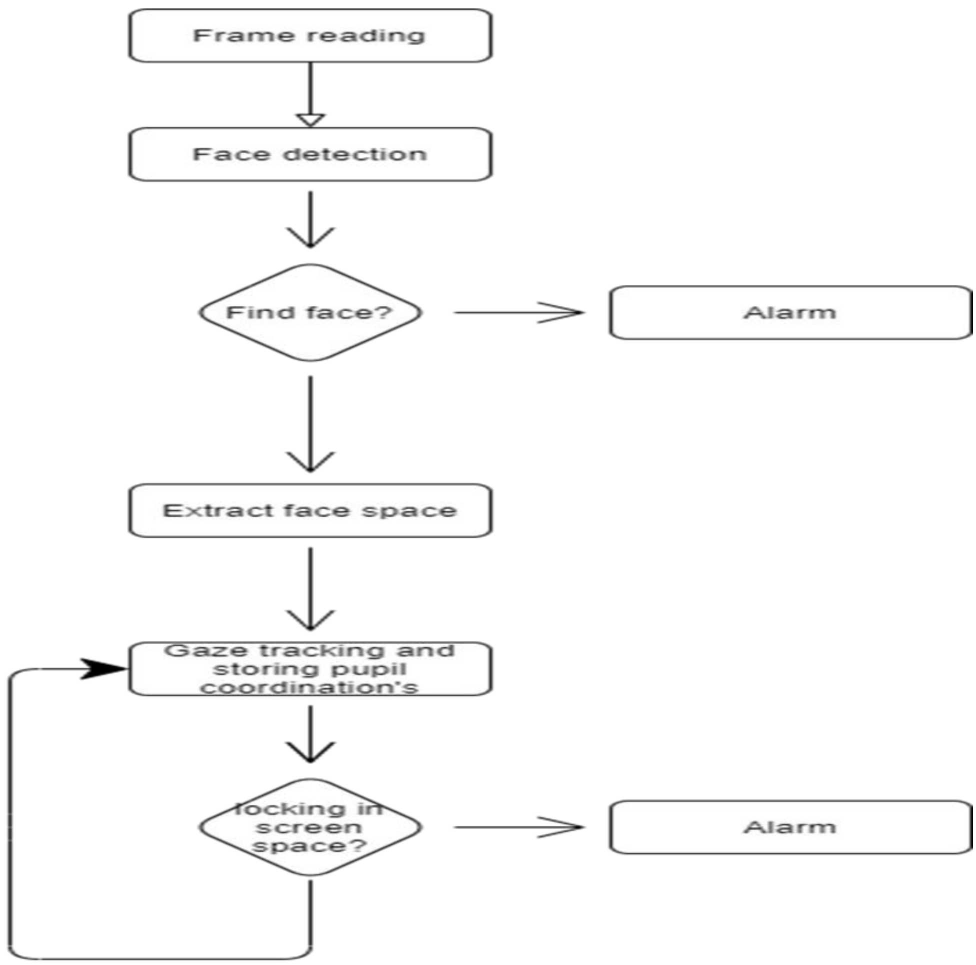
E-tests are one of the most significant problems and restrictions with distance learning since institutions use a variety of techniques to administer exams and prevent incidents of cheating. As a result, in this part, we have created a new method to monitor learners during exams and alert them if they behave strangely or peek outside the computer screen's allowed exam space.

The four steps that make up the work's basic structure are as follows: the first is to use a trained model according to the ResNet-34 and deep learning algorithms to verify a person's face to make sure they are in the exam; the second is to use a trained model according to gaze tracking to track the students' eyes and identify where in the image they are located (Ahmed, 2021). The model was trained on a Gi4E dataset containing roughly 1380 images, divided into 70% training data and 30% test data (Zubairu et al., 2021). The student can be warned if they are gazing away from looking at a book or cheat sheet on the computer screen, or any other aid, because we can determine the student's focus area thanks to this. In the third phase, the eye movement is calculated using a model trained on a (FEI) face dataset that includes approximately 2800 faces from 100 different persons, divided into 70% training data and 30% test data (Arriaga, Valdenegro-Toro, & Plöger, 2017). This model employs the Haar cascade methods, which function in the absence of the frontal face (Behera et al., 2021). The fourth phase involves looking for anything else in the image outside the face, such as a phone, piece of paper, a book, or a hand; the fifth step involves looking for multiple faces. The COCO dataset was used to train the YOLO (V3) model in the fourth and fifth phases, to recognize objects in the camera in real-time, including people, books, watches, iPads, and other objects (Behera et al., 2021). 5000 photos make up this dataset, with 70% of them being training data and 30% being test data (Ploumpis et al., 2019).

Thus, we enhanced the software in this section to keep an eye on the students during the exam and warn them if their sight wanders outside the designated exam area displayed on computer. The task is based on two steps: the first is to verify that the student is taking the test by looking at their face, and the second is to monitor their eyes (gaze tracking) and determine where they are in the picture (figure 12). Using an exam sheet, a book, or any other assistance, we can identify the learner's concentration region and, as a result, inform the student when he or she is gazing away from the workstation.

Figure 12

The Follow-up Exam System



A detailed explanation of the follow-up system during the exam is shown in figure 12, with the explanation of the two main operations given below:

1. Face detection

The Haar cascade technique was used in this step to determine whether or not a face is present in the image. There are instances of cheating, such as moving through an exam or paying close attention to where this algorithm just conducts front face detection. To do this, this study used the method reported by Li et al. (2015).

2. Pupillary Tracking

When a face was recognized, the applied algorithm was engaged and the search for the eyes started. The gaze tracking algorithm uses the coordinates of the eyes to recognize the learner's range of view and alerts him if he glances outside it. In this section, the system creates a model to track learners as they take the online test by tracking the movement of the entire eye as well as the iris of the eye and the absence of the face entirely. The technology informs the student audibly if the iris leaves more than five seconds were spent staring at the computer screen. Additionally, if the alarm is repeated more than five times, it will be assumed that the student is cheating. Moreover, the system is compiling comprehensive statistics about the student's circumstances during this time. If the student does not receive any alerts during the exam, the system summarizes the conclusion of the test by stating that the learner was in a sound state. If the student does, however, receive warnings and give feedback through the system, indicating the number of alerts and the duration of the student's face being off the screen.

3.8. Data Analysis

Statistics looks at how different research results can be organized and quantitatively examined, as well as how different inferences can be drawn from the results of the study. Statistics were used to analyze the datasets. The replies from the interviews were analyzed using the descriptive analytic method. The queries and answers were categorized into subjects. The findings were shown as means and percentages.

3.9. Ethical Approval

The ethical an application was made to the Rapporteur of the Scientific Research Ethics Committee of Near East University (NEU). The authorization letter was received on April 8, 2022 (Appendix A) before this study was conducted.

CHAPTER IV

FINDINGS

4.1. Introduction

This section discusses the findings based on the collected data analyzed. The descriptive and inferential statistics as well as the steps involved were discussed. The selected algorithms' performance and accuracy were discussed. The key findings covered include convolutional neural network training, facial emotion recognition, the student identification system, the system follow-up during class, and the system follow-up during the exam.

4.2. Training of Convolutional Neural Network

The mechanism of CNN is depicted in figure 13. The middle box was used four times throughout the session. The majority of the parameters were positioned at the end, where a distinction was observed from the rest of the typical CNN architectures that depend on completely connected layers. The following techniques, among others, were employed in this study to construct deep neural networks for computer vision:

1. Data Augmentation

The transformation method is used to produce data using a set of training that was obtained beforehand. It is needed if the training sets is no longer sufficiently precise with respect to the learning representation. However, the training images were transformed to create the image of the data, including by rotating, cropping, shifting, shearing, zooming, flipping, reflecting, and other techniques.

2. Kernel_regularizer

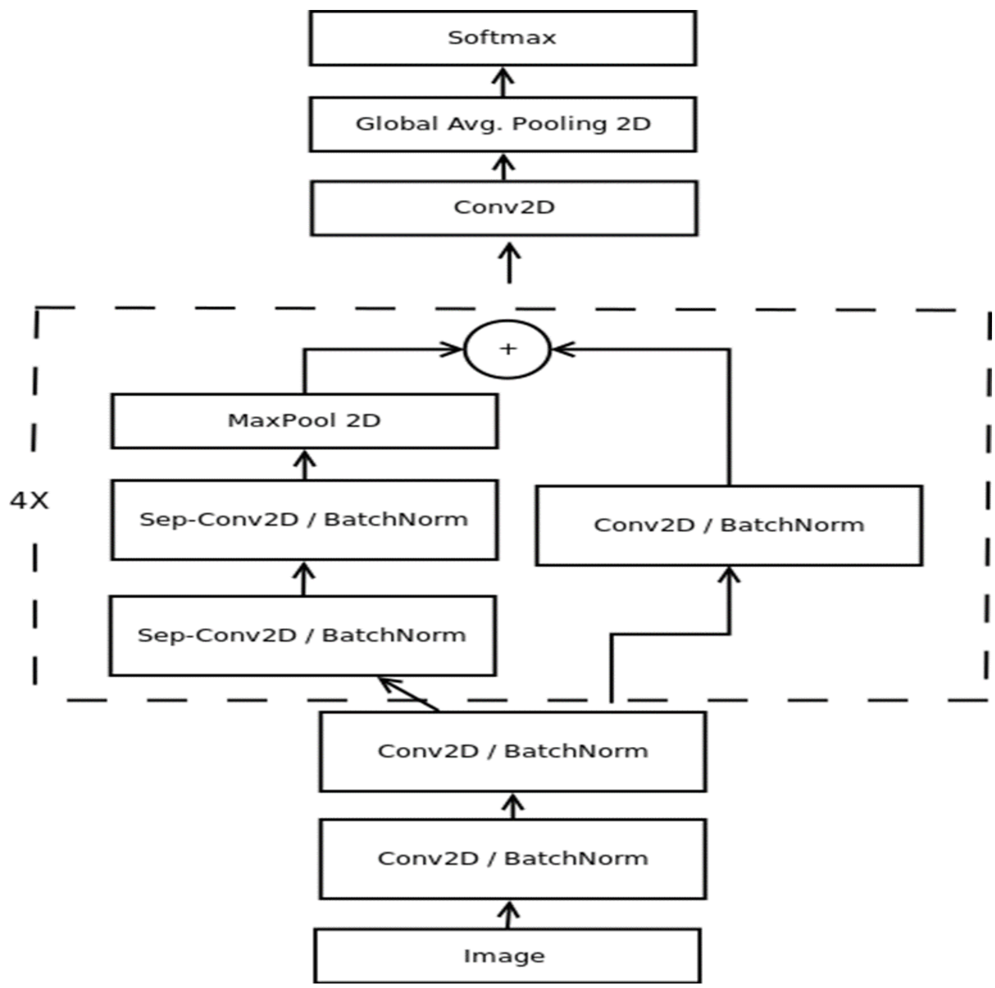
Kernel_regularizer permits the application of penalties via optimization to the layer parameters. These fines were particularly collected in the network's development loss function. As a result, the convolution layer's argument centers on the L2 regularization of weights, which penalizes large weights while taking input into account.

3. Batch Normalization

Batch normalization was done by applying a transformation that keeps the activation mean near to zero and the activation standard deviation close to one while increasing the activation for the preceding layer in every batch. Consequently, it deals with the internal covariate shift problem. By occasionally removing the requirement for a dropout, it also serves as a regularizer. Thus, it contributes to the training process moving more quickly.

Figure 13

The Architecture Of Trained CNN



4. Global Average Pooling

It transformed each feature map to a scalar value by averaging all of the feature map components. As a result, in order to average completion of the task, the network extracts the overall characteristics of the key image.

5. Depth smart Separatable Convolution: Contain two Types of Layers

The pointwise and depth-wise convolutions of the first one can be identified by their separable convolutions, which require fewer parameters and so require less processing than ordinary convolutions. A convolutional neural network was trained to recognize and express the emotions that the learning process that the pupils go through. In essence, all of these procedures were carried out starting with the gathering and preprocessing of data, utilizing algorithms to pinpoint the face's location, and training the CNN.

During this CNN training process, the system notified the student when it failed to recognize any faces. If the notice is made six times, either the student records an absence for this session, or the lecturer makes the final decision. The system records feedback for each student at the conclusion of each session in the form of an illustrated graph for the students' emotions throughout the session, the number of times a message was sent to them, and other information. Moreover, the lecturer is free to access them at any time, which is quite useful, particularly in sessions with a high number of students (figure 4.1).

4.3. Descriptive Statistics of the Facial Emotion Detection

The results of the descriptive statistics of facial emotion detection are presented in Figures 4.2 to 4.6. The Mini Xception CNN model was developed to recognize faces with 48 x 48 pixel input dimensions and estimate the likelihood of each of the seven emotions. The results showed the emotions expressed by students during the identification process, class, and exam encoding through the facial recognition system.

The facial recognition detects the faces of the students just before the student's identification process initiation to be mostly expressing "understand (240%)" followed by "neutral (180%)" and subsequently "angry (48%)" (Figure 14). Expression of other emotions such as scared (1%) and absentminded (1%) had a negligible percentage, while disgust and surprised had no facial expression results (Figure 14).

Figure 14

Facial Recognition Detection Just Before Student's Identification Initiation

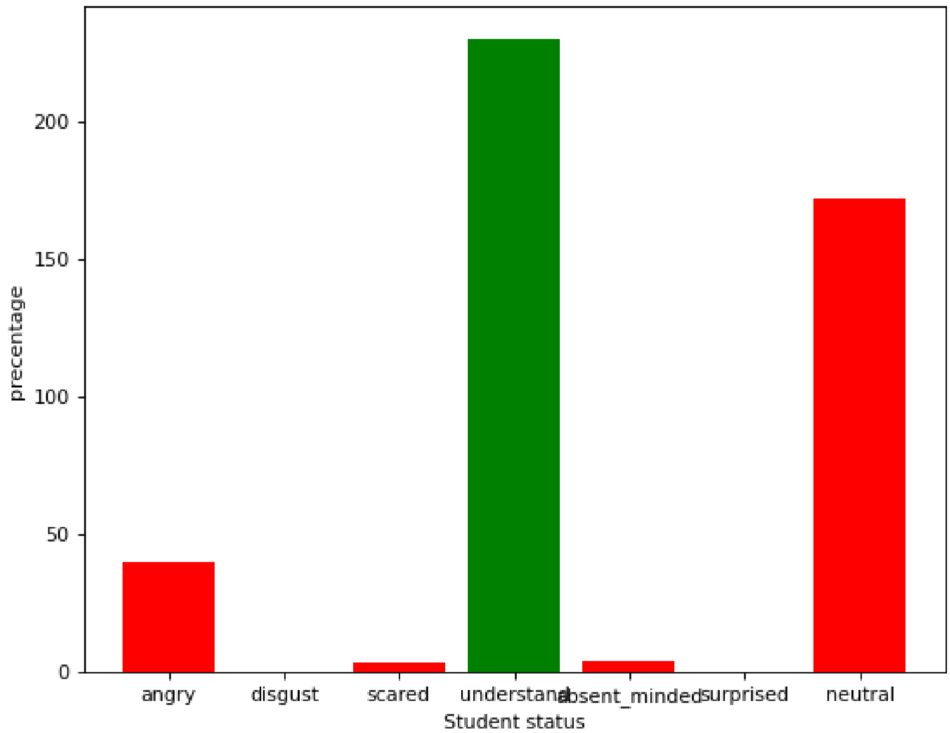


Figure 15 illustrates facial recognition during student identification. The facial recognition detects the faces of the students during the identification process, with faces mostly expressing "scared (242%)" followed by "neutral (239%)" and subsequently "understand (151%)" (figure 15). Expression of other emotions such as absentminded had a low (50%) percentage, while disgust and surprised had no facial expression results (figure 15).

Figure 15

Facial Recognition During Student Identification

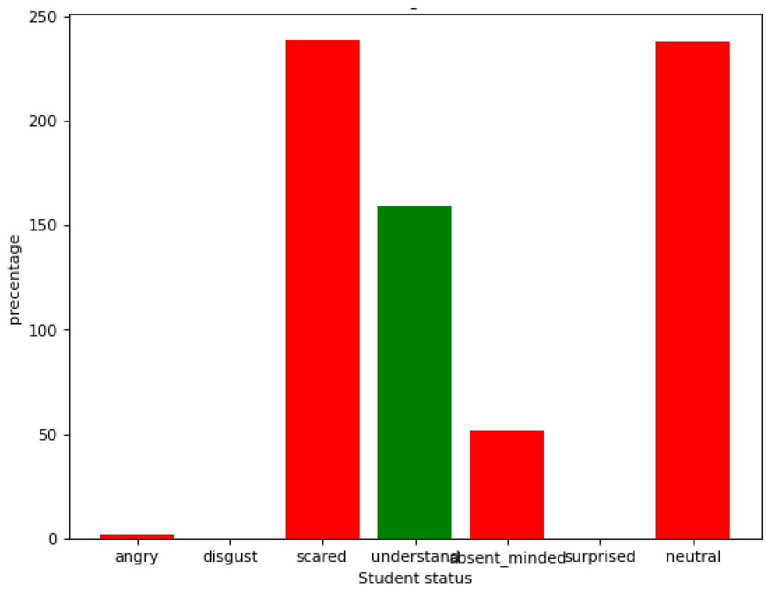


Figure 16 displays facial recognition during a lesson or class. The facial recognition was able to detect the faces of the students during the lesson or class, with most faces showing “understand (210%)” followed by “neutral (175%)" and then “angry (115%)” (figure 16). The absentminded had moderate expression (80%). Expression of other emotions such as scared had a low (5%) percentage, while disgust and surprised had no facial expression results (figure 16).

Figure 16

Facial Recognition During Lesson Or Class

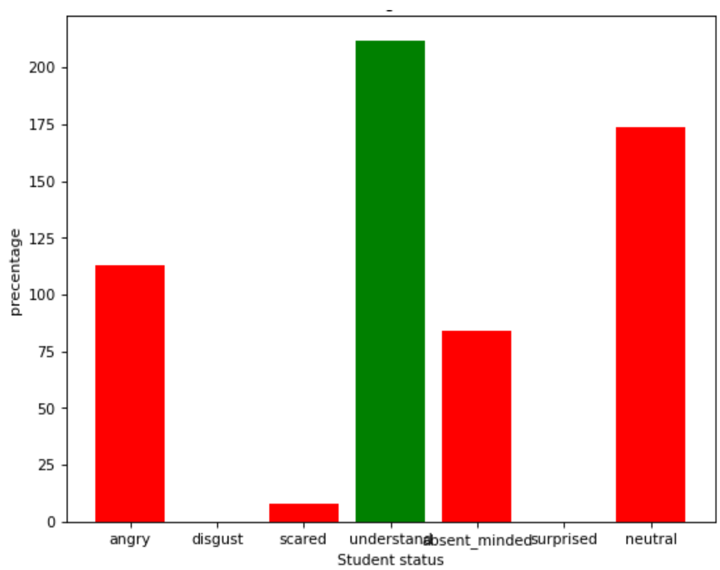


Figure 17 shows the facial recognition just before the start of the exam. The facial recognition was able to detect the faces of the students just before starting the exam, with most faces showing “understand (130%)” followed by “neutral (110%)” and “scared (50%)” (figure 17). Expression of other emotions, including anger, had a low (10%) percentage, while disgust, absentminded, and surprised had no facial expressions (figure 17).

Figure 17

Facial Recognition Just Before Start Of Exam

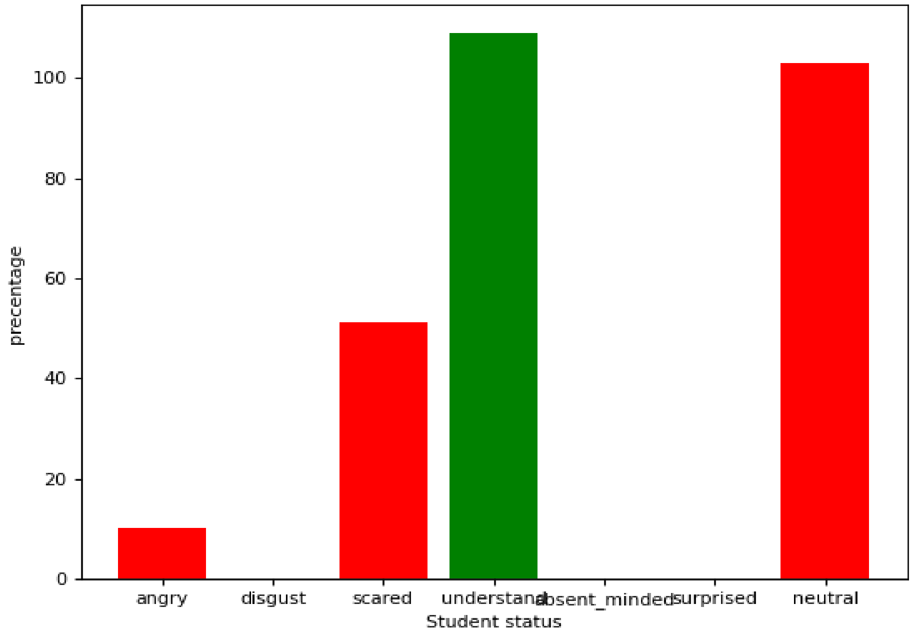
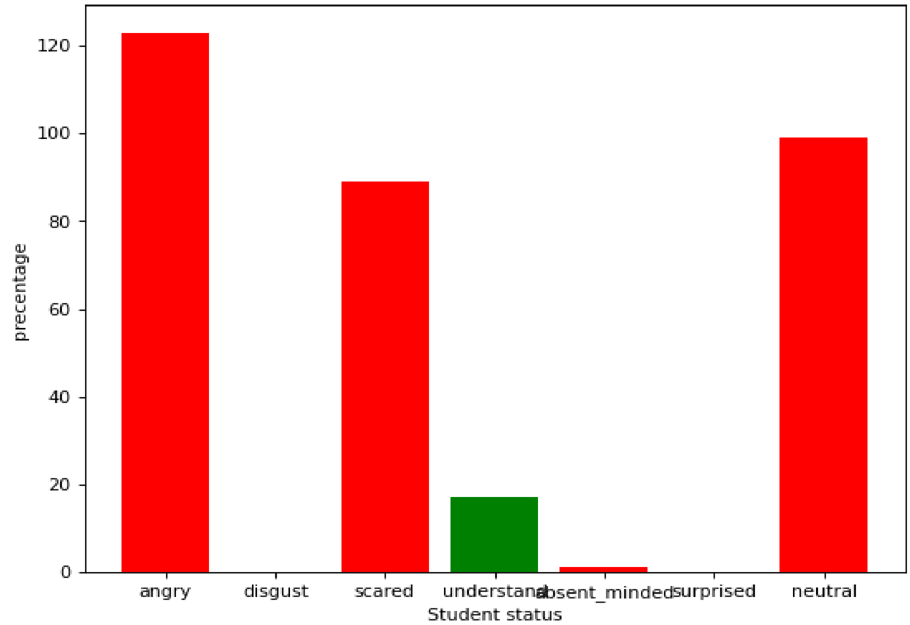


Figure 18 illustrates facial recognition during the exam. The facial recognition was able to detect the faces of the students during the exam, with most faces showing “angry (102%) followed by “neutral (95%)” and “scared (88%)” (figure 18). Expression of other emotions, including understand had a low (18%) percentage, whereas disgust, absentminded, and surprised had no facial expressions (figure 18).

Figure 18

Facial Recognition During Exam



4.4. First: The student identification system

4.4.1. Performance and Accuracy of the Facial Recognition System

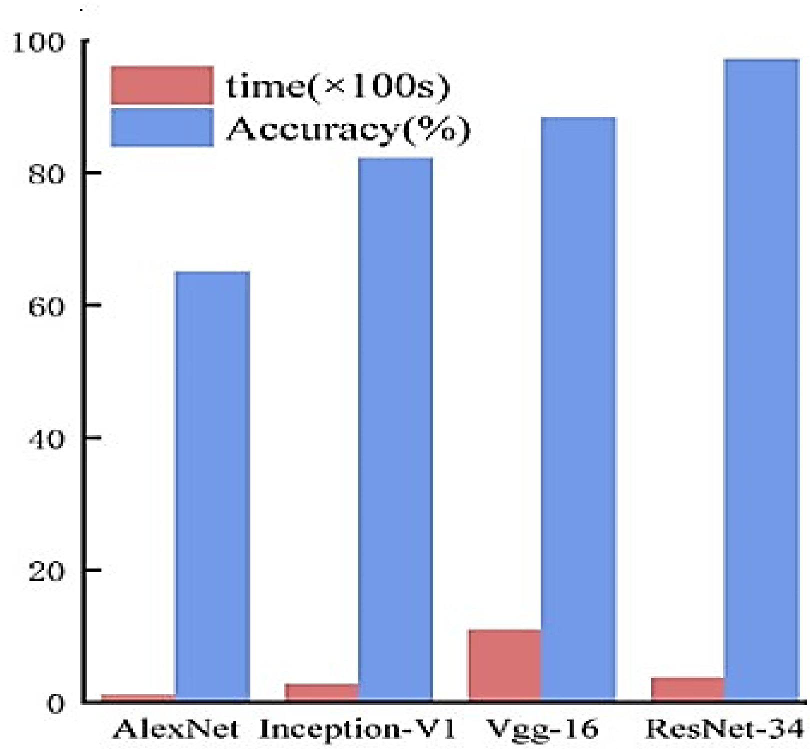
Step 1:

It was discovered that it is simple to match the current face in the database with the face that is captured by the camera during the creation of the student recognition system, which validates a student's personality according to the utilized methods. The results are displayed as "unknown" when the face is not recognized or matched. Alternatively, when the face is identified, the label of the face that was saved in the database shows. As a consequence, this system's algorithm and ResNet-34 method's performance and accuracy were both about 99.38 percent (Figure 19).

Following the experts' evaluation of the system's effectiveness, changes were made in response to the professionals' and instructors' suggestions that the system directly record the unidentified student as being absent. The improvement increased ResNet-34's effectiveness and decreased processing time.

Figure 19

Deep learning algorithms with metrics' efficiency and accuracy



Step 2:

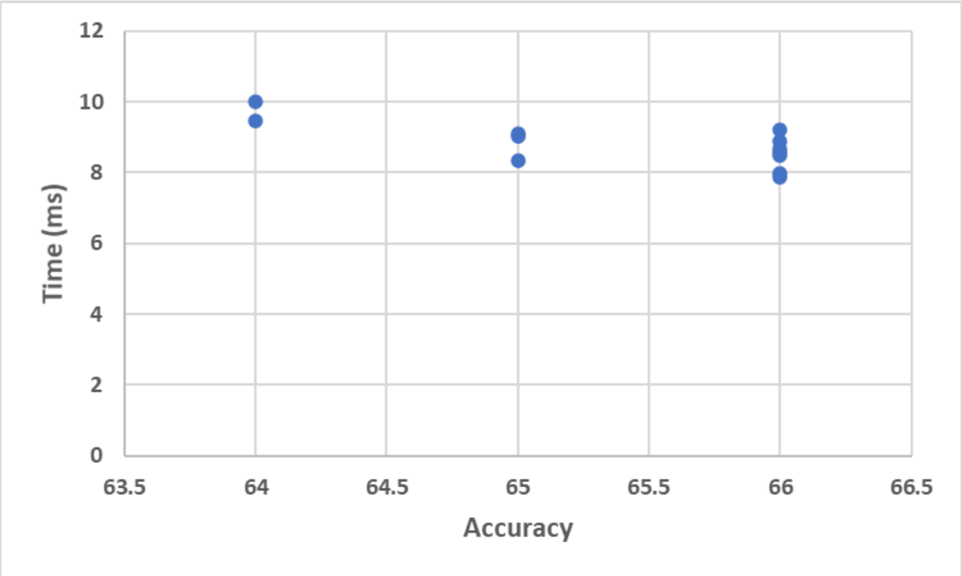
The facial identification system exhibits good performance and accuracy in identifying students' feelings. Following training, the model had an average accuracy of 66 percent (figure 20), in spite of the fact that different students have different ways of expressing the same emotion. This method takes numerous successive images of each pupil, saves them, and displays the results graphically. As a result, the technology enables the professor to review the outcomes following each session. Additionally, by clicking on a student's label in class, the lecturer can follow up with any student in real time.

The learner is informed if the algorithm is unable to identify any faces. This method is the best at recognizing faces. After six alerts, either the lecturer receives a decision or the student's absence is recorded for this session. Second, throughout the lesson, the technology monitors each student's emotions and facial expressions. The system retains the comments and response for each student at the end of each session in the form of a graph that shows the amount of messages they got as well as other data. Moreover, the presentation is open to anyone who wants to view the feedback from the students.

Additionally, modifications done in response to the expert recommendations advise that the system gave post-class response to all learners on a single graph so that it can function as a class feedback graph. This is based on the professionals and instructors. The instructors proposed modifying the titles of various facial expressions or emotions to better reflect the students' mental states at the time of the instruction. For instance, the term of the emotional condition of grief may be changed to "state of absent mind."

Figure 20

Comparing the system's accuracy to time



Step 3:

The most crucial element in the effectiveness of distance learning, which is keeping track of students' e-exam behavior, is covered in the system's last portion. As a result, the system was developing a model to track learners throughout the online exam by tracking the movement of the entire eye as well as the eye's iris using eye tracking methods in the full absence of the face. When the system was being developed, this was done in accordance with advice and judgment from experts. The technology will inform the learner audibly if the iris leaves the computer monitor for longer than five seconds. If the alarm is given more than five times, it will be assumed that the student is cheating. The system will also send the learner an auditory alarm if any of the following situations are noticed, including eye movement, the presence of any object other than the eye, or the appearance of several faces.

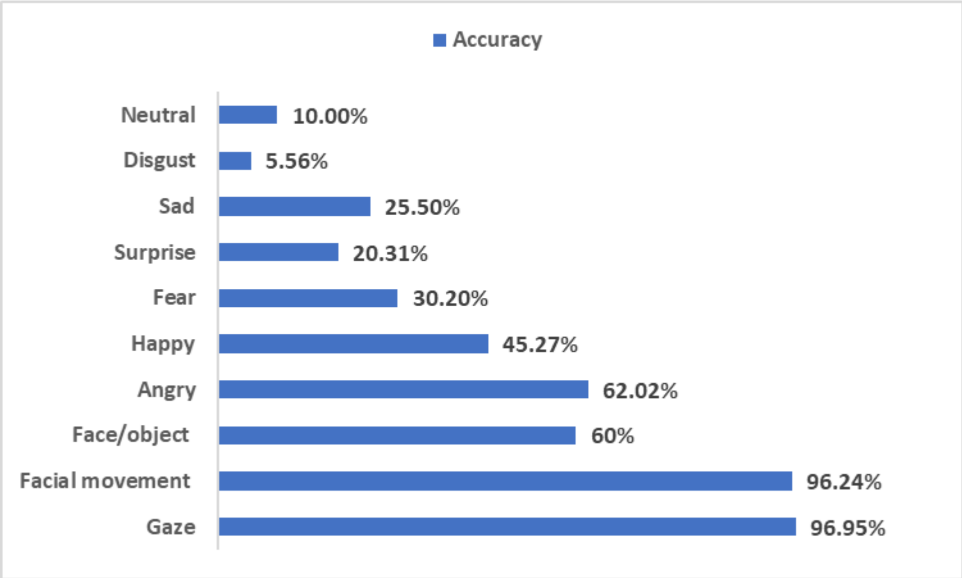
The technology also creates a detailed statistic for the student's circumstances at that time. For instance, if the student is not alerted during the exam, the framework will report that the student's status was typical after the test has ended. Otherwise, the system will give the student feedback indicating how many alerts and how long each aberrant case lasted by applying the YOLO (V3) trained model.

Step 4:

The outcomes of accuracy and performance with respect to the students' indicated actions are shown in Figure 21. With the gaze tracking algorithm achieving 96.95 percent accuracy and the facial movement tracking algorithm achieving an accuracy of up to 96.24 percent, this system displays the precision and greater performance in detecting the anomalous attitudes of learners in the e-exam. Additionally, the accuracy of the face recognition and object identification models was about 60%. Additionally, whereas fear was accurate to 30.20 percent, pleasant behavior was 45.27 percent accurate. From the perspective of the lecturers, this technology enables instructors to efficiently identify incidents of anticipated cheating during online tests.

Figure 21

Performance and Accuracy Regarding Students' Expression of Behavior



4.4.2. Experts' Feedback

A decision was taken based on the received replies from the test examiners after adjustments were made in response to expert comments. Professionals and instructors advised sends a real-time notification to the exam invigilators for each anomalous behaviour (gaze, resentment, facial expression, etc.) during e-exams. Additionally, the professionals and lecturers recommended describing each inappropriate behavior in the feedback summary. After receiving comments, a mechanism for student invigilation was ultimately designed based on the needs and opinions of the lecturers. These reviewers' perspectives and remarks, professionals and instructors, summarized the significance of having such well-unified systems in distant learning for keeping track of students taking electronic exams. This is due to the system's success in enhancing the learning experience, boosting the validity of the online assessments, and saving the lecturer's time.

The instructor's comprehension of the requirements of the learning instrument or system that helps them in providing high level supervision is among the most crucial components in ensuring the quality of remote learning. The technology that can accurately check and detect students' attempts in online exams, as well as their faces and emotions. This has been accomplished by the approach developed here by enhancing the effectiveness and legitimacy of e-testing systems. By real-time recording of students' emotions, it also assists in the detection of exam cheating.

4.5 Second: The system follow-up during the class

The section explained the findings of the application of the system during the class to monitor the students' facial emotions based on the seven measurement scales in distance learning. Figure 22 to 26 illustrate the facial recognition system during the class. The follow-up showed interesting findings where the "angry" scale was found to increase with an increase in the number of times the class session was taken. The "neutral" scale has no significant variations.

Figure 22 displays facial recognition during 10 minutes of lesson. The results showed that the angry, disgust, and surprised emotions had 0.0% each during the 10 minute period of the commencement of the lecture. The students also indicated emotions such as 34.6% scared, 23.0% understand, 34.5% neutral, and 7.5% absent-minded.

Figure 22

Facial Recognition During 10 Minutes Of Lesson

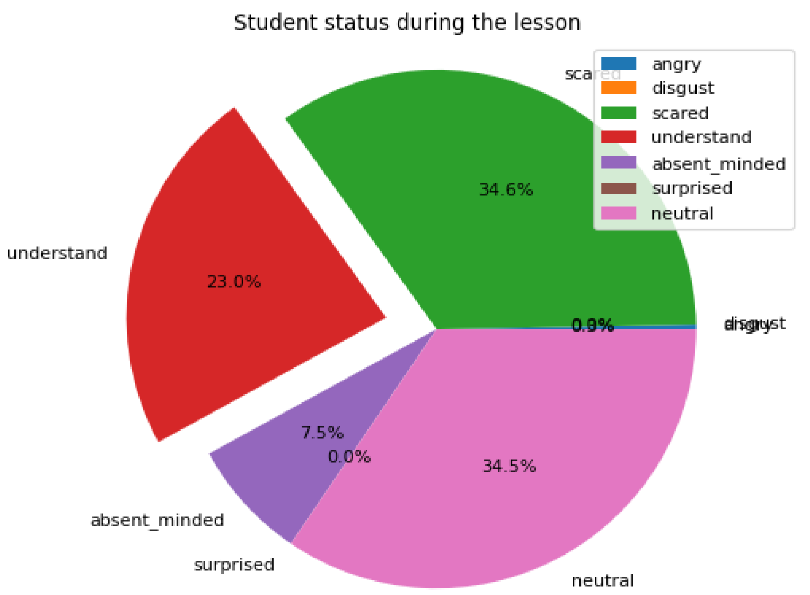


Figure 23 displays facial recognition during 20 minutes of lesson. The results revealed that the disgust, surprised, and absent-minded emotions had 0.0% each during the 20 minute period of the commencement of the lecture. However, the angry emotion had 3.7% of the facial expression. The students also exhibited 18.7% scared, 39.9% understand, and 37.7% neutral.

Figure 23 displays facial recognition during 30 minutes of lesson. The results revealed that the disgust, surprised, absent-minded, and scared emotions had 0.0% each during the 30 minute period of the beginning of the lecture. However, the angry emotion increased to 8.9% for facial expression. The students also exhibited 51.2% understand and 38.3% neutral.

Figure 23

Facial Recognition During 30 Minutes Of Lesson

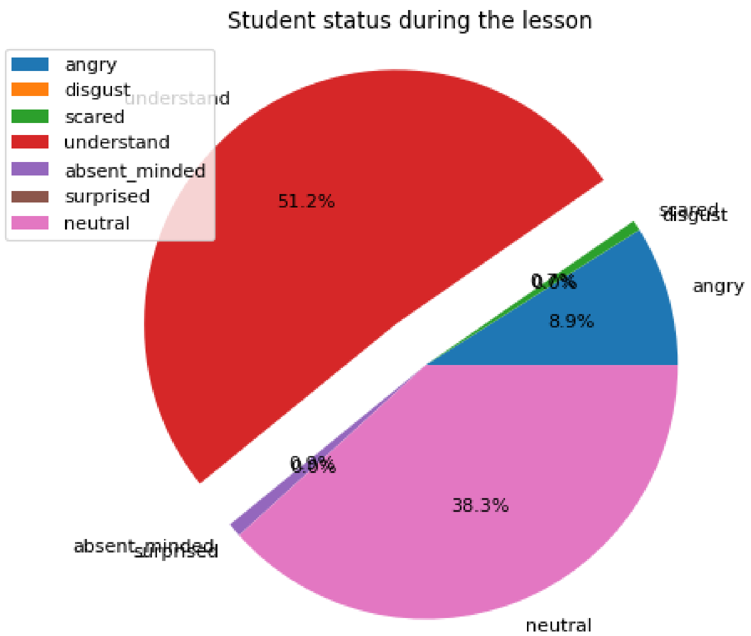


Figure 24 displays facial recognition during 40 minutes of lesson. The results uncovered that the disgust, surprised, and scared emotions had 0.0% each during the 40 minute period of the start of the lecture. However, the angry emotion increased to 19.1% for facial expression. The students also demonstrated 35.9% understand and 29.4% neutral, in addition to 14.0% absent-minded.

Figure 24

Facial Recognition During 40 Minutes Of Lesson

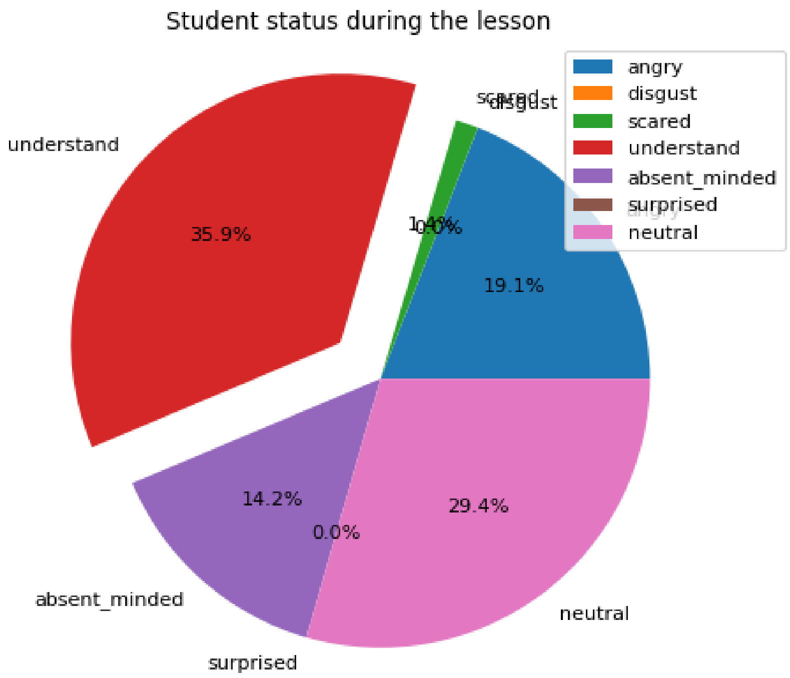
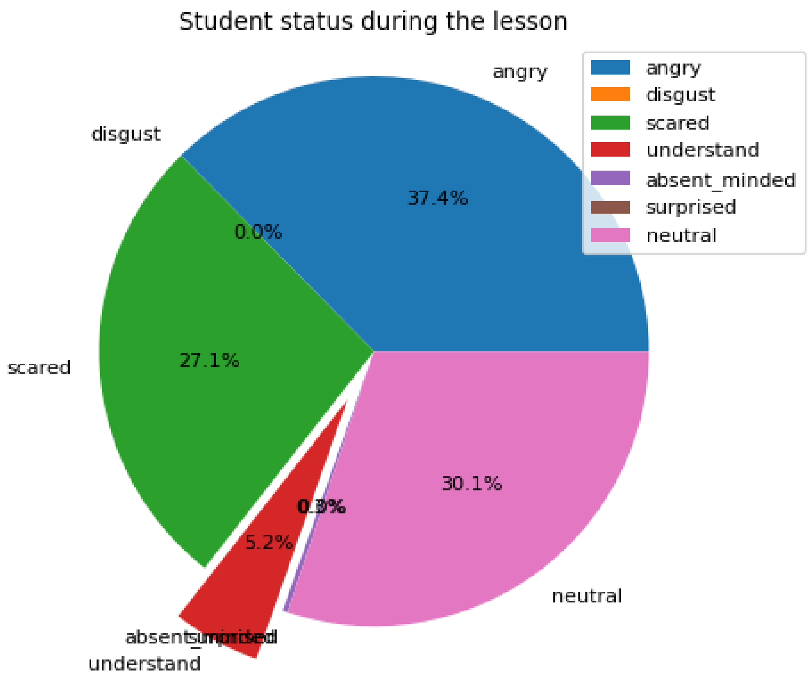


Figure 25 displays facial recognition during 50 minutes of lesson. The results revealed that the surprised, disgust, and absent-minded emotions had 0.0% each during the 50 minute period of the start of the lecture. However, the angry emotion increased substantially to 37.4% for facial expression, while understand emotion decreased considerably to 5.2%, in addition to the scared emotion suddenly increasing to 27.1%. The students also showed a high neutral of 30.1%.

Figure 25

Facial Recognition During 50 Minutes Of Lesson



4.6 Third: Follow-up system during the exam

4.6.1. Cheating attempt recognition

Figure 26 displays the facial movement of gaze tracking to the center. The system detects and measures any slight movement or shift of the student's gaze to the center while looking at other student materials or objects during an exam session in distance learning. Figure 26 (a) depicted the student's gaze looking center in the downward direction at an angle of 382, 293 toward the student on the left and 469, 296 toward the student on the right. Figure 26 (b) showed that the student's gaze was centered in the upward direction at an angle of 355, 189 toward the student on the left and 461, 188 toward the student on the right. Figure 26 (c) revealed that the gaze of the student was looking center in the sideways direction at an angle of 399, 187 toward the student on the left and at an angle of 512, 198 toward the student on the right.

Figure 26

Facial Movement Of Gaze Tracking To The Center

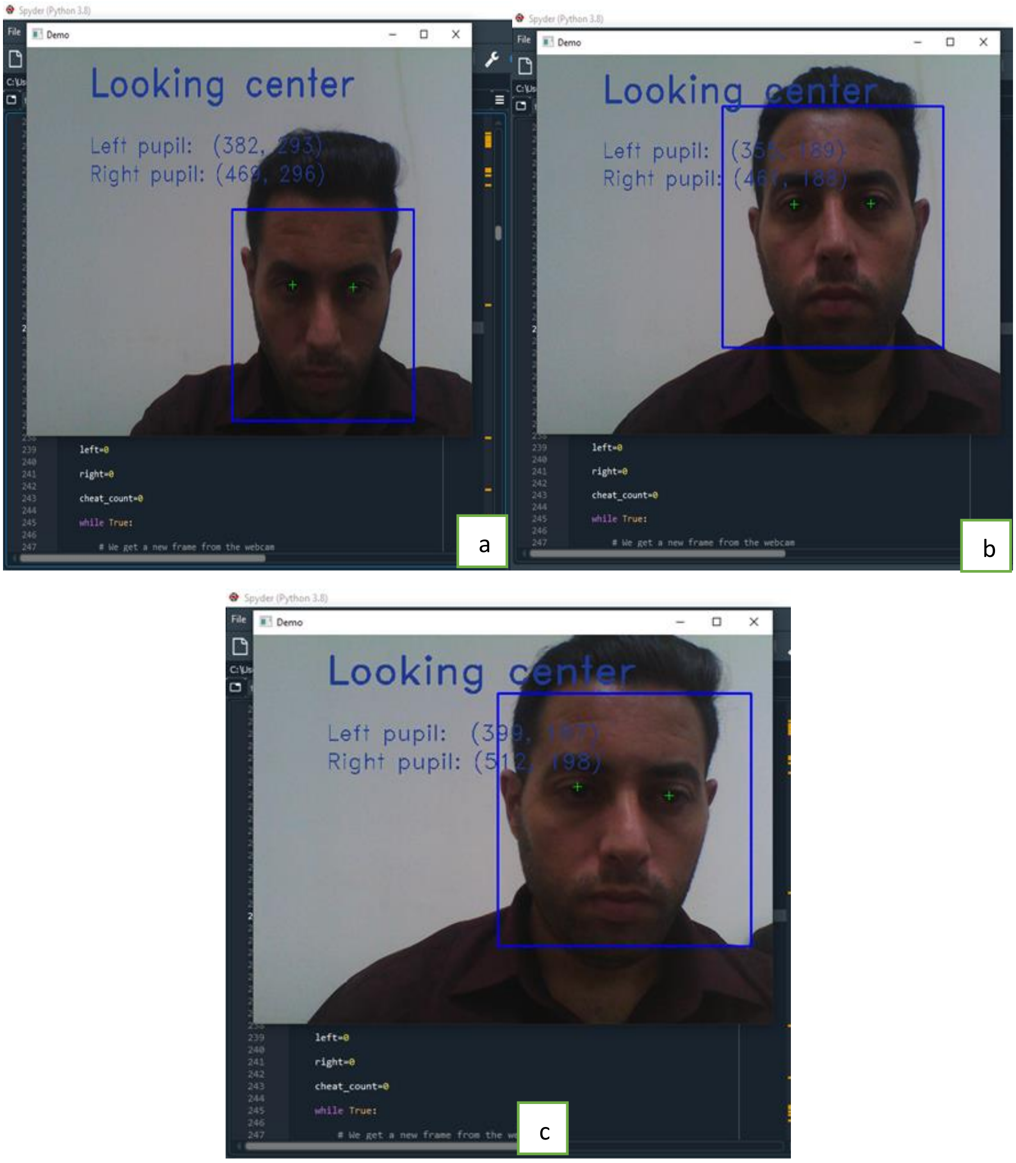


Figure 27 displays the facial movement of gaze tracking to the left. The system detects and measures any slight movement or shift of the student's gaze to the left while looking at other student materials or objects in the exam session. Figure 27 (a) portrayed the student's gaze looking left in the upward direction at an angle of 351, 205 toward the student on the left and 443, 206 toward the student on the right. Figure 27 (b) demonstrated that the student's gaze was left in the sideways direction at an angle of 380, 212 toward the student on the left and 482, 211 toward the student on the right.

Figure 27

Facial Movement Of Gaze Tracking To The Left

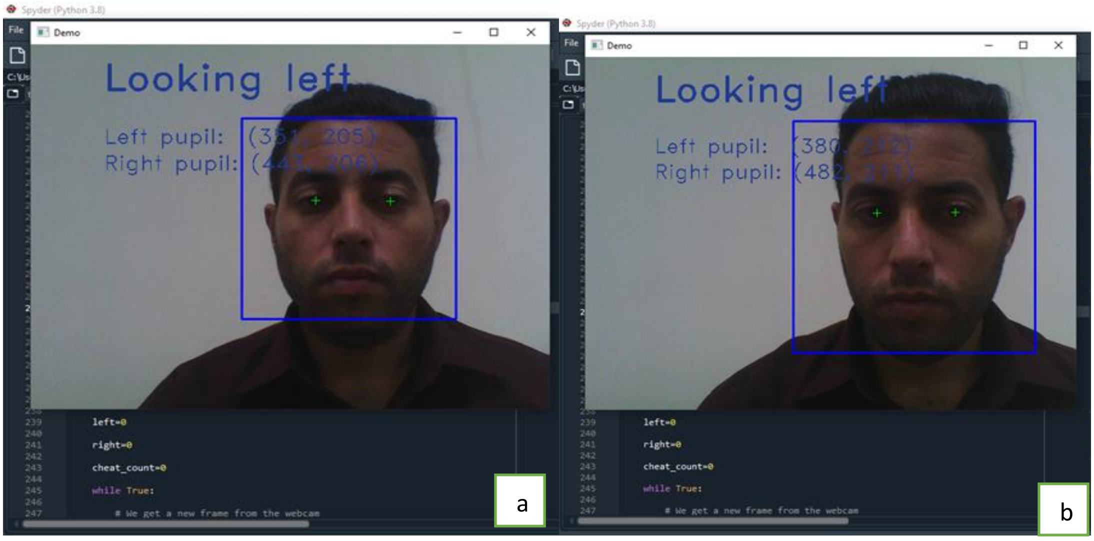
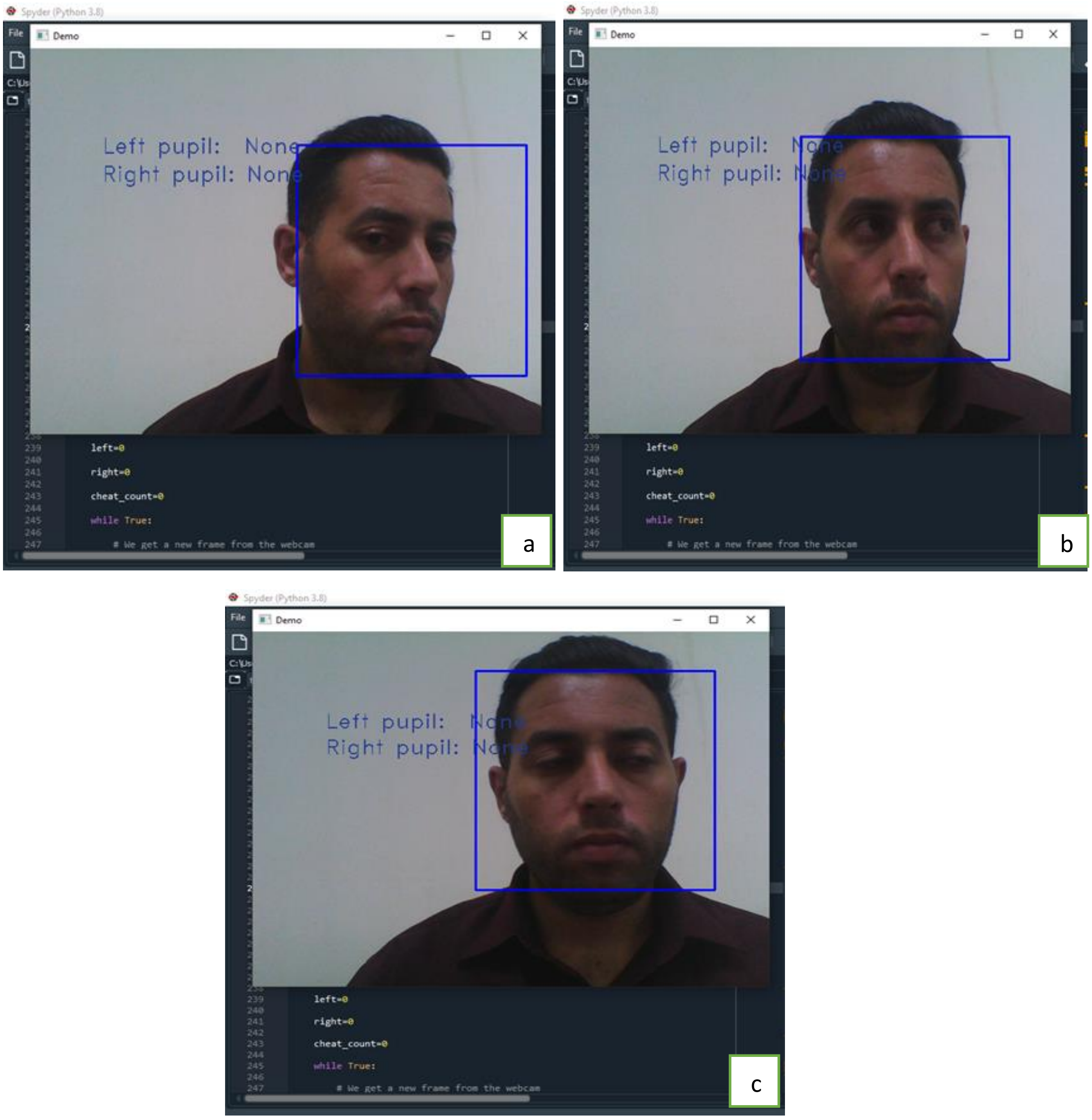


Figure 28 illustrates the facial movement of gaze tracking to the right. Figure 28 (a) exhibited the student's gaze looking right in the rightward direction (zero angle). Figure 28 (b) exhibited that the student's gaze was right in the upward direction (zero angle). Figure 28 (c) exhibited that the gaze of the student was looking right in the centered direction (zero angle).

Figure 28

Facial Movement Of Gaze Tracking To The Right


Spyder (Python 3.8)
Demo
Left pupil: None
Right pupil: None
left=0
right=0
cheat_count=0
while True:
# We get a new frame from the webcam
a
Spyder (Python 3.8)
Demo
Left pupil: None
Right pupil: None
left=0
right=0
cheat_count=0
while True:
# We get a new frame from the webcam
b
Spyder (Python 3.8)
Demo
Left pupil: None
Right pupil: None
left=0
right=0
cheat_count=0
while True:
# We get a new frame from the webcam
c

CHAPTER V

DISCUSSION

5.1. Introduction

This section presents the discussion of the results obtained in this study as supported by past studies. This study has developed the facial recognition system to monitor students in distance learning and e-exams to detect cheating behavior.

5.2. Performance of Deep Learning Algorithms

The findings of this study validate the effectiveness and efficiency of combined CNN and computer vision algorithms that support emotion forecasting and pattern analysis in facial recognition systems. The precision of these algorithms has allowed lecturers in distance learning manage interaction with the learners during the class in order to effectively run a classroom and detect cheating behavior in e-exams. In addition, the combination of the CNN algorithm with other algorithms such as RNNs has been reported to produce greater efficiency and accuracy in FER (Banerjee et al., 2019; Zhang et al., 2020). The most recent systems for categorizing emotions employ a combination of numerous features. The estimation of an emotion is part of the smart feature combination. Studies on feature combinations showed an improvement in classification accuracy rate when compared to systems that still rely on personal features (Kerkeni et al., 2017; Jain et al., 2020). The result has proven that OpenCV is a strong source of CVA. It has been previously shown that OpenCV achieves a high rate of face recognition accuracy (Zhu et al., 2018). Though it is frequently used in picture classification and identification, this finding can add to the literature. Yang et al. (2020) indicated that CVA with the support of CNN is an effective tool for facial recognition systems. In this study, to create a highly effective and dependable system, the processes of face identification and detection were assessed with high accuracy using image processing. Due to its capacity to identify nonlinear borders and linear processing conditions, the CNN is used in emotion recognition (Swain et al., 2018). Once the CNN's architecture is established, it is simple to construct and define training algorithms. As a result, it serves as the primary classifier in the field of emotion recognition (Kwon, 2020).

The current system evaluates the students' facial characteristics and generates the outcomes. The system's effectiveness is measured by how well it identifies students' facial expressions during tests, according to lecturers. Students can also use the system to confirm their identity. It also includes a method for detecting cheating that makes use of face recognition, eye movement recognition, and face tracking. The system also scans the image for faces or items being used while the head and hand are moving, which could be a test-cheating tactic. Furthermore, this system has an easy-to-use user interface that makes it simple to access any of these features. This system's creation was according to semi-structured interviews with instructors to learn more about the barriers and difficulties they face when instructing online or through distance learning. Up until the time of the system's most recent design, their comments and opinions were taken into account and used to enhance the system. Following the system's completion in its final version, their opinions were requested in order to determine their level of satisfaction with it and whether they would support its use in remote learning.

5.3. Accuracy of the Facial Recognition System

The current study's CNN algorithm yielded a performance accuracy of 99.38 percent for the recognition system.Some systems attempted to develop facial recognition technology to investigate student attendance fraud and cheating by capturing and transmitting numerous images of the student in various positions and appearances.The technique predicted 90 percent of student attendance fraud and cheating correctly.This technology demonstrated that accuracy increased with the number of images in the database (Okokpujie et al., 2017). As a result, the findings of such a tool are very accurate in an research conducted by Winarno et al. (2014), where the degree of dependability can reach 95.7 percent on average and has quicker computation for face detection results, particularly when compare with traditional PCA approaches. Because Mahalanobis Distances Classification is supported, the typical computational speed value applying the 3WPCA-MD tool is approximately 5-7 milliseconds for each facial recognition operation. This

Mahalanobis distance is a well-known method for creating classification results that take advantage of the data structure (Roth et al., 2014). Winarno et al. (2017) demonstrate how the 3WPCA is utilized to prevent face information falsification with identification precision exceeding 98 percent and provides a consistent attendance system according to face identification.

Mery, Mackenney, and Villalobos (2019) designed a method to track students' bibliometric attendance and identify them in order to enhance educational platforms. However, compared to our system's accuracy of 99.38 percent, that system's accuracy was just 95.38 percent. Additionally, our results were closely linked to those previously published by Golwalkar and Mehendale (2022), who found that their method had a performance time of less than 10 ms and an accuracy rate of 88.92%. Due to the system's ability to conceal facial recognition in real-time, it was determined that it was effective for identifying people in CCTV footage. Additionally, our system successfully identified anomalous behaviors in students during the electronic exam, with the gaze tracking system achieving an accuracy of up to 96.95 percent and the facial movement tracking system reaching a precision of up to 96.24 percent. Additionally, the accuracy of the face detection and object detection models was about 60%. Furthermore, while fear was only 30.20 percent accurate, pleasant behavior was 45.27 percent accurate.From the perspective of the lecturers, this technology enables instructors to efficiently identify incidents of anticipated cheating during online tests. Our results were in line with those of other studies (Chuang, Craig, & Femiani, 2017; D'Souza & Siegfeldt, 2017; Dendir & Maxwell, 2020) that looked at the ways students use to cheat on online tests. In those studies, the systems precisely (87.5%) recorded the movements of the learner's head, face, and indications of fear excitement.

5.4. Emotion Recognition

Particularly when using deep learning to forecast behaviors based on facial expressions, researchers' ability to read the emotions of others differs substantially. When the data from this study were analyzed, the accuracy of the emotion identification system increased as each facial emotion, such as angry, neutral, scared, understood, disgust, absentminded, and surprised, increased.

There are various emotion forms that are obvious through the integration of data from facial expressions, movement, and body motions. This showed that various emotions were easily distinguished by the facial recognition system. This is in accordance with earlier research. For instance, Pesonen and Hannula (2014) indicated that interactions between a real person and a computer-controlled agent include observations of various emotions, including anger, happiness, fear, disgust, sadness, disregard, and humour. Recordings of dyadic interactions between actors are available in Asokan, Kumar, Ragam, and Shylaja (2022), which also includes observations of various emotions, including happiness, anger, grief, excitement, and neutrality.

The facial recognition software was able to identify the pupils' emotional states and levels of enthusiasm during the online lesson. This device instantly transmits the emotional conditions of the students to the lecturer, fostering a more engaged learning environment. This technology uses a webcam linked to a computer to record physiological signs and emotional movements. The data, such as frustration, grief, fear, rage, and neutrality, is extracted and processed on a centralized computer.

Further, by further creating a system to identify the seven primary emotions (anger, surprise, disgust, happiness, sorrow, fear, and neutrality), Ma et al. (2022) divided emotions into four categories: fear, anger, sadness, and happiness. The feelings of fear might range from a slight level of worry to outright terror. Therefore, emotions offer helpful solutions to the cheating behavior among students in distance learning. They are therefore considered to be a product of the technology and power of deep learning algorithms.

5.5. Experts' Feedback

The problems with distance learning have been addressed with experts' feedback (Kilinc, Okur, & lker, 2021; Lim et al., 2021). The degree to which instructors comprehend the conditions of students' emotions and behaviours during the learning session is one of the most critical factors that determines the systems for distance learning are effective. This understanding enables lecturers to promptly modify their teaching strategies in order to capture the interest of the greatest number of students. The lecturers' capacity to manage the classroom population while administering exams is another consideration. Based on professional recommendations and opinions throughout the development of the facial recognition system through follow-up with students in the class, it was decided to ascertain the emotions of the students by featuring each expression in a timely manner or at a specific interval of time during the class session or exams. This system takes many consecutive images of each student at a 10-minute interval to increase its performance. This process in a timely manner is supported by the report of Behera et al. (2021), who statistically predicted and analysing time series data and facial expressions with Mini Xception CNN, and the results showed positive system performance based on different time intervals. In addition, our technology saves the outputs for later utilize and displays them graphically on the monitor. As a result, the technology enables the professor to review the outcomes following each session. Additionally, by clicking on a student's name during class, the lecturer can follow up with any student in real time.

The learner is informed if the algorithm is unable to identify any faces. The first system to recognize faces is this one. After six alerts, either the lecturer receives a decision or the student's absence is recorded for this session. Second, throughout the lesson, the technology monitors each student's emotions and facial expressions. The system records the comments and feedback (from interviews) for each student at the end of each session in the form of a graph that shows how many messages and other pieces of information they have received. The instructor can access the student feedback whenever they want by logging in. This system exhibits good performance and accuracy in identifying students' emotions. After training, the model had an average accuracy of 66 percent, despite the fact that different students may display the same emotion in different ways. Tam, da Costa Moura, Oliveira, and Varajo (2020) created a method to identify students' facial expressions, and they discovered that it was only 51.28 percent accurate. During the online session, the Chuang, Craig, and Femiani (2017) systems achieved a 62 percent accuracy rate for student follow-up. Our results showed enhanced student detection and verification in remote learning systems, outperforming prior results by 66%. In general, this makes it easier for professors to understand students' emotions during online sessions.

CHAPTER VI

CONCLUSION AND RECOMMENDATIONS

This chapter offers suggestions based on conclusions drawn from the research findings in accordance with the main purpose.

6.1. Conclusion

The results of this study demonstrated that the facial identification system was very effective and accurate at identifying students' normal and deviant behaviors as well as their classroom behaviors. The system was created to oversee distant learning students. The system has a student verification system and was designed to be used by university lecturers to keep an eye on students taking electronic exams. This system was created using a number of deep learning algorithms, and the objective was successfully attained.

The CNN and computer vision algorithms were used successfully in developing the facial recognition system in this thesis. The findings of this study validate the effectiveness and efficiency of combined CNN and computer vision algorithms because of their robust support for emotion prediction and pattern analysis. A CNN was trained to recognize and express the emotions that the students experience and express during educational sessions. The results showed the emotions expressed by students during the identification process, class, and exam encoding and decoding through the facial recognition system. The system records feedback for each student at the conclusion of each session in the way of a graph that shows the students' emotions throughout the session. The facial recognition algorithm performs extremely well and accurately when determining the emotions of kids. Each student is imaged multiple times in a row by this technology, which then saves the images and displays the results graphically. Additionally, it enables the lecturer to contact any learner directly by clicking on their name.

Real-time information to identify cheaters was one of the difficulties we encountered during the development process. As a result, we used input from the lecturers through interviews in the system. We also use data from earlier studies, gather information for the system's creation and analysis. In order to increase the system's effectiveness and efficiency for distance learning, both types of information were combined.

The development of the student identification system involved enhancing the efficacy and legitimacy of online testing platforms. By live-tracking students' emotions, it also assists in identifying exam cheating. This is due to its ability to accurately discern students' expressions and emotions as well as to verify and detect their e-exam attempts. To identify students' unusual behaviour during an online exam, the e-exam framework employs a trained model. This means that if the student is not alerted during the test, the system will report that the learner's condition was regular at the conclusion of the test. The facial recognition detects the faces of the students just before the student's identification process initiation to be mostly expressing "understand" followed by "neutral" and subsequently "angry". Expression of other emotions such as scared had a low percentage, while disgust and surprised had no facial expression results. However, the results of follow-up during class and exam showed interesting findings where the “angry” scale was found to increase with an increase in the number of times the class and exam session were taken. The “neutral” scale has no significant variations.

The results of the system follow-up throughout class also showed that the system tracks the interchange of the whole eye while simultaneously keeping an eye on the iris of the eye. Additionally, it monitors each student's emotions and facial expressions throughout the lesson. The system saves each student's comments and feedback at the end of each session in the form of a graph. Results showed that the angry, disgust, and surprised emotions had 0.0% each during the 10-minute period of the lecture. The students also indicated emotions such as 34.6% scared, 39.9% understand, and 37.7% neutral. However, the angry emotion increased substantially, reaching 37.4% for facial expression.

The findings of the system follow-up during the exam indicated that the system detects and measures any slight movement or shift of a student's eye to the center while looking at other student materials or objects. The student's gaze was mostly looking center in the downward direction at an angle of 382, 293 toward the students on the left and 469, 296 toward the student on the right. In addition, the system detects and measures any slight movement or shift of the student's gaze while looking at other student materials or objects.

In conclusion, this research offers knowledge about combining several models to enhance student monitoring in remote learning systems in terms of architecture, imagination, and statistics analyzing data using deep learning algorithms and an agile methodology.

6.2. Recommendations

The recommendations of this study include the possibility of future studies including some educational activities and features that assist students with special needs, such as certain instructional games and other features that aid students.

Future studies might explore novel ways for one student to communicate the same feeling to another in order to support students with special needs, as well as facial detection technology to improve the effectiveness of the follow-up system used to detect cheaters during exams.

The goal of a potential future study might be to improve the system's front-tool performance. Based on the assessment of this study, the entire system would be usable when the front-tool performance might be improved such that the recognition of complete head movement and tracking of all the facial angular emotions reaches greater levels of precision.

Future studies can use questionnaires in combination with interviews to collect opinions of the lecturers regarding the system performance to allow control and deeper understanding and improvement of the facial recognition system. It is also important to undertake further design research on the student’s side's graphical user interface.

Future research should use techniques that are in line with the agile model when modeling student faces as biometric logins for distance learning. These techniques could support the theories and forecasts of what would be presented to students in online tests even further.

REFERENCES

Abu-Saqer, M. M., Abu-Naser, S. S., & Al-Shawwa, M. O. (2020). Type of Grapefruit Classification Using Deep Learning. *International Journal of Academic Information Systems Research (IJAISR)*, *4*(1).

Ahmed, A. A. A., Keezhatta, M. S., Khair Amal, B., Sharma, S., Shanan, A. J., Ali, M. H., & Farooq Haidari, M. M. (2022). The Comparative Effect of Online Instruction, Flipped Instruction, and Traditional Instruction on Developing Iranian EFL Learners' Vocabulary Knowledge. *Education Research International*, *2022*.

Ahmed, N. Y. (2021). Real-time accurate eye center localization for low-resolution grayscale images. *Journal of Real-Time Image Processing*, *18*(1), 193-220.

Aifanti, N., Papachristou, C., & Delopoulos, A. (2010, April). The MUG facial expression database. In *11th International Workshop on Image Analysis for Multimedia Interactive Services WIAMIS 10* (pp. 1-4). IEEE.

Albastroiu, R., Iova, A., Gonçalves, F., Mihaescu, M. C., & Novais, P. (2018, October). An e-Exam platform approach to enhance University Academic student's learning performance. In *International Symposium on Intelligent and Distributed Computing* (pp. 404-413). Springer, Cham.

Ali, D., Touqir, I., Siddiqui, A. M., Malik, J., & Imran, M. (2022). Face Recognition System Based on Four State Hidden Markov Model. *IEEE Access*, *10*, 74436-74448.

Alsaadi, B., & Saeedi, K. (2022). Data-driven effort estimation techniques of agile user stories: a systematic literature review. *Artificial Intelligence Review*, 1-32.

Al-Shalchi, O. N. (2009). The effectiveness and development of online discussions. *Journal of Online Learning and Teaching*, *5*(1), 104-108.

Amirgaliyev, Y., Hahn, M., & Mussabayev, T. (2017). The speech signal segmentation algorithm using pitch synchronous analysis. *Open Computer Science*, *7*(1), 1-8.

Andrejevic, M., & Selwyn, N. (2020). Facial recognition technology in schools: critical questions and concerns. *Learning, Media and Technology*, *45*(2), 115-128

Andrychowicz, M., Denil, M., Gomez, S., Hoffman, M. W., Pfau, D., Schaul, T., ... & De Freitas, N. (2016). Learning to learn by gradient descent by gradient descent. In *Advances in neural information processing systems* (pp. 3981-3989).

Arinaldi, A., & Fanany, M. I. (2017, May). Cheating video description based on sequences of gestures. In *2017 5th International Conference on Information and Communication Technology (ICoIC7)* (pp. 1-6). IEEE.

Arriaga, O., Valdenegro-Toro, M., & Plöger, P. (2017). Real-time convolutional neural networks for emotion and gender classification. *arXiv preprint arXiv:1710.07557*.

Arriaga, O., Valdenegro-Toro, M., & Plöger, P. (2017). Real-time convolutional neural networks for emotion and gender classification. *arXiv preprint arXiv:1710.07557*.

Asadullah, M., & Nisar, S. (2016, August). An automated technique for cheating detection. In *2016 Sixth International Conference on Innovative Computing Technology (INTECH)* (pp. 251-255). IEEE.

Asokan, A. R., Kumar, N., Ragam, A. V., & Shylaja, S. S. (2022, July). Interpretability for multimodal emotion recognition using concept activation vectors. In *2022 International Joint Conference on Neural Networks (IJCNN)* (pp. 01-08). IEEE.

Asokan, A. R., Kumar, N., Ragam, A. V., & Shylaja, S. S. (2022, July). Interpretability for multimodal emotion recognition using concept activation vectors. In *2022 International Joint Conference on Neural Networks (IJCNN)* (pp. 01-08). IEEE.

Athoillah, M., Irawan, M. I., & Imah, E. M. (2015). Study comparison of svm-, k-nn-and backpropagation-based classifier for image retrieval. *Jurnal Ilmu Komputer dan Informasi*, *8*(1), 11-18.

Babu, A. R., Rajavenkatanarayanan, A., Brady, J. R., & Makedon, F. (2018, October). Multimodal approach for cognitive task performance prediction from body postures, facial expressions and EEG signal. In *Proceedings of the Workshop on Modeling Cognitive Processes from Multimodal Data* (pp. 1-7).

Balachandran, L., & Kirupananda, A. (2017, December). Online reviews evaluation system for higher education institution: An aspect based sentiment analysis tool. In 2017 11th international conference on software, knowledge, information management and applications (SKIMA) (pp. 1-7). IEEE

Banerjee, I., Ling, Y., Chen, M. C., Hasan, S. A., Langlotz, C. P., Moradzadeh, N., ... & Lungren, M. P. (2019). Comparative effectiveness of convolutional neural network (CNN) and recurrent neural network (RNN) architectures for radiology text report classification. *Artificial intelligence in medicine*, *97*, 79-88.

Bashitialshaaer, R., Alhendawi, M., & Lassoued, Z. (2021). Obstacle comparisons to achieving distance learning and applying electronic exams during COVID-19 pandemic. *Symmetry*, *13*(1), 99.

Behera, B., Prakash, A., Gupta, U., Semwal, V. B., & Chauhan, A. (2021). Statistical Prediction of Facial Emotions Using Mini Xception CNN and Time Series Analysis. In *Data Science* (pp. 397-410). Springer, Singapore.

Behera, B., Prakash, A., Gupta, U., Semwal, V. B., & Chauhan, A. (2021). Statistical Prediction of Facial Emotions Using Mini Xception CNN and Time Series Analysis. In *Data Science* (pp. 397-410). Springer, Singapore.

ben Othmane, L., Angin, P., Weffers, H., & Bhargava, B. (2014). Extending the agile development process to develop acceptably secure software. *IEEE Transactions on dependable and secure computing*, *11*(6), 497-509.

Bobyliev, D. Y., & Vihrova, E. V. (2021, March). Problems and prospects of distance learning in teaching fundamental subjects to future mathematics teachers. In *Journal of Physics: Conference Series* (Vol. 1840, No. 1, p. 012002). IOP Publishing.

Boekaerts, M. (2010). The crucial role of motivation and emotion in classroom learning. *The nature of learning: Using research to inspire practice*, 91-111.

Boekaerts, M., & Pekrun, R. (2015). Emotions and emotion regulation in academic settings. In *Handbook of educational psychology* (pp. 90-104). Routledge.

Breazeal, C. (2003). Emotion and sociable humanoid robots. *International journal of human-computer studies*, *59*(1-2), 119-155.

Brinkmann, S. (2014). Unstructured and semi-structured interviewing. *The Oxford handbook of qualitative research*, 277-299.

Cabada, R. Z., Estrada, M. L. B., Hernández, F. G., Bustillos, R. O., & Reyes-García, C. A. (2018). An affective and Web 3.0-based learning environment for a programming language. *Telematics and Informatics*, *35*(3), 611-628.

Carragher, D. J., Towler, A., Mileva, V. R., White, D., & Hancock, P. J. (2022). Masked face identification is improved by diagnostic feature training. *Cognitive research: principles and implications*, *7*(1), 1-12.

Chaffar, S., & Frasson, C. (2004, September). Using an emotional intelligent agent to improve the learner's performance. In *Social and emotional intelligence in learning Environments workshop, 7th International Conference on Intelligent Tutoring System* (Vol. 30, pp. 37-43).

Chen, C. M., & Wang, H. P. (2011). Using emotion recognition technology to assess the effects of different multimedia materials on learning emotion and performance. *Library & Information Science Research*, *33*(3), 244-255.

Chen, H., Dai, Y., Feng, Y., Jiang, B., Xiao, J., & You, B. (2017). Construction of affective education in mobile learning: The study based on learner's interest and emotion recognition. Computer Science and Information Systems, 14(3), 685-702.

Cheng, G., Xie, X., Han, J., Guo, L., & Xia, G. S. (2020). Remote sensing image scene classification meets deep learning: Challenges, methods, benchmarks, and opportunities. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 3735-3756.

Cherry, K., & Snyder, C. (2019). Understanding the psychology of positive thinking. *Retrieved on January, 27,* 2021.

Chuang, C. Y., Craig, S. D., & Femiani, J. (2017). Detecting probable cheating during online assessments based on time delay and head pose. *Higher Education Research & Development*, *36*(6), 1123-1137.

Coghlan, S., Miller, T., & Paterson, J. (2021). Good proctor or "big brother"? Ethics of online exam supervision technologies. *Philosophy & Technology*, *34*(4), 1581-1606.

Coman, C., Țîru, L. G., Meseșan-Schmitz, L., Stanciu, C., & Bularca, M. C. (2020). Online teaching and learning in higher education during the coronavirus pandemic: Students' perspective. *Sustainability*, *12*(24), 10367.

da Silva, L. M., Dias, L. P., Barbosa, J. L., Rigo, S. J., dos Anjos, J., Geyer, C. F., & Leithardt, V. R. (2022). Learning analytics and collaborative groups of learners in distance education: a systematic mapping study. *Informatics in Education*, *21*(1), 113-146.

Danelljan, M., Gool, L. V., & Timofte, R. (2020). Probabilistic regression for visual tracking. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 7183-7192).

Darban, M., & Polites, G. L. (2016). Do emotions matter in technology training? Exploring their effects on individual perceptions and willingness to learn. *Computers in Human Behavior*, *62*, 644-657.

Dave, N. (2013). Feature extraction methods LPC, PLP and MFCC in speech recognition. *International journal for advance research in engineering and technology*, *1*(6), 1-4.

David, V. (2017). *Computational analysis of personality and emotion in semi-structured interviews* (Doctoral dissertation, Carleton University).

Dendir, S., & Maxwell, R. S. (2020). Cheating in online courses: Evidence from online proctoring. *Computers in Human Behavior Reports*, *2*, 100033.

Devi, B., & Preetha, M. M. S. J. (2020, June). Algorithmic Study on Facial Emotion Recognition model with Optimal Feature Selection via Firefly Plus Jaya Algorithm. In *2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184)* (pp. 882-887). IEEE.

Dharmawansa, A. D., Nakahira, K. T., & Fukumura, Y. (2013). Detecting eye blinking of a real-world student and introducing to the virtual e-Learning environment. *Procedia Computer Science*, *22*, 717-726.

Dhiman, C., & Vishwakarma, D. K. (2019). A review of state-of-the-art techniques for abnormal human activity recognition. *Engineering Applications of Artificial Intelligence*, *77,* 21-45.

Dobkin, C., Gil, R., & Marion, J. (2010). Skipping class in college and exam performance: Evidence from a regression discontinuity classroom experiment. *Economics of Education Review*, *29*(4), 566-575.

Dong, Q., Zhu, X., & Gong, S. (2019, July). Single-label multi-class image classification by deep logistic regression. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 33, No. 01, pp. 3486-3493).

Doulik, P., Skoda, J., & Simonova, I. (2017). Learning Styles in the e-Learning Environment: The Approaches and Research on Longitudinal Changes. *International Journal of Distance Education Technologies (IJDET)*, *15*(2), 45-61. http://doi.org/10.4018/IJDET.2017040104

Drye, S. L., Lomo-David, E., & Snyder, L. G. (2018). Normal Deviance: An Analysis Of University Policies And Student Perceptions Of Academic Dishonesty. *Southern Journal of Business & Ethics*, *10*.

D'Souza, K. A., & Siegfeldt, D. V. (2017). A conceptual framework for detecting cheating in online and take-home exams. *Decision Sciences Journal of Innovative Education*, *15*(4), 370-391.

Ebner, N. C., Riediger, M., & Lindenberger, U. (2010). FACES—A database of facial expressions in young, middle-aged, and older women and men: Development and validation. *Behavior research methods*, *42*(1), 351-362.

Ekman, P. (1992). An argument for basic emotions. *Cognition & emotion*, *6*(3-4), 169-200.

Ekman, P. (1999). Basic emotions. *Handbook of cognition and emotion*, *98*(45-60), 16.

Emami, S., & Suciu, V. P. (2012). Facial recognition using OpenCV. *Journal of Mobile, Embedded and Distributed Systems*, *4*(1), 38-43.

Engelbrecht, A. P. (2007). *Computational intelligence: an introduction*. John Wiley & Sons.

Escadas, M., Jalali, M. S., & Farhangmehr, M. (2019). Why bad feelings predict good behaviours: The role of positive and negative anticipated emotions on consumer ethical decision making. *Business Ethics: A European Review*, *28*(4), 529-545.

Essa, I. A. (1995). *Analysis, interpretation and synthesis of facial expressions* (Doctoral dissertation, Massachusetts Institute of Technology).

Fan, X., & Tjahjadi, T. (2019). Fusing dynamic deep learned features and handcrafted features for facial expression recognition. *Journal of Visual Communication and Image Representation*, *65*, 102659.

Faria, A. R., Almeida, A., Martins, C., & Gonçalves, R. (2015). Emotional adaptive platform for learning. In *Methodologies and Intelligent Systems for Technology Enhanced Learning* (pp. 9-16). Springer, Cham.

Faria, A. R., Almeida, A., Martins, C., Gonçalves, R., Martins, J., & Branco, F. (2017). A global perspective on an emotional learning model proposal. *Telematics and Informatics*, *34*(6), 824-837.

Farokhi, S., Flusser, J., & Sheikh, U. U. (2016). Near infrared face recognition: A literature survey. *Computer Science Review*, *21*, 1-17.

Farooq, M. S., Kalim, Z., Qureshi, J. N., Rasheed, S., & Abid, A. (2022). A blockchain-based framework for distributed agile software development. *IEEE Access*, *10*, 17977-17995.

Fatahi, S., Moradi, H., & Kashani-Vahid, L. (2016). A survey of personality and learning styles models applied in virtual environments with emphasis on e-learning environments. *Artificial Intelligence Review*, *46*(3), 413-429.

Figueroa-Cañas, J., & Sancho-Vinuesa, T. (2020). Early prediction of dropout and final exam performance in an online statistics course. *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje*, *15*(2), 86-94.

Fox, K., Ford, I., Steg, P. G., Tendera, M., Robertson, M., & Ferrari, R. (2008). Heart rate as a prognostic risk factor in patients with coronary artery disease and left-ventricular systolic dysfunction (BEAUTIFUL): a subgroup analysis of a randomised controlled trial. *The Lancet*, *372*(9641), 817-821.

Fukushima, K. (1988). Neocognitron: A hierarchical neural network capable of visual pattern recognition. *Neural networks*, *1*(2), 119-130.

Gardner, A. K., & Dunkin, B. J. (2018). Evaluation of validity evidence for personality, emotional intelligence, and situational judgment tests to identify successful residents. *JAMA surgery*, *153*(5), 409-416.

George, A., & Routray, A. (2016). Fast and accurate algorithm for eye localisation for gaze tracking in low-resolution images. *IET Computer Vision*, *10*(7), 660-669.

Ghojogh, B., Karray, F., & Crowley, M. (2019). Fisher and kernel Fisher discriminant analysis: Tutorial. *arXiv preprint arXiv:1906.09436*.

Golwalkar, R., & Mehendale, N. (2022). Masked-face recognition using deep metric learning and FaceMaskNet-21. *Applied Intelligence*, 1-12.

Goodfellow, I. J., Erhan, D., Carrier, P. L., Courville, A., Mirza, M., Hamner, B., ... & Bengio, Y. (2013, November). Challenges in representation learning: A report on three machine learning contests. In *International conference on neural information processing* (pp. 117-124). Springer, Berlin, Heidelberg.

Graham, M. C., Priddy, L., & Graham, S. (2014). *Facts of Life: ten issues of contentment*. Outskirts Press.

Guennouni, S., Ahaitouf, A., & Mansouri, A. (2015). A comparative study of multiple object detection using haar-like feature selection and local binary patterns in several platforms. *Modelling and simulation in Engineering*, *2015*.

Hadinejad, A., Moyle, B. D., Scott, N., & Kralj, A. (2019). Emotional responses to tourism advertisements: the application of FaceReader™. *Tourism Recreation Research*, *44*(1), 131-135.

Handel, S. (2011). Classification of emotions. *The Emotion Machine*.

Harmon, O. R., & Lambrinos, J. (2008). Are online exams an invitation to cheat?. *The Journal of Economic Education*, *39*(2), 116-125.

Hayat, M., & Bennamoun, M. (2014). An automatic framework for textured 3D video-based facial expression recognition. *IEEE Transactions on Affective Computing*, *5*(3), 301-313.

Haykin, S. (2010). *Neural networks and learning machines, 3/E*. Pearson Education India.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).Bobyliev, D. Y., & Vihrova, E. V. (2021, March). Problems and prospects of distance learning in teaching fundamental subjects to future Mathematics teachers. In *Journal of Physics: Conference Series* (Vol. 1840, No. 1, p. 012002). IOP Publishing.

Heckel, C., & Ringeisen, T. (2019). Pride and anxiety in online learning environments: Achievement emotions as mediators between learners' characteristics and learning outcomes. *Journal of Computer Assisted Learning*, *35*(5), 667-677.

Heidig, S., Müller, J., & Reichelt, M. (2015). Emotional design in multimedia learning: Differentiation on relevant design features and their effects on emotions and learning. *Computers in Human behavior*, *44*, 81-95.

Hendryli, J., & Fanany, M. I. (2016, May). Classifying abnormal activities in exam using multi-class Markov chain LDA based on MODEC features. In *2016 4th International Conference on Information and Communication Technology (ICoICT)* (pp. 1-6). IEEE.

Hollister, K. K., & Berenson, M. L. (2009). Proctored versus unproctored online exams: Studying the impact of exam environment on student performance. *Decision Sciences Journal of Innovative Education*, *7*(1), 271-294.

Hrastinski, S. (2010). How do e-learners participate in synchronous online discussions? Evolutionary and social psychological perspectives. In *Evolutionary psychology and information systems research* (pp. 119-147). Springer, Boston, MA.

Huang, C. J., Chen, Y. H., Ma, Y., & Kuo, P. H. (2020). Multiple-input deep convolutional neural network model for covid-19 forecasting in china. *MedRxiv*, 2020-03.

Hubel, D. H., & Wiesel, T. N. (1968). Receptive fields and functional architecture of monkey striate cortex. *The Journal of physiology*, *195*(1), 215-243.

Hussein, M. J., Yusuf, J., Deb, A. S., Fong, L., & Naidu, S. (2020). An evaluation of online proctoring tools. *Open Praxis*, *12*(4), 509-525.

Imani, M., & Montazer, G. A. (2019). A survey of emotion recognition methods with emphasis on E-Learning environments. *Journal of Network and Computer Applications*, *147*, 102423.

Jabid, T., Kabir, M. H., & Chae, O. (2010). Robust facial expression recognition based on local directional pattern. *ETRI journal*, *32*(5), 784-794.

Jain, M., Narayan, S., Balaji, P., Bhowmick, A., & Muthu, R. K. (2020). Speech emotion recognition using support vector machine. *arXiv preprint arXiv:2002.07590*.

Jain, S., Hu, C., & Aggarwal, J. K. (2011, November). Facial expression recognition with temporal modeling of shapes. In *2011 IEEE international conference on computer vision workshops (ICCV workshops)* (pp. 1642-1649). IEEE.

Jena, R. K. (2019). Sentiment mining in a collaborative learning environment: capitalising on big data. *Behaviour & Information Technology*, *38*(9), 986-1001.

Jibrin, F. A., & Muhammad, A. S. (2017). Dual-Tree Complex Wavelets Transform Based Facial Expression Recognition using Principal Component Analysis (PCA) and Local Binary Pattern (LBP). *International Journal of Engineering Science*, *10909*.

Kan, A. (2017). Machine learning applications in cell image analysis. *Immunology and cell biology*, *95*(6), 525-530.

Kaur, P., Krishan, K., Sharma, S. K., & Kanchan, T. (2020). Facial-recognition algorithms: A literature review. *Medicine, Science and the Law*, *60*(2), 131-139.

Kawamata, T., & Akakura, T. (2020, December). Face Authentication for E-testing Using Sequential Reference Update. In *2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)* (pp. 658-661). IEEE.

Kerkeni, L., Serrestou, Y., Mbarki, M., Raoof, K., & Mahjoub, M. A. (2017, May). A review on speech emotion recognition: Case of pedagogical interaction in classroom. In *2017 International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)* (pp. 1-7). IEEE.

Khosravy, M., Nakamura, K., Hirose, Y., Nitta, N., & Babaguchi, N. (2022). Model Inversion Attack by Integration of Deep Generative Models: Privacy-Sensitive Face Generation from a Face Recognition System. *IEEE Transactions on Information Forensics and Security*, *17*, 357-372.

Kilinc, H., Okur, M. R., & İlker, U. S. T. A. (2021). The Opinions of Field Experts on Online Test Applications and Test Security During the COVID-19 Pandemic. *International Journal of Assessment Tools in Education*, *8*(4), 975-990.

Kumar, V. D., Kumar, V. D., Malathi, S., Vengatesan, K., & Ramakrishnan, M. (2018). Facial recognition system for suspect identification using a surveillance camera. *Pattern Recognition and Image Analysis*, *28*(3), 410-420.

Kwon, S. (2020). A CNN-assisted enhanced audio signal processing for speech emotion recognition. *Sensors*, *20*(1), 183.

Labib, A. E., Canós, J. H., & Penadés, M. C. (2017). On the way to learning style models integration: a Learner's Characteristics Ontology. *Computers in Human Behavior*, *73*, 433-445.

LeCun, Y. (2015). What’s wrong with deep learning. *CVPR*, *keynote*.

LeDoux, J. E., Barrett, L. F., & Russell, J. A. (2015). Emotional construction in the brain. *The psychological construction of emotion*, 459-464.

Lee, K., & Fanguy, M. (2022). Online exam proctoring technologies: Educational innovation or deterioration?. *British Journal of Educational Technology*, *53*(3), 475-490.

Lennarz, H. K., Hollenstein, T., Lichtwarck-Aschoff, A., Kuntsche, E., & Granic, I. (2019). Emotion regulation in action: Use, selection, and success of emotion regulation in adolescents' daily lives. *International Journal of Behavioral Development*, *43*(1), 1-11.

LFW Online. Available: http://vis-www.cs.umass.edu/lfw/results. html#combined-bg

LFW, 2022. Available online: http://vis-www.cs.umass.edu/lfw/index.html#views (accessed on 1 March 2022).

LFW. Available online: http://vis-www.cs.umass.edu/lfw/index.html#views (accessed on 1 March 2022).

Li, H., Lin, Z., Shen, X., Brandt, J., & Hua, G. (2015). A convolutional neural network cascade for face detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 5325-5334).

Li, J., Jin, K., Zhou, D., Kubota, N., & Ju, Z. (2020). Attention mechanism-based CNN for facial expression recognition. *Neurocomputing*, *411*, 340-350.

Li, S., & Deng, W. (2020). Deep facial expression recognition: A survey. *IEEE transactions on affective computing*, *6*(2), 46-60.

Lim, L. A., Dawson, S., Gašević, D., Joksimović, S., Pardo, A., Fudge, A., & Gentili, S. (2021). Students' perceptions of, and emotional responses to, personalised learning analytics-based feedback: an exploratory study of four courses. *Assessment & Evaluation in Higher Education*, *46*(3), 339-359.

Linnainmaa, S. (1976). Taylor expansion of the accumulated rounding error. *BIT Numerical Mathematics, 16*(2), 146-160.

Lockwood, T. W. (2015). Redefining the role of emotion in critical language teaching and learning.

López, M. G. M., & Cárdenas, M. A. F. (2014). Emotions and their effects in a language learning Mexican context. *System*, *42*, 298-307.

Lu, J., Wang, G., Deng, W., Moulin, P., & Zhou, J. (2015). Multi-manifold deep metric learning for image set classification. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1137-1145).

Lucey, P., Cohn, J. F., Kanade, T., Saragih, J., Ambadar, Z., & Matthews, I. (2010, June). The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression. In *2010 ieee computer society conference on computer vision and pattern recognition-workshops* (pp. 94-101). IEEE.

Ma, H., Wang, J., Lin, H., Pan, X., Zhang, Y., & Yang, Z. (2022). A multi-view network for real-time emotion recognition in conversations. *Knowledge-Based Systems*, *236*, 107751.

Mao, S., Ching, P. C., & Lee, T. (2019). Deep Learning of Segment-Level Feature Representation with Multiple Instance Learning for Utterance-Level Speech Emotion Recognition. In *Interspeech* (pp. 1686-1690).

Marx, D. B., & Longer, D. E. (1986). Cheating on multiple choice exams is difficult to assess quantitatively. *NACTA Journal*, 23-26.

Masud, M. M., Hayawi, K., Mathew, S. S., Michael, T., & El Barachi, M. (2022, February). Smart Online Exam Proctoring Assist for Cheating Detection. In *International Conference on Advanced Data Mining and Applications* (pp. 118-132). Springer, Cham.

Mathew, N. G., Sreehari, P., & Al-Rubaat, A. M. (2019). Challenges and implications of virtual e-learning platform in EFL context: Perceptions of teachers. *International Journal of English Language Teaching*, *7*(2), 100-116.

McClellan, E. (2019). Facial Recognition Technology: Balancing the Benefits and Concerns. *J. Bus. & Tech. L.*, *15*, 363.

Mery, D., Mackenney, I., & Villalobos, E. (2019, January). Student attendance system in crowded classrooms using a smartphone camera. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)* (pp. 857-866). IEEE.

Moeller, A. J. (2021). The Interplay of Emotion, Cognition, and Learning in the Language Classroom.C *entral States Conference on the Teaching of Foreign Languages Report*, 3, 1-16.

Motamed, S., Setayeshi, S., & Rabiee, A. (2017). Speech emotion recognition based on a modified brain emotional learning model. *Biologically Inspired Cognitive Architectures*, *19*, 32-38.

Mukhopadhyay, M., Pal, S., Nayyar, A., Pramanik, P. K. D., Dasgupta, N., & Choudhury, P. (2020, February). Facial Emotion Detection to Assess Learner's State of Mind in an Online Learning System. In *Proceedings of the 2020 5th International Conference on Intelligent Information Technology* (pp. 107-115).

Nanthini, N., Puviarasan, N., & Aruna, P. (2021). An Efficient Velocity Estimation Approach for Face Liveness Detection using Sparse Optical Flow Technique. *Indian Journal of Science and Technology*, *14*(25), 2128-2136.

Ngoc Anh, B., Tung Son, N., Truong Lam, P., Le Chi, P., Huu Tuan, N., Cong Dat, N., ... & Van Dinh, T. (2019). A computer-vision based application for student behavior monitoring in classroom. Applied Sciences, 9(22), 4729.

Niedenthal, P. M., & Ric, F. (2017). *Psychology of emotion*. Psychology Press.

Nikolić, N., Grljević, O., & Kovačević, A. (2020). Aspect-based sentiment analysis of reviews in the domain of higher education. The Electronic Library.

O'Mahony, N., Campbell, S., Carvalho, A., Harapanahalli, S., Hernandez, G. V., Krpalkova, L., ... & Walsh, J. (2020). Deep learning vs. traditional computer vision. In *Advances in Computer Vision: Proceedings of the 2019 Computer Vision Conference (CVC), Volume 1 1* (pp. 128-144). Springer International Publishing.

Ogochukwu, M. (2019). Identification Management in Nigeria: Innovations for Financial Inclusion. *Ind. Int'l & Comp. L. Rev.*, *30*, 33.

Okokpujie, K., Noma-Osaghae, E., John, S., & Oputa, R. (2017, October). Development of a facial recognition system with email identification message relay mechanism. In *2017 international conference on computing networking and informatics (ICCNI)* (pp. 1-6). IEEE.

Olszanowski, M., Pochwatko, G., Kuklinski, K., Scibor-Rylski, M., Lewinski, P., & Ohme, R. K. (2015). Warsaw set of emotional facial expression pictures: a validation study of facial display photographs. *Frontiers in psychology*, *5*, 1516.

OpenCV: Cascade Classifier. https://docs.opencv.org/3.4/db/d28/tutorial_cascade_classifier.html. Accessed 11 Mar. 2022.

Pace-Schott, E. F., Amole, M. C., Aue, T., Balconi, M., Bylsma, L. M., Critchley, H., ... & VanElzakker, M. B. (2019). Physiological feelings. *Neuroscience & Biobehavioral Reviews*, *103*, 267-304.

Pellas, N., & Mystakidis, S. (2020). A Systematic Review of Research about Game-based Learning in Virtual Worlds. *J. Univers. Comput. Sci.*, *26*(8), 1017-1042.

Perez-Gaspar, L. A., Caballero-Morales, S. O., & Trujillo-Romero, F. (2016). Multimodal emotion recognition with evolutionary computation for human-robot interaction. *Expert Systems with Applications*, *66*, 42-61.

Pesonen, J. A., & Hannula, M. S. (2014). Analyzing Students' Emotional States during Problem Solving Using Automatic Emotion Recognition Software and Screen Recordings. *North American Chapter of the International Group for the Psychology of Mathematics Education*.

Picard, R. W., Vyzas, E., & Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE transactions on pattern analysis and machine intelligence*, *23*(10), 1175-1191.

Ploumpis, S., Wang, H., Pears, N., Smith, W. A., & Zafeiriou, S. (2019). Combining 3d morphable models: A large scale face-and-head model. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 10934-10943).

Prathish, S., & Bijlani, K. (2016, August). An intelligent system for online exam monitoring. In *2016 International Conference on Information Science (ICIS)* (pp. 138-143). IEEE.

Prezelj, J., Murovec, J., Huemer-Kals, S., Häsler, K., & Fischer, P. (2022). Identification of different manifestations of nonlinear stick–slip phenomena during creep groan braking noise by using the unsupervised learning algorithms k-means and self-organizing map. *Mechanical systems and signal processing*, *166*, 108349.

Quan, C., & Ren, F. (2016). Weighted high-order hidden Markov models for compound emotions recognition in text. *Information Sciences*, *329*, 581-596.

Rad, P., Roopaei, M., Beebe, N., Shadaram, M., & Au, Y. (2018, January). AI thinking for cloud education platform with personalized learning. In Proceedings of the 51st Hawaii international conference on system sciences.

Rahimi, A., & Bigdeli, R. A. (2014). The broaden-and-build theory of positive emotions in second language learning. *Procedia-Social and Behavioral Sciences*, *159*, 795-801.

Rahulamathavan, Y., Phan, R. C. W., Chambers, J. A., & Parish, D. J. (2012). Facial expression recognition in the encrypted domain based on local fisher discriminant analysis. *IEEE transactions on affective computing*, *4*(1), 83-92.

Rainey, E. C., Maher, B. L., Coupland, D., Franchi, R., & Moje, E. B. (2018). But what does it look like? Illustrations of disciplinary literacy teaching in two content areas. *Journal of Adolescent & Adult Literacy*, *61*(4), 371-379.

Redmon, J., & Farhadi, A. (2018). Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.

Reisenzein, R. (2022). Tasks for a theoretical psychology of emotion. *Cognition and Emotion*, *36*(2), 171-187.

Revina, I. M., & Emmanuel, W. S. (2021). A survey on human face expression recognition techniques. *Journal of King Saud University-Computer and Information Sciences*, *33*(6), 619-628.

Romanyuk, O. N., Vyatkin, S. I., Pavlov, S. V., Mykhaylov, P. I., Chekhmestruk, R. Y., & Perun, I. V. (2020). Face recognition techniques. *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska*, *10*.

Roschelle, J., Dimitriadis, Y., & Hoppe, U. (2013). Classroom orchestration: synthesis. *Computers & Education*, *69,* 523-526.

Roth, P. M., Hirzer, M., Köstinger, M., Beleznai, C., & Bischof, H. (2014). Mahalanobis distance learning for person re-identification. In *Person re-identification* (pp. 247-267). Springer, London.

Roy, D., Panda, P., & Roy, K. (2020). Tree-CNN: a hierarchical deep convolutional neural network for incremental learning. *Neural Networks*, *121*, 148-160.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1985). *Learning internal representations by error propagation*. California Univ San Diego La Jolla Inst for Cognitive Science.

Rundo, L., Militello, C., Russo, G., Garufi, A., Vitabile, S., Gilardi, M. C., & Mauri, G. (2017). Automated prostate gland segmentation based on an unsupervised fuzzy C-means clustering technique using multispectral T1w and T2w MR imaging. *Information*, *8*(2), 49.

Rydell, L. (2022). Predictive Algorithms, Data Visualization Tools, and Artificial Neural Networks in the Retail Metaverse. *Linguistic & Philosophical Investigations*, *6*(2), 14-16.

Sabri, N., Musa, N. H., Mangshor, N. N. A., Ibrahim, S., & Hamzah, H. H. M. (2020). Student emotion estimation based on facial application in E-learning during COVID-19 pandemic. *Int. J. Adv. Trends Comput. Sci. Eng*, *9*(1.4).

Salama AbdELminaam, D., Almansori, A. M., Taha, M., & Badr, E. (2020). A deep facial recognition system using computational intelligent algorithms. *Plos one*, *15*(12), e0242269.

Sander, D. (2013). Vers une définition de l'émotion. *Cerveau & Psycho*, *56*, 46-53.

Schacter, D. L. (2012). Adaptive constructive processes and the future of memory. *American Psychologist*, *67*(8), 603.

Selwyn, N., O'Neill, C., Smith, G., Andrejevic, M., & Gu, X. (2021). A necessary evil? The rise of online exam proctoring in Australian universities. *Media International Australia*, 1329878X211005862.

Shahin, I., Hindawi, N., Nassif, A. B., Alhudhaif, A., & Polat, K. (2022). Novel dual-channel long short-term memory compressed capsule networks for emotion recognition. *Expert Systems with Applications*, *188*, 116080.

Shuck, B., Albornoz, C., & Winberg, M. (2013). Emotions and their effect on adult learning: A constructivist perspective.

Singh, M., Singh, R., Vatsa, M., Ratha, N. K., & Chellappa, R. (2019). Recognizing disguised faces in the wild. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, *1*(2), 97-108.

Slusky, L. (2020). Cybersecurity of online proctoring systems. *Journal of International Technology and Information Management*, *29*(1), 56-83.

Smys, S., Basar, A., & Wang, H. (2020). Artificial neural network based power management for smart street lighting systems. *Journal of Artificial Intelligence*, *2*(01), 42-52.

Sokolova, A. D., Savchenko, A. V., & Nikolenko, S. I. (2022). Open-set face identification with automatic detection of out-of-distribution images. *Computer Optics*, *46*(5), 801-807.

Spiers, D. L. (2016). Facial emotion detection using deep learning. Engineering and Technology, *2*(1), 84.

Stein, M. K., Newell, S., Wagner, E. L., & Galliers, R. D. (2015). Coping with information technology. *Mis Quarterly*, *39*(2), 367-392.

Stöckli, S., Schulte-Mecklenbeck, M., Borer, S., & Samson, A. C. (2018). Facial expression analysis with AFFDEX and FACET: A validation study. *Behavior research methods*, *50*(4), 1446-1460.

Stojic, H., Orquin, J. L., Dayan, P., Dolan, R., & Speekenbrink, M. (2019, May). Rewards and uncertainty jointly drive the attention dynamics in reinforcement learning. In *Ninth International Symposium on Biology of Decision Making (SBDM 2019)* (pp. 135-136).

Sun, A., Li, Y. J., Huang, Y. M., & Li, Q. (2017, September). Using facial expression to detect emotion in e-learning system: A deep learning method. In *International Symposium on Emerging Technologies for Education* (pp. 446-455). Springer, Cham.

Sun, L., Lian, Z., Tao, J., Liu, B., & Niu, M. (2020, October). Multi-modal continuous dimensional emotion recognition using recurrent neural network and self-attention mechanism. In *Proceedings of the 1st International on Multimodal Sentiment Analysis in Real-life Media Challenge and Workshop* (pp. 27-34).

Sun, L., Zou, B., Fu, S., Chen, J., & Wang, F. (2019). Speech emotion recognition based on DNN-decision tree SVM model. *Speech Communication*, *115*, 29-37.

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. In *Advances in neural information processing systems* (pp. 3104-3112).

Swain, M., Routray, A., & Kabisatpathy, P. (2018). Databases, features and classifiers for speech emotion recognition: a review. *International Journal of Speech Technology*, *21*(1), 93-120.

Talahua, J. S., Buele, J., Calvopiña, P., & Varela-Aldás, J. (2021). Facial recognition system for people with and without face mask in times of the covid-19 pandemic. *Sustainability*, *13*(12), 6900.

Tam, C., da Costa Moura, E. J., Oliveira, T., & Varajão, J. (2020). The factors influencing the success of on-going agile software development projects. *International Journal of Project Management*, *38*(3), 165-176.

Tang, M. (2020). ‘Awe’some Choice: An Expansion of the Broaden and Build Theory.

Tharwat, A., Mahdi, H., Elhoseny, M., & Hassanien, A. E. (2018). Recognizing human activity in mobile crowdsensing environment using optimized k-NN algorithm. *Expert Systems with Applications*, *107*, 32-44.

Tian, F., Gao, P., Li, L., Zhang, W., Liang, H., Qian, Y., & Zhao, R. (2014). Recognizing and regulating e-learners’ emotions based on interactive Chinese texts in e-learning systems. Knowledge-Based Systems, 55, 148-164.

Tian, M., Yi, S., Li, H., Li, S., Zhang, X., Shi, J., ... & Wang, X. (2018). Eliminating background-bias for robust person re-identification. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 5794-5803).

Tibingana-Ahimbisibwe, B., Willis, S., Catherall, S., Butler, F., & Harrison, R. (2022). A systematic review of peer-assisted learning in fully online higher education distance learning programmes. *Open Learning: The Journal of Open, Distance and e-Learning*, *37*(3), 251-272.

Tolba, A. S., El-Baz, A. H., & El-Harby, A. A. (2006). Face recognition: A literature review. *International Journal of Signal Processing*, *2*(2), 88-103.

Tzimiropoulos, G., & Pantic, M. (2017). Fast algorithms for fitting active appearance models to unconstrained images. *International journal of computer vision*, *122*(1), 17-33.

Uludağ, Ö., Philipp, P., Putta, A., Paasivaara, M., Lassenius, C., & Matthes, F. (2022). Revealing the state of the art of large-scale agile development research: A systematic mapping study. *Journal of Systems and Software*, 111473.

Van Der Schalk, J., Hawk, S. T., Fischer, A. H., & Doosje, B. (2011). Moving faces, looking places: validation of the Amsterdam Dynamic Facial Expression Set (ADFES). *Emotion*, *11*(4), 907.

Wang, L., & Siddique, A. A. (2020). Facial recognition system using LBPH face recognizer for anti-theft and surveillance application based on drone technology. *Measurement and Control*, *53*(7-8), 1070-1077.

Wen, J., Fang, X., Cui, J., Fei, L., Yan, K., Chen, Y., & Xu, Y. (2018). Robust sparse linear discriminant analysis. *IEEE Transactions on Circuits and Systems for Video Technology*, *29*(2), 390-403.

Wetcho, S., & Na-Songkhla, J. (2022). An Investigation of Pre-Service Teachers Using Mobile and Wearable Devices for Emotion Recognition and Social Sharing of Emotion to Support Emotion Regulation in mCSCL Environments. *Contemporary Educational Technology*, *14*(2), ep359.

Wibowo, H., Firdausi, F., Suharso, W., Kusuma, W. A., & Harmanto, D. (2019). Facial expression recognition of 3D image using facial action coding system (FACS). *Telkomnika*, *17*(2), 628-636.

Winarno, E., Hadikurniawati, W., Al Amin, I. H., & Sukur, M. (2017, September). Anti-cheating presence system based on 3WPCA-dual vision face recognition. In *2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)* (pp. 1-5). IEEE.

Winarno, E., Harjoko, A., Arymurthy, A. M., & Winarko, E. (2014). Improved real-time face recognition based on three level wavelet decomposition-principal component analysis and mahalanobis distance. *Technology*, *29*(2), 390-403.

Wingenbach, T. S., Ashwin, C., & Brosnan, M. (2016). Validation of the Amsterdam Dynamic Facial Expression Set–Bath Intensity Variations (ADFES-BIV): A set of videos expressing low, intermediate, and high intensity emotions. *PloS one*, *11*(1), e0147112.

Xu, C., Yan, C., Jiang, M., Alenezi, F., Alhudhaif, A., Alnaim, N., ... & Wu, W. (2022). A novel facial emotion recognition method for stress inference of facial nerve paralysis patients. *Expert Systems with Applications*, *197*, 116705.

Yang, F., Jiang, Z., Wang, C., Dai, Y., Jia, Z., & Hirota, K. (2018, December). Student Eye Gaze Tracking During MOOC Teaching. In *2018 Joint 10th International Conference on Soft Computing and Intelligent Systems (SCIS) and 19th International Symposium on Advanced Intelligent Systems (ISIS)* (pp. 875-880). IEEE.

Yang, G. R., & Wang, X. J. (2020). Artificial neural networks for neuroscientists: a primer. *Neuron*, *107*(6), 1048-1070.

Yang, H., & Yin, L. (2017, October). CNN based 3D facial expression recognition using masking and landmark features. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)* (pp. 556-560). IEEE.

Yang, R., Singh, S. K., Tavakkoli, M., Amiri, N., Yang, Y., Karami, M. A., & Rai, R. (2020). CNN-LSTM deep learning architecture for computer vision-based modal frequency detection. *Mechanical Systems and signal processing*, *144*, 106885.

Yang, R., Singh, S. K., Tavakkoli, M., Amiri, N., Yang, Y., Karami, M. A., & Rai, R. (2020). CNN-LSTM deep learning architecture for computer vision-based modal frequency detection. *Mechanical Systems and signal processing*, *144*, 106885.

You, J. W., & Kang, M. (2014). The role of academic emotions in the relationship between perceived academic control and self-regulated learning in online learning. *Computers & Education*, *77*, 125-133.

Young, D. A. (1970, June). A computerized face identity-verification system (fais). In *Photo-Optical Instrumentation: Present & Future Developments* (Vol. 22, pp. 119-126). SPIE.

Zeinstra, C. G., Meuwly, D., Ruifrok, A. C., Veldhuis, R. N., & Spreeuwers, L. J. (2018). Forensic face recognition as a means to determine strength of evidence: a survey. *Forensic Sci Rev*, *30*(1), 21-32.

Zhang, G., Tang, S., & Li, J. (2018, April). Face landmark point tracking using LK pyramid optical flow. In *Tenth International Conference on Machine Vision (ICMV 2017)* (Vol. 10696, p. 106962B). International Society for Optics and Photonics.

Zhang, H., Huang, B., & Tian, G. (2020). Facial expression recognition based on deep convolution long short-term memory networks of double-channel weighted mixture. *Pattern Recognition Letters*, *131*, 128-134.

Zhou, D. X. (2020). Universality of deep convolutional neural networks. *Applied and computational harmonic analysis*, *48*(2), 787-794.

Zhou, M. (2016). The roles of social anxiety, autonomy, and learning orientation in second language learning: A structural equation modeling analysis. *System*, *63*, 89-100.

Zhu, Y., Zhu, C., & Li, X. (2018). Improved principal component analysis and linear regression classification for face recognition. *Signal Processing*, *145*, 175-182.

Zubairu, H. A., Mohammed, I. K., Etuk, S. O., Babakano, F. J., & Anda, I. (2021, March). A Context-Aware Framework for Continuous Authentication in

Online Examination. Proceedings of the 2nd International Conference on ICT for National Development and Its Sustainability, Faculty of Communication and Information Sciences, University of Ilorin, Ilorin, Nigeria.

APPENDICES

Appendix A

NEAR EAST UNIVERSITY

SCIENTIFIC RESEARCH ETHICS COMMITTEE

08.04.2022

Dear Aayat Amin Ahmed Aljarrah

Your application titled "**Face Recognıtıon System for Dıstance Learnıng Courses to Monıtor and Detect Students' Cheatıng Behavıor ın Real-Tıme**" with the application number NEU/ES/2022/821 has been evaluated by the Scientific Research Ethics Committee and granted approval. You can start your research on the condition that you will abide by the information provided in your application form.

Assoc. Prof. Dr. Direnç Kanol

Rapporteur of the Scientific Research Ethics Committee

Direnc Kanol

Note: If you need to provide an official letter to an institution with the signature of the Head of NEU Scientific Research Ethics Committee, please apply to the secretariat of the ethics committee by showing this document.

Appendix X

Turnitin Similarity Report

Thesis

by Ayat Al-jarrah

Submission date: 15-Mar-2023 03:14PM (UTC+0200)
Submission ID: 2037759988
File name: Thesis_Aayat__15_March-2023.docx (7.21M)
Word count: 31832
Character count: 181131

Thesis

ORIGINALITY REPORT

15%	10%	9%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	mdpi-res.com Internet Source	3%
2	Fezile Ozdamli, Aayat Aljarrah, Damla Karagozlu, Mustafa Ababneh. "Facial Recognition System to Detect Student Emotions and Cheating in Distance Learning", Sustainability, 2022 Publication	1%
3	docs.neu.edu.tr Internet Source	1%
4	Submitted to University of Mauritius Student Paper	<1%
5	Submitted to NCC Education Student Paper	<1%
6	Submitted to College of Banking and Financial Studies Student Paper	<1%
7	Submitted to University of Hertfordshire Student Paper	<1%

Curriculum Vitae

PERSONAL DATA

Name: Aayat Amin Aljarrah

Nationality: Bahraini

Date of Birth: June 17th, 1989

Marital Status: Married

Mobile: +97333560635

E- mail: ayataljarrah89@gmail.com

Languages:

Arabic Mother Language, full command of speaking, reading and writing.

English Fluent in writing, speaking and reading.

Objective

Seeking a Trainer position where I can share my knowledge with passion to enlighten the trainees to excel is computer science field with innovation technologies.

Educational Qualifications

2019 - 2023 **PhD in Computer Information System** (Artificial Intelligence) from Near East University, Cyprus

2017 - 2019 **Master in Computer Science** (Information |Retrieval and Database) from Amman Arab University, Jordan

2007 – 2012 **Bachelor in Science & Engineering** (Biomedical System Engineering) from Yarmouk University, Jordan

Work Experience (x Years)

2022 –Present Currently Working as Faculty of Artificial Intelligence at Naser vocational and Training Centre (NVTC), Bahrain

2021-2022 Part-time Faculty St Christopher's School, Bahrain

2017- 2019 Amman Arab University (15-01-2017 - 15-01-2019) Laboratory Instructor for (C++, Vb, C#, HTML, SQL)

2016-2017 Part-time Faculty St Christopher's School, Bahrain

2015-2016 Maintenance Engineer at Let's Talk for Consultation and Trading Company, Jordan

2013-2015 Maintenance Engineer at Sea World Company in Maintenance Engineering Department, Bahrain

2011-2012 Trainee Engineer at King Abdullah Hospital in Equipment Maintenance Department, Bahrain

PUBLICATIONS

[1] Al-Jarrah, Ayat Amin, Ghassan Kanaan, and Mustafa Abdel-Kareem Ababneh. "Retrieving Arabic Textual Documents Based on Queries Written in Bahraini Slang Language." Modern Applied Science 13.6 (2019).

[2] Ababneh, Mustafa Abdel-Kareem, Ghassan Kanaan, and Ayat Amin Al-Jarrah. "Enhanced Arabic Information Retrieval by Using Arabic Slang." Modern Applied Science 13.6 (2019).

[3] M. Ababneh, A. Al-Jarrah, D. Karagozlu. "The Role of Big Data and Machine Learning in COVID-19". In BRAIN. Broad Research in Artificial Intelligence and Neuroscience on Web Science. 2020.

[4] Ababneh, M., Aljarrah, A., Karagozlu, D., & Ozdamli, F. (2021). Guiding the Students in High School by Using Machine Learning.

[5] Aljarrah, A., Ababneh, M., Karagozlu, D., & Ozdamli, F. (2021). Artificial Intelligence Techniques for Distance Education: A Systematic Literature Review. Tem Journal-Technology Education Management Informatics, 1621-1629.

[6] Ozdamli, F., Aljarrah, A., Karagozlu, D., & Ababneh, M. (2022). Facial Recognition System to Detect Student Emotions and Cheating in Distance Learning. Sustainability, 14(20), 13230.

[7] Ozdamli, F., Ababneh, M., Karagozlu, D., & Aljarrah, A. (2022). Development and Testing of Performance Scale Application as an Effective Electronic Tool to Enhance Students' Academic Achievements. Electronics, 11(23), 4023.

[8] M. Ababneh, A. Al-Jarrah, N. Cavus. Social media usage in education: Big Data Perspective." Proceedings of the 11th ACM Conference on Web Science. 2020.

[9] Aljarrah, A. A., Ababneh, M. A. K., & Cavus, N. (2020). The role of massive open online courses during the COVID-19 era: Challenges and perspective. New Trends and Issues Proceedings on Humanities and Social Sciences, 7(3), 142-152.

Courses Taught

[1] Programming Basics in JavaScript through Grasshopper from Google.

[2] Python Programming Course using PyCharm from Python Institute.

[3] Machine learning Course with Raspberry pi from IBM.

[4] Data base programming course from Amman Arab University.

[5] Multimedia Systems.

[6] Introduction to Information Technology from Pearson level 3&4.

[7] Mobile Application Development from Pearson level 3&4.

[8] Computer vision from Pearson level 3&4.

[9] Principles of Programming Languages from Pearson level 3&4.

[10] Big data management from Pearson level 3&4.

[11] Deep Learning from Pearson level 3&4.

[12] Data Mining from Pearson level 3&4.

Computer Skills

Operating Systems	:	Microsoft Windows, Mac, Linux
Languages	:	C, C++, C#, Java, JavaScript, HTML, python
Scripting	:	JavaScript
Databases	:	Oracle

REFEREES

[1] Assist. Professor Dr. Damla Karagozlu, Computer Education and Instructional Technology department, Near East University, Mersin 10, Turkey

E-mail: damla.karagozlu@neu.edu.tr

[2] Assoc. Prof. Dr. Fezile Özdamli, Computer Education and Instructional Technology department, Near East University, Mersin 10, Turkey

E-mail: fezile.ozdamli@neu.edu.tr

[3] Assist. Prof. Raghu D, Bahrain Polytechnic, Computer Science Department, Bahrain, E-mail: Raghu.dhumpati@polytechnic.bh

[4] Prof. Ghassan Kanaan, Dean of IT College, Amman Arab University, Jordan Mobile: +962-795687155 E-mail: Ghassan.Kanaan@yahoo.com

[5] Assoc. Prof. Dr. Mohammed Shatnawi, Faculty of Computer and Information Technology, Jordan University of Science & Technology (JUST), Jordan Mobile: +962-797266261 E-mail: mshatnawi@just.edu.jo