EMOTIONS EXPRESSION CLASSIFICATION USING NEURAL NETWORKS

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
HAMZA ELAMOURI. E. ELWAER

In Partial Fulfillment of the Requirements for the Degree of Master of Science in

Electrical and Electronics Engineering

NICOSIA, 2018

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, last name:

Signature:

Data:

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All praises and thanks to Allah. It is by His grace that I have been able to access this point in my life.

I would like to express my sincere gratitude to my supervisor, Assist. Prof. Dr. Sertan Kaymak who has supported and directed me with his vast knowledge and also for his patience that ensured the completion of this thesis.

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To my family and parents.......

ABSTRACT

Recently, artificial neural networks are started to be implemented in a manner that can identify a person emotional status, whether a perosn is happy, sad, afraid, etc.. This improvement in the neural network applications motivated researchers to train differnt artificial intelligent models to recognize and classify human emotions by checking the faces. This might help in Human machine interaction where a machine can be oriented by checking the face of human and understanding his/her mood. İn this thesis, a backpropagation neural network of three layers is implemented for the classification of human emotional expressions through faces. The network is trained using a public database named as The Japanese Female Facial Expression (JAFFE), that contains seven different expressions of different faces. Many examples of same expressions are fed into network so that it gives it the robustness in identifying the emotioanl stauts of a person.

Experimentally, the network is trained using two learning schemes where an input of size 64*64 pixels is first used, and then input of 256*256 pixels is simulated. Upon testing, it is shown that the neworks were capable of achieving a good generalization power in identifying the unseen face images and correclty classifying their emotioanl expressions. Moreover, it is seen that the smaller size of images has contributed in obtainig a smaller error rates during training and also a higer recognition rate during testing.

Keywords: Neural network; emotional expressions; emotional status; classification; generalization; intelligent

ÖZET

Son zamanlarda yapılan yapay sinir ağlar aracılığıyla insanın ruh halini, mutlu, üzgün veya korkmuş olup olmadığı yönünden incelemelere başlanmıştır. Sinir ağları uygulamaları konusundaki bu gelişmeler araştırmacıları yüz hatları aracılığıyla insan duygularını tanımak ve sınıflandırmak üzere farklı yapay modeller denemeleri yönünde teşvik etmiştir. Böylece yüz hatlarından kişinin ruh halini çözümleyip anlamasıyla makinenin yönlendirilmesi sağlanacak ve insan ile makine arasındaki etkileşim kolaylaşacaktır. Bu tez ile sinir ağlarla ilgili üç katmanlı geri yayılım çalışmasının yüz hatları aracılığıyla kişinin ruh halinin sınıflandırılmaları üzerinde uygulanmıştır. Bu çalışma devlet veri tabanından elde edilen yedi farklı insana ait farklı yüz ifadeleri kullanılması şeklinde yürütülmüştür. Aynı yüz ifadelerinin örnekleri bu çalışmaya konulmuş ve bu sayede insanlara ait ruh hallerine tanı konulmasında dirençli bir çalışma yaratılmaya çalışılmıştır.

Deneysel yönden bu çalışma, ilk olarak 64*64 boyutlu iki öğrenme düzeneği kullanılarak test edilmiş, ardından 256*256 boyutları kullanılmıştır. Testin ardından görülmeyen yüz ifadelerinin teşhis edilmesinde iyi derecede genelleme gücü sağlandığı ortaya konmuş, duygusal tepkilerin doğru şekilde tanımlandığı gözlemlenmiştir. Buna ek olarak, daha küçük boyutlardaki görsellerin daha az sayıda hata oranı elde etmede ve daha fazla doğruluk oranı sağlamakta yararlı olduğu görülmüştür.

Anahtar Kelimeler: Sinir ağları; duygusal tepkiler; ruh halleri; sınıflandırma; genelleme; akıllı

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LIST OF ABBREVIATIONS

ANN:	Artificial Neural Network
BPNN:	Back Propagation neural network
HCI:	Human Machine Interaction
MSE:	Mean Square Error
SEC:	Second
CNN:	Convolutional Neural Network

CHAPTER 1
INTRODUCTION

1.1 Introduction

Artificial intelligence frameworks to perceive human feeling have pulled in much research premium, and potential uses of such frameworks proliferate, spreading over areas, for example, client mindful showcasing, wellbeing observing, and candidly savvy mechanical interfaces. In light of the critical part that facial expression plays in conveying feeling in humans, there has been generous research enthusiasm for PC vision frameworks to perceive human feeling.

Facial expression is the best type of non-verbal correspondence and it gives suggestion about enthusiastic state, attitude and aim. Facial expressions can change the stream of discussion as well as gives the audience members an approach to convey an abundance of data to the speaker without articulating a solitary word. At the point when the facial expression does not coordinate with the talked words, at that point the data pass on by the face gets more power in translating the data (Song et al., 2014).

From the point of view of programmed acknowledgment, a facial expression can be considered to comprise of disfigurements of facial segments and their spatial relations, or changes in the pigmentation of the face. Facial expressions speak to the progressions of facial appearance in response to a man's inside passionate states, social interchanges or expectations. To impart the feelings and express the goals the Facial expression is the most intense, normal, non-verbal and moment route for humans. It is speedier to convey the feelings through facial expressions than through verbalization. The prerequisite for capable correspondence channels amongst machines and humans turns out to be logically basic in light of the way that machines and people begin to share an assortment of assignments. Frameworks to shape these correspondence channels are known as human machine interaction (HMI) frameworks.

Advances in innovation make it conceivable the improvement of more helpful HMI frameworks which no more rely upon general gadgets for instance console, mouse and shows however take charges straightforwardly from client's voice and copies. Such frameworks expect to recreate human-human interaction by just using correspondence channels used amongst humans and not requiring simulated hardware. Human-machine interaction ought to be upgraded to all the more about mimic human to human interaction before machines take more places in our lives.

As change of expressions on human face is an extreme technique for passing emotions, facial expression acknowledgment (FER) will be outstanding amongst other strides for enhancing HMI frameworks. A programmed facial expression acknowledgment framework by and large involves three primary parts: face identification, facial element focuses extraction and facial expression grouping. In the initial step, framework gets input picture and plays out some picture handling strategies on it with a specific end goal to find the face district.

In this thesis, we attempt to develop a neural network system that can get the ability of identifying the human emotional status by reading the faces. The neural network selected to be the heart of the work is the backpropagation neural network that showed promising accuracies in classification and face detection tasks. This network is first trained on faces of seven different human emotions expressions of different persons. Upon training, the network is tested on different images of faces that have some specific expressions and it is seen that the network was capable of identifying the real emotional expressions of faces.

Experimentally, the network was trained and tested on two input images sizes (64*64 pixels) and (256*256) and the performance was discussed and compared of each size.

1.2 Aim of Thesis

The neural networks have been recently applied in very tough tasks such as classification, detection, and prediction. The success of backpropagation neural networks in classification and identification tasks give positive and optimizing hopes to be used in classifying the human emotional expression into sad, happy, neutral, surprise, fear, angry. Thus, researchers have conducted many researches on how to develop a neural system that has a high accuracy in identifying the human emotional expression by checking the human face. Thus, in this thesis, we aim to design a neural system trained using gradient descent to classify different man emotional expressions by only reading their faces. The aim is to obtain a high recognition rate with a small error and training time compared to other recent works when the network is tested in new images. This thesis aims also to investigate the effects of input sizes in the learning and performance of the neural network.

1.3 Overview of the Thesis

The presented thesis is structured as the following:

Chapter one is an introduction of the presented thesis. In here, the facial expression recognition importance is presented, as well as the aims of the thesis.

Chapter two is an overview of the facial expressions classification using neural network and machine learning. Moreover, this chapter provides a detailed review of the facial expression classification researches that have been conducted recently. In addition this chapter shows a brief overview of the neural network and its working principles

Chapter three sows the methodology of the proposed work in addition to the image preparation and analysis stage.

Chapter four discusses the learning phase of the network in which we show the training parameters and results of both network learning schemes.

Chapter five shows the performances of the networks when they are tested on face images. In this chapter, the recognition rates are calculated and also compared between both networks.

Finally, chapter 6 shows the conclusion and recommendations of the whole work.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction to Facial Expressions Recognition

As of late, albeit many advances has been done in the field of human-computer connection (HCI) however facial expression recognition with high recognition rate is as yet an extremely difficult issue and turn into a center subject in the field of computer science and HCI. Facial conduct is the wellspring of data to decide individual's inclination and feelings. Facial expressions have been ordered in mid 1970s by Ekman's investigations. He has expressed that humans have six detects where each sense speaks to a particular feeling, for example, outrage, upbeat, pitiful, dread, shock and sicken (Majumder et al., 2014). There are numerous applications that utilizations Facial expression recognition, for example, Robotics, security, social insurance, human machine correspondence, human conduct indicator and so on. For the most part, Facial Expression Recognition fundamentally performed in three noteworthy advances:

- Face detection
- Feature Extraction
- Facial Expression Classification

The essential need of Face Expression Recognition framework is Face Detection which is utilized to identify the face. The following stage is highlight extraction which is utilized to choose and separate important features, for example, eyes, eyebrow, nose and mouth from confront. It is extremely basic that exclusive those features ought to be separated from pictures that have exceedingly commitment in expression distinguishing proof. The last advance is facial expression classification that orders the facial expressions in view of extricated significant features.

There are diverse techniques for features extraction, for example, appearance based strategy, geometric based technique, surface based technique and so forth and in the ebb and flow investigate for the most part utilized strategies are geometric based strategy and appearance based technique. Geometric based element extraction strategy, remove highlight data utilizing shape, separation and position of facial segments and appearance based element extraction technique utilizes appearance data, for example, pixel power of face picture. Subsequent to getting the features, classification techniques are connected to perceive facial expression.

2.2 Literature Review

Majumder et al. (2014), have displayed an appearance highlight based facial expression recognition framework utilizing Kohonen Self-Organizing Map (KSOM). Appearance features are extricated utilizing uniform Local paired examples (LBPs) from similarly sub-separated pieces connected over face picture. The dimensionality of the LBP highlight vector was decreased utilizing vital segment examination (PCA) to expel the excess information that prompts superfluous calculation cost.

Jizheng et al. (2014) have proposed a novel FER calculation by misusing the auxiliary attributes and the surface data covering up in the picture space. Initially, the element focuses were set apart by a dynamic appearance demonstrates. Furthermore, three facial features, which are include point separate proportion coefficient, association edge proportion coefficient and skin twisting vitality parameter, were proposed to kill the distinctions among the people.

At long last, a spiral premise work neural system was used as the classifier for the FER.

Song et al. (2014), displayed a temporal reinforced way to deal with upgrading feeling recognition from facial pictures. Shape and surface models of facial pictures were registered by utilizing dynamic appearance show (AAM), from which facial element focuses and geometrical element esteems were extricated. The removed features were utilized by pertinence vector machine (RVM) to perceive enthusiastic states. They have proposed a worldly examination way to deal with perceiving probability of passionate classifications, to such an extent that more unpretentious feeling, for example, degree and proportion of fundamental enthusiastic states can be gotten.

Li et al. (2014) have proposed a novel calculation for Facial Expression Recognition (FER) which depended on combination of gabor surface features and Local Phase Quantization (LPQ).

Right off the bat, the LPQ highlight and gabor surface element were separately extricated from each expression picture. LPQ features are histograms of LPQ change. Five scales and eight introductions of gabor wavelet channels are utilized to remove gabor surface features and adaboost calculation was utilized to choose gabor features. At that point they get two expression recognitions comes about on both expression features by Sparse Representation-based Classification (SRC) strategy. At long last, the last expression recognition was performed by combination of residuals of two SRC calculations.

Li Xia et al. [5] proposed the expression classification technique in view of SVM for the deformities of the customary classification strategies. It understands quick classification with a generally little sub-classifier blend, diminishing the classification mistake. Investigations demonstrated that the multi-classification strategy in light of SVM can clearly lessen the preparation and testing time and enhance the classification execution.

Abdulrahman et al. (2014) proposed a facial expression recognition approach in view of Gabor wavelet change. Gabor wavelet channel is first utilized as pre-preparing stage for extraction of the component vector portrayal. Dimensionality of the element vector is diminished utilizing Principal Component Analysis (PCA) and Local parallel example (LBP) calculations. K-Nearest Neighbor with Euclidean separation (L2) utilized as the classifier.

Sobia et al. (2014), have created a model of a wheelchair summon interface that does not require alternate's hands. It incorporates 3 noteworthy modules. They are confront location, facial expression recognition and charge age. The product contains advanced picture handling for confront discovery, central segment investigation for facial expression recognition and creating a charge signals for interfacing the wheelchair.

Suk et al. (2014) have created framework utilizes an arrangement of Support Vector Machines (SVMs) for grouping 6 essential feelings and unbiased expression alongside checking mouth status. The facial expression features for feeling recognition were separated by Active Shape Model (ASM) fitting points of interest on a face and after that dynamic features were created by the uprooting amongst unbiased and expression features.

Singh et al. (2014) have exhibited a facial expressions recognition framework utilizing Bayesian system. They have prepare the system utilizing probabilistic displaying that draws connection between facial features, activity units lastly perceives six essential feelings. They have likewise proposed features extraction techniques to get geometric element vector containing rakish data's and appearance highlight vector containing minutes extricated in the wake of applying gabor channel over certain facial locales. Both the element vectors are additionally used to draw connections among Action Units (AUs).

Su et al. (2013), have introduced a programmed facial expression recognition framework in view of self-sorting out component maps. Above all else, Viola and Jones was utilized to identify a face from a picture. After a human face is recognized, a composite strategy was proposed to find understudies with the goal that the found face picture can be pivoted, trimmed, and facial features; we propose the utilization of SOMs. At long last, a multi-layer perceptron (MLP) was received for the classification of the seven expressions including six essential facial expressions.

Kaur al. (2014), have proposed KNN Regression calculation with SURF highlight for facial expression discovery. At first the eigenspace was made with eigenvalues and eigenvectors. From this space, the eigenfaces are built, and the most significant eigenfaces have been chosen utilizing Principal Component Analysis (PCA).

Liu et al. (2014), have introduced a novel Boosted Deep Belief Network (BDBN) for playing out the three preparing stages iteratively in a brought together loopy system. Through this BDBN structure, an arrangement of features, which is successful to portray expression-related facial appearance/shape changes, can be learned and chosen to frame a helped solid classifier factually. As learning proceeds with, the solid classifier is enhanced iteratively and all the more essentially, the discriminative capacities of chose features are reinforced also.

Ameen et al. (2014) have built up a strategy for the facial expression recognition in view of Local Binary Patterns (LBP) removed from the surface data. The LBP administrator and its expansions were connected to various shading models which are dark scale, RGB, oRGB, YCbCr and HSV. Frontal face pictures among six fundamental facial expressions which are outrage, sicken, fear, bliss, pity and shock were considered. Bolster Vector Machine (SVM) was utilized as the classifier.

Glad et al. (2014) proposed a novel system for expression recognition by utilizing appearance features of chose facial patches. A couple of conspicuous facial patches, contingent upon the situation of facial points of interest, was removed which are dynamic amid feeling elicitation. These dynamic patches are additionally prepared to acquire the notable patches which contain discriminative features for classification of each match of expressions, consequently choosing diverse facial fixes as remarkable for various combine of expression classes. One-against-one classification strategy is embraced utilizing these features. The appearance features from these patches are sustained to a multi-class classifier to arrange the pictures into six essential expression classes.

Meher et al. (2014), have broken down the technique for Principal Component Analysis (PCA) and its execution when connected to confront recognition and used to recognize different facial expressions.

Bakshi et al. (2014), have acquainted another method with perceive human face misleadingly utilizing DCT, PCA and SOM neural system. Foremost part investigation (PCA) is a traditional and fruitful technique for measurement lessening. Discrete Cosine Transform (DCT) is an outstanding pressure procedure and Self Organize Map (SOM) go about as a classifier and has been utilized for confront space portrayal.

Kumar et al. (2014) have introduced another way to deal with facial expression recognition, which utilizes Wavelet for diminishing the high dimensional information of facial expression pictures into moderately low measurement information and afterward utilizes K closest neighbor (KNN) as the classifier for the expression classification a short time later.

Xun et al. (2014), have proposed another FER framework, which utilizes the dynamic shape mode (ASM) calculation to adjust the faces, at that point removes neighborhood paired examples (LBP) features and uses bolster vector machine (SVM) classifier to anticipate the facial feeling.

2.3 Artificial Neural Network

Artificial neural systems are structure that originated from the cerebrum of the human brain that is used for reasoning. The structure has been used to deal with troublesome issues in science. The vast majority of the structures of neural systems are like the organic mind in the requirement for preparing before having the capacity to complete a required assignment (Zurada, 1992). Like the standard of the human neuron, neural system processes the aggregate of every one of its data sources.

On the off chance that that aggregate is more than a decided level, the journalist yield would then be able to be enacted. Something else, the yield isn't go to the actuation work. Figure 1 illustrates the principal assembly of the neural system where the source of the weight and info on summation of work is shown. The quantity of neuron that is find in a structure can is referred to as the yield work. The equation that is used in the calculation of initial work is precisely explained in Equation 3.1:

$$TP = \sum X\, nW_n \tag{2.1}$$

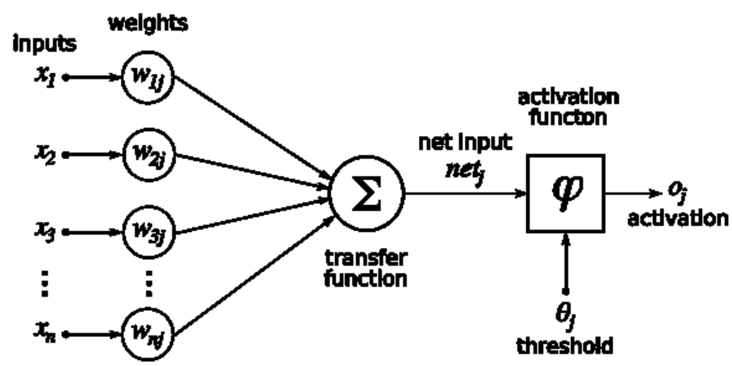

Figure 1: Artificial neural network's basic structure (Zurada, 1992)

2.4 Structure of ANN

The ANNs structure contains three layers despite the learning technique. These angles are the layers, weights, and initiation capacities. Every last one of these three sections plays an imperative lead in the ANN limit. The three sections or segments work collectively to ensure proper working of the system (Sathya and Abraham, 2013).

2.4.1 ANN layers

The mutual relationship that occurs between the layers of ANN is the major derivative to its creations. The layers interact by sending information between each other using the synaptic weight. The Ann structure can be subdivided into three layers that are listed in the subsequent section below.

1. Input layer: This is the first layer that is found in the neural system of ANN. This layers is major that send information or data to other layers in the neural system. It can be regarded as a sensor because it doesn’t process later but only pass information processed by other layers.

2. Hidden layers: this can be regard as the central bit of the neural system. It involves no less than one of the layers which is the input layer and the neural layer. This layer transmits the data to the output layers. The Hidden layer can be regards as the intermediate layers or as a principal layer because the synaptic weights found in it are reliable (Sathya and Abraham, 2013).

3. Output layer: This layer is regard as the output layers because its last contact where the results of the neural system are gotten, the output layer got its information that is processed from the Hidden layer.

The Figure 2 shows the neural system and the interactions that occur between its three layers. The first layer which is the input layers is the source of the data that is passed to the hidden layer and later to the output layer. The yield or result of the neural system is gotten from the output layer.

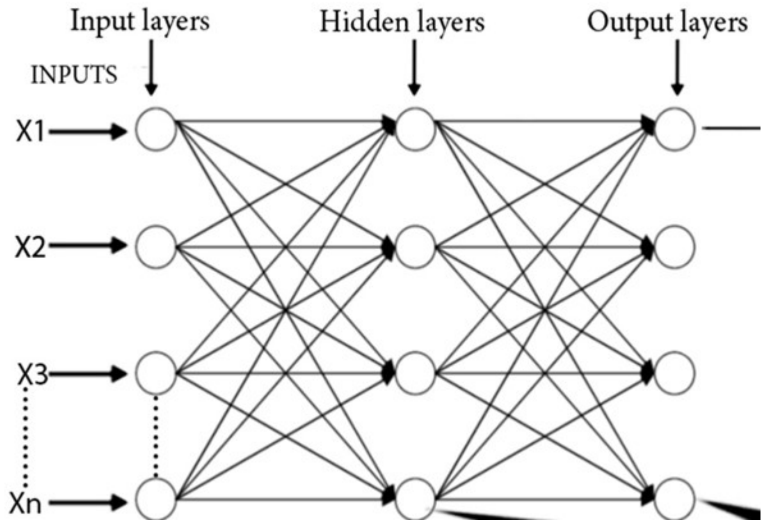

Figure 2: The ANNs Structure showing the three layers (Zurada, 1992)

2.4.2 Weights

The ANN weights stands for the network memory in which all information is provided. The weights estimations are invigorated reliably in the midst of the planning of the system until the point when the yield is met. The weights or memory are then secured to be used as a piece of future. The estimations of the weight of ANNs can be regards as the network memory (Rojas, 1996).

- The Activation capacities

Once the data are enacted from the source and passed across the layers through the synaptic weight, the yield or output is known or gotten by using a trade work. Also, on the other hand in some actuation capacities, the capacity is utilized to decide how much the handled information will partake in developing the aggregate yield of the system.

The neural system are very reliable in determining whether the neuron can adequate transmit its self to the associated layers or not and this made the initiation capacity to be very critical (Rojas, 1996).

- **Linear initiation functions or slope**

In this sort of the enactment work, the yield is fluctuating straightly when the input is close to zero. When the input value is massive, the preeminent yield is limited by 1 as showed up in figure 3.6. The limit of this exchange work is described by:

$$O(TP) = \begin{cases} -1 & TP \leq -1 \\ TP & -1 \leq TP \leq 1 \\ 1 & 1 \leq TP \end{cases} \quad (2.2)$$

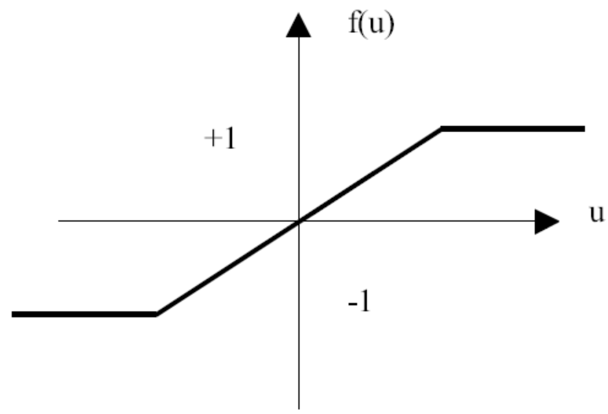

Figure 3: Activation function for ramp (Rojas, 1996)

- **Threshold function (Hard activation function)**

The limit yield is zero if the summed input isn't as much as certain estimation of edge, and 1 if the summed input is more significant than edge. The yield can be located between zero and one. The limits yield can be enacted and be deactivated as found in the Figure 4 below. The activation function of the hard limits is illustrated by:

$$o(TP) = \begin{cases} 0, & TP < \theta \\ 1, & TP > \theta \end{cases}$$

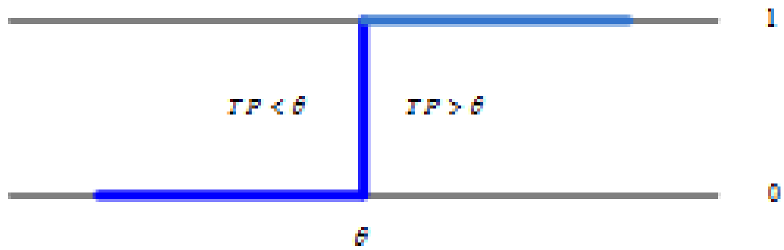

Figure 4: The hard limit activation function (Rojas, 1996)

- **Sigmoid function**

This function can run in the vicinity of 0 and 1, however sometimes it's better to run it within -1 and 1. The most perceived sigmoid limits are the logarithmic sigmoid and hyperbolic digression. The above listed functions are the most utilized as a part of the back proliferation since they are differentiable. The recipes of these two capacities notwithstanding the bends are displayed in Figure 5. The incline of the bends can be changed in light of the purpose is to be utilized for (Michael, 2005).

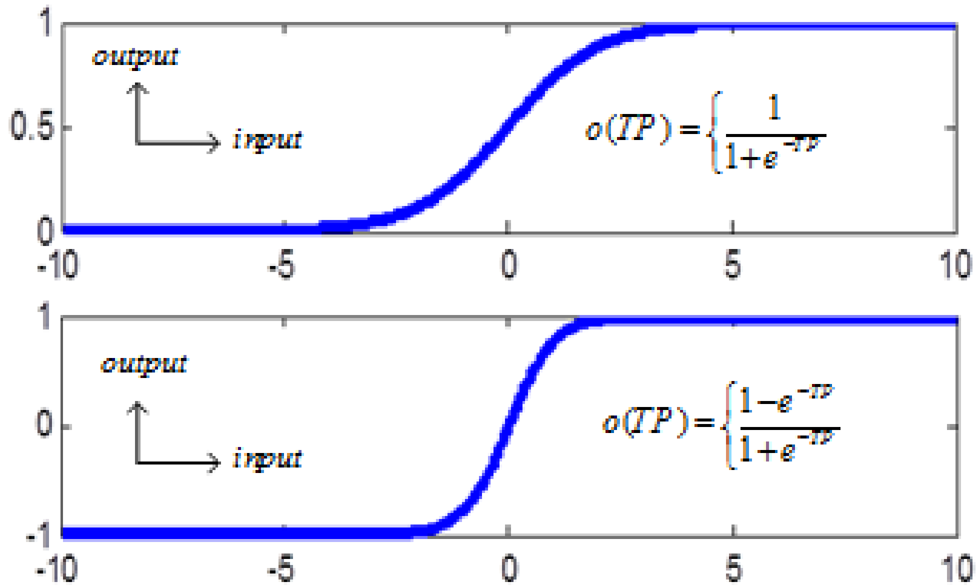

Figure 5: Hyper Distracting and Logarithmic Sigmoid Initiation Functions (Rojas, 1996)

In the process of calculating the back-induction, the log-sig and tan-sig capacities are utilized. This two function listed above can also be used separately. The log-sigmoid auxiliary is given as:

$$\frac{d}{dt} o(\theta) = o(\theta) * (1 - o(\theta)) \tag{2.3}$$

2.5 Classification of ANNS

ANNs are sometimes described using different approach such as; information, limits and preparatory system. The transmission of data in the ANNs system started from the input later to the hidden layer and later to the yield or output layer. On the aspect of functions, neural system can dedicated to verities of assignment and can be accomplished with it. This functions can subdivided into four major classes:

- Classification: This is when enquiry is passed out but done using a known arrangement.

- Association: This is creating interaction or relationship between articles to achieve a more outline program.
- Optimization: This is when the action is to establish a better response to an issue or case.
- Organization: The ANNs attributes is needed to factor out using the preparation method.

2.5.1 ANNs' training methods

The main purpose of preparing a system is in order to achieve a wanted result or yields (Krenker et al., 2011). The two fundamental learning method which comprises of the; coordinated and the unsupervised learning method are utilized in order to enlighten the systems,

- Verified learning method

The ANNs values are gotten from the input information. The system at that point refreshes its weights as indicated by a characterized calculation govern until the point that it unites to a base mistake or achieves a most extreme number of emphases. An imperative case of the directed learning technique is the mistake back engendering strategy.

- Unsupervised learning

In this technique, the input information is given to the system which thusly alters its weights as per characterized conditions.

2.6 Backpropagation Algorithm

The Back propagation neural network algorithm is executed utilizing an encourage forward network, back spread updating process, and lastly supervised learning topology. This method of neural network algorithm was developed in the late 1980s. Back propagation is a multipurpose in the field of recognition algorithm. Even though this algorithm is a very efficient and accurate model it has a major constrained, which is time consuming. Back propagation network when given a certain amount of elements to simulate can produce a certain level of correctness (Krenker et al., 2011).

Back propagation since its creation has a simple attribute thus making it a legacy algorithm by maintaining its initial attributes till today. The first layer is the input layer in which the initial weights are being inputted, next is the activation function layer in which the weights are processed before the last layer which is the output layer for the weights to be presented. Lastly is the error layer in which the weights are update in the input layer before the network is run again for another iteration until a minimal level of error is achieved which can be neglected
The said process above is repeated until a certain level of error achieved which is to a bare minimal then the network can be said as learned network. The Figure 6 shows the artificial neural network layer with error back propagation

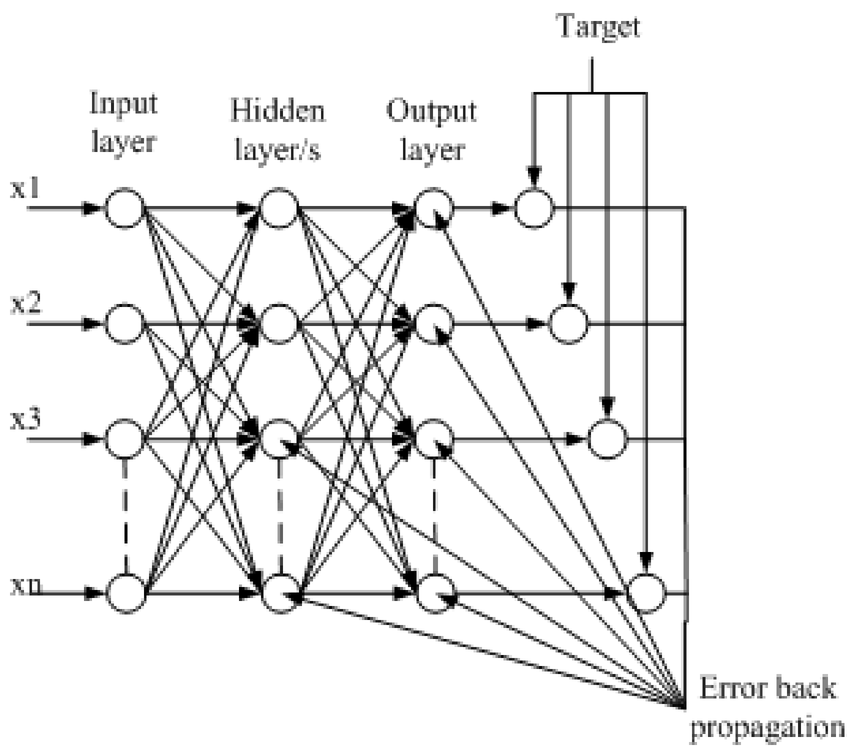

Figure 6: The artificial neural network structure with error backpropagation (Krenker et al., 2011)

There exist two basic protocols in the process of back propagation which are learning rate and momentum factor, the first which is the learning rate determines after a test of the network if the network weights shall be updated or not, thus for every iteration the learning rate determine if there should be an update of the weights or not, eventually learning rate should be set to the minimal because a network with a higher learning rate makes the network to memories instead of learning the updates, and lastly is the factor of momentum utilized in organizing the update intensity that the system can do.

2.6.1 Modeling of backpropagation algorithms

As an algorithm, back propagation utilizes the error minimization theory coupled with gradient descent to figure and point out errors that are least squared, doing so ensures every iteration done will have gradient error calculated which results to a hindered delivery of functions.

In most of cases, the tangent or logarithmic sigmoid functions are used. The sigmoid function is defined by (Jaleel et al., 2012):

$$o(x) = \frac{1}{1+e^{-ax}} \tag{2.4}$$

The above equation is the constant, which control the slant, consequently the derived sigmoid is:

$$o^{\backslash}(x) = f(x)(1-f(x)) \tag{2.5}$$

Training of neural network can be categorized into sub divisions as equated below:

1- Feed forward tarining: used in training as well as testing the network.
2- Error back propagation: categorically used to train the network.

In a feed forward network, output and can be denoted as

$$TP = \sum x_n \omega_n + b_n \tag{2.6}$$

The x_n is the (input data), the w_n is the (weight matrix), while the b_n is the (double values). The total values of each layers is the Tp. The starting functions exist as a straight or as a non-direct function. A typical straight capacity that is broadly conveyed in neural networks is the sigmoid capacity which is characterized in the capacity, another case which is the digression of the sigmoid that is specified by:

$$o(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{2.7}$$

Another fact about this function is that it can be continuous and derived also, the derived function can be equated by: T

$$o^{\backslash}(x) = 1 - \frac{(e^{x} - e^{-x})^{2}}{(e^{x} + e^{-x})^{2}} \tag{2.8}$$

the consequence of the past activation function is the right aftereffect of the NN, the output is define as the objective which is utilized to deliver the amount of error, the error rate is expressed by the equation underneath, the reason for preparing NN is to decrease the amount of error in the Neural network.

$$E = \sum (T - o)^{2} \tag{2.9}$$

T is the objective output, while E is value of the error functions which:

$$\Delta_{j} = (T_{j} - o_{j}) o_{j} (1 - o_{j}) \tag{2.10}$$

The values gotten from the network is defined in the equations and the network becomes updated, the weights are updated using:

$$\omega_{jhnew} = \omega_{jhold} + \eta \Delta_{j} o_{h} + \alpha(\delta \omega_{jhold}) \tag{2.11}$$

The hidden layers weights are updated using error update which is given as:

$$\Delta_{h} = o_{h}(1 - o_{h}) \sum \omega_{jh} \Delta_{j} \tag{2.12}$$

The new weights would be given by:

$$\omega_{hinew} = \omega_{hiold} + \mu \Delta_{h} o_{i} + \alpha(\delta \omega_{hiold}) \tag{2.13}$$

the momentum factor values is known as the α which is used in reducing the number of updates and η as the learning rate which is used in updating the weights, after successful network run, a new iteration is done until a desired until it arrives to an acceptable error value (Jaleel et al., 2012).

CHAPTER 3
METHODOLOGY

This chapter describes the methodology of the proposed work that aims to develop a neural intelligent system to identify the emotional expressions of faces. In this chapter we explain the different stages of the proposed framework. These stages include the analysis of faces images in which they are processed and prepared to be inputs for the neural systems that will classify them based on their facial expressions.

3.1 Human Faces Emotional Expressions

Seemingly the most imperative commitment essential science has made to our comprehension of emotion concerns the all-inclusiveness of facial expressions of emotion. Darwin (1872) was the first to propose that they were widespread; his thoughts regarding emotions were a centerpiece of his hypothesis of advancement, recommending that emotions and their expressions were naturally intrinsic and developmentally versatile, and that likenesses in them could be seen phylogenetically. Early research testing Darwin's thoughts, in any case, was uncertain (Ekman, Friesen, and Ellsworth, 1972), and the predominant point of view in brain science was that facial expressions were culture-particular – that is, similarly as each culture had its own particular verbal dialect, it had its own particular dialect of facial expressions. Darwin's cases were restored by Tomkins (1962, 1963), who recommended that emotion was the premise of human inspiration and that the seat of emotion was in the face. Tomkins led the main examination showing that facial expressions were dependably connected with certain emotional states (Tomkins and McCarter, 1964).

Afterward, Tomkins selected Paul Ekman and Carroll Izard to direct what is referred to today as the "all-inclusiveness thinking of." The first of these showed high multifaceted assention in judgments of emotions in faces by individuals in both proficient (Ekman, 1972, 1973; Ekman and Friesen, 1971; Ekman, Sorenson, and Friesen, 1969; Izard, 1971) and preliterate societies (Ekman and Friesen, 1971; Ekman, et al., 1969). At that point Friesen's (1972) think about recorded that similar facial expressions of emotion were created immediately by individuals from altogether different societies in response to emotion-inspiring movies.

Since the first comprehensiveness contemplates more than 30 thinks about analyzing judgments of facial expressions have recreated the all-inclusive recognition of emotion in the face (surveyed in Matsumoto, 2001). What's more a meta-examination of 168 datasets looking at judgments of emotion in the face and other nonverbal jolts demonstrated all inclusive emotion recognition well above possibility levels (Elfenbein and Ambady, 2002a). Furthermore, there have been more than 75 examines that have shown that these exceptionally same facial expressions are delivered when emotions are evoked suddenly (Matsumoto, Keltner, Shiota, Frank, and O'Sullivan, 2008). These discoveries are amazing given that they have been created by various scientists around the globe in various research facilities utilizing distinctive techniques with members from a wide range of societies yet all uniting on a similar arrangement of results. In this way there is solid proof for the widespread facial expressions of seven emotions – anger, contempt, disgust, fear, joy, sadness, and surprise (see Figure 8).

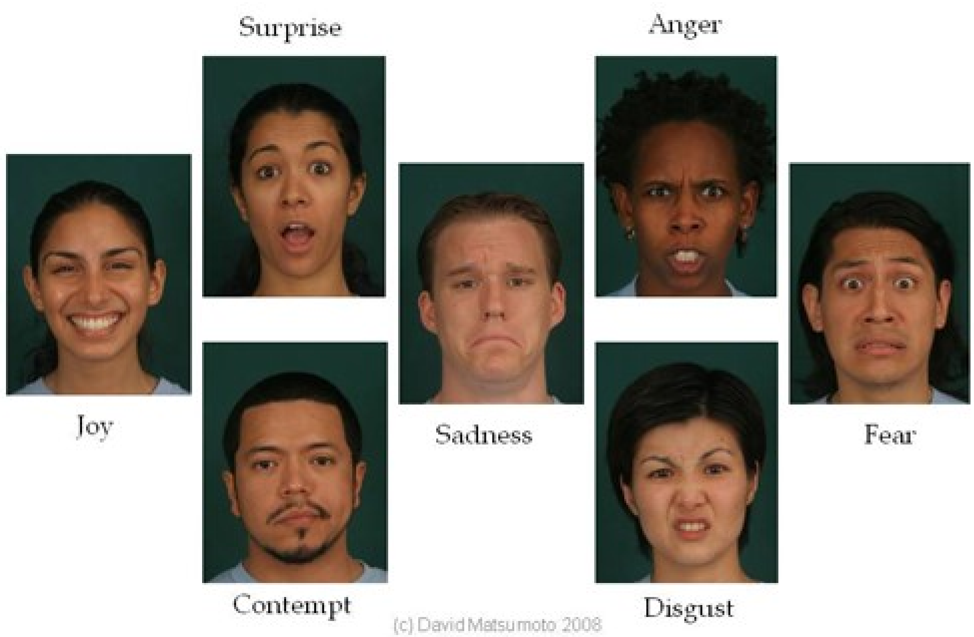

Figure 7: Different emotions facial expressions (Matsumoto, 2008)

3.2 Methodology of the Proposed Work

There is a need for intelligent and automatic systems that can recognize and identify the emotions of humans by checking their faces. These are needed as they make systems smarter such as the robots. Robots that can identify facial emotions by checking human faces are more intelligent and valuable than conventional robots. The first step of developing such system is to train a neural network that can gain the capability of identifying the emotional expression of human faces.

Therefore, in this thesis; an emotional facial expression identification system is proposed. This system is image based work, means that it uses face images in order to recognize their emotional expressions and classify them into seven different emotions: Sad, Happy, Nervous, Surprised, Disgust, Fear, Angry. The classification phase is where the images are classified based on their facial emotional expressions and here a feedforward backpropagation neural network is used. This network is trained using backpropagation learning algorithm, which uses gradient descent algorithm to minimize the error and learn.

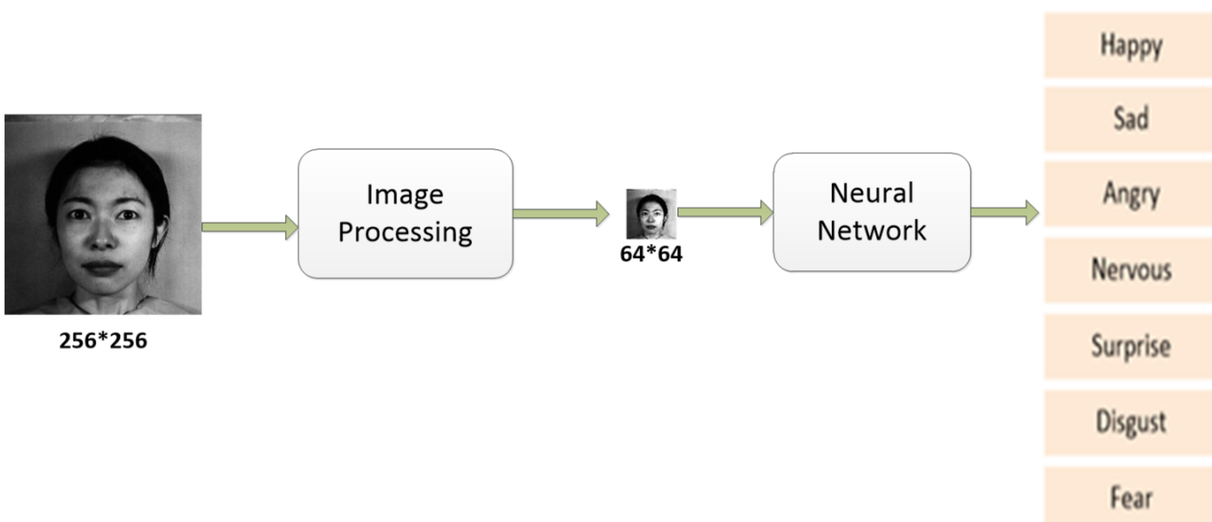

Figure 8: Flowchart of the proposed emotional expression identification system

Figure 9 shows the flowchart of the emotional facial expressions system. As seen in the figure, the system is comprised of two main stages. In the first stage, the images are analyzed and processed in which the image intensity adjustment is applied to input images which helps in enhancing the contrast of images that might have some illumination effects from the source. Moreover, in this stage image sizes are reduced to 64*64 pixels which make them suitable for the neural network input layer.

In the stage, the processed images are fed into a neural network that uses a backpropagation learning algorithm to learn the features that distinguish the different emotional expression for the human faces. Once trained, the network should be capable of classifying the input human faces based on their emotional expressions, i.e. Sad, Happy, Nervous, Surprised, Disgust, Fear, Angry.

3.3 Image Preparation and Analysis

This work presents a neural system that would have the capability of identifying of the emotional expressions of human faces after it is trained on many images of different human faces. Note that the images are not fed into network however; they are analyzed and rescaled first.

Images obtained from public databases may have some noises in them. Hence, they must be filtered and enhanced. In this work, images are enhanced in which intensities are increased which may results in brighter images where emotional expressions are clearer.

Moreover, images must be rescaled to a suitable size which helps network to learn faster. Note that reducing size shouldn’t result in losing the good features of images.

Figure 10 shows the analysis of the images which is done for each image, in order to enhance the images and make them ready to be fed into the network.

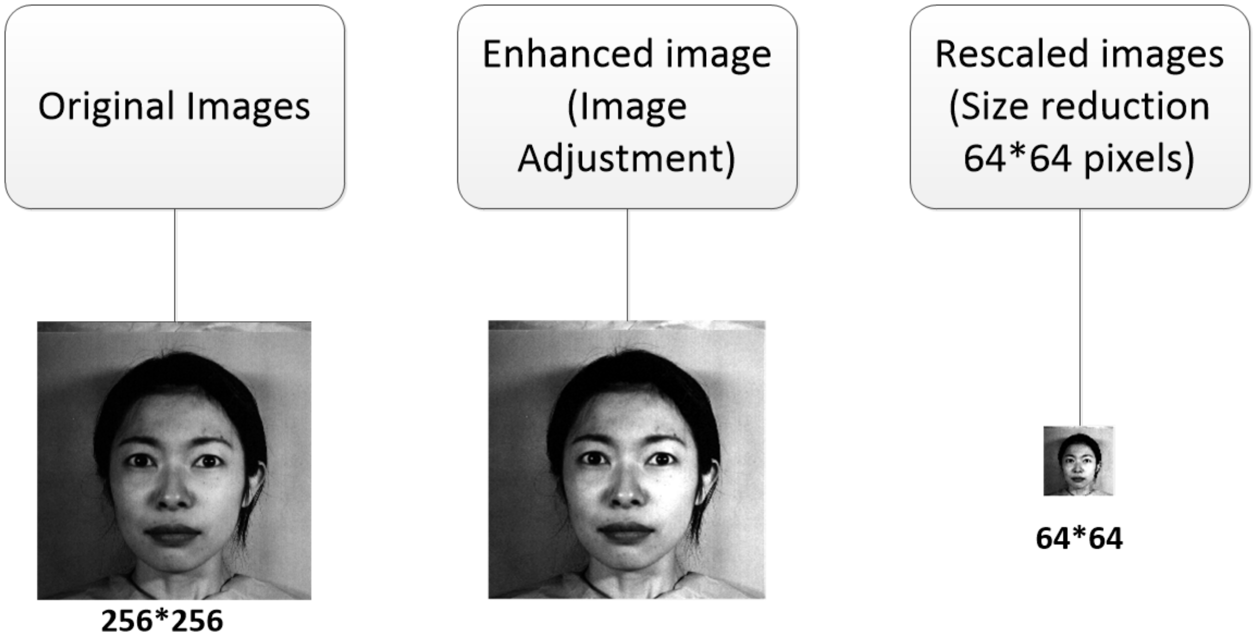

Figure 9: Flowchart of the image analysis stage of the **system**

3.3.1 Image intensity adjusting

Image obtained from public databases may have some noise and illumination problems due the capturing techniques that were used when taking those images. Hence, to process these images some image processing must be used in order to enhance the quality of the images and reduce the risks of illumination effects. Luckily, there are many image processing techniques to enhance images. Thus, in this work we enhance the contrast of the images by using a simple technique called image intensity adjustment.

This technique is to highlight the images more and more in which the intensities of pixels are increased by mapping them into other values (Gonzalez and Woods, 2002). Therefore, if the images are low contrast, adjusting their intensities will make them brighter. This ends up with brighter images where the cells are clearer (Figure 11).

Figure 10: Image intensity adjustment of one face image

Figure 11 shows the adjustment of intensities of one image in which the image on the left shows the original image while the right image shows the same image after adjusting its intensities and mapping them into another value's range.

3.3.2 Size reduction

Upon the enhancement of images the rescaling of images sizes take place. This rescaling method aims to get rid of some pixels which represent the useless features of image that can be removed without affecting the resolution of images. In addition to keeping the meaningful features, size reduction of images helps in reducing the number input layer neurons which yields to a faster convergence of the network and consequently shorter training time, which is needed in such neural systems. For this purpose, size reduction is applied on the adjusted images in this work. Various techniques can be used for this aim; however, our goal is to choose the best technique which reduces image size with keeping the original and important features that contribute to identifying the emotional expression of the images. Thus, in this thesis, size reduction using nearest neighbors is used which shrinks the image size in a very fast way and also it produces good quality image.

The images are reduced to size of 64*64 pixels which is a good size as it keeps the features of original images and is good for network learning processing time.

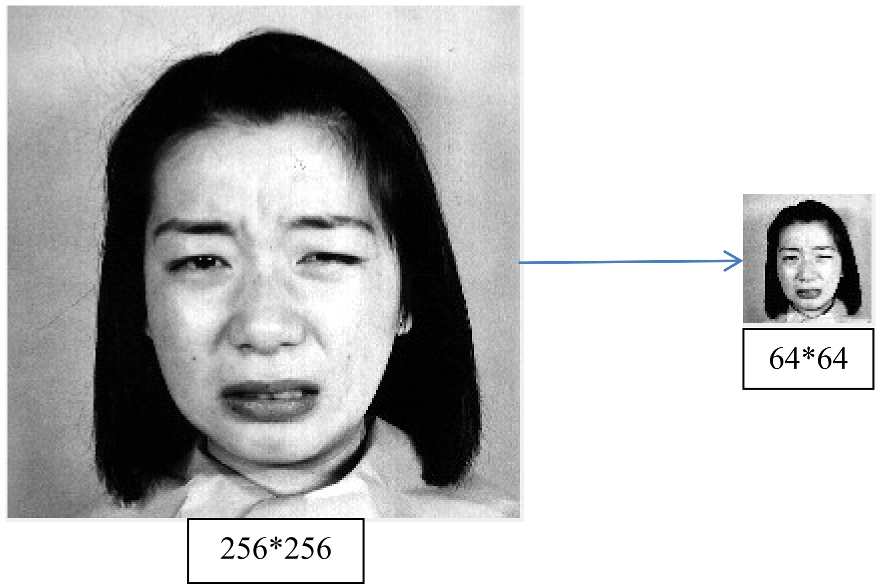

Figure 11: Image size reduction

3.4 Image Database

Images can be described as the "food" of the neural networks. More images mean the smarter and more accurate network will be. Thus, the first step in developing a neural based system is to find a good and public database which will be used for training the network. In this work, face images of different emotional expressions are needed to train our system to be capable of identifying the emotional expressing by checking the human faces. Therefore, the best face expression database was chosen for this task. This database is called The Japanese Female Facial Expression (JAFFE) Database and it is a public database available online for research usage (Lyons et al., 1998).

The database contains of 216 images of 10 females. Among those images there are 7 different facial emotions such as Sad, Happy, Nervous, Surprised, Disgust, Fear, Angry. For each facial emotion there are 3 examples of each female face.

Table 1 shows the description of database and the amount of images it has. As seen, the database contains 216 images of different emotional face expressions.

Table 1: Database description

Facial expression	Number of poses per expression	Number of females
Angry	30	10
sad	31	10
happy	31	10
neutral	31	10
surprise	31	10
disgust	31	10
fear	31	10
Total	216	10

Figure below shows a sample of the face images that are found in the database in which various females are posing different emotional expressions.

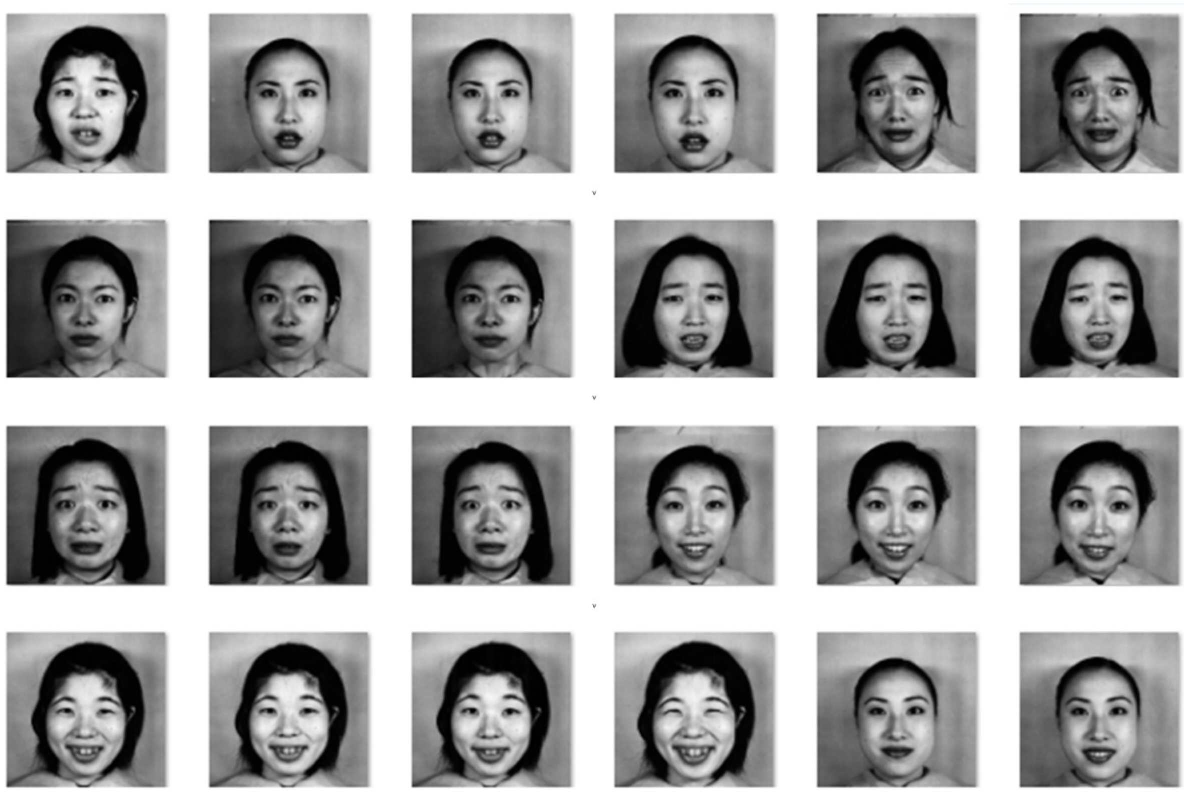

Figure 12: A sample of the database images of different emotional expressions (Lyons et al., 1998)

CHAPTER 4
NETWORK SIMULATION AND TRAINING

In this chapter, we show the learning phase of the network in which the network is trained on different learning parameters and the results are shown.

4.1 Network Simulation

In this thesis, an intelligent system for the identification of the emotional facial expression is developed. The system is based on a neural network that uses processed face images of different human faces with different emotional expressions. A feedforward neural network that uses backpropagation algorithm as a learning algorithm is selected to be used in this work, and it is named as BPNN. Two learning schemes are used for training the neural networks models on the same number of images. The first learning scheme involves images of size 64*64 pixels (BPNN1), while the learning scheme uses images of their original size 256*256 (BPNN2). The use of two learning schemes of different sizes aims to compare the networks performances with different image input sizes.

The data or images obtained for the database are divided into two sets: training and testing sets. All networks models are trained and tested on the same number of images. Moreover, for fair comparison both network models are trained using the same learning parameters values shown in Table 3.

Table 2: Training and testing number of images

	Number of images
Training	146
Testing	70

As seen in table 2 the network models are trained on 146 images and tested on 70 different images of the same emotional facial expressions.

Figure 14 shows a sample of the emotional expressions images used in training the network models.

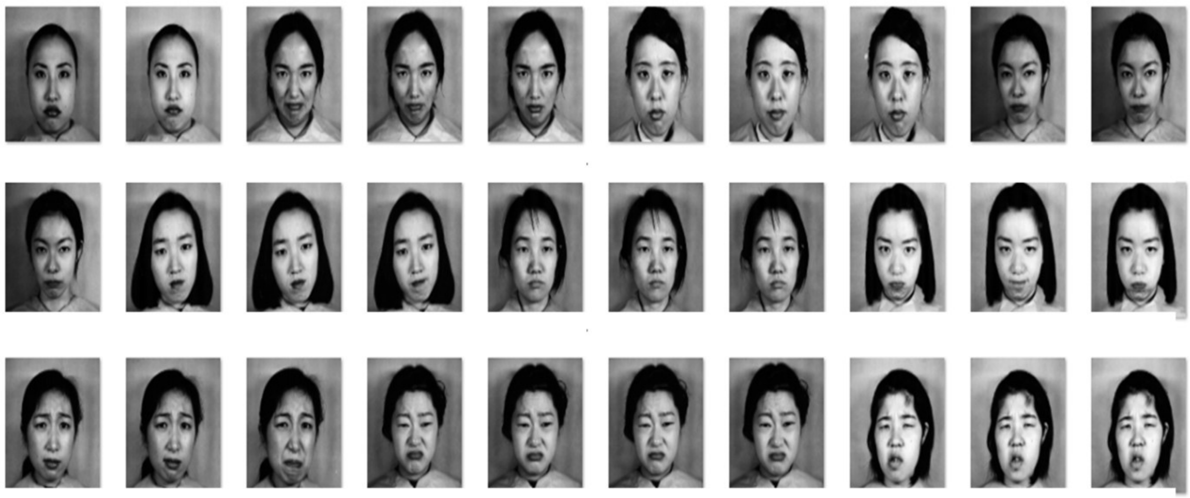

Figure 13: A sample of training images

Note that all networks are simulated using MATLAB software , 2013 version.

4.2 Backpropagation Learning Algorithm

The Back propagation neural network algorithm is executed utilizing a feed forward network, back spread updating process, and lastly supervised learning topology. This method of neural network algorithm was developed in the late 1980s. Back propagation is a multipurpose in the field of recognition algorithm. Even though this algorithm is a very efficient and accurate model it has a major constrained, which is time consuming. Back propagation network when given a certain amount of elements to simulate can produce a certain level of correctness.

Back propagation since its creation has a simple attribute thus making it a legacy algorithm by maintaining its initial attributes till today. The first layer is the input layer in which the initial weights are being inputted, next is the activation function layer in which the weights are processed before the last layer which is the output layer for the weights to be presented. Lastly is the error layer in which the weights are update in the input layer before the network is run again for another iteration until a minimal level of error is achieved which can be neglected

The explained process above is repeated until a certain level of error achieved which is to a bare minimal then the network can be said as learned network.

4.3 Network Training Scheme 1: 64*64 Pixels

The network was trained on 146 emotional expression images obtained from the JAFFE Dataset: 7 images for each different expression. The table 3 shows the number of training sets which involves different facial expressions. It displays the overall number of database pictures that were trained; the trained pictures are used in the back propagation learning with adaptive learning and momentum focus the function called "trained"

In this part, images of size 64*64 are used for training the network.

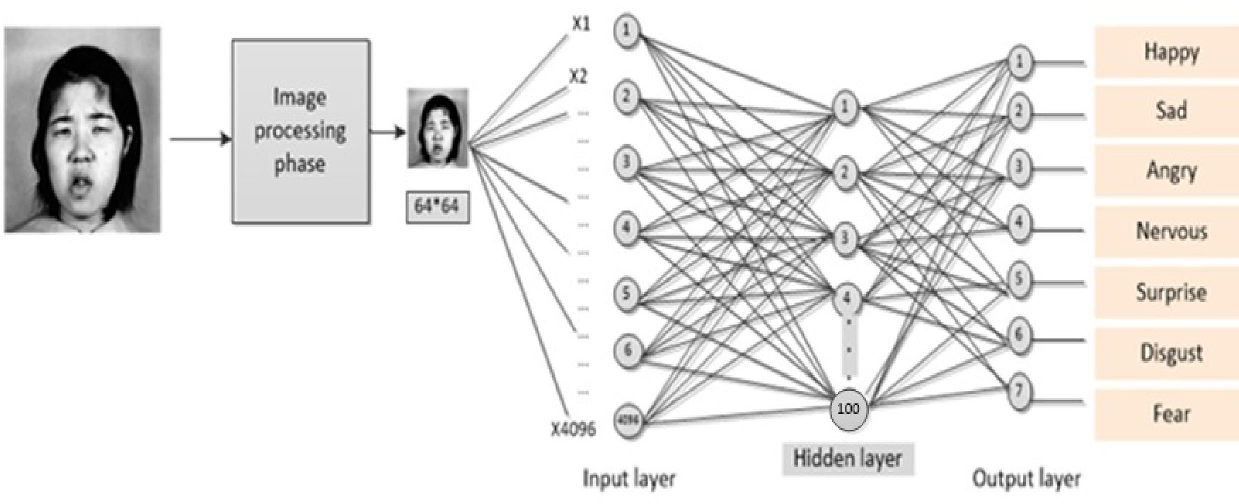

Figure 14: The proposed Backpropagation neural network architecture of BPNN1 (64*64)

During this phase, the emotional facial expression images are categorized with supervised back propagation neural network because of its common and enough number of images.

Figure 15 delineate the topology of the neural network's backpropagation utilized as a part of the system that has been created. It layers of the neural network is three which includes; input layer, hidden layer, and output layer. The input layer comprises 4096 neurons since the picture estimate is 64*64, however; the hidden layer consists of 100 neurons, which proves significant training while keeping the time expense to a minimum. The output layer contains of 7 neurons; since the emotional expression types are 7 different emotional expressions types.

Table 3 shows the training parameters of the network trained using learning scheme 1.

Table 3: Training input parameters of BPNN1 (64*64)

Network data	**Values**
Training images number	146
Input image size	64*64 pixels
Hidden neurons number	100
Type of activation function	Sigmoid
Learning rate (η)	0.14
Momentum rate (α)	0.6
Epochs	3000/3000
Training time (secs)	218.13
Reached MSE	0.0006

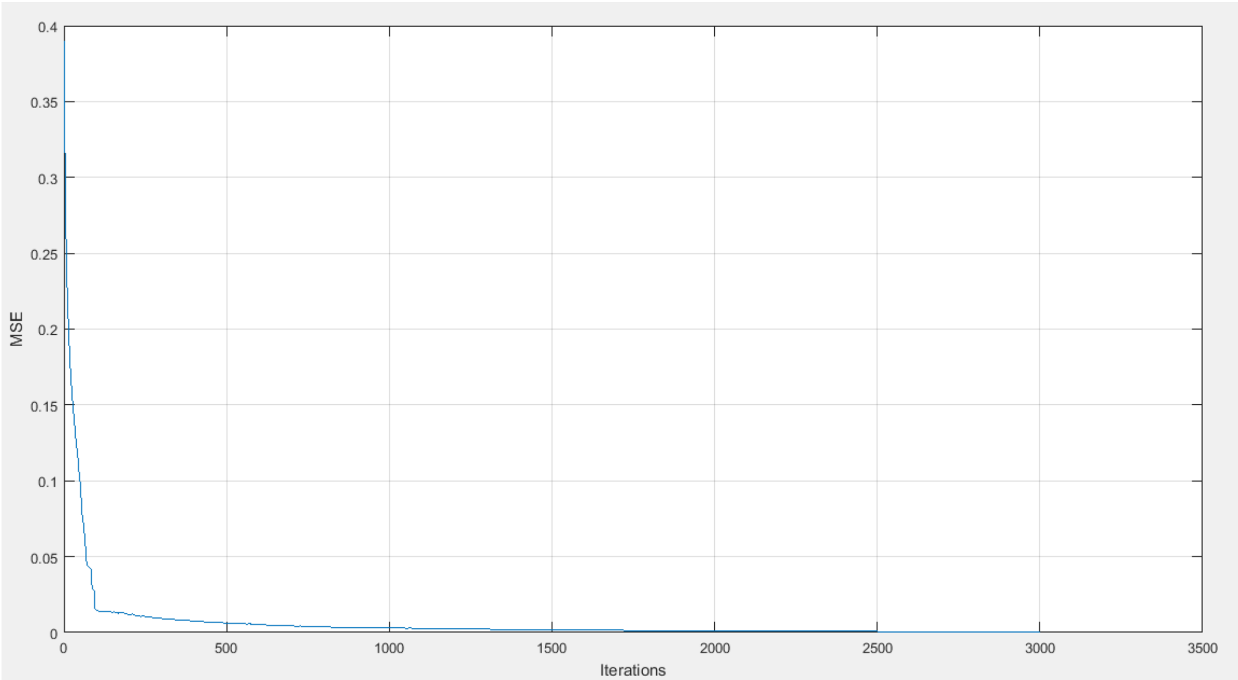

Figure 15: Learning curve of BPNN1 (64*64)

Figure 16 shows the learning curve of the proposed system when it was trained to learn the different facial expressions images. It can be seen the network was effectively learning since the error was reducing with the increase of iteration numbers.

4.4 Network Training Scheme 2: 256*256 Pixels

Same network was also trained on the same images but with their original size which is 256*256. Moreover, in this scheme histogram was analyzed for each training image. Figure 16 shows the network architecture that uses learning scheme of input images size 256*256. It shows that the number of input neurons changes hence the input images size is changed. The result of the learning of network is display in Figure 17 below.

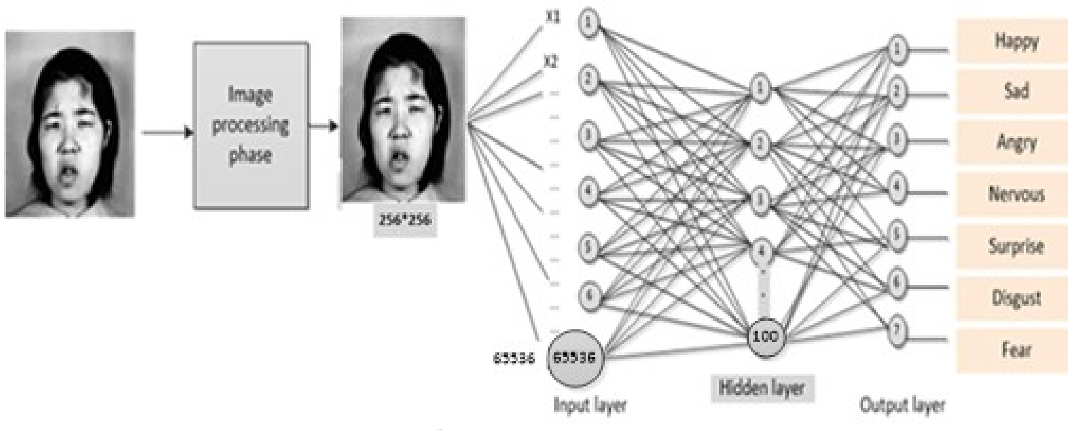

Figure 16: Network Architecture of BPNN2 (256*256)

Table 5 shows the training parameters of the second learning scheme.

Table 5: Training input parameters (256*256)

Network data	**Values**
# of training images	146
Input image size	256*256 pixels
# of hidden neurons	100
Type of activation function	Sigmoid
Learning rate (η)	0.14
Momentum rate (α)	0.6
Epochs	759/3000
Training time (secs)	1365.13
Reached MSE	0.0140

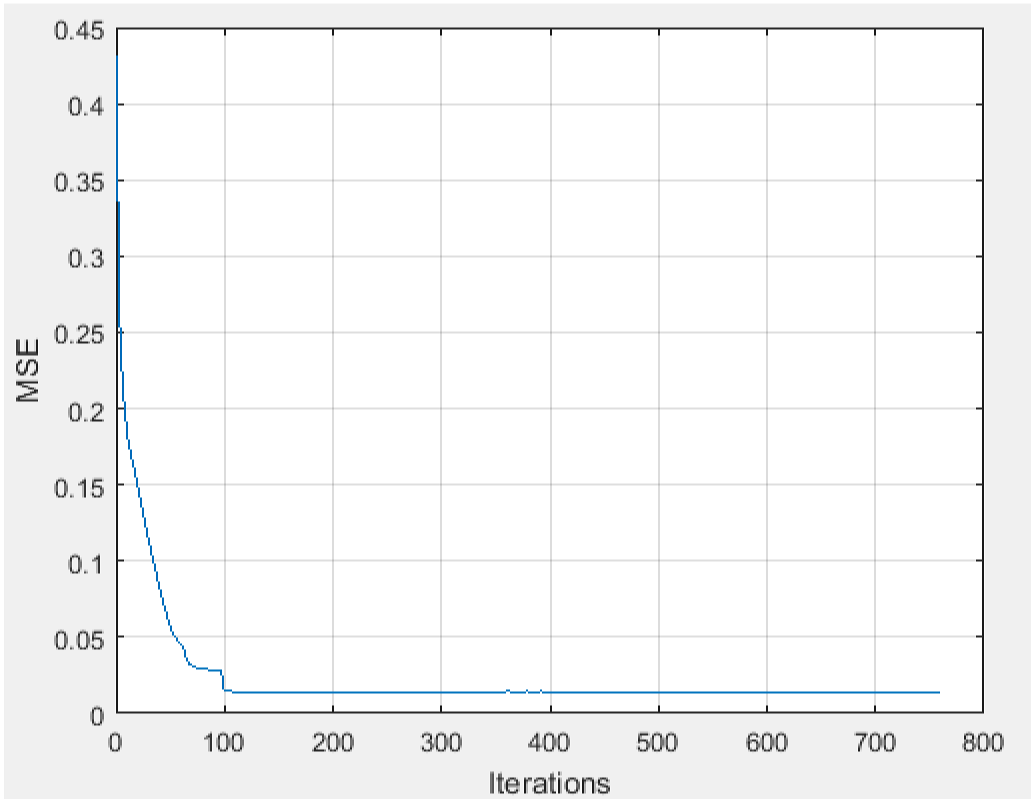

Figure 17: Learning curve of BPNN2 (256*256)

4.5 Training Recognition Rates of Learning Schemes 1&2

As can be interpreted from Table 6, the network has shown some differences when trained on different input image sizes. Table 6 shows that the network (BPNN1) has achieved a minimum square error of 0.0006 with 3000 as maximum iterations when input images are of size 64*64. Note that this was achieved in 218.14 seconds. On the other hand, Table 6 shows that the network has achieved a higher minimum square error (0.014) than that of learning scheme 1; when input images of size 256*256 are used for training the network. Also, this is achieved in very long time of 1365.13 seconds minutes but with smaller number of iterations 759.

Overall, it can be seen that using learning scheme 2 which involves input images of size 256*256 results in a higher MSE and required a lower number of iterations then that of learning scheme 1 (64*64). However, it is seen that the training of learning scheme 1 requires shorter training time

(218.14 seconds) than that of learning scheme 1 (1365.13 seconds), and it achieved a lower error compared to that of BPNN2.

Furthermore, it is noticeable that the learning scheme 1 contributes to obtain a better training recognition rate for the network where it achieved 99% which is slightly greater than that obtained when using learning scheme 2 (90%), as shown in Table 6.

Table 6: Training recognition rates between both learning schemes

	Images size	Total number of images	Recognition rate	Error achieved	Training time (secs)
Learning scheme 1	64*64	146	99%	0.0006	218.14
Learning scheme 2	256*256	146	90%	0.0140	1365.13

As seen in Table 6, the network that was trained using learning scheme 1 outperformed the one that uses learning scheme 2 in terms of training recognition rate, error reached, and training time. This may be due to the large size of input images used in learning scheme 2 where images are of size 256*256.

CHAPTER 5
SYSTEM PERFORMANCE EVALUATION AND RESULTS DISCUSSION

5.1 Testing the network models

Once the network models are trained and achieved a minimum square error rates, they should be tested in order to evaluate their performance in generalizing the recognition of new images, testing means simulating the networks using new images which were not used in training. This aims to investigate the capability of the models of recognizing new images of emotional expressions.

Note that all network models are tested on the same number of images which are 70 images containing 7 different emotional expressions. Figure 12 shows a sample of images used in testing the networks.

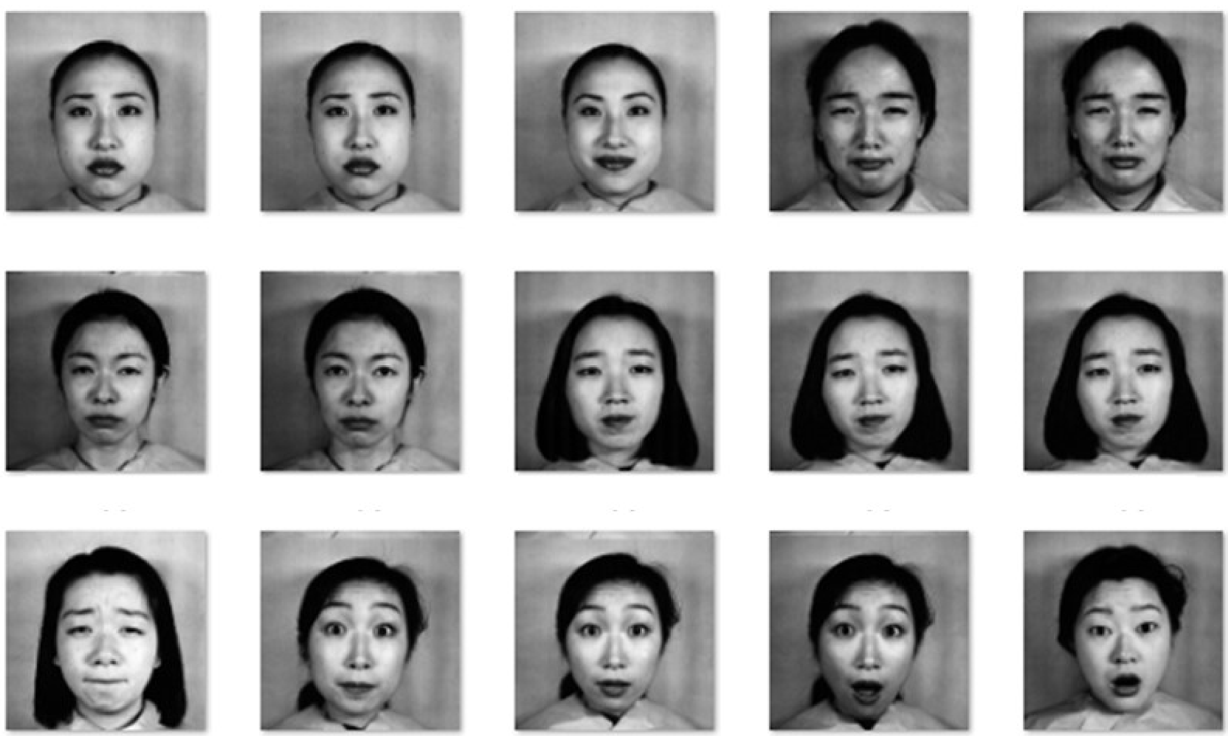

Figure 18: A sample of testing images

5.1.1 Testing the trained network that uses learning scheme 1 (BPNN1)

After successful iteration of the network, the network is being tested, in which the weights are being checked, in this dissertation new expression images that are non-existent in the literature are being proposed, models like shift and illuminations etc. The system was simulated using Matlab software (R2013). 70 various emotional expressions pictures were used in testing the evaluation of the trained network that uses learning scheme 1 (BPNN1).

The after effects of testing and preparing stages are appeared in the accompanying table 7.

Table 7: Classification rate of the network (learning scheme 1)

	Number of images	**Recognition rate of BPNN1**
Training	146	99%
Testing	70	89%
Both		94%

As seen in table 7 the network that uses learning scheme 1 has achieved a high recognition rate of 94% which is considered good for such application.

5.1.2 Testing the trained network that uses learning scheme 2 (bpnn2)

Similarly the network that was trained on learning scheme 2 is tested on the same 70 emotional expressions images to investigate the outperformance of the networks. Table 8 shows the classification rate that the network achieved.

Table 8: Classification rate of the network (learning scheme 2)

	Number of images	**Recognition rate of BPNN2**
Training	146	90%
Testing	70	82%
Both		86%

As seen in Table 8 the network (BPNN2) achieved a lower recognition rate in the testing phase (82%). This consequently made its overall classification rate (86%) to be lower than that of BPNN1 (94%).

5.2 Results Discussion

This thesis features an overwhelming assignment in AI, in like manner in image processing. We have demonstrated that neural system (BPNN) backpropagation can be utilized in understanding the grouping/detection of emotional expression images. The Back Propagation Neural Network that is thouroughly trained is then utilized as a part of a non-covering inspecting design to 'identify' pictures that contain faces of different emotional expressions.

The efficiency of the developed system has been tested when the segmentation of the images was finished; the system was particularly tested for recognition of emotional expressions in faces. Furthermore the system is insignificantly affected when there is change in conditions or differences in facial expressions which implies the system is found to be intelligent.

The Table 9 summarized the results obtained by training and testing both network models. It compares the performance of both models in terms of errors, training time, and accuracies achieved. It is seen that the BPNN1 was capable of achieving a higher recognition rate (94%) than that obtained by BPNN2 (86%). Moreover, BPNN1 has reached a smaller error (0.0006) that that achieved by BPNN2 (0.0140). This error is also achieved with shorter time (218.14 seconds) than the time need for BPNN2 (1365.13 seconds) to converge.

Table 9: Performance comparison of both network models

	Images size	Training number of images	Testing number of images	Error achieved	Training time (secs)	Recognition rates
Learning scheme 1	64*64	146	70	0.0006	218.14	94%
Learning scheme 2	256*256	146	70	0.0140	1365.13	86%

Table 10: Recognition rates of each expression

Expressions	Recognition rates
Happy	78%
Nervous	80%
Sad	86%
Surprised	96%
Neutral	93%
Fear	90%
Angry	94%

Table 10 shows the recognition rates of each different expression tested on the network that uses 64*64 pixels (BPNN2).

5.3 Challenges Encountered During the Work

The training phase of this work faced a significant challenge in getting an impressive rate of recognition, which was a result of the images which are fuzzy, which implies the network will have difficulty in learning any difference from the images. To handle the fore mentioned challenge the system was designed to extract the needed features of images in order to significantly reduce the learning process of the network.

Amongst the issues of the system is the verity of arranging recognition that is hard to be gotten at the initial cycle. Along these lines, the system was set up for a couple of running until the moment that the mean square mix-up is achieved and an elevated recognition rate is derived. Therefore, the framework must be rechecked and orchestrated twice or thrice prior to testing it with the target of correct weights will be capable while ensuring the realization of basic recognition.

In any case, the arrangement of the neural system learning rate was high during recognition; moreover the network couldn't have generalized new facial expression images. This problem is common with back propagation networks, the fact the stage learning rate becomes a memorizing one, thus becoming not intelligent, and this can be prevented by reducing the total number of iterations used in the neural network.

5.4 Results Comparison

Many researchers have attempted to develop intelligent systems to recognize emotional expression images. Each of the researches is mainly based on processing the images and then using a machine learning technique to classify emotional expression images. Similarly, in this work used the emotional expression images recognition by the extraction of features from the image after it is adjusted and reduced using some image processing techniques. Then, the images are fed into a feedforward neural network trained using gradient descent to learn the generalization of new faces of emotional expressions that were not seen before.

The table below depicts the outcomes of the emotional expression images recognition system as compared with other significant systems with similar classifier although different database.

Table 10: Results correlation with different works

Paper title	Methods and classifier used	Recognition rate
Deep Architectures for Automatic Emotion Recognition Based on Lip Shape(Popović et al., 2013)	Image processing and deep belief network	92%
Emotion Recognition based on 2D-3D Facial Feature Extraction from Color Image Sequences(Niese et al., 2010)	Features extraction and backpropagation neural network	90%
Facial Expression Recognition Using Image Processing Techniques and Neural	Image processing and backpropagation neural network	92.8%

Networks(Lee et al., 2013)		
Proposed work	Image processing backpropagation NN	94%

As seen in table 10, many researches were conducted for the purpose of recognizing the different emotional expressions. Moreover, each of these researches used different types of machine learning techniques. It is noted that the proposed system was capable of achieving a higher recognition rates in classifying the 7 different emotional expressions than those obtained by other researches

CHAPTER 6
CONCLUSION

6.1 Conclusions

The neural networks have been recently applied in very tough tasks such as classification, detection, and prediction. The success of backpropagation neural networks in classification and identification tasks give positive and optimizing hopes to be used in classifying the human emotional expression into sad, happy, neutral, surprise, fear, angry. Thus, researchers have conducted many researches on how to develop a neural system that has a high accuracy in identifying the human emotional expression by checking the human face. Thus, in this thesis, we aim to design a neural system trained using gradient descent to classify different man emotional expressions by only reading their faces. The aim is to obtain a high recognition rate with a small error and training time compared to other recent works when the network is tested in new images. This thesis aims also to investigate the effects of input sizes in the learning and performance of the neural network.

The neural network selected to be the heart of the work is the backpropagation neural network that showed promising accuracies in classification and face detection tasks. This network is first trained on faces of seven different human emotions expressions of different persons. Upon training, the network is tested on different images of faces that have some specific expressions and it is seen that the network was capable of identifying the real emotional expressions of faces.

Experimentally, the network was trained and tested on two input images sizes (64*64 pixels) and (256*256) and the performance was discussed and compared of each size. Note that the 64*64 size was selected as it reduces the computation time of network as well as it preserves the useful features of the image so that the network can learn the different features that distinguish the various expressions.

Finally, it is concluded that the smaller input size can result in a smaller error achieved during training in addition to shorter training time that those obtained when 256*256 size is used. Moreover, it is seen that the input images of 64*64 pixels result in a higher performance in terms of recognition rate that that obtained when 256*256 pixels input images are used.

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APPENDICES

APPENDIX 1
IMAGE PROCESSING CODE

```
%%%%% Normal images processing

clear all

close all

clc

AN =[];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%# Load the image,

cd hamza

%angry

for k = 1:10

I = imread(strcat(['AN',num2str(k),' (1).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T =imresize(S5, [64 64], 'nearest');

vec=T(:);

AN=[AN vec];

end

for k = 1:10

I = imread(strcat(['AN',num2str(k),' (2).tiff']));
```

```
I=imresize(I, [256 256], 'nearest');
g2=imadjust(I);
S5=g2;
T = blkproc(S5, [4 4], @mean2);
vec=T(:);
AN=[AN vec];
end
for k = 1:10
I = imread(strcat(['AN',num2str(k),' (3).tiff']));
I=imresize(I, [256 256], 'nearest');
g2=imadjust(I);
S5=g2;
T = blkproc(S5, [4 4], @mean2);
vec=T(:);
AN=[AN vec];
end
%DI
DI=[];
for k = 1:10
I = imread(strcat(['DI',num2str(k),' (1).tiff']));
I=imresize(I, [256 256], 'nearest');
```

```
g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

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DI=[DI vec];

end

for k = 1:10

I = imread(strcat(['DI',num2str(k),' (2).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

DI=[DI vec];

end

for k = 1:10

I = imread(strcat(['DI',num2str(k),' (3).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;
```

```
T = blkproc(S5, [4 4], @mean2);

vec=T(:);

DI=[DI vec];

end

%FE

FE=[];

for k = 1:10

I = imread(strcat(['FE',num2str(k),' (1).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

FE=[FE vec];

end

for k = 1:10

I = imread(strcat(['FE',num2str(k),' (2).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);
```

```
vec=T(:);

FE=[FE vec];

end

for k = 1:10

I = imread(strcat(['FE',num2str(k),' (3).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

FE=[FE vec];

end

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%HA

HA=[];

for k = 1:10

I = imread(strcat(['HA',num2str(k),' (1).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);
```

```
vec=T(:);

HA=[HA vec];

end

for k = 1:10

I = imread(strcat(['HA',num2str(k),' (2).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

HA=[HA vec];

end

for k = 1:10

I = imread(strcat(['HA',num2str(k),' (3).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

HA=[HA vec];

end
```

```
%NE

NE=[];

for k = 1:10

I = imread(strcat(['NE',num2str(k),' (1).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

NE=[NE vec];

end

for k = 1:10

I = imread(strcat(['NE',num2str(k),' (2).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

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vec=T(:);

NE=[NE vec];

end
```

```
for k = 1:10

I = imread(strcat(['NE',num2str(k),' (3).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

NE=[NE vec];

end

%SA

SA=[];

for k = 1:10

I = imread(strcat(['SA',num2str(k),' (1).tiff']));

I=imresize(I, [256 256], 'nearest');

g2=imadjust(I);

S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

SA=[SA vec];

end

for k = 1:10
```

```
I = imread(strcat(['SA',num2str(k),' (2).tiff']));
I=imresize(I, [256 256], 'nearest');
g2=imadjust(I);
S5=g2;
T = blkproc(S5, [4 4], @mean2);
vec=T(:);
SA=[SA vec];
end
for k = 1:10
I = imread(strcat(['SA',num2str(k),' (3).tiff']));
I=imresize(I, [256 256], 'nearest');
g2=imadjust(I);
S5=g2;
T = blkproc(S5, [4 4], @mean2);
vec=T(:);
SA=[SA vec];
end
%SU
SU=[];
for k = 1:10
I = imread(strcat(['SU',num2str(k),' (1).tiff']));
```

```
80
I=imresize(I, [256 256], 'nearest');
g2=imadjust(I);
S5=g2;
T = blkproc(S5, [4 4], @mean2);
vec=T(:);
SU=[SU vec];
end
for k = 1:10
I = imread(strcat(['SU',num2str(k),' (2).tiff']));
I=imresize(I, [256 256], 'nearest');
g2=imadjust(I);
S5=g2;
T = blkproc(S5, [4 4], @mean2);
vec=T(:);
SU=[SU vec];
end
for k = 1:10
I = imread(strcat(['SU',num2str(k),' (3).tiff']));
I=imresize(I, [256 256], 'nearest');
g2=imadjust(I);
```

```
S5=g2;

T = blkproc(S5, [4 4], @mean2);

vec=T(:);

SU=[SU vec];

end

cd ..

target=[eye(70) eye(70)];

pattern=[AN(:,1:10) DI(:,1:10) FE(:,1:10) HA(:,1:10) NE(:,1:10) SA(:,1:10) SU(:,1:10)];

pattern=[pattern  AN(:,11:20)  DI(:,11:20)  FE(:,11:20)  HA(:,11:20)  NE(:,11:20)  SA(:,11:20)
SU(:,11:20)];

test=[AN(:,21:30) DI(:,21:30) FE(:,21:30) HA(:,21:30) NE(:,21:30) SA(:,21:30) SU(:,21:30)];

pattern=double(pattern)./255;

test=double(test)./255;

net = newff(minmax(pattern),[100 70],{'logsig','logsig','logsig'},'traingdx');

net = init(net);

net.LW{2,1} = net.LW{2,1};

net.b{2} = net.b{2};
```

APPENDIX 2
NEURAL NETWORKS CODE

```
% TRAINING THE NETWORK

net.trainParam.goal = 0.000001;

net.trainParam.show = 50;

net.trainParam.epochs = 3000;

net.trainParam.mc = 0.6;

net.trainParam.lr= 0.14;

net.trainParam.min_grad=1e-25;

[net,tr] = train(net,pattern,target);

train = sim(net,pattern);

test = sim(net,test);

disp('Training results');

train;

disp('Test results');

test;

for k=1:70

if(train(k,k)>0.3)

msg=strcat(['training image no: ',num2str(k),' is recognized']);

else

msg=strcat(['training image no: ',num2str(k),' is not recognized']);
```

```
end
disp(msg);
tic;
while(toc<0.2)
end
end
for k=71:140
if(train(k-70,k)>0.3)
msg=strcat(['training image no: ',num2str(k),' is recognized']);
else
msg=strcat(['training image no: ',num2str(k),' is not recognized']);
end
disp(msg);
tic;
while(toc<0.05)
end
end
for k=1:70
if(test(k,k)>0.3)
msg=strcat(['test image no: ',num2str(k),' is recognized']);
else
```

```
msg=strcat(['test image no: ',num2str(k),' is not recognized']);
end
disp(msg);
tic;
while(toc<0.1)
end
end
plot(tr.perf);
grid;
xlabel('Iterations');
ylabel('MSE');
disp(strcat('learning rate = ', num2str(tr.trainParam.lr)));
disp(strcat('momentum factor = ', num2str(tr.trainParam.mc)));
disp(strcat('training time = ', num2str(max(tr.time)),' Seconds'));
```