JOHN BUSH IDOKO
DEEP LEARNING-BASED SIGN LANGUAGE TRANSLATION SYSTEM
NEU 2020

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

By
JOHN BUSH IDOKO

In Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Computer Engineering

NICOSIA, 2020

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John Bush Idoko: Deep Learning-Based Sign Language Translation System

Approval of Director of Graduate School of Applied Sciences

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We certify this thesis is satisfactory for the award of the degree of Doctor of Philosophy in Biomedical Engineering

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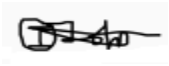
Signature: 

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ABSTRACT

In this thesis, we propose sign language translation system which utilizes deep learning based convolutional neural network. Sign Language refers to language that enables dumb and hearing-impaired individuals to facilitate communication. It is a non-verbal, natural and visually oriented channel of communication among individuals that communicate via bodily/facial expressions, postures, and some setting gestures. Such language is essentially used for non-verbal exchange with deaf/dumb people. Recognition/translation of Sign Language happen to be an essential field of study due to its potential to advance the interplay between the individuals deaf/dumb.

Nevertheless, the existing methods have several limitations. Some of which requires special hardware tools such as specific cameras or sensor-based/multi-colored gloves. The other classical approach uses special methodologies for solving extraction of features and classification problems. In this thesis, classification and extraction of features stages were combined within the body of the sign language translator (SLT). The presented approach simplifies the execution of SLT capable of solving object detection and identification problems. In the thesis, we incorporated Multibox, Fixed Priors, Multiscale Feature Maps, Hard Negative Mining and Non-Maximum Suppression deep learning attributes for improving performance of the designed system. Incorporation of these learning features makes localization easy and accurate, and simplifies feature extraction leading to a seamless and faster model for sign language translation.

This implemented sign language translator comprises three major modules. In the first module, hand region segmentation is applied using deep learning based on Single Short Detector (SSD). SSD is an object detection approach that utilizes regional partitioning in a looped algorithm. In the second module, feature vector extraction is performed using deep learning structure based on inception v3 learning technique. Feature vectors are selected amongst low-level features including center of mass coordinates, bounding box and bounding ellipse, because of their robustness to segmentation errors resulting from images with low resolution. After feature vector extraction, the extracted vector is supplied to the classifier. We performed transfer learning on the first two deep learning models (SSD and Inception v3) which are in turn concatenated to the SVM model forming a compact deep learning structure named Sign Language Translator (SLT). With the aid of the employed deep learning structures, SLT can constructively translate the

detected hand gestures into text. To measure SLT success rate, validation tests were conducted on two phases; American Sign Language Fingerspelling Datasets where the system obtained 99.90% accuracy, and in real time it obtained 99.30% accuracy. Results of the proposed translator and comparative analysis exhibit the effectiveness of the usage of SLT in translation of sign language.

***Keywords*:** CNNs; DCNNs; Single short multibox detector; inceptions v3; support vector machine; sign language

ÖZET

Bu tezde, derin öğrenme tabanı evrişimli sinir ağını kullanan işaret dili çeviri sistemini öneriyoruz. İşaret Dili, dilsiz ve işitme engelli bireylerin iletişimi kolaylaştırmasını sağlayan dili ifade eder. Bedensel / yüz ifadeleri, duruşlar ve bazı ayar hareketleriyle iletişim kuran bireyler arasında sözsüz, doğal ve görsel olarak yönlendirilmiş bir iletişim kanalıdır. Bu dil esasen sağır / dilsiz insanlarla sözsüz değişim için kullanılır. İşaret dilinin çevirisi / tanınması, sağır / dilsiz bireyler arasındaki etkileşimi ilerletme potansiyeli nedeniyle önemli bir araştırma alanıdır.

Bununla birlikte, mevcut yöntemlerin bazı sınırlamaları vardır. Bazıları belirli kameralar veya sensör tabanlı / çok renkli eldivenler gibi özel donanım araçları gerektirir. Diğer klasik yaklaşım, özelliklerin çıkarılmasını ve sınıflandırma problemlerini çözmek için özel yöntemler kullanır. Bu tezde, işaret dili çevirmeni (SLT) bünyesinde özelliklerin sınıflandırılması ve çıkarılması aşamaları birleştirilmiştir. Sunulan yaklaşım, nesne algılama ve tanımlama sorunlarını çözebilen SLT'nin yürütülmesini basitleştirir. Tezde, tasarlanan sistemin performansını artırmak için Çoklu Kutu, Sabit Öncelikler, Çok Ölçekli Özellik Haritaları, Sert Negatif Madencilik ve Maksimum Olmayan Bastırma derin öğrenme özellikleri eklenmiştir. Bu öğrenme özelliklerinin birleştirilmesi yerelleştirmeyi kolay ve doğru hale getirir ve işaret dili çevirisi için kesintisiz ve daha hızlı bir modele yol açan özellik çıkarmayı basitleştirir.

Bu uygulanan işaret dili çevirmeni üç ana modül içermektedir. İlk modülde, el bölgesi segmentasyonu, Tek Kısa Dedektör (SSD) tabanlı derin öğrenme kullanılarak uygulanır. SSD, döngüsel bir algoritmada bölgesel bölümlemeyi kullanan bir nesne algılama yaklaşımıdır. İkinci modülde, özellik vektörü çıkarma, derin öğrenme yapısı temel başlangıç v3 öğrenme tekniği kullanılarak gerçekleştirilir. Özellik vektörleri, düşük çözünürlüklü görüntülerden kaynaklanan bölümleme hatalarına karşı sağlamlıklarından dolayı kütle koordinatları merkezi, sınırlayıcı kutu ve sınırlayıcı elips dahil olmak üzere düşük seviyeli özellikler arasından seçilir. Özellik vektörü ekstraksiyonundan sonra, ekstrakte edilen vektör sınıflandırıcıya verilir. İlk iki derin öğrenme modelinde (SSD ve Inception v3) transfer öğrenimi gerçekleştirdik, bu da İşaret Dili Çevirmeni (SLT) adında kompakt bir derin öğrenme yapısı oluşturan SVM temel modeliyle birleştirilmiştir. Kullanılan derin öğrenme yapılarının yardımıyla, SLT tespit edilen el hareketlerini yapısal olarak metne dönüştürebilir. SLT başarı oranını ölçmek için validasyon testleri iki aşamada

gerçekleştirilmiştir; Sistemin% 99,90 doğruluğu ve gerçek zamanlı olarak% 99,30 doğruluğu elde ettiği Amerikan İşaret Dili Parmakla Yazma Veri Kümeleri. Önerilen tercümanın sonuçları ve karşılaştırmalı analiz, işaret dili çevirisinde SLT kullanımının etkinliğini göstermektedir.

***Anahtar Kelimeler*:** CNN'ler; DCNN'ler; Tek kısa multiboks dedektör; inceptions v3; destek vektör makinesi; işaret dili

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Sign language is a medium of communication that utilizes movements of the body/facial, postures, with some setting motions in human to human communicuation as well as through television and social media. Huge number of hearing impaired individuals use Sign Language as the first language, and individuals who have different speech difficulties. According to the British deaf association investigation, it is estimated that around 151,000 individuals use Sign Language to communicate (Jala et al., 2018). There is no universal sign language and almost all nations of the world have their own national non-verbal communication medium and fingerspelling alphabet. The signers use both lips articulation, facial imitations and hand gestures. There is a special grammar in Sign Languages that has basic variations in the spoken languages based on voice. The American sign language (ASL), having its own grammar and rules, happens to be one of the most common sign languages in the world. There are also other sign systems including the signed English; this borrows signs from the American sign language but uses them in order of English Language (Parton, 2016). It is a two-way operation, since Sign Language involves both rendering the signs (expressive skills) and reading the signs (receptive skills). The translation and understanding of Sign Language is a very crucial field of study since it brings individuals with hearing impairments into the community and offers equal opportunity. The development of a human-machine interface that has the capability to enhance the common correspondence amongst healthy and hearing impede individuals is a significantly important problem, targeted at supplanting the third human factor (translator). The sign language recognition problem is often limited to the translation of fingerspelled words to text, where sign language alphabet recognition is the major task (Dong et al., 2015). Characterized by their own rules and grammar, sign languages are comprised of dynamic configuration of a set of palm and hand gestures positions, body movements, and finally, expression of the face (http://www.nidcd.nih.gov/health/hearing/asl.asp Retrieved 17 April, 2020). For most if not all known natural dialects/languages, there are different signs.

We have few number of hearing individuals who are capable of using sign language to communicate. Gesture based communication mediators can be utilized to help correspondence

among hard of hearing and hearing individuals however this is frequently troublesome because of the restricted accessibility and significant expense of translators. These challenges in correspondence among hearing and hard of hearing individuals can prompt issues in the integration of hard of hearing individuals into society and clashes with a self-determined and independent way of life. Hearing individuals learn and see composed languages as a visual portrayal of verbal languages in which alphabets encode phonemes. And for hard of hearing individuals, this mutual communication doesn't exist along these lines, alphabets are simply observed as meaningless symbols (Dong et al., 2015). Hard of hearing individuals in this way have incredible challenges in reading as well as writing since there is no immediate relation between their written languages and natural languages (gesture based communication). To enhance communication between hard of hearing and hearing individuals, research in automated translation/recognition is highly required. Current developments in automatic sign language recognition are apparently 30yrs behind automated recognition of speech (Dong et al., 2015). Communication via gestures is passed on through various interfacing channels of information, in this way the examination of gesture based communication is a more perplexing issue than that of analyzing speech in 1D audio channel.

Because some individuals don't comprehend Sign Language, and some persons typically find it pretty challenging to comprehend, developing a sign language translator based on vision has become important. The design of such a system permits a substantial reduction of the contact barrier between people. There are two key approaches for interpreting the Sign Language. Vision-based method is the first approach and uses mounted camera in order to capture the target image that is further supplied to the module for image processing (Abiyev, 2014), (Tao et al., 2018), and (Aly et a., 2019). The second strategy is the glove-based method which implements gloves and sensors. I this method, the glove is used to alleviate the limitations of the conventional approaches based on vision. Although users/signers frequently find glove-base methods to be burdensome and challenging, the findings are much reliable and consistent (Chuan et al., 2014) and (Aly et al., 2019). These applications need special hardware tools such as the utilization of specific camera or sensor-based/multi-colored. The other approaches Dong et al. (2015) use special methodologies for solving the extraction of features and classification problems. In this thesis, CNN that combines these two stages is proposed to implement SLT. The proposed method simplifies the design of the Sign Language recognition framework that solves object detection and

identification stages using single video camera for capturing complex hand movements for their recognition.

1.1 Motivation for the Proposed Hybrid Model

The conventional methods for object detection are implemented on shallow trainable architectures and handcrafted features. They have difficulties in constructing more complex systems integrating high-level context with several low-level image features. One powerful approach that is capable of learning high-level, semantic and deeper features is the implementation of deep learning structures for detection of object. Recently, deep learning-based methods for instance SSD, R-CNN, YOLO and Faster R-CNN algorithms Bao et al. (2015) and Zhao et al. (2019) are applied for detection of object. R-CNN uses selective search to create bounding boxes or region proposals (Uijlings et al., 2013). The selective search takes the image of various sizes and for each size, it tries to group together adjacent pixels using intensity, color or texture for object identification. And for every bounding boxes using CNN, classification of image is performed. The algorithm has some disadvantages. Used selective search is fixed algorithm that does not use learning and this may generate bad candidate region proposal. Also, the algorithm takes a lot of time during training of network that classifies many regions of proposals and because of this, the algorithm cannot be implemented in real-time. Later, a faster version of the R-CNN algorithm that uses CNN instead of selective search is designed so as to solve above-mentioned problems. But faster version requires many passes (systems) through a single image so as to extract all possible objects. The performance of this system depends on how the previous system is performed. The algorithm YOLO (You Only Look Once) Redmon et al. (2016) actually looks at images one time, although in a clever way. The algorithm (YOLO) splits the image into grid of SxS cells, each of which is responsible for forecasting m bounding boxes that enclose some objects. And for each of these bounding boxes, a class prediction is performed by the cell. The predicting of bounding boxes is performed by calculating the confidence score. The architecture of YOLO is based on CNNs. An input image given to the YOLO is processed a single pass by the convolutional layers, and at the end of the network, the tensor characterizing the grid cells bounding boxes are derived. After determining the final scores for the bounding boxes the outputs are determined. YOLO is a simple and fast algorithm.

One of the limitations of YOLO is its inability to perform well with smaller objects within images. As a result, there may be challenges in floc of birds' detection. And this is because of algorithms spatial constraints. Later, a faster version of YOLO algorithm was developed, but it is less accurate than the first version.

Single Short Detector Liu et al. (2016) is based on CNN which generates collection of fixed-size of bounding box. In these boxes, by scoring object class instances detection, the final detection of objects is implemented. The model is the object detector which classifies the detected objects. The network uses Multibox, Fixed priors and Priors sub-components. In this model structure, a set of new SSD layers and new faster R-CNN modules or some of their combination are used to replace Convolution/Pooling layers. Using SSD a better balance between swiftness and precision is achieved. By running a convolutional network only one time, SSD determines a feature map of the input image. SSD also utilizes anchor boxes at a range of aspect ratios similar to Faster-RCNN and learns the off-set to some degree than learning the box (Liu et al., 2016). After multiple convolutional layers, SSD predicts the bounding boxes in order to hold the scale. Objects of a mixture of scales are readily detected because every convolutional layer has the capability of functioning at a diverse scale. In this study, we use SSD based on CNN. SSD is faster than YOLO, and more accurate than Faster R-CNN. More detailed comparisons of object detection methods are provided in the papers (Liu et al., 2016) and (Zhoa et al., 2019). From these comparative results, it was clear that SSD approach recorded higher result as compared to the other methodologies.

Recently, feature extraction methodologies including Principal Component Analysis (PCA), local binary patterns, Gabor filters, Speeded Up Robust Features (SURF) semantic analysis, Scale Invariant Feature Transform (SIFT), independent component analysis, histogram of gradient are widely used for feature extraction (Di Ruberto et al., 2016) and (Wang et al., 2018). The extracted features are used in classification. Conventional classification algorithms are based on k-means, linear discriminant analysis, c-means, supervised clustering, fuzzy c-means, etc (Wang et al., 2018). Some studies including (Liu et al., 2016) and (Zhoa et al., 2019) addressed the limitations of the existing conventional tools. Some of the limitations include low speed and accuracy. The latest version of Inception fixes these limitations by the introduction of factorization method. Factorization of higher dimensions into smaller dimensions reduces

execution time and increases accuracy. Nowadays machine learning techniques are extensively used for feature extraction and classification purpose. These are neural networks, SVM, radial based networks, neuro-fuzzy networks, different types of deep learning structures. The integration of deep learning structures and SVM (Kundu and Ari (2020)) are becoming extensively used for solving feature extraction and classification problems. In the paper Kundu and Ari (2020), a 2D convolutional layer-based CNN architecture, Fisher ratio (F-ratio) based feature selection and SVM classifier are used for P300 detection. Another novel deep structure which utilizes support vector machines including class probability output systems is presented in Kim et al. (2015) for the provision of higher generalization power for problems relating to pattern classification. The paper Zareapoor et al. (2018) presents a combination of deep belief structure as well as kernelized SVM for classification of multiclass dataset. Chen et al. (2018) proposed a Deep Ranking Structural SVM with deep learning to tag image. In the paper Qi et al. (2016) integration of deep learning and SVM is proposed for acquisition of deep features afterwards, standard SVM is used for classification. The paper Li and Zhang (2017) proposes deep neural mapping support vector machine which was trained utilizing Gradient Descent. In Fernandes et al. (2019) combination of CNN and SVM is presented for Grapevine variety identification, and theses integrated models yielded great performance in terms of accuracy and speed.

At the phases of feature extraction as well as classification, the speed, sensitivity, occlusion and accuracy of the system are very important. This thesis propose sign language translation system based on a hybrid structure that uses SSD to detect hand gestures and then uses Inception v3 plus SVM to obtain features for classification purposes. Here, the inception v3 module is a CNN which transforms and extracts feature matrices from the detected hand gesture to smaller dimensional spaces for further examination. After this, the incorporated SVM classifier performs the sign classification. At the end of training and testing, the outcome of the presented hybrid network has shown the efficiency of the system in the execution of the sign language translation problem and many other human-machine interface related problems.

Some of the goals of this thesis are:

- To develop deep learning model based on CNN that processes and classifies the different sign language communication signs.

- To develop algorithms based on deep learning to detect and segment hand gestures in on-line.

The thesis depicts the following contributions to the above mentioned goals:

- Designing the structure of a vision-based sign language translator (SLT) based on Inception 3 algorithm without the use of external/extra hardware
- Designing algorithms of CNN based deep learning for detection, identification of sign languages.
- Performing transfer learning at object detection phase by reusing SSD object detection features. This would enable easy application of SLT to other nations' sign languages
- Implementation of robust supervised training algorithm by using multiple instance learning density matrices (incorporated in the second module).

1.2 Thesis Outline

Remaining part of the thesis is organized thus:
Chapter 2 presents the state-of-the-art sign language translation. The used signs, a discussion of how particular signs are formed and distinguished from each other are given. The overview of the sign language translation systems, their analysis is described. Furthermore, we demonstrate the significant ideas in the state-of-the-art in gesture based communication recognition and further discuss previous unsolved tasks.

Chapter 3 presents the deep learning based CNN. The structure and operating principles of CNN-based deep learning is discussed. Implementation of CNN for detection of hand gestures and classification is presented.

Chapter 4 presents modeling of sign language translation system. Hand gesture recognition using CNN is given. Thorough discriminatory properties assessment and evaluation of sign language translator features is discussed in this chapter.

Results, simulation and discussion of sign language translator are demonstrated in chapter 5.

In chapter 6, we summarize the fundamental contributions of SLT as well as details of future thoughts.

CHAPTER 2

THE STATE OF THE ART OF SIGN LANGUAGE TRANSLATION USING DEEP LEARNING

2.1 Sign Languages and Hand Gestures

Sign to text conversion is afundamental application of Sign Language translation framework. This requires total translation/interpretation of signed sentences to speech, or text, of a communicated language. Such an interpretation framework isn't the main utilized methodology for gesture based communication recognition frameworks. There are other visualized applications for gesture based communication recognition frameworks; an instance is a translation framework for explicit transactional domains, for example, banks, post offices and so on. One other application of sign language recognition system is bandwidth conserving framework which enables communication amongts signers where the recognized sign that is the input of the communication framework at a terminal, could be converted into avatar-base animation at another terminal. Another suggested application is a computerized sign language teaching model. This application supports users experiencing hearing misfortune, hard of hearing individuals with gesture based communication insufficiencies and hearing individuals wishing to learn gesture based communication.

Other proposed applications are automated or semi-automated framework for annotating native signing video databases. Etymological research on gesture based communication requires huge scale annotated corpora as well as automated strategies for investigating sign language videos would incredibly enhance annotation effectiveness. At long last, gesture based communication recognition frameworks can be consolidated to application that allow interface of input for augmentation of communication frameworks. Assistive innovation designed for human to human correspondence by dumb individuals frequently needs joystick, keyboards and mouse inputs. Frameworks that can fuse natural aspects of gesture based communication would improve the availability of these frameworks. The techniques proposed in SLT are not constrained to Sign Language translation. The techniques we proposed in this research can possibly be applied to various tasks that emphasis on human gesture modeling and recognition, for example, control of

gesture in Human Computer Interface (HCI) frameworks, analysis of human activity/action as well as analysis of social interaction.

2.2 Hand Pose Estimation

Estimation of accurate hand pose is highly essential in many augmented reality or human-computer interaction tasks, and has lately become very important in the field of computer vision.

2.2.1 Estimation of hand pose in RGB images

A lot of significant works that treated estimation of hand pose utilizing RGB images has been proposed. Those methodologies can be split into two classes: appearance-based methodologies and model-based methodologies (Rastgoo et al., 2020). Model based methodologies create position of hand hypotheses and assess them using the input images. In (Rastgoo et al., 2018), the authors presented a technique to fit a 3-D model of hand mesh with the hand surface by a mesh built through principal component analysis from training data. The real time tracking is accomplished through calculating the nearest potentially deformed system that matches the given image. Henia et al. (2010) utilized two-step minimization technique for system based on tracking of hand. The authors presented a novel a minimization procedure and dissimilarity function which works in two stages: the first gives the global hand parameters, that is position and direction of the palm, while the subsequent stage gives the local hand parameters, that is finger joint points. Be that as it may, those approaches can't deal with the occlusion task.

Appearance based techniques utilize the exact information present in the images. They don't utilize an express hand prior model but instead extricate the hand’s region of interest (ROI). Bretzner et al. (2002) recognize hand shapes using color features. Along these lines, the hand could be depicted as a palm’s huge blob feature, with fewer blob features indicating the fingers, and this turned into a well-known strategy however has a few downsides, for example, detection of skin color which is exceptionally delicate to lighting conditions. Garg et al. (2009) is referenced for a review of estimation of hand pose based on RGB methodologies.

2.2.2 Depth images hand pose estimation

Recently, estimation of pose of hand became a very popular research interest in computer vision. The presentation of item profundity sensors and the huge number of potential applications stimulates novel innovations. Be that as it may, it is as difficult to accomplish proficient and powerful estimation execution in light of enormous potential varieties of pose of the hand, extreme self-similarities with self-occlusions between fingers in the profundity image. Distinctive estimation of hand pose approaches are described below:

a. Estimation of hand pose based on tracking

We centered our investigation on single frame techniques. Nonetheless, for culmination, Oikonomidis et al. (2011) presented a tracking methodology and, thusly, require a ground-truth introduction. The authors designed the difficult issue of 3-D tracking of articulations of hand as a problem of optimization that limits contrasts between 3-D hypotheses of model of hand cases and real visual perceptions. Optimization was carried out with a stochastic methodology known as Particle Swarm Optimization (PSO) (Krishnaveni et al., 2016). Figure 2.1 demonstrates their pipeline. Here, hand's ROI was first extracted from a profundity image and afterward fitted a 3-D model of hand utilizing PSO. Considering images at step t the system is instated utilizing the last one found from the image t - 1.

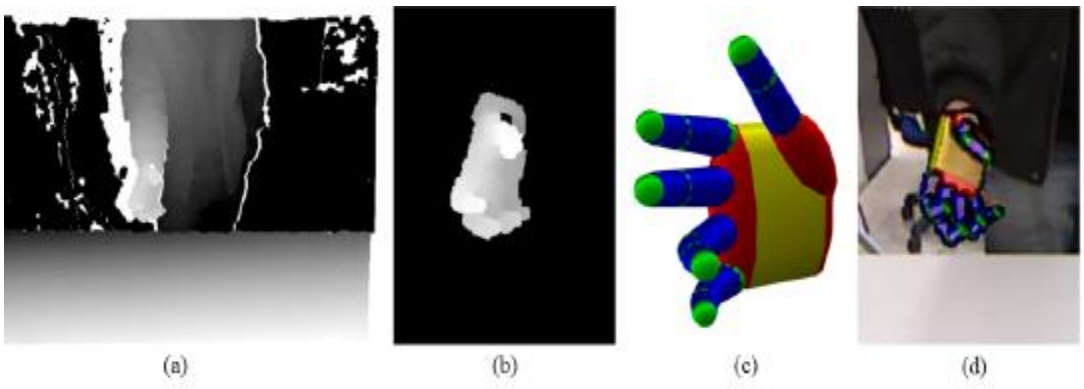

Figure 2.1: Oikonomidis et al. (2011) pipeline illustration; (a) Image current depth. (b) Firstly, extraction of hand region of interest. (c) Secondly, presented technique was fitted to retrieve model of the hand from previous image depth (d) Method applied to active depth image to recover pose of hand

Manual introduction may give poor output however single frame techniques are very valuable, and in many cases performed better than the tracking based methodologies. The major reason is, the single frame techniques reinitialize themselves at every frame, but trackers can't recuperate from constant errors.

b. Estimation of hand pose based on single frame

Numerous ongoing methodologies explored the tree hierarchy architecture of the model of the hand. Tang et al. (2014) divides the hand into smaller bits along the topological tree of the hand making new inert joints. Utilizing random decision forest technique, the authors carried out localization of coarse to fine of the finger joints as delineated in Figure 2.2.

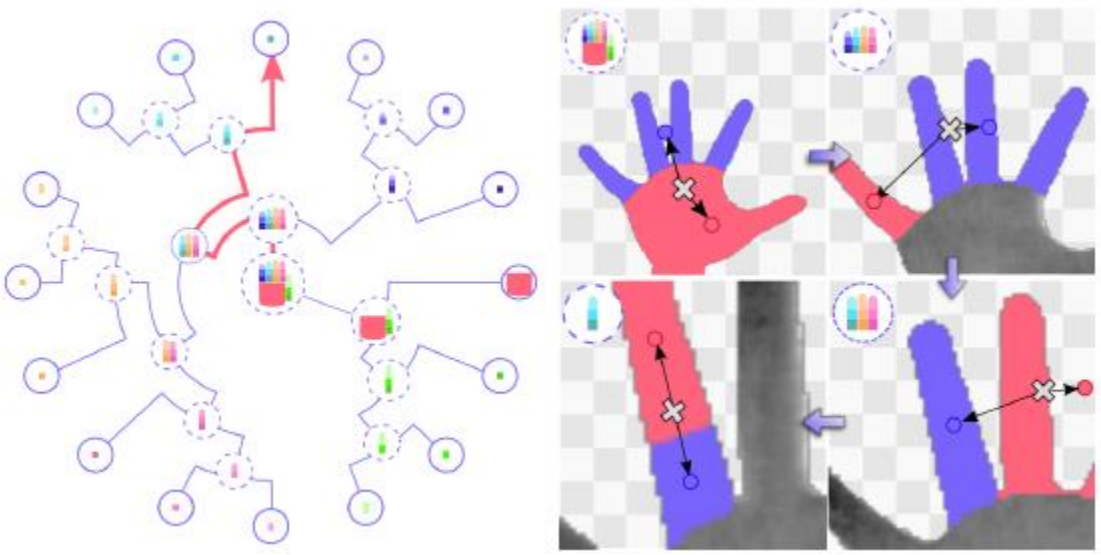

Figure 2.2: Searching process for just one finger joint (Tang et al., 2014)

Tang et al. (2015) broadened their thought utilizing energy function targeted at keeping just the best partial poses via iterations of optimization. Sun et al. (2015) utilize progressive regression of the pose of the hand from the palm to tip regions of the finger. Yang and Zhang (2015) presented utilization of specific hand pose regressors by firstly, classifying the incoming image of depth hand by using a vocabulary of finite hand pose to train separate posture regressors for all the

categories. Every one of these methodologies require multiple estimations, one for every joints, hand pose classes or finger and regularly numerous regressors for various stages of the technique. In this way, regression systems number starting from 10 to in excess of 50 distinct systems which must undergo training and assessed.

Deep neural networks brought great advancement in numerous computer vision problems. In 2015, Oberwerger et al. (2015) assessed many CNN models and estimated 3D joint regions of hand depth map. Here the authors expressed that a compelled prior on 3D posture could be initiated as a bottleneck layer after the convolutional neural network as demonstrated in Figure 2.3. This strategy greatly enhanced the dependability and accuracy of the prediction.

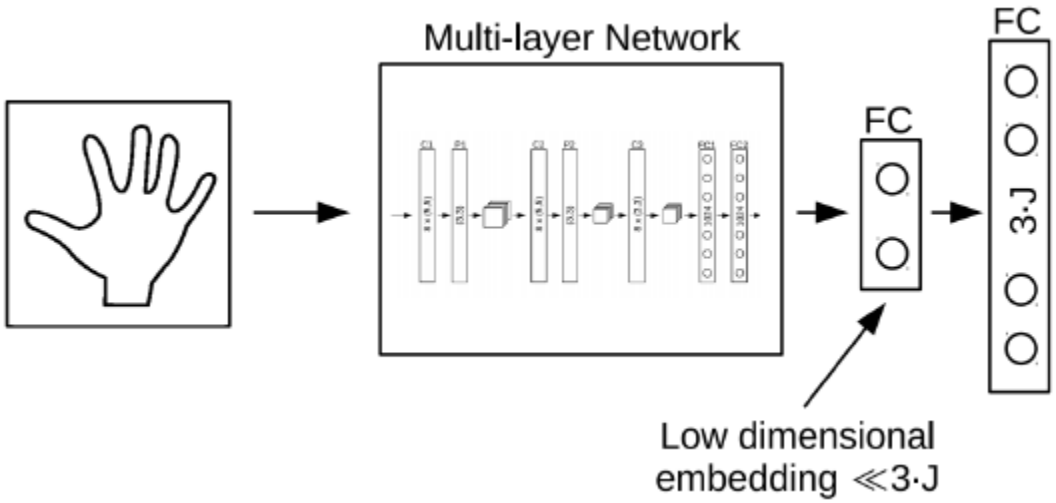

Figure 2.3: Evaluation of the usage of low dimensional embedding layer with less number neurons, (Oberwerger et al., 2015)

Zhou et al. (2016) integrated real physical limitations into a convolutional neural network to add extra layer which penalizes unnatural estimated postures. These limitations were manually characterized. In addition, a few works incorporated the hierarchy of hand model into one convolutional neural network architecture. Ye et al. (2016) presented the spatial attention-base CNN which specialize on every joints and an extra optimization stage in order to affirm kinematic limitations. Guo et al. (2017) trained a lot of systems for various spatial image region

and Madadi et al. (2017) utilized a tree-shaped convolutional neural network structure in which all the branches center around one finger. Neverova et al. (2017) integrated segmentation of hand part based on convolutional neural network with a regression in order to predict locations of joint but segmentation demonstrated high sensitivity to sensor noise.

A few portrayals of the input depth image have additionally been explored. Deng et al. (2017) transformed image depth into 3D voxel volume and utilized a 3DCNN to forecast locations of joint. Be that as it may, 3DCNN demonstrated a low computerize effect. Alongside, rather than direct prediction of 3D joint regions, Ge et al. (2018) utilized many convolutional neural networks in order to estimate heatmaps from various propagation of the depth image and train particular convolutional neural networks for all the projections as portrayed in Figure 2.4. This methodology required an intricate post-processing face so as to recreate a model of hand posture from the heatmaps.

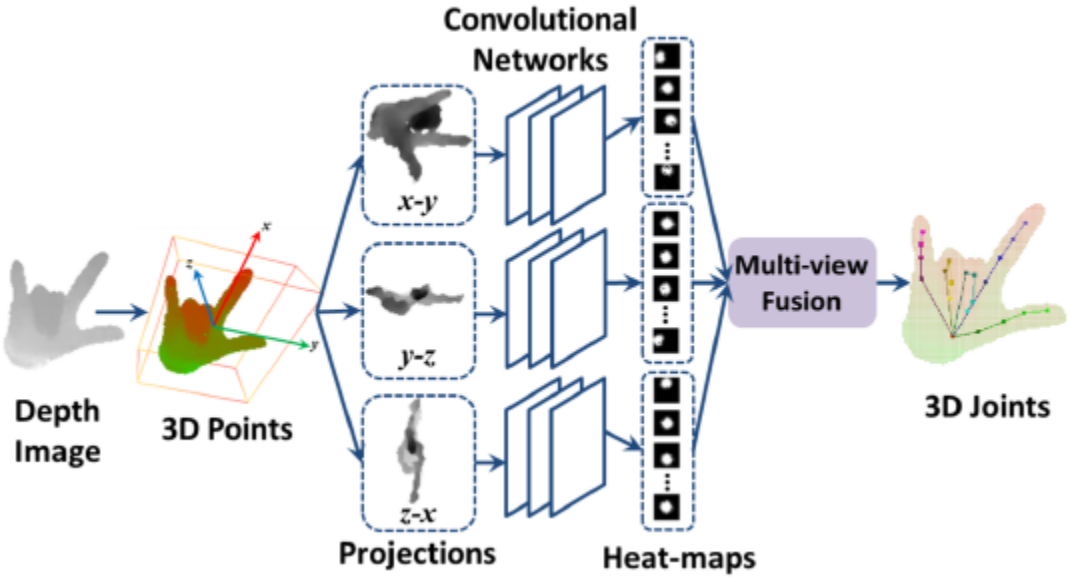

Figure 2.4: Fusion of heatmap for 3D hand joint locations estimation (Ge et al., 2018)

2.3 Sign Language Translation State of the Art

This section reviews state-of-the-art designs of gesture recognition and sign language, and indicate some problems in the present literature which we solved in this thesis. To build a system

for automatic learning and translation of sign language, it is significant that robust approaches that models spatiotemporal gestures and hand pose be constructed.

Recently, significant advances have been made in this research area of Sign Language translation. And this section reviews gesture translation systems that deal with temporal hand poses and gestures. Ong and Ranganath (2005) is referenced for a thorough comprehension of automated recognition of sign language.

2.3.1 Acquisition of gesture data

Focal point of the work described in the study is the construction of automated systems for the automated learning and translation of signs in Sign Language. In order to capture gesture based communication data, input date obtained utilizing direct measure gadgets or cameras. Here, we demonstrate some methods of data acquisition utilizing cameras and direct measure gadgets realized in this study.

a. Data acquisition based on wearable device computation

Application of methods of wearable device computation of Sign Language dataset collection provides precise measures for data extraction on signer's hand shape as well as hand development. Kim et al. (2008) presented a framework that integrated sensor data from EMG and accelerometers, which was utilized to determine electrical activity generated via muscles of the hand. It was indicated that the signal initiated by electromyogram incredibly improved the performance of the system. Figure 2.5 depicts a representation of the sensor arrangement for a single hand.

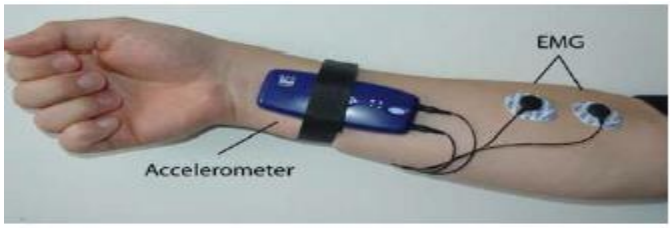

Figure 2.5: Recognition framework of bi-channel (Kim et al., 2008)

Vogler and Metaxas (2004) hand movement data and recorded arm utilizing "ascension technologies" recorded hand pose information and MotionStar 3D tracking framework utilizing "virtual technologies" cyberglove™. Fang et al. (2003) and Gao et al. (2004) built up a huge vocabulary sign recognition framework utilizing 3 pohelmus 3SPACE position trackers and 2 cybergloves™. Two trackers are situated on the wrist of all the hands and the other situated on signer's back and are utilized to gather position and orientation information. And these cybergloves™ gathered 18D shape of the hand information for all hands. Additionally, Oz and Leu (2007) used cyberglove™ alongside flock of birds 3D gesture tracker for hand pose attributes extraction. Figure 2.6 depicts the flock of birds 3D movement tracker and cyberglove™.

Figure 2.6: From right: cyberglove, and from left: flock of birds 3D gesture tracker (Oz and Leu, 2007)

Also, McGuire et al. (2004) proposed another data glove base framework where a mobile gesture based communication interpreter is actualized utilizing an acceleglove as shown in Figure 2.7. Here, the acceleglove comprises of five small scale two-pivot accelerometers positioned on rings reads finger flexion. The other two mounted at the back of the palm to calculate orientation. There are other devices not displayed in Figure 2.6 and these are 2 potentiometers that calculates

twist for the elbow as well as shoulder, and the other is 2 pivot accelerometer that quantifies the upper arm points.

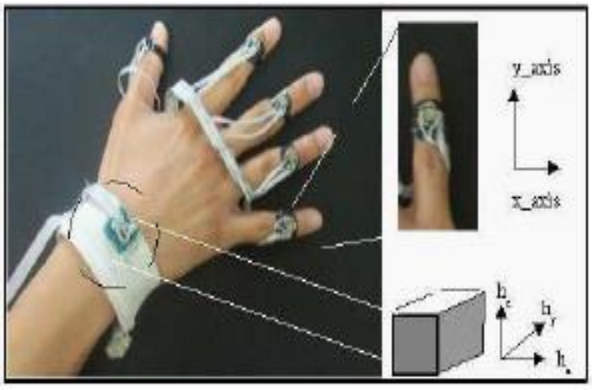

Figure 2.7: Caption of acceleglove (McGuire et al., 2004)

Another new method for data acquisition via sign language was demonstrated by Brashear et al. (2003) here properties/features obtained from the accelerometer and camera placed on a hat information are utilized for ssymbols/signs classification as shown in Figure 2.8. Wang et al. (2007) presented viewpoint invariant information collection approach. The idea of the authors is based on virtual stereo vision framework, utilizing gloves having a specific design for color pattern and a camera to represent the five distinct fingers; back as well as palm.

Figure 2.8: Accelerometer and a camera mounted on the hat data collection framework (Brashear et al., 2007)

Figure 2.9 depicts the visualization of how the gloves are designed.

Figure 2.9: Data collection system by gloves (Wang et al., 2007)

b. Data acquisition via vision based

While wearable device computation methods for data collection could extract precise features that represent the performed signs, few of these methodologies necessitate that the signers puts on huge gadgets that could ruin the naturalness and ease of process. Another methodology is to obtain signer's data via input image from a camera. In order to capture gestures from camera, hands ought to be situated in the image sequence and this is regularly computed utilizing edge information, color and motion Ong and Ranganath (2005). Many researchers have presented approaches for hand segmentation from image sequence and some of these techniques will be discussed in this section:

Yang et al. (2008) executed a motion-based segmentation and skin color strategy which incorporated displacement prediction utilized when there is an overlap between the hands and the face. One template hand which is stored on the last frame is utilized if the recognized hand location is bigger than the region of the hand identified within the last frame else the hand detection system fails to identify the hand area.

Holden et al. (2005) utilized principal component analysis (PCA) base skin color framework for hand detection. The authors' strategy to crop occluded objects, utilizing an integration of snake algorithm and motion cues, was utilized when there is an overlap between the face and the hands as demonstrated in figure 2.10.

Figure 2.10: Samples of results of segmentation of hand (Holden et al., 2005)

Cooper and Bowden (2007) designed a segmentation of hand approach utilizing a skin color framework constructed from automation of face region detection. A background model is constructed utilizing a standardized histogram as well as application of threshold to the probability ratio of background to face for each of the pixels as depicted in figure 2.11.

Figure 2.11: Samples of results of segmentation of hand (Cooper and Bowden, 2007)

Askar et al. (2004) designed a skin color segmentation technique which adjusts automatically to the brightening conditions. To represent skin segment, for example, overlapping hands and head, a set of rules were implemented in order to track the hand when hand and face contact occur as shown in Figure 2.12.

Figure 2.12: Samples of results of hand segmentation (Askar et al., 2004)

Barhate et al. (2004) computed hand segmentation utilizing motion cues and skin in an on-line prescient eigen-tracking system that which determined motion of the hand by a relative change. The strategy of the authors was displayed to function admirably with under poor illumination and occlusion as shown in figure 2.13.

Figure 2.13: Samples of results of segmentation of hand (Barhate et al., 2004)

Donoser and Bischof (2008) performed a hand segmentation method which integrated a reconstructed version of the Maximally Stable Extremal Region (MSER) tracker with skin color probability maps. The MSER tracker discovered illuminated connected segments in the skin color maps that had thusly darker qualities along their limits as shown in Figure 2.14.

Figure 2.14: Samples of results of hand segmentation (Donoser and Bischof, 2008)

Buehler et al. (2009) executed a certain upper body framework for capturing signer's arms, hands, head as well as torso. Graph slice technique was utilized to fragment the hand area estimated by the tracker into background signer or hand as shown in Figure 2.15.

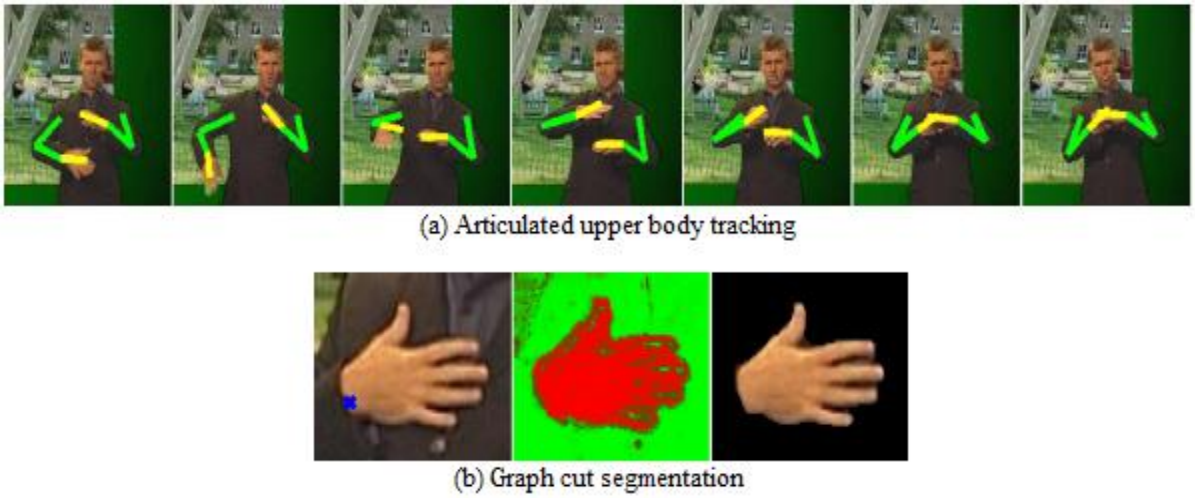

Figure 2.15: Samples of results of segmentation of hand (Buehler et al., 2009)

Liwicki and Everingham (2009) presented a hand segmentation framework in which pixels are categorized as non-hand or hand by combining three parts: a spatial coherence prior, a signer explicit skin color model and a spatially-differing non-skin color model shown in figure 2.16.

Figure 2.16: Samples of results of hand segmentation (Liwicki and Everingham, 2009)

As earlier mentioned in this section, there are a wide range of strategies that have been implemented for robust hand segmentation from image sequence. To accomplish the maximum capacity these segmentation techniques have in the field of gesture based communication recognition, we should create algorithms that could identify symbols from data of hand segmentation. In our research, we describe the propose set of methods for automated learning

and Sign Language recognition. Our strategies are constructed to use computer vision-base segmentation of hand information. The proposed models are evaluated utilizing extraction of data from image sequence, however the data extraction methods utilized are not the novel part of the research.

2.3.2 Spatiotemporal gesture recognition

Investigation into sign recognition and spatiotemporal gesture has two fundamental classes: constant recognition as well as isolation. For continuous/constant recognition, the signer performs gestures consistently and the point is to spot and categories significant motion fragments from within the persistent stream of communication via gestures. But isolated recognition centers on characterization of the single motion of hand.

a. Continuous gesture recognition

Isolated recognition extension to continuous/consistent signing is a challenging problem. This requires automated recognition of gestures such that the recognition algorithms could be applied for signs segmentation. A suggested remedy to detect movement epenthesis is an unequivocal segmentation framework where features subsets from motion information are utilized as signs for legitimate hand motion start-and-end-point identification. Oz and Leu (2007) presented a nonstop recognition system that detects "not signing" and "signing" regions utilizing velocity network. This velocity network performs classification of signing region from when the hand previously demonstrated an adjustment in velocity to the time when the velocity indicated low velocity progression. Neural network base classifier is trained for recognition of 60 distinctive one handed signs of the American sign language. Investigations performed on a sum of 360 words of ASL utilizing feature vectors histograms demonstrated 95% accuracy. Short coming of this unequivocal segmentation framework emerges from the challenge in the creation of generalized standards for boundary of sign identification which can to a wide range of non-manual and manual motions (Ong and Ranganath, 2005). For instance, accurate signer carry out sign language sentences in a characteristic way and sign boundaries frequently don't occur when velocity of the hand change swiftly.

Another method of tackling continuous recognition without unequivocal segmentation is to utilize HMMs for certain segmentation of sentence. Bauer and Karl-Friedrich (2001) modeled subunit or each word using HMM which they trained with data gathered from full sentences. They performed investigations on a 40 signs vocabulary utilizing 478 sentences to train and test. They achieved 96.8% word recognition rate. One of the disadvantages of these techniques is that performance of complete sentence data training might bring about loss in substantial recognition of sign precision when tried with sentences that are not utilized during training, and this is because of the huge varieties of the presence of all conceivable motion epenthesis which can happen between 2 symbols. Brashear et al. (2003) further improved the research of Starner et al. (1998) by designing the recognition system for motion signs. The authors' sign recognition framework based on HMM was executed to detect continuous sentences utilizing accelerometer and camera data. Investigations performed on a 5 signs vocabulary demonstrated achieved 90.5% recognition accuracy. It was likewise demonstrated that combination of vision and accelerometer data increase the performance as contrasted with just accelerometer data (65.9%) and just vision data (52.4%).

Some researches tackled movement epenthesis by expressly modeling gestures between signs. Gao et al. (2004) presented transition movement models (TMM) in which HMMs transitions were constructed to model transitions between every unique pairs of symbols. Sum of TMMs were decreased by a procedure of progressively clustering parts of transitions. A looped segmentation algorithm was executed to automate segmentation of continuous sentences. Trials carried out on a set of 3000 sentence cases with 5113 signs of vocabulary from Chinese Sign Language (CSL), indicated that the explored technique achieved 90.8% accuracy. Vogler and Metaxas (2004) presented a framework to combine hand pose and hand motion data into just one recognition system. One set of parallel HMMs were executed to detect symbols from 22 signs of vocabulary. Other HMMs were executed in order to model epenthesis movement between every unique starting and ending point of signs. Their investigations depict 87.88% detection rate when tried on 99 sentences containing an aggregate of 312 signs.

In as much as these researches that explored express epenthesis models recorded great performance movement epenthesis detection and sign language recognition, training of such frameworks entails a lot of additional data gathering, labeling of data manually and training of

model because of the additional number of HMMs needed to identify movement epenthesis. Very few numbers of authors treated the issue of movement epenthesis without unequivocally modeling the movements. Junker et al. (2008) presented a novel technique to deal with gesture spotting where an integration of HMM classification of gesture and explicit movement segmentation was performed. To detect relevant motion activities, the authors implemented a pre-selection phase. Segments of candidate motion were classified in isolation utilizing HMMs. Investigations performed to assess the motion spotting framework demonstrated that the technique did great in terms of spotting motions in two distinctive event situations. The results demonstrated an average recall of 0.93 as well as an absolute precision of 0.74 in the first experiment. In the second scenario, a total recall of 0.79 and a total precision of 0.73 were achieved. Another way to segment signs/symbols from nonstop streaming of information without movement modeling epenthesis is the utilization of grammar-base data. Yang et al. (2007) and Yang et al. (2009) presented ASL translation system-based trigram grammar model as well as an improved level building algorithm. The authors' approach is based on automated method to spot symbols without express movement epenthesis model. 83% rate of recognition was achieved using 39 symbols/signs effective in 150 unique sentences. Research by the authors depends on two-advance approach to perceive nonstop signs where the underlying advance recognized the expected signs in the sentence and the ensuing stage applied punctuation model to the possible signs. The authors uncovered only the results gained after the second step which applied trigram punctuation structure to the signs. The reliance of the structure to the punctuation model was portrayed in the preliminaries where the recognition rate of the system diminished from 83% to 68% when trigram structure was superseded by bigram system. Likewise, Holden et al. (2005) implemented translation framework for Australian gesture based communication where each sign is displayed using HMM structure. The translation system utilized language structure rules to distinguish constant sentences, in view of 21 particular signs. Investigations indicated that their system recorded 97% recognition rate on 163 test sign expressions, from 14 distinctive sentences. The investigation acknowledge that the vocabulary sign utilized in tests comprised of signs that were essentially recognizable from only motion. Yang et al. (2008) recommended an exceptionally encouraging strategy, without the requirement for formal guidance in grammar or epenthesis. In a CRF model, they establish threshold models that conducted threshold adapted to differentiate between the symbols in the non-sign sequence as well as vocabulary. Studies

indicated that their framework could recognize symbols from constant information with 87.0% rate of recognition from a 48 sign vocabulary in which the framework was trained on 10 different instances of every one of the 48 symbols. The framework was then tried on persistent sentences containing in the sign jargon 480 examples of the signs.

b. Isolated gesture recognition

Yang et al. (2002) utilized a time delay NN to derive motion trajectories from American Sign Language (ASL) images and graded signals. Experiments based on a 40-sign vocabulary showed the average unseen test trajectory recognition rate was 93.4%. Fang et al., 2003) tackled the question of the recognition of huge vocabulary signs by recommending the integration of self-organizing feature maps, a hierarchical decision tree and HMMs for the recognition of isolated signs, with low computational costs. Experiments were performed on a data collection of 5113 separate indications with 61365 isolated symbols. Results showed a 91.6% average recognition rate. Juang and Ku (2005) suggested Recurrent Fuzzy Network for the processing of fuzzy temporal sequences. The authors applied their approach to the task of recognition of gesture and tests presented a 92 percent rate of recognition. In line with the combination of Maximum A Posteriori Estimation and Maximum Likelihood Linear Regression, Ulrich et al. (2006) suggested an independent sign recognition method. Their method for considering the details of Sign Languages including One Handed Signs was developed. The authors have introduced some chosen speech recognition adaptation methodologies to enhance efficiency of their program while carrying out independent identification of users. Recognizing 153 isolated signs, a recognition rate of 78.6% was recorded. Shanableh et al. (2007) suggested isolated temporal gesture method for Arabic sign language translation. The authors suggested temporal characteristics that were derived by backward, forward and bidirectional forecasts. These prediction errors were thresholded and averaged into one picture which portrayed motion sequence. Tests dependent on dataset of detached signs demonstrated that while characterizing 23 diverse sign gatherings, their framework accomplished a classification productivity extending from 97% to 100%.

Wang et al. (2007) proposed a technique for the identification of invariant sign perspectives. The recognition task was transformed into a verification task in their proposed method, in light of the

mathematical limitation that the basic matrix related with two perspectives ought to be indistinguishable when the indications of perception and model are gotten simultaneously under virtual sound system vision and the other way around. Examinations performed on a 100-sign vocabulary where five secluded examples of each sign were enlisted, indicated accuracy of 92%. Cooper and Bowden (2007) used 1st order Markov Chains to introduce an independent sign recognition method. The signs are split into visems (phonemes in speech) in their model, also group of Markov Chains are utilized to identify visems as they are formed. Investigations reported thea recognition precision of 72.6% base on five known samples of every 164 symbols of the vocabulary. Kim et al. (2008) measured a 7-word-level sign recognition device based on the accelerometer and EMG, and the performances depicted a total accuracy of 99.80 percent when validated on 560 isolated symbols. Gunes and Piccardi (2008) implement an effect detection system utilizing hand gestures as well as facial indications. Using an HMM-based system, temporary segments of hand movements and facial expressions were identified. Experiments showed that when tested on isolated images, their proposed method obtained 88.5% accuracy. Ding and Martinez (2009) made a model for the acknowledgment of gesture based communication that incorporated shape of hand, 3D location and motion into a solitary system. The signs are identified utilizing a classifier of tree-base where for instance, in the event that two signs had a comparative state of the hand, at that point the tree's root would assume the hand shape and the branches would depict the various motion of the hand. For a vocabulary of 38 signs, a rate of recognition of 93.9% was accomplished. While these works offer promising methods for recognition of gesture, the investigations depend on tests of detached motions. There are nonstop characteristic developments which happen in communication via gestures. Recognition of communication through signing along these lines includes recognizing the motion from nonstop recordings (for example distinguishing the start and finishing points of a specific example of signal).

2.3.3 Non-manual signals

Recognizing the communication of Sign Language involves simultaneous monitoring of non-manual and manual signals and their precise integration and synchronization of signals. Thus learning Sign Language includes work on the monitoring of identification of facial expressions,

and study of body movement and identification of gestures. Recently a considerable amount of research has been carried out studying the non-manual signals role in communication via gesture and trying to determine their distinct relevance. Research like Van et al . (2006) concentrated on the function of head position as well as head movements in Sign Language, finding the clear connection to questions or statements between head tilts and forward motions. There has also been growing interest in studying facial expressions for sign language interpretation (Grossman and Kegl, 2006), and (Grossman and Kegl, 2007). Computer-based methods suggested for modeling facial expression using Adaptive Appearance Models (AAM) (Von et al., 2008) and (Von et al., 2008).

Grossman et al. performed a fascinating analysis on ASL, where movement of eyebrow and eye aperture movement degree were shown to have a direct relation to emotions and questions (Grossman and Kegl, 2006). They showed the rage, wh-questions (where, who, why, what, how) and quizz questions showed squinted eyes and lowered brows, while yes/no and surprise questions depicted raised brows and widened eyes. Developing a device that incorporates manual and non-hand signals is a non-trivial problem (Ong and Ranganath, 2005). And this is proven through small amount of effort involved in understanding multimodal communication networks in communication via gesture. Ma et al. (2000) utilized HMMs to train knowledge about multimodal Sign Language although the one non-manual signal utilized is movement of lips. Their analysis is dependent on the premise that the knowledge conveyed by motion of the lip correlated with hand signals. In as much as this is a rational mouthing concept, it can not be applied to other signals that are non-manual since they also span several manual symbols and ought be tried separately.

2.3.4 Important issues to recognition of spatiotemporal gesture

The complexity in interpreting spatiotemporal gestures is that the hand must move from the end point of the preceding gesture to the beginning point of the next. These process intergesture phases are called epenthesis of movement (Choudhury et al., 2017), and are not a part of any of the symptoms. Thus the problem with the creation of continuous recognition systems is designing algorithms that can distinguish between segments of true signs and epenthesis of movement. As stated, much of the previous work involved clear modeling of each epenthesis, or

unique grammar rules needed. Although these researches had great results in recognition of gesture and detection of movement epenthesis, because extra HMMs number needed to recognize epenthesis motion, training of specific epenthesis model included extra data collection, labeling of data manually, training of model, as well as computation of recognition.

Another technique used is to use grammar rules to decrease the number of potential combination of signs that appear in the signed sentences. And when sign vocabularies expand to represent significant part of the signs utilized in Sign Language communication, grammar rules may become a more critical feature of Sign Language recognition.

State of the art work on recognition of sign is now at a point where primary emphasis is on model sign algorithms. The sign recognition models that enforce grammar rules on the vocabulary of restricted signs are difficult to determine. One instance in a corpus of 30 signs containing 8 nouns is when grammar rules have been used to determine the next symbol is likely to emerge from the noun category, and then the number of possible symbols where the recognition model will be chosen is diminished to 8. Given the fact the ultimate objective of recognizing large cluster symbols, research should be conducted to test recognition models in their ability to differentiate one sign as much as possible from other signs. It is unclear how these models would perform if the grammar models were created from a larger real-world corpus, in the works discussed in Section 2.3 which employ specific grammar rules.

In order to promote continuous identification, other studies concentrate on explicit segmentation of the gestures. Particular gesture signals, such as changes in velocity of the hand, are utilized in determining the starting as well as ending spots of the gesture. And while it has been shown that these explicit segmentation methods function greatly recognition problems, developing specific rules of segmentation for sign language recognition tasks is impractical because of the variation in speed and gesture structure that exists in natural communication via gesture.

Without applying segmentation or grammar rules or specifically epenthesis modeling, few researchers discussed the issue of epenthesis in motion. We propose a solution to this through the development of spatiotemporal gesture system that solves the epenthesis detection task of movement. We develop a training and recognition framework based on the HMM threshold model for the classification of spatiotemporal gestures and the identification of epenthesis of movement without explicit training on examples of epenthesis of movement.

Regardless of any grammatical laws, our proposed models can effectively distinguish movements from within sign sentences. Moreover, while non-manual signals are an important feature of sign language recognition, only few studies have taken these non-manual signals into consideration when designing hand gesture recognition systems. Also, we demonstrate that by developing robust head movement and facial expression recognition models our paradigm of spatiotemporal recognition is applicable to communication modes other than manual signs.

2.4 Review of Sign Language Translation Systems

Different methods to sign language understanding have been proposed. Sensor-base methods with NNs as well as Bayesian networks are investigated in the early 2000s (Koch et al., 2002), (Fels and Geo, 2002) and (Singh et al., 2006). To predict sign language, low-cost wearable devices including wearable sensor gloves are used to obtain relative motion of fingers and hands (Singh et al., 2006). The utilization of restricted colored gloves and grammars during training and testing created low error rates (Starner, 1995). Using sensor instruments, isolated sign language translation is implemented with a multimodal system (Kumar et al., 2017). For classification purposes, the sensors are used to capture finger, palm locations, and then Bidirectional Deep Short-Term Memory Neural Network (BLSTM-NN) and HMM. Extensive Sign Language knowledge can contribute to acute awareness of the difficulty of classifying gestures. Bheda et al . (2017) tackled the issue of classifying movements using DCNN for this reason. The color and depth of the photos was used for reconnaissance purposes in other studies. Here, Ameen et al. graded ASL using CNN having depth and color of the images and obtained 80 percent recall and 82 percent accuracy in their experiments (Ameen and Vadera, 2017). Another widely explored classifier for gesture and posture is the linear classifier. The structure is relatively simple as compared to Bayesian networks, and the frequently produce high accuracies (Singha and Das, 2013). The paper Ibrahim et al. (2018) presents a sign language recognition framework base segmentation, tracking, feature extraction and classification of gestures of the hand. Euclidian distance is applied for the classification of features. In Yang et al. (2016), the "likelihood of hidden Markov model" is presented for sign language translation. In addition to HMM, the paper Kumar et al. (2018) used an independent Bayesian classification combination for improving recognition accuracy. In Nguyen and Ranganath (2012), facial expressions are

recognized and used in sign language communication. The probabilistic principal component analysis model is combined with the schemes of recursive tracker for feature extraction. The recognition of tracked results is performed using HMM and SVM. The paper uses texture attributes and skin color with NNs to separate the hand from the background (Dahmani and Larabi, 2014). KNN and SVM classifiers are applied for recognition purposes. The construction of a mobile application using a speech-based system to translate text from Indian Sign Language is described in (Amrutha et al., 2016). Here, the authors implemented the model using a pre-built domain of locally stored images on a system then further triggered it at the time of execution. The classical method used to recognize sign language is essentially focused on extraction and classification of features. In the study, the two modules are integrated for the design of the Sign Language recognition model in a convolutionary neural network (CNN). The method presented simplifies the way the sign language recognition system is applied. CNN is also widely used to solve multiple problems. These include the recognition of human behavior Uddin and Kim (2017), the detection of vehicles in aerial photographs Shen et al . (2019), the detection of smoke as a moving object Dung et al . (2018), the detection of Naseer and Saleem intrusion into the network (2018), and the identification of tomato nutritional disorders (Zhang et al., 2019).

The proposed system (Sign Language Translator) comprise of three fundamental modules in this work: detection of object, extraction of features as well as sign classification. The combination of these three efficient models; SSD, Invention 3 and SVM is proposed for solving these problems. These algorithms are applied to detect objects, to extract characteristics and to identify signals. Robustness, precision, high speed were requirements proposed for device. There are designed set of techniques for object detection. The more used techniques are Viola-Jones algorithm Benjdira et al. (2019), histograms of oriented gradients (HOG) Tomasi (2012), recognition using regions Gu et al. (2009), R-CNN Bao et al. (2015) and Chen et al. (1993), You Only Look Once (YOLO) Redmon et al. (2016) and Redmon and Farhadi (2018), and SSD Liu et al. (2016) techniques.

Viola-Jones algorithm Benjdira (2019) is based on Haar feature selection used for different parts of images. The algorithm use Adaboost training and cascade clustering architecture. The algorithm has good feature selection properties. One of the disadvantages of the algorithm is that it is sensitive to lighting conditions and possibly detects different degree of the exact object due to subwindows overlapping. The algorithm is not effective in detecting titled or turned images.

Next algorithm, HOG Tomasi (2012) significantly outperformed Viola-Jones algorithm in this task. The algorithm uses handcoded features. For every pixel, the surrounding pixels are selected and the direction (arrow) showing change of colour of darker region is determined. For each pixel this process which is called gradient is repeated. The whole image is replaced with the arrows (directions) which are characterized by histogram of gradient (HOG). Even after having successful in several instances, it still employed hand-coded features that struggled in a more generic environment with lots of background noise and obstacles.

The sign language is known to be the most formal of movements in all groups. Sign languages begin as spoken languages, which develop naturally with hearing deficiency in cultures. Sign languages grow wherever there's a population of hearing impairments. The sign language develops irrespective of the language spoken in the field. Each sign language has its own grammar and rules, with the common property both are visually interpreted.

There are several various sign languages in the world, as spoken language. For example, a signer of an Irish Sign Language could not understand a signer of the ASL except they had learned the language specifically. Although Sign Language is conveyed mainly through hand gestures (manual signing), it also includes non-manual signals transmitted through facial expressions, head movements, body postures and torso movements. The field of research on sign language recognition is a multidisciplinary research area that includes the processing of natural language, pattern recognition, computer vision, machine learning and linguistics, due to the difficulty and multimodal nature of the Sign Language.

Signing via gesture has its own grammar and syntax. One misconception of communication via gestures is; they are structured in line with the vocally generated languages of such nation, additionally, the symbols are manually generated like the English words. The sign language has its own phonology, grammar, morphology as well as syntax which are autonomous of verbal languages. At a same time, the phenotypic structure of hand gestures is such that the different morphemes of a word are superimposed on each other simultaneously rather than being strung together, as is usually the case with those of the spoken languages. This is one of the big differences between the signed languages and those spoken. For example, manual signals are transmitted sequentially, where each sign comes in one at a time. However, in addition to being sequentially transmitted, each manual sign occurs in combination with manual signs executed by

the other hand, as well as actions like head and body gestures or facial expressions. The linguistic features of sign languages therefore differ greatly from those of the spoken languages. Research has shown that this morphological structure is not unique to any sign language and thus shows that in their morphological structures there are significant cross-linguistic similarities between different sign languages (Aronoff et al. 2005).

Many psycholinguistic studies have been performed on human movements, and in particular on sign language. The Stokoe study (2005) is one of the most important studies in sign language psycholinguistics. Stokoe identified three aspects in this work which are combined at the same time in the creation of a particular manual sign: what acts, where it acts, and the act. These aspects translate into building blocks that linguists describe as: a hand shape , position, orientation and movement. These four manual sign components are sometimes considered as two distinct sources of information in sign language recognition. The first channel is the channel for hand positioning, which relates to the finger position and hand orientation. Spatiotemporal channel is the second channel which refers to the direction of motion and where the hands articulate in space.

For finger spelling, hand positions on their own may be used where various hand postures are used to represent the letters and numbers in writing and numeral systems. Finger spelling can be used to communicate words from a spoken language that do not have a corresponding sign, or to demonstrate, describe, or teach or practice a sign language.

Communication via gesture is a dynamic language and a large amount of knowledge is transmitted by the majority of signs through the combination of hand position and hand motion. Only when all the information from the manual networks is available can we discern a large number of signals.

Figure 2.17 shows an example where the signs 'play' and 'school' share the same postures of the hand but have different movements. Likewise, the 'paper' and 'big' signs share the same movement and can be distinguished only by hand posture. In Figure 2.18, only their hand form could discern the signs ‘water', 'eat', 'sweets' and ‘warm'. Recognition of sign language communication therefore involves simultaneous study of spatiotemporal movements and of the networks of hand posture.

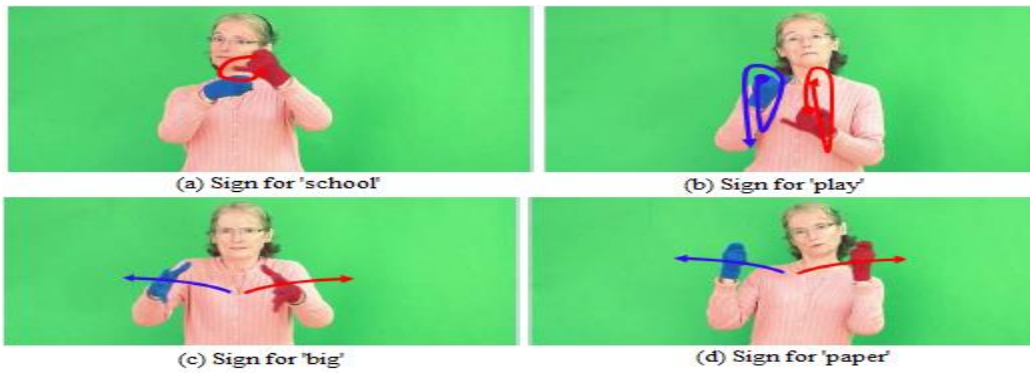

Figure 2.17: Samples of signs with similar hand pose. Hand posture (a) and (b) defers from (c) and (d); motion utilized to distinguish signs (Stokoe, 2005)

When spatiotemporal movements are carried out in a continuous sentence in sign language, the hands must switch from the end position of one sign to the start position of the other. Such inter-gesture transition interval is known as epenthesis of movement Liddell and Johnson (1989). And is not part of any of the gestures. Therefore, study of the spatiotemporal gesture channel must differentiate between the segments of appropriate sign and the epenthesis of motion.

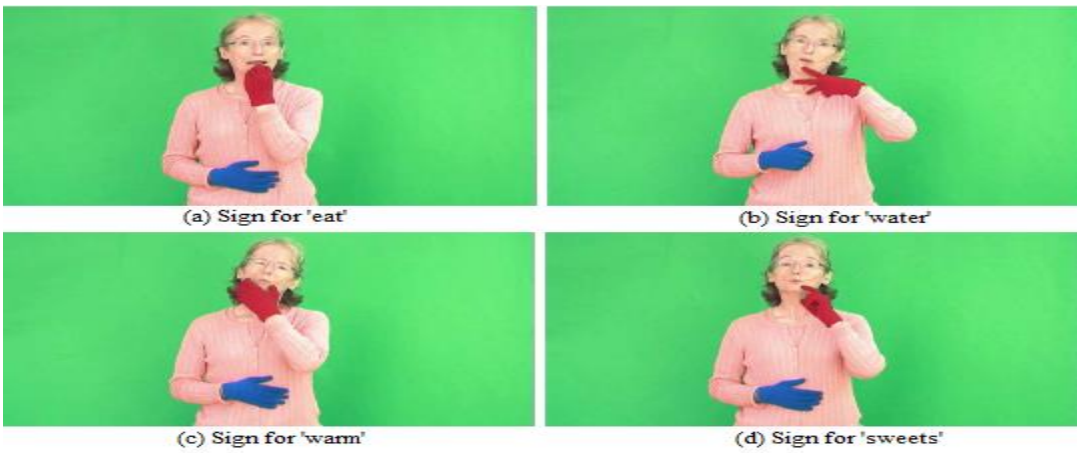

Figure 2.18: Samples of signs including articulation of similar location. Hand poses utilized to distinguish Signs (Liddell and Johnson, 1989)

CHAPTER 3

DEEP LEARNING BASE CONVOLUTIONAL NEURAL NETWORK

3.1 Evolving of Deep Learning Structures

It is in record that Artificial Intelligence (AI) is one of the most computer science's popular research subjects, and has series of experimental applications. We asked machines yesterday to execute routine work. We are asking them today to understand videos, speech and images, or even to help doctors perform diagnosis.

The big question in AI is: how to make a computer learn on its own. The typical way to do this, as we saw in the previous segment, is to find an expert on the topic you want the machine to know about. You can write a rules-based program with its problem-specific prior knowledge which makes the machine helpful. What makes deep learning very fascinating is that in order to learn a potential solution, experts do not need to have a deep interpretation on a particular question. One thing to keep in mind is that we still need label data and human intuitions to find an effective, objective function so far. Warren McCulloch and Walter Pitts had developed a neural networking model as early as 1943. They recreated neurons based on threshold switches and showed that any logic or arithmetic function can be determined even by simple networks of this nature (McCulloch and Pitts, 1943). Frank Rosenblatt created the concept of an artificial neuron named Perceptron Rosenblatt (1958) in the 1950s, following their statements and inspired by the successfully working brain systems and its wonderful learning capacity.

3.1.1 Similarities between biological neurons

There's still a lot of unknown in biological neurons about how the brain trains itself. A neuron collects electrical signals from many others within the human brain through fine structures called dendrites. The nucleus gets the number of inputs. If a sufficiently high signal is received it will give a spike in electrical activity. The latter is dispatched through the axon. At long last, structures known as synapse transfer this conduct to the following associated neurons. The learning takes place via modification of the effectiveness of the synapses, with the goal that modification of one neuron affects the other. Figure 3.1 shows a simplified image of a biological neuron.

Perceptron is a mathematical model depicted in Figure 3.1 for a biological neuron. It takes a set X of Boolean values as its input.

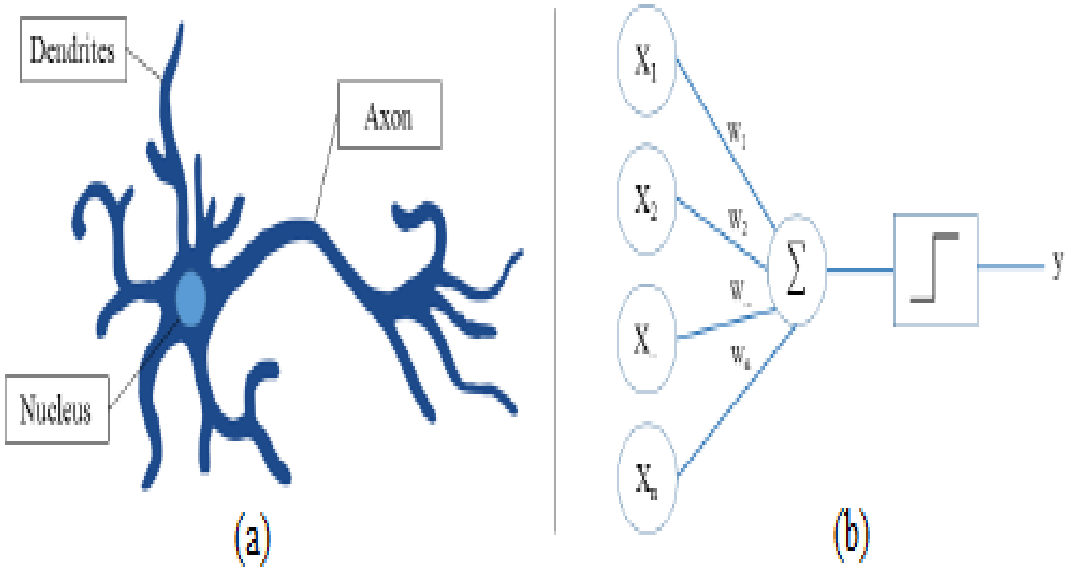

Figure 3.1: (a) Biological neuron representation. (b) Artificial neuron representation (Rosenblatt, 1958)

Weighted sum of inputs $\sum WiXi$ is used to model nucleus. And hyperbolic tangent is used to represent synaptic potential thus,

$$Z = \tanh(\sum WiXi) \qquad (3.1)$$

Furthermore, in order to binarize the output Y, the system utilizes heaviside step function thus,

$$Y = \begin{cases} 0 \text{ si } Z < 0 \\ 1 \text{ si } Z \geq 0 \end{cases} \qquad (3.2)$$

Recently, deep learning technologies have become popular, trusted, essential and powerful. Most notable advancement is that nowadays we can provide the necessary tools for algorithms to succeed: massive data sets with great hardware

.

a. Datasets size

During the last few years the scale of CV datasets has increased dramatically. This is possible via societal acceptance of digitization of data. As human transactions increases on the internet, most of human information and activities including photos and videos are recorded. Algorithm of deep learning could exploit huge amounts of data and even surpass human efficiency. Recently, huge data set Abu-El-Haija et al. (2016), consisting of 8,000,000 youtube-labeled videos in accordance with 4700 visual entities vocabulary, has been made publicly accessible by the organization. In addition, the ImageNet project Deng at al. (2009) constructed huge visual dataset designed to be used for recognition of visual objects, containing over ten million labeled images.

b. Models size

Deep neural network architectures are higher-depth, NNs. We do not have any widely accepted depth threshold which divides depth learning from shallow learning. A lot of field surveyors believe that there is more than one nonlinear layer in deep learning, and that it's known that more than 10 have very deep learning. Schmidhuber (2015) proved that, initially, hardware technologies had limited the number of neurons in artificial neural networks. Until quite recently, the neural networks were fairly small.

Today, neurons number is largely a choice of design. A number of neural ANs Coates et al. (2013) consists many connections per neuron as a cat ($\approx 10^{13}$). Explosion of model sizes for the NN is as a result faster computers with huge memory. Huge network can gain greater precision in complicated problems. NVIDIA DiGiTS DevBox is the latest hardware developed by NVIDIA in 2017 and dedicated to learning the deep neural networks. The DevBox NVIDIA DiGiTS comprises four strong graphic processing units for deep learning structures.

3.1.2 Multilayer perceptron

A simple example of deep learning model is the multilayer perceptron (MLP) or neural feedforward network. An MLP aims in determining arithmetic function *f* which links outputs to some values of input. As described in section 4.1, *f* is the function in the CV recognition process which maps input set *x* to a class variable *y*. Also, it attempts to learn parameters *q* of function $f(x, \Theta)$ resulting in the best approximation function $f : x \rightarrow \hat{y}$ set of a particular problem of classifications. Network is so-called since it contain series of numerous simpler vector-to-vector functions known as layers that makes writing of function $\hat{y} = f(x, \Theta)$ in the form $\hat{y} = f4(f3(f2(f1(x, \Theta_1), \Theta_2), \Theta_3), \Theta_4)$ to be possible. The function f in this case is made up of four distinctive layers shown in Figure 3.2. One can see each layer to be an arithmetic function that provides new input representations. Such layers are intended for generalization of statistics. Layers number determines model's depth. First layer is called input layer, second is known as output layer while middle layers are known as the hidden layers because the data don't give their values. Such network is known as feedforward since data progresses from input *x* to output *y*. For recurrent network layer, there exist feedback connections in a layer. Section 3.6 illustrates these networks.

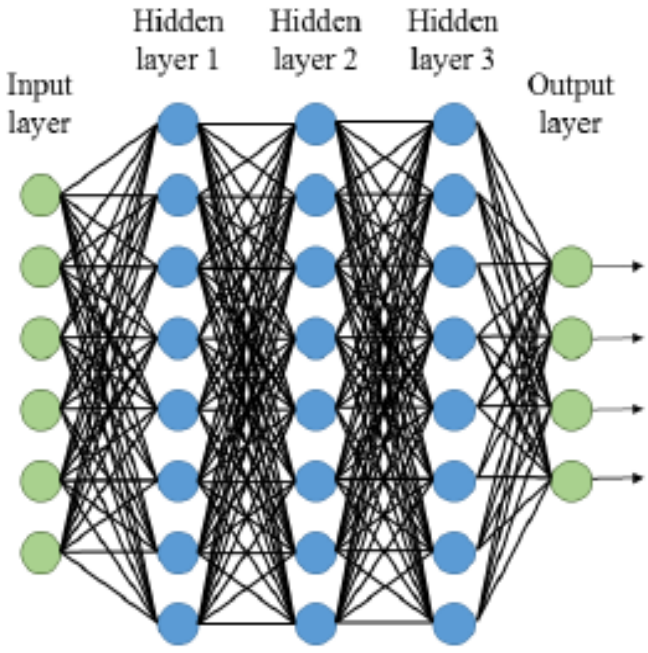

Figure 3.2: 4 depth multilayer perceptrons (Coates et al., 2013)

A layer of an MLP is made up of many units that act in parallel, called artificial neurons (ANs). Defines its width by the AN number in a layer. Artificial network is the perceptron evolution mentioned earlier and is a function of scalar-to-vector. The units are known as neurons since they acknowledge inputs from numerous different past units and ascertain their value for initiation. Artificial neuron yields weighted total of its activation function and input data follows:

$$Z = \text{activation\_function}(\sum \text{WiXi}) \tag{3.3}$$

Where Z represents scalar output, W represents neuron weight, X is the input vector and the operation $\sum WiXi$ determines linear input mapping. To add non-linearity to the transformation an activation function is used here. There are many activation functions but the tangent-hyperbolic, sigmoid, and rectified linear unit are the 3 well known in the state-of-the-art shown Figure 3.3. One can define learning algorithms with fairly simple ingredients: a collection of cost, data, optimization process, function and the system.

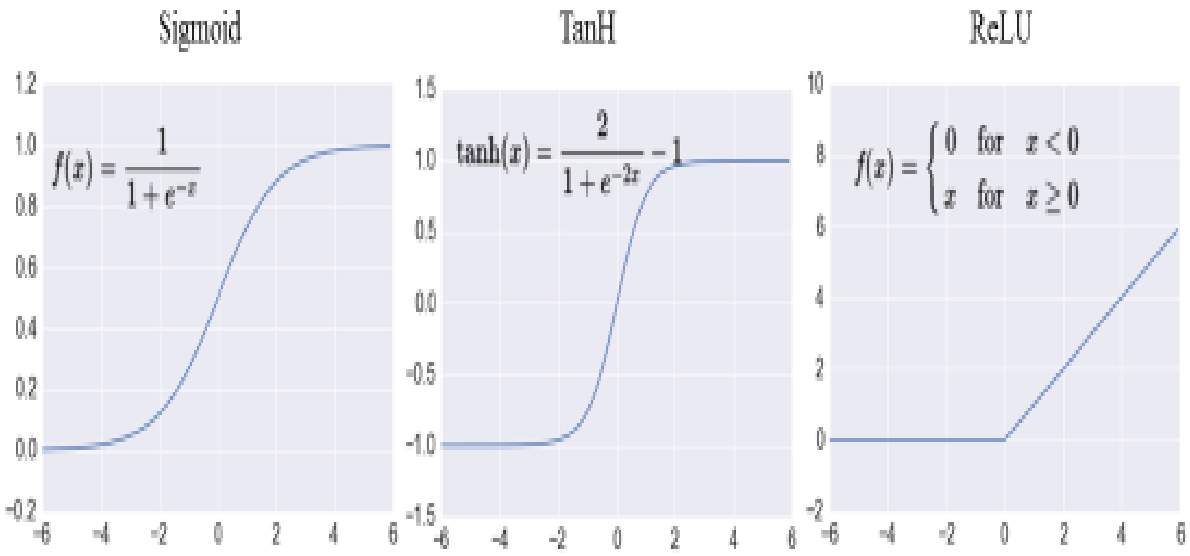

Figure 3.3: Sigmoid, tangent-hyperbolic and rectified linear unit activation functions (Coates et al., 2013)

3.1.3 Feedforward neural network training

Role of NN *f* is to use a collection of labeled data to reduce the differences between its output and the *y* label of a given input *x*, such a cost function is often known as loss function and an optimization process. We train the model in order to accomplish this task by updating the parameters Θ of *f* to be the best approximation function $\hat{y} = f(x, \Theta)$. Backpropagation algorithm is the common optimization process of training the model. Its name derives from the backward error propagation process (Rumelhart et al., 1985). The algorithm functions in two steps:

a. Propagation

When At the point when input vector is introduced to the system it is proliferated forward, layers by layers, via the model till it arrives at output layer. Network output will be contrasted with target label, utilizing cost function, and error rate calculated. The error will be proliferated backward, beginning from the output, till every neuron has a corresponding error rate which is its commitment to the error.

b. Weight update

Backpropagation utilizes such error rate in order to estimate gradient of cost function. Such gradients are supplied to optimization framework that utilizes it to modify weight so as to decrease the cost function. Step of backpropagation is iterated till entire data is transformed numerous intervals by the model. Complete shift over the whole data is known as epochs. By so doing, the network would have been once presented to each instance in the training data before the operation of the first epoch end. In the event that the NN performance for a particular problem is profoundly subject to its structure, cautious selection of a few meta-parameters training is assumed. In Algorithm 1, a typical iterative circle is designed to train an NN.

Algorithm 1: An iterative loop to train a NN

Inputs:

- Training data: $L = \{(d^i, y^i)\}i = 1...N$ such that d^i represent inputs while y^i represent the output labels.
- NN model: M_Θ;

Output:

- Trained model: M_{Θ}.

Parameters:

- Epoch number=*E*
- Learning rate=λ
- Amount of data in batches=*B*
- Cost function=*C*

1 Initialize the values of θ ;
2 $i \leftarrow 0$;
3 $nbDataSaw \leftarrow 0$;
4 **while** $i < E$ **do**
5 Extract a subset $(D,Y) = \{(d^i, y^i)\}_{i=1..B}$ from $\mathcal{L}$;
6 $nbDataSaw := nbDataSaw + B$;
7 /* Backpropogation procedure */
8 $\hat{Y} = \mathbb{M}_{\theta}(D)$;
9 $\Delta\theta = \frac{\partial C(\hat{Y},Y)}{\theta}$;
10 $\theta \leftarrow \alpha \times \theta - \lambda \times \Delta\theta$;
11 **if** $nbDataSaw = N$ **then**
12 Randomly shuffle $\mathcal{L}$;
13 $nbDataSaw \leftarrow 0$;
14 $i := i + 1$;

Algorithm of stochastic gradient descent enhances gradient descent as well as reduces loss function at training phase of the network as shown in algorithm 1; rows 9 and 10, this is called stochastic since randomness is involved. Learning rate l is utilized to assign the current update a weight. We also decrease learning rate while increasing the number of epochs to gradually reach local minima. Parameter B determines training samples number at each iteration, which will be propagated across the network. Utilization of batches in SGD enables gradient variance changes (average gradient application in batch) to be minimized and the optimization of the model accelerated.

The book deep learning, Goodfellow et al. (2016) is referenced in depth knowledge of deep learning. It is composed by Aaron Courville, Ian Goodfellow as well as Yoshua Bengio, uninhibitedly open at http:/www.deeplearningbook.org, for further information about current

layers, techniques of optimization, implementations on deep and machine learning innovation by and large. In summary, a model of deep learning is a sequence of less difficult function known as layer. There are several distinct layers to deal with specific dataset, for example, vectors, images and various difficulties like dealing with sequences and so on. The deep NNs are modeled by: nature of data, output character, problem nature, and hardware context. Layers Likewise, layers could be adjusted by their activation function and width. Such parameters are, amongst numerous others, called hyper parameters or meta parameters, because they could not be directly learned from the dataset.

3.2 Deep Learning Elements

Here, we include comprehensive examples of basic elements for a method of deep learning recognition. For hand gesture recognition we present several important elements of deep learning:

- As we research classification problem, we implement softmax activation function that is required to output the class-conditional vector of probability, which is important to represent class variables, as well as the cost function of cross-entropy.
- Computer vision usually uses images as input. Here, we demonstrate convolution layer that is layer specialized in grid-shaped input processing.
- Due to the time consuming in 3D data sets, hard to collect and use of deep learning algorithms with limited size datasets leads to a poor generalization during the training process known as overfitting. One means to solve such task is by using transfer learning approach to extract features from another similar larger dataset.

3.2.1 Softmax function

The performance of a classification function (as opposed to quantitative variable) is a categorical variable. A class variable has, by definition, fixed number of discrete values. An instance is found in image-based platform, for animal recognition classes may include bird, fish, dog and cat. Every instance is allocated to a finite class in the dataset. This is different from the quantitative variable because, regardless of the number of categories, the distances from one category to another are equal. We might utilize one single scalar to be the output but it would not

be equal to the distances between each classes. The deep learning frameworks constructed for categorization utilize single-hot encoding to depict their output in order to solve issue. It comprises of feature in which its size is equivalent to the class number, filling the class cell in which the input belong with 0 and a 1. We may also see this encoding scheme as a common stochastic vector representing the probabilities that one input belong to each group, known as vector of class conditional probability. A model requires two elements for output of a stochastic vector. Firstly, the last layer of the model must have the maximum number of classes. Secondly, the last layer uses the softmax activation function to compute a class conditional probability matrix. Softmax function output represent class distribution of probability that indicate the probability which an input belong to any one of the groups.

In the classification problem, let *K* denote classes and *Z* represent the weighted sum of the last layer input as shown in Section 3.2.1. We define the softmax function thus,

$$S\text{oftmax(z)j} = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}} \tag{3.4}$$

Here, *j = 1 . . . K* while the last layer output is *z*. The second aim of this method is to show the biggest input and to remove every substantially smaller ones, using the exponential terms.

3.2.2 Cost function of cross entropy

The choice of cost function is a primary part of profound NN training. For neural networks, the cost functions are more or less the same as with any trainable classifier. For cost function; cross-entropy between model prediction and ground-truth was utilized.

Let $L = \{(\beta^i, y^i)\}i=1...N$ represent labeled data set. Also, let probability output of the class-conditional of the DNN be $\hat{y}^i = f(\beta^i, \delta)$. Therefore, cross-entropy is calculated thus,

$$L(W) = \frac{1}{N}\sum_{i=1}^{N}\left[y^i \log\hat{y}^i + \left(1 - y^i\right) \log(1 - \hat{y}^i)\right] \tag{3.5}$$

Where *L(W)* is the lowest, while approximation function quality *f* is the best. Figure 3.4 depicts cross-entropy error values in accordance with *y* and ŷ values.

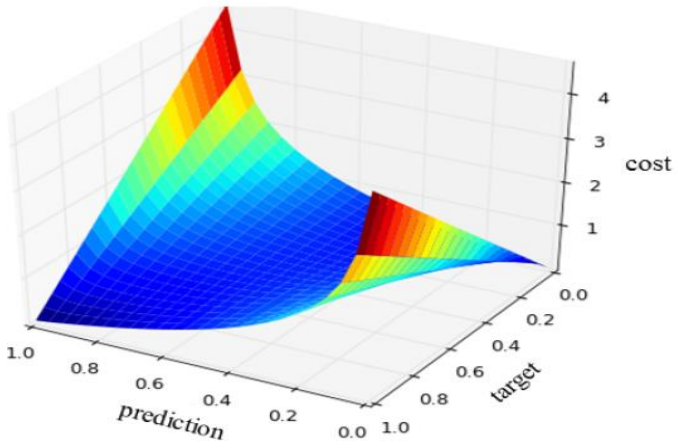

Figure 3.4: Cross-entropy cost function L(W) values (https: //github.com/matplotlib/matplotlib/issues/6027 Retrieved 20 April, 2020)

3.3 CNNs Based Deep Learning

The performance of conventional machine learning algorithms, such as SVM Hearst at el. (1998), random forest Breiman (2001) or HMM Rabiner and Juang (1986), depends heavily on the representation of the selected data. Nevertheless, feature from handcraft usually suffers information loss. Recently, algorithms of deep learning have yielded especially great performances on several CV challenges but often experience some shortcomings. Such algorithm requires huge data in order to function well, and this is a major challenge in a certain field in which dataset are not freely generated. Also, network training and parameterization of deep NNs require much of computational data and time for experiment. Are algorithms from handcraft getting outdated? There is still a wide range of applications needing features from handcraft. Let us look at two realistic examples to know where and when we can utilize one or another:

CNNs are a specific kind of NN that has a grid-like topology for processing data. This comprises vector time-series, which when concatenated are grid-like data as well as 2D pixel grid images. LeCun et al. (1999) in 1999 presented the first 7-level convolutional neural network known as

the LeNet-5 for the classification of 32 x 32-digit images taken from checks in the bank. Given that hand posture as input is usually 2-dimentional image, we implement CNN design motivations:

a. Motivations

Every output interacts with each input in typical layers of NN including multilayer perceptron, as described in section 3.2, where a NN model's number of parameters is proportional to input size. Moreover, given that there are *m* input and *n* output, multiplication of the matrix implies parameters of *m x n*, where such algorithm has runtime of *O(m x n)*. The input may have thousands or millions of values when processing an image and a traditional multilayer perceptron would see the number of parameters burst and runtime. Such network architecture also takes no account of the image's spatial structure. This doesn't enable the network benefit from strong image spatial correlations that are essential elements in problem of recognition, by treating images as a vector of pixels.

b. Version inspired by biological knowledge

The CNN's architecture was influenced by Neuroscience. The history of the CNN starts with experiments involving neuroscience, before it produces the pioneer model. For many years, there has been collaboration between neurophysiologists Torsten Wiesel and David Hubel in order to find most fundamental details on functioning of the vision system of mammalian (Hubel and Wiesel, 1968). The authors studied how cat brain neurons reacted to data that were displayed on a computer at specific locations. They identified two essential types of visual cells. The common cells within the older visual framework react to basic light patterns for instance directed bars, but hardly react to patterns that are complex. Additionally, larger receptive fields and complexer cells are invariant to little motions in feature locations.

c. Design

One of the pioneering structures of CNN is made of stacked of different layers to mimic the visual cortex. Figure 3.5 provides this pioneering structure. Firstly, there's convolutional layer

that's at the heart of a CNN. The parameters of the layer comprise of collection of learnable filters that have a small size but are sliding over entire images. Filter is converted across Grid-like input; height and width. This follows activation function that provides map of response in two dimensions, one for each of the filters. For this reason, model learns filter which activate when certain different features are identified at certain spatial regions of the data. One easy step toward convolution is shown in Figure 3.6.

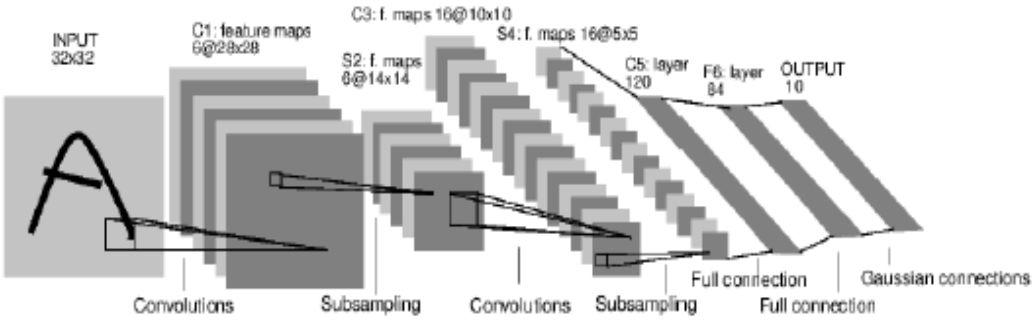

Figure 3.5: LeNet-5 architecture (Lecun et al., 1989)

From Figure 3.5,

- C1 layer C1 represent a convolution layer with 28 x 28 filters 6 response maps.
- S2 layer represent a subsampling layer with 14 x 14 filters 6 response maps.
- C3 layer represent a convolution layer with 10 x 10 filters 16 response maps.
- S4 layer represent a subsampling layer with 5 x 5 filters 16 response maps.
- C5 layer represent a size 120 multilayer perceptron known as fully connected layer.
- F6 layer represent a size 84 fully connected layer.

The convolution layer is denoted by C: $R^{hxwxc} \rightarrow R^{hxwxn}$ function here, *h*, *w* and *c* represent height(H), width(W) and input grid channels respectively, and *n* represent filters number learned by the layer. Convolutional layers are constructed to mimic the characteristics of the above mentioned cells that attempts to learn basic as well as input grid local features.

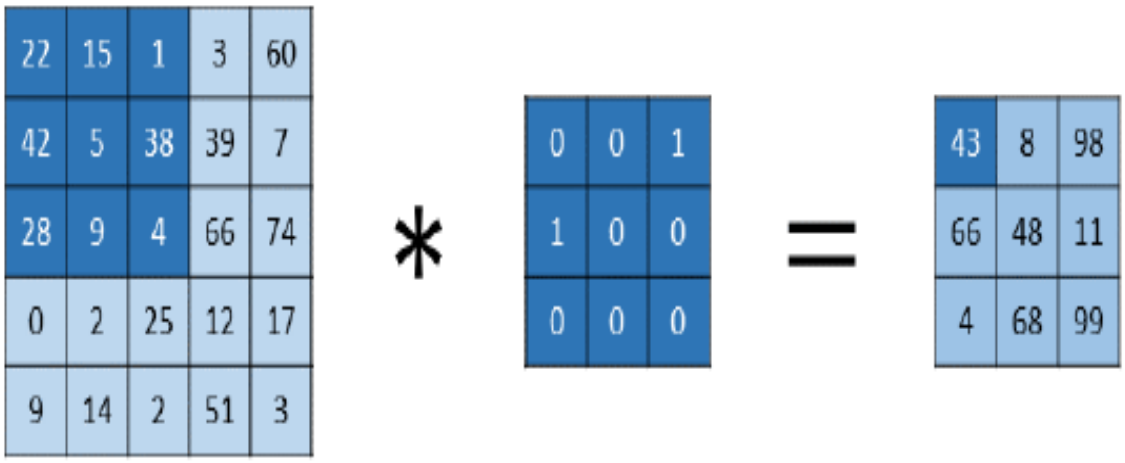

Figure 3.6: Operation involving two-dimensional convolution (Lecun et al., 1989)

A subsample layer executed by non-linear process known as pooling is followed by the convolutional layer. Where we have non-linear function for the execution of pooling, the most common is max pooling. Input image is partitioned to several non-overlapping regions as well as maximum outputs. Figure 3.7 provides structure of max pooling sheet. The intuition is that the exact position of features in relation to other features is less important than their locations. The pooling layer helps to slowly reduce representation size, number of parameters and computation amount as the information flows through the network. This also provides for a kind of invariance to translate. The complex cells inspires pooling layer since enables the system to be invariant to little motions in location of element. The pooling layer is expressed as function P: $R^{hxwxc} \rightarrow R^{h/p1xw/p2xc/p3}$ here, *h, w* and *c* represent height, width as well as input grid channels respectively, while *p1, p2, p3* are fixed pooling layers hyperparameters.

d. Summary

Basic methods of detecting the convolutional function accompanied by pooling are applied several times as we step deeper into the network. This lets CNN learn from features that are small to higher abstracts. The stacking of several layers result in non-linear local filters which are becoming increasingly global. The idea is depicted in Figure 3.8.

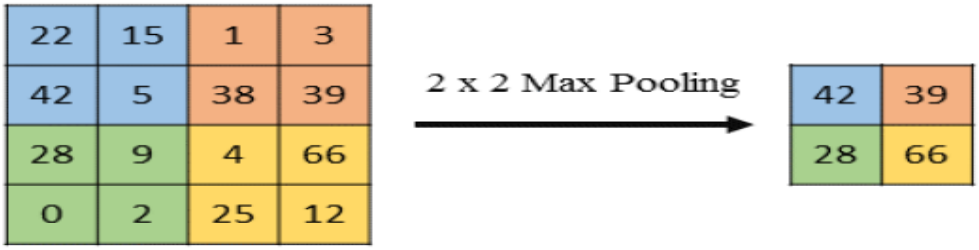

Figure 3.7: 2 x 2 max pooling layer (Lecun et al., 1989)

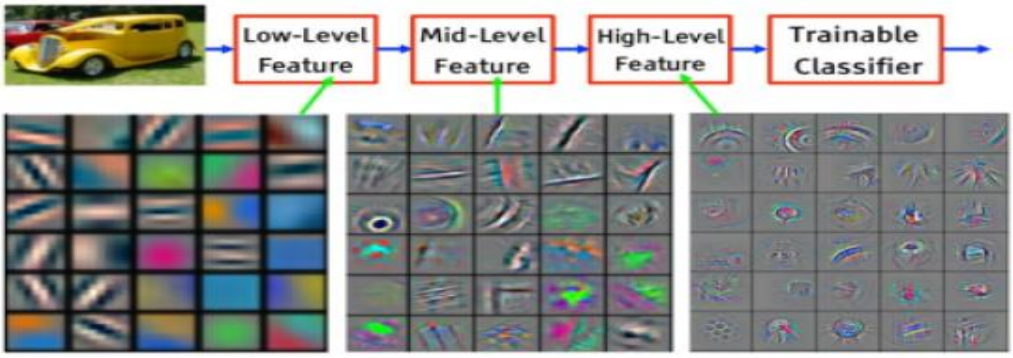

Figure 3.8: A stacked convolutional layers (LeCun and Ranzato, 2013)

In general, the output of stacked convolution layers is eventually flattened so that learned features can be used as input of subsequent layers which require vector as input. This process is referred to as architecture of the CNN that enables certain classification tasks to be carried out on images. A significant benefit of this independence is from previous experience and human effort in feature design. The network will learn filters which have been hand-engineered in conventional algorithms. Furthermore, each filter is used over the whole image. In a given convolutional layer, it implies that all neurons react to same input. The property known as sharing of weight decreases number of parameters learned. Convolutional NN could measure one dimensional temporal sequence, as well as images, depicted as stacked vectors. Concept of one dimensional temporary sequence convolution is for parameters sharing over time. Output of sequence convolution refers to sequence in which every output vector is a function of small number of input vectors adjacent to it.

3.3.1 Transfer learning and overfitting problem

The aim of a process of classification is presentation of classifiers that functions accurately on unseen input that has not been seen before. The ability to manage stimuli that are not known is referred to as generalization. Dataset is usually made up of two non-overlapping sets. First one, known as the train set is made up of data from which network learns. The second, called test collection is composed during the training process of data not used by the algorithm. By an optimization process, the classifier must reduce error measure between ground-truth and output. Error measurement is known as the error recorded at training phase when processed on training data, and when executed on test data is called test error or generalization. What characterizes learning algorithm's viability is its capacity to reduce training error and discrepancy between training and test error, called generalization gap. Deep learning model's capacity is its capacity to suit specific task. There are principal hyper-parameters that characterize model's ability; its width and depth. Low capacity network might not be able to match train data. High-capacity network will overfit by learning unique training set properties that don't serve for generalization. High-capacity model could treat difficult task but it requires huge data in order to skip overfitting problems. To sum up, the job is harder, the model's depth and width must be higher, and thus the volume of data requires an increase. Figure 3.9 indicates the relationship between a model's capability and the measure of error. Regrettably, there is no hope of discovering right architecture of network which completely generalize training data as there are infinite numerous solutions.

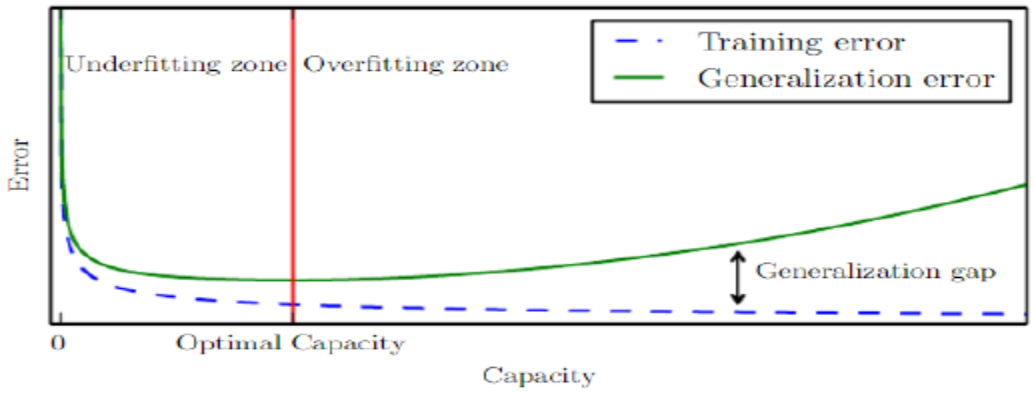

Figure 3.9: Correlation between error measures and capacity of a model (Goodfellow et al., 2016)

As shown in the figure above, we may increase the capacity to find a better generalization of the training set at the left of the optimum range. That state is known as underfitting. The model is too big to the right of the optimal range, or the training set is too small, and the algorithm begins to learn the specification of the training data. It results from a declining training error, an unfortunate increase in the test error and a greater gap in generalization. Such condition is referred to as overfitting (Goodfellow et al., 2016).

The CV group has access to very broad data sets for image classification or object detection problems, such as the Open Images dataset Krasin et al. (2017) which consists of 10,000,000 labeled images. The datasets are composed of only thousands of sequences in the field of hand gesture recognition. If the only way to avoid overfitting would be to generate more data, it's time consuming and not always feasible. Nevertheless, methods and techniques exist to avoid overfitting of the model:

- Utilize smaller structural design
- Utilize weight decay. Weight decay is a term for regularization applied to the cost function, which penalizes big weights. When the weight decay coefficient is large, the penalty for large weights is also large, if small weights can grow freely
- Using technique for dropout. Dropout randomly "drop out" nodes in the neural network by setting them to zero, which forces the network to focus on other functionalities. It leads to more general representation of the dataset
- Using augmentation of data. We may artificially generate additional training data because deep networks need a large amount of training data to achieve good efficiency. An instance is, new images can be generated to train a CNN architecture via random rotations, motions and so on
- Utilization of early stopping. Halting of training before the system begins learning of training data specifications
- Transfer learning usage

In transfer learning, Pan and Yang (2009) in their survey on transfer learning, gives definitions of a task and domain. Domain $\mathcal{D}$ comprises two elements: a marginal probability distribution $P(X)$ where $X = \{x_1, x_2, \ldots, x_n\} \in \mathcal{X}$ and a feature space $\mathcal{X}$. In view of the domain $\mathcal{D} = \{\mathcal{X}, P(X)\}$, the task consists of two components: an objective predictive function f (denoted by $T = \{ \mathcal{Y}, f \}$)

and $\mathcal{D} = \{\mathcal{X}, P(X)\}$, which is not observed but learned from the training data consisting of pairs $\{x_i, y_i\}$, where $x_i \in \mathcal{X}$ and $y_i \in \mathcal{Y}$ respectively. For instance, $\mathcal{X}$ is the image depth space in the field of hand pose estimation, x_i is hand depth images, $\mathcal{Y}$ is R^{3*k} where k is the number of joints in the hand model, y_i are 3D joint positions for each sample in the dataset and, finally, f is the mapping regression function described as $f : \mathcal{X} \rightarrow \mathcal{Y}$ learnt from the training set. We describe a $\mathcal{D}_S$ source domain, and a $\mathcal{D}_T$ destination domain. In particular, we refer to $\mathcal{D}_S = \{(x_{1s}, y_{1s}), \ldots, (x_{ns}, y_{ns})\}$, where $x_{is} \in \mathcal{X}_S$ is a data sample, and the corresponding label is $y_{is} \in \mathcal{Y}_S$. Likewise, $\mathcal{D}_T = \{(x_{1T}, y_{1T}), \ldots, (x_{nT}, y_{nT})\}$. Notice that, for the most part, $0 \leq n_T \ll n_S$. Instead of a $\mathcal{D}_S$ source domain and a T_S learning task, a $\mathcal{D}_T$ target domain and a T_T learning task, transfer learning is aimed at helping to learn the f_T target predictive feature in $\mathcal{D}_T$ utilizing $\mathcal{D}_S$ and T_S information where $\mathcal{D}_S \neq \mathcal{D}_T$ and $T_S \neq T_T$ but identical.

It is a complex task to learn features of the images. In addition, CNN architecture includes a lot of parameters and so is typically not trained with random initialization from scratch. It is because a target dataset of sufficient size is fairly difficult to train a network with a depth that is broad enough to manage the difficulty of the task. Rather, it is normal to train a CNN on another larger source dataset and then use the so-called pre-trained weights for the task as either a fixed feature extractor or an initialization. Two key factors in transfer learning are: the size and similarity of the source dataset to the original dataset.

CHAPTER 4

CNN BASED SIGN LANGUAGE TRANSLATION SYSTEM

4.1 Structure of the System

This proposed translation model includes three distinctive structures - SSD, Inception v3 and SVM that are integrated to form the hybrid model that constructively translates sign gestures (Figure 4.1). In this thesis, for designing such a translation system, the American Sign Language (ASL) fingerspelling dataset is utilized. In this hybrid model, SSD is utilized for hand detection, Inception v3 is applied for feature extraction and the last module, SVM, is utilized for classification purposes.

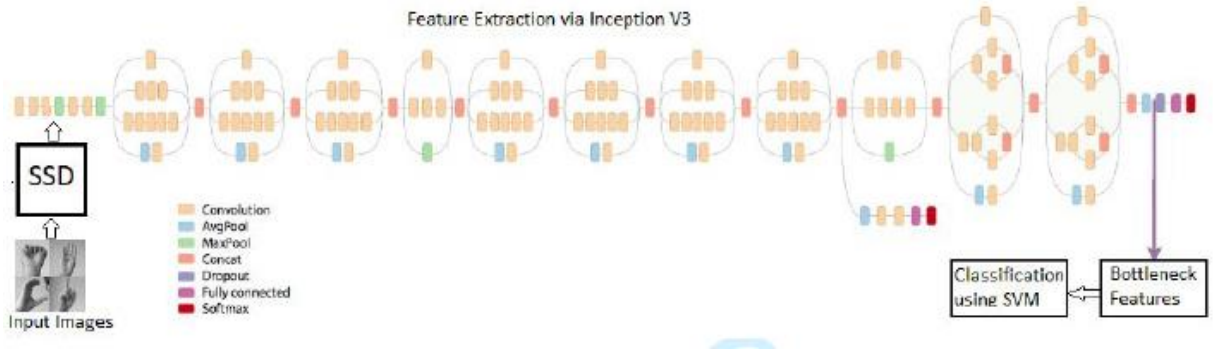

Figure 4.1: Structure of the proposed system

Inception v3 which is based on CNNs is a basic module of the translation system which is used to extract features for future classification purpose. CNNs are forms of architecture of deep learning that has one or more convolution, pooling, and feedforward layers. They are a multilayer perceptron (MLP) variation of biological motivation. Each neuron in an MLP has a weight vector of its own, but CNN neurons share weight vectors, and weight sharing decreases the number of trainable weights. Neurons compute convolutions on the input dataset using weight-sharing technique with the convolution filters. The output properties obtained from the convolution layers are fed to the ReLU layer. After applying $f(x)=max(0,x)$ as the activation function to the obtained feature map, the obtained signals are entered into the pooling layer. The

image size is decreased after multiple layers of convolution and pooling, and more complex feature extraction is carried out. Afterwards, the contents are transferred into 1D vector with small feature maps supplied to the classification module. And this module works out the CNN performance. Convolutional neural networks have convolution layers characterized by input map *I*, biases *b*, and a filter bank Abiyev and Ma'aitah (2018) amd Abiyev and Arslan (2020). Lets assume that $l = 1$ represent the first layer and $l = L$ represent the last layer, and *x* is the *H x W*-dimensional input that has *i* and *j* as iterator. As iterators, the kernel ω with $k_1 \times k_2$ dimension has *m* by *n*. $\omega_{m,n}^{l}$ is the weight matrix that connects the neurons of the layer *l* with the neurons of the layers *l-1*. The bias variable at layer *l* is b^l. The transformed input vector plus bias is represented on layer l as:

$$x_{i,j}^{l} = \sum_m \sum_n \omega_{m,n}^{l} \, o_{i+m,j+n}^{l-1} + b^l \tag{4.1}$$

Convolutional and pooling layers output is computed thus:

$$o_{i,j}^{l} = pool(f\left(\sum_m \sum_n \omega_{m,n}^{l} \, o_{i+m,j+n}^{l-1} + b^l\right)) \tag{4.2}$$

Flatten operation which concatenate acquired feature is performed after pooling utilizing$o_{flatten}^{L} = flatten(o_{i,j}^{L})$. The computed feature vector is modified into outputs of the model utilizing fully connected network $y = F(o_{flatten}^{L})$. Once the signals of output are obtained, the training of CNN's weight coefficients (unknown parameters) will begin. Let's denote some of CNN's unknown parameters *Θ*.

To evaluate the accurate values of parameters *Θ*, an effective loss function is constructed. This is done by minimizing the loss function by using input-output training pairs$\{\left(x^{(i)}, y^{(i)}\right); i \in [1, \dots, N]\}$. Here, $x^{(i)}$ is the *i-th* input data and is the corresponding destination data for the output. If we denote CNN's current performance as $o^{(i)}$, then CNN's loss is calculated thus,

$$L = \frac{1}{N} \sum_{i=1}^{N} l(\Theta;\, y^{(i)}, o^{(i)}) \quad (4.3)$$

Training of CNN parameters is carried out through loss function minimization. During training, the parameter values are calculated. Updating of the network parameters is carried out using an Adam optimizer (adaptive moment estimation) (Kingma and Ba, 2014). During parameter learning, the Adam optimizer uses loss function gradients of first order. The approach is a Stochastic Optimization which utilizes first and second moments of gradients for computing individual adaptive learning rates for several parameters (Kingma and Ba 2014). Effective Deep CNN training requires large quantities of training data.

Data incrementation is used to solve this problem. Also, this approach mitigates the relative data shortage to equal the number of CNN parameters. Data augmentation being explored here modifies the existing dataset into new set without modifying their shape. In augmentation of data, geometric changes including zooming, rotating, shearing, mirroring and shifting are utilized. In this study, we used Inception v3 as a CNN model for feature extraction. The descriptions of Inception v3 is given in section 4.4.

4.2 Dataset Analysis

We used the 'Kaggle' ASL fingerspelling data for evaluation of the proposed hybrid method. This database consists of 24 symbol / sign or letter groups. All the English letters except Z and J are in info. This is because there are no static postures at Z and J. Training and test sets consist of 27,455 items, and 7,172 objects. The data is given as a pixel to pixel intensity [0-255], in its raw class-wise distributed XLS file format. Each of the images is transformed to a 28x28 grayscale image to achieve high efficiency.

As shown in the discussion file on the data , at least 50 + types of image transformation were performed. One example is; three degrees rotation, + /-15% contrast / brightness/, 5% random pixelation, and so on. As a result of these changes, researchers face various difficulties when investigating this area, which in turn alters the images' resolutions. Fragments of the data being examined are shown in Figure 4.2.

Figure 4.2: Fragment of ASL fingerspelling dataset

From the dataset above, letter Q is translated by the proposed hybrid model (SLT) thus;

- SLT captures letter Q equivalent sign
- Convert the sign to letter Q
- Letter Q is displayed on the screen to the privileged
- Now the privileged can understand the deaf person's demands
- The reverse is applied for the deaf person to understand the feedback of the privileged. Snippet of this procedure is demonstrated in Figure 4.3 below:

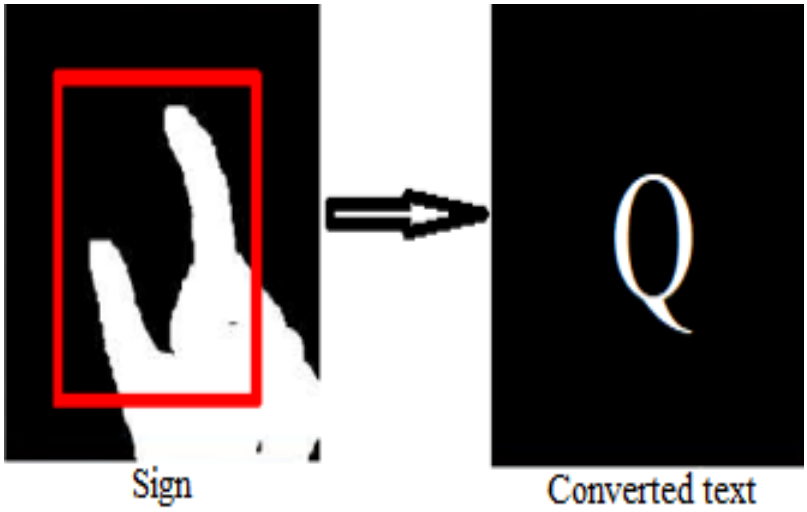

Figure 4.3: Conversion of sign to text using SLT

4.3 Single Shot Multibox Detector

In this thesis, the single shot multibox detector (SSD) (Liu et al., 2016) is used to detect the hand. And after this, detected hand is used as the input for the classification system. SSD has been utilized by Szegedy et al. (2015) for detection of object problems and very high performance was achieved. In this work, SSD structure is based on structure of VGG-16, as demonstrated in Figure 4.4. In the classification system, a set of convolutional layers is added for feature extraction and fully connected layers are removed.

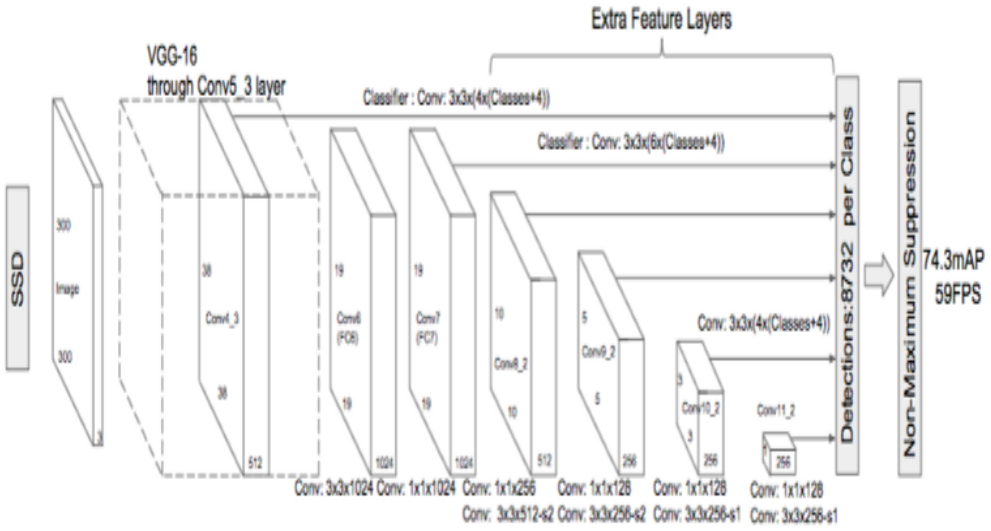

Figure 4.4: SSD network structure (Szegedy et al., 2015)

Along these lines, the CNN extract important vector maps on different scales and dynamically lessens the input size to every one of the ensuing layers. Multi Box is checked for the pre-determined, consistent dimensional-restricting privileges that firmly fit the dissemination of the first ground truth boxes. Furthermore such priorities are chosen so that the rate of intersection over Union is higher than 0.5.

As shown in Figure 4.5, 0.5 IoU is not sufficient although the limit box gives Regression Algorithm a reasonable starting point. Because of this, multi boxes begin as estimators and attempt to move closer to the bounding boxes ground reality.

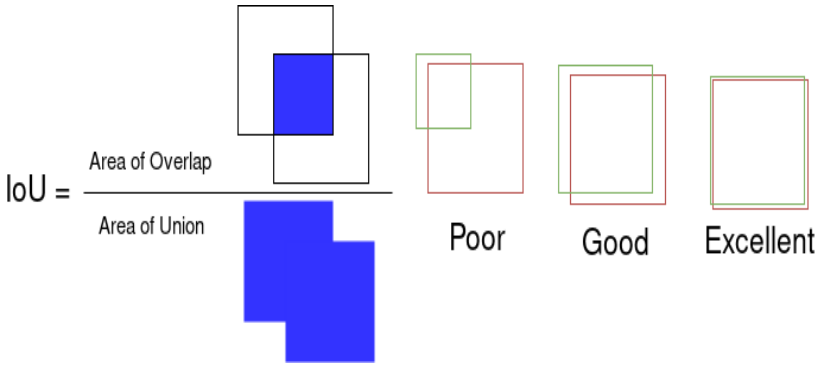

Figure 4.5: SSD structure generating box overlapping (Szegedy et al., 2015)

Conclusively, SSD multibox assumes the top K prediction that minimize the confidence and location loss.

4.4 Inception V3

In this research work, we explore the Inception v3 CNN model for feature extraction. As seen in the convolutional layers of the traditional CNN structure, this model handles both data pre-processing and feature extraction. The inception deep convolutional structure was introduced as GoogLeNet Szegedy et al. (2015) and referred to as Inception v1. After this, the Inception v1 structure was reconstructed considering several factors. At first, batch normalization by Ioffe and Szegedy (2015) is introduced after which the architecture was renamed as Inception v2. Furthermore, in the third iteration, additional factorization ideas by Szegedy et al. (2015) were introduced and the new architecture is called Inception v3. Thus, while Inception v2 is made of batch normalization, Inception v3 is made of factorization ideas. The Inception v3 structure comprises building blocks such as asymmetric and symmetric, including convolutions, average pooling, max pooling, concats, dropouts, and fully connected layers. However, in this study, we replace the fully connected layers with an SVM classifier. The Inception v3 architecture incorporates factorization of initial convolutions into smaller convolutions and the inclusion of batch normalization to the fully connected layer correspondingly. Inception model structure is predominantly a *299x299x3* input, which represents a field of 299 pixels and 3 channels representing the standard RGB image, converged with a set of convolutional layers, a series of

max-pooling operations, and sequential inception modules stacks (set of different convolution filters and max-pool filter) performing concatenation of filters. Ultimately, softmax layer is the output. Usually, a 2048-dimensional vector is the input of the top layer of Inception v3 model where the softmax layer is trained. For instance, a softmax layer with *X* labels learns *X + 2048*X* parameters in line with the learned biases and weights.

In Inception v3, the goal of factorizing convolutions is to minimize parameters/connections number without limiting efficiency of the network (Li and Zhang, 2017). For example, Figure 4.6 depicts two *3×3* convolutions replacing one *5×5* convolution. As demonstrated in the figure, in utilizing 1 layer of *5×5* filter, parameters number = *5×5=25*, and by utilizing 2 layers of *3×3* filters, parameters number = *3×3+3×3=18*. This implies that further factorization of the filter of the same layer decreases parameters number leading to an increase in learning speed and system efficiency. With the factorization technique, the parameters number is decreased in the entire model, and consequently, the network can go deeper.

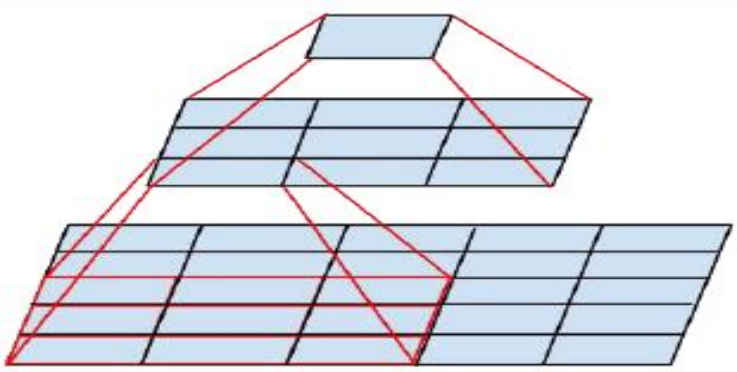

Figure 4.6: Two 3×3 convolutions replacing one 5×5 convolution (Li and Zhang, 2017)

In the case of asymmetric convolutions factorization, let's consider one *3×1* convolution and one *1×3* convolution replacing one *3×3* convolution, as depicted in Figure 4.7. By using a *3×3* filter, the number of parameters will be equal to *3×3=9*, and by utilizing *3×1* and *1×3* filters, parameters number becomes *3×1+1×3=6*. It can be questioned why two *2×2* filters are not used to replace one *3×3* filter. If two *2×2* filters are used, parameters number becomes *2×2×2=8*. Comparing the rate of reduction of the parameters between two *2×2* filters and one *3×1* and *1×3*

filters, it is evident that the latter produces a lower parameters number as compared to the parameters number produced by the former.

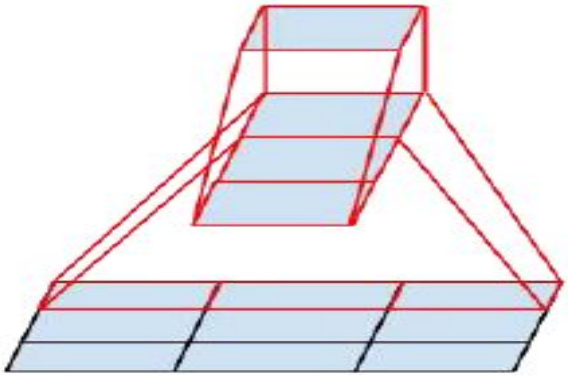

Figure 4.7: One 3×3 convolution replaced by one 3×1 convolution with one 1×3 convolution (Li and Zhang, 2017)

4.5 Support Vector Machines

SVMs uses a learning technique which computes a hyperplane. This hyperplane produces the best separation using the largest distance to the nearest inpute data point of any of the classes (Abiyev et al., 2017). In many experiments, the support vector machine has proven to be successful, especially when dealing with a high-dimensional feature space, as demonstrated in (Vapnik, 2013). Using a hyperplane, SVM in its simplest structure can classify data into two classes (binary classification). The support vector machine maximises the margin between the closest samples to the hyperplane (the support vector) utilizing an optimization strategy. SVM can also support nonlinear classification problems. In several ways, SVM can support multi-class classification including the one-versus-one Hsu and Lin (2002), one-versus-all Rifkin and Klautau (2004) and directed acyclic graph (DAG) Platt et al. (2000). A support vector machine library (LIBSVM) was utilized in Chang and Lin (2011) to support the multi-class nature of the domain. Practically, the support vector machine performs classification between two classes by drawing a border between the two classes in a plane. The drawn border separates the two classes from each other, as illustrated in Figure 4.8. To this end, two parallel and two near border lines are drawn across the two classes and these boundaries are drawn closer to each other to produce a corresponding boundary demarcation.

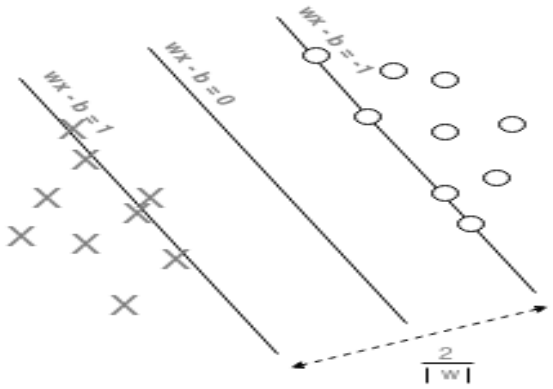

Figure 4.8: SVM boundaries (Chang and Lin, 2011)

As depicted in the figure above, two classes appeared on a 2D plane. This is conceivable to perceive these dimensions and planes as attributes. The SVM operation can be viewed from the feature extraction perspective. Here, extraction of feature is carried out on every input entering the model in a simple sense, bringing about an alternate point demonstrating every input of the 2D plane. Classification of inputs is simply the classification of these points with respect to extracted properties. In this plane, if we let $x_i \in R^p$, $i=1,\ldots, n$ be the training vectors in the two categories, and $y \in \{1, -1\}^n$ be a vector then the following primal task is solved by the support vector classifier as follows:

$$\min_{f,k,c} \frac{1}{2} f^T f + C \sum_{i=1}^{n} c_i$$

$$subject\ to\ y_i(f^T \phi(x_i) + k) \geq 1 - c_{i,} \qquad (4.4)$$

$$c_i \geq 0, i = 1, \ldots, n$$

The dual of the support vector classifier becomes:

$$\min_{\alpha} \frac{1}{2} \alpha^T Q\alpha - e^T \alpha$$

$$subject\ to\ y^T \alpha = 0, \qquad (4.5)$$

$$0 \leq \alpha_i \leq C, \quad i = 1, \ldots, n$$

Here, all ones vector is represented as *e*, upper bound is denoted as *C > 0*, *Q* is an *nxn* positive semi-definite matrix, $Q_{ij} \equiv y_i\, y_i\, K(x_i, x_i)\, where\, K(x_i, x_i) = \phi(x_i)^T\, \phi(x_j)$ represent the kernel. During training, training vectors are explicitly spread into higher dimensional space via function ϕ. After this, the decision function is computed thus:

$$sgn(\sum_{i=1}^{n} y_i \alpha_i\, K(x_i, x) + \rho\,) \tag{4.6}$$

The support vector classifier parameters are usually accessed using the members: $y_i \alpha_i$, kernel and the independent term ρ.

CHAPTER 5

SIMULATION AND RESULTS OF SIGN LANGUAGE TRANSLATION SYSTEM

5.1 Overview

The proposed model, provided in Figure 4.1, is constructed using finger-spelling data from ASL, where each hand image of the data is an American sign language symbol. This proposed system convert the given sign in real time into one of the 24 signs in the ASL. In relating convolutional learning methodology, SLT was built utilizing SSD+Inception v3+SVM classifier. The feedback for proposed system comes from camera photos placed on the signer 's hat. Here hand images of the signer are fed through the SSD module unto SLT. Then the image of the cropped hand is forwarded to Inception v3, where extraction of vector maps is performd. Hand gesture features extracted from the user are used in the input of the vector machine classifier for shape support. This built in support vector machine classifier uses the hand gesture features extracted from the user to evaluate the signer 's hand status. In our experiments, this decided state communication through gesture, which is ASL.

5.2 Simulation and Result

Considering of research, inception module is defined with four parameters, namely depth(D), height(H), width(W), classes number (signs). *H* and *W* represent input size. Depth represents input images channels. Input size is *299x299x3*, where the *W* is 299, *H* is 299 finally, *D* is 3 corresponding to RGB standard. As previously mentioned, we subjected this high dimensional input space to factorization operations, which drastically reduced the high input space to a lower dimension. After this, the factorized low space is utilized as support vector machine classifier's input. Modules of the proposed hybrid model have been sequentially described since we sequentially add the layers as demonstrated in Figure 4.1.

The Figure 5.1 depicts a classification report and Figure 5.2 depicts a confusion matrix of the proposed hybrid model used for translation of hand gestures into American Sign Language. These results were obtained from an experiment conducted using a cross-validation method. As

shown in both the table and the figure, miss-classification occurred once on the letters m, s and u out of the total of 24 signs/letters (classes) in the explored dataset. From these results, it is clear that the miss-classification rate is minimized and this depicts the efficiency of the hybrid model (SLT).

Letters	Precision	Recall	F1-score	Support
a	1.00	1.00	1.00	137
b	1.00	1.00	1.00	152
k	1.00	1.00	1.00	145
l	1.00	1.00	1.00	137
m	0.99	0.99	0.99	167
n	1.00	0.99	1.00	146
o	1.00	1.00	1.00	146
p	1.00	1.00	1.00	165
q	1.00	1.00	1.00	153
r	1.00	0.99	1.00	147
s	0.99	1.00	1.00	147
t	1.00	1.00	1.00	146
c	1.00	1.00	1.00	141
u	0.99	1.00	1.00	151
v	1.00	1.00	1.00	158
w	1.00	1.00	1.00	155
x	1.00	1.00	1.00	140
y	1.00	1.00	1.00	155
d	1.00	1.00	1.00	174
e	1.00	1.00	1.00	143
f	1.00	1.00	1.00	137
g	1.00	1.00	1.00	152
h	1.00	1.00	1.00	177
i	1.00	1.00	1.00	155

Figure 5.1: Classification report of the proposed model

In this thesis, a LinearSVC estimator was utilized as the SVM class. LinearSVC has a seamless/simplified learning structure, is significantly less tuneable and is basically just a linear interpolation. It is integrated with the Inception v3 for classification purposes. The SVM classifier is comprised of parameters including *loss='Squared_Hinge'* representing hinge loss square. *Penalty='l2'* specifying penalization norm, *C=5* representing the error term parameter *C*, and finally, *'ovr'=Multi_Class* determining strategy of multiclass when *y* has above two classes.

```
Labels:    a   b  k  l  m  n  o  p  q  r  s  t  c  u  v  w  x  y  d  e  f  g  h  i
[[137   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0 152   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0 145   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0 137   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0 166   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   1 145   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0 146   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0 165   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0 153   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0 146   0   0   0   1   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0 147   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0 146   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0 141   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0 151   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0 158   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 155   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 140   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 155   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 174   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 143   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 137   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 152   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 177]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 155]]
```

Figure 5.2: SLT Confusion matrix

SLT design process was performed using cross-validation on the hybrid model introduced in the first simulation. This experiment uses ten-fold cross-validation. The sample being examined here is split into ten equal parts. Training phase utilizes nine of the ten portions, and rest portion is used at test phase. Training procedure is repeated by flipping training and testing signals ten times. LinearSVC learning algorithm is also applied for implementation of training using 150 training epochs. The demonstrated value of accuracy represents result of the average of ten simulations. Accuracy rate average value at test phase 99.9% and the error is 0.0126.

In the second simulation, Monte Carlo-style estimation is explored on same database where our hybrid framework halt at 500 epochs, at each epoch, randomly dividing dataset into 60% for training and 40% for testing. Monte Carlo estimators are an expansive class of algorithms which depend on the iteration of random sampling to produce numerical outcomes. Here, the main idea is utilizing randomness for solving deterministic tasks. They are regularly utilized in mathematical and physical tasks. It is also helpful when it's impossible/extremely difficult in utilizing another methodology. Monte-Carlo estimator is majorly utilized for solving 3 classes of problems: generating solutions using a probability distribution, numerical integration and

optimization (Kroese et al., 2014). On a basic level, Monte Carlo estimators can be utilized for solving any task with a probabilistic interpretation. As previously mentioned, Monte Carlo experiments were carried out utilizing ASL fingerspelling database where our proposed model obtained 0.023 error rate and the accuracy was 98.91%. The table 5.1 contains outcomes of simulations of our hybrid network using both cross-validation and Monte Carlo approaches.

Table 5.1: Simulation results of the proposed model

Methods	Accuracy (%)	RMSE
Monte Carlo Method	98.91	0.023
Cross-Validation Method	99.90	0.0126

5.3 Other Tested Models

To deduce the best model for ASL fingerspelling dataset, we applied other machine learning approaches such as CNN Bheda and Radpour (2017) and Rastgoo et al. (2018), a Histogram of Oriented Gradient plus neural networks (NN) and finally, HOG plus SVM. After a set of simulations, a comparative analysis is made in order to determine the best performing model.

5.3.1 CNN simulation

In the first stage, the fully connected network of the CNN structure is applied for performing translation of ASL signs. Table 5.2 demonstrate the CNN structure used for ASL translation. Structure of CNN includes 2 layers of convolution, Maxpooling and fully connected network.

Table 5.2: CNN structure

Layer type	Output Shape	Param #
Conv2d_1 (Conv2D)	(None, 26, 26, 16)	160
Max_pooling2d_1	(None, 13, 13, 16)	0
Conv2d_2 (Conv2D)	(None, 11, 11, 32)	4640
Max_pooling2d_2	(None, 5, 5, 32)	0
Conv2d_3 (Conv2D)	(None, 3, 3, 64)	18496
Max_pooling2d_3	(None, 1, 1, 64)	0
Flatten_1 (Flatten)	(None, 64)	0
Dense_1 (Dense)	(None, 768)	49920
Dense_2 (Dense)	(None, 128)	98432
Dense_3 (Dense)	(None, 24)	3096

Explored dataset is split into two sections for CNN training: 80 percent and 20 percent. Using 80 percent for preparation and 20 percent for testing. 60 percent of the data reserved for testing is used for testing, while 40 percent is used for validation. To evaluate the CNN output signals, we used equations (4.1–4.3). Normalization method (Z-score) is utilized during simulation for scaling every input signal and the mentioned method improved the generalization of the model. The training of the model is based on an RMSprop learning algorithm. In addition, we used 150 epochs to train the CNN model. CNN consists of two convolutional layers. Model inpute size is 4096, and kernel size 3. The completely integrated network is thus extended for the purpose of classifying the American Sign Language. CNN was trained using 150 epochs as mentioned earlier. 60 per cent was used to practice at each iteration of each epoch, and 40 per cent was used to validate. Figure 5.3 shows the performances obtained from loss function as well as precision, and table 5.3 shows performances of CNN simulation. The achieved loss function value during training is 1.5676e-08. For validation data collected, the value of the loss function is 0.0054 while test data achieved 0.0054. 92.21 percent is the accuracy value for test data and the error is as low as 0.0234.

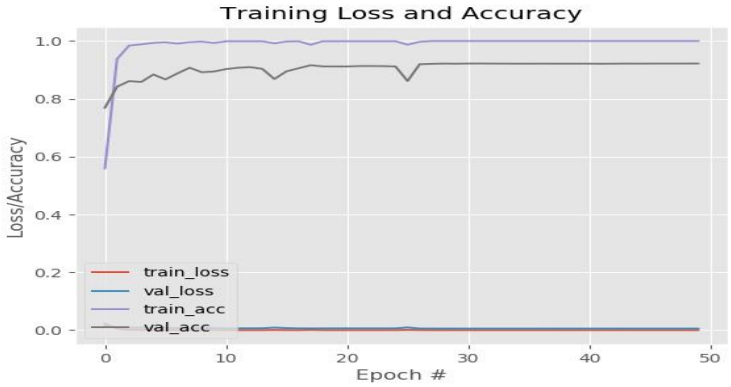

Figure 5.3: Loss function and accuracy of CNN

Table 5.3: CNN simulation results

Partitions	Loss Function	AUC (%)	RMSE	Accuracy (%)
Training	105676e-08	100	2.2019e-05	100
Validation	0.0054	97.72	0.0234	92.22
Testing	0.0054	97.71	0.0234	92.21

5.3.2 Simulation using HOG plus NN

In the next simulation, the ASL finger-spelling database was utilized to construct the translation system, using histogram of oriented gradient (HOG) plus neural networks (NN) structure. Here, every image of the hand in the domain donote a sign in ASL. As mentioned, this model is capable of translating real-time hand gestures into one of the 24 signs in the ASL. The design of this model is in line with that of the proposed hybrid model. Here, we use the HOG module for data pre-processing and feature extraction, while the NN module classifies the extracted features into American Sign Language. Table 5.4 depicts the structure of the HOG plus NN utilized for the classification.

Table 5.4: HOG plus NN structure

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 768)	787200
dense_2 (Dense)	(None, 128)	98432
dense_3 (Dense)	(None, 24)	3096
activation_1(Activation)	(None, 24)	0

The data are split into two parts during training: 80 percent and 20 percent. During training 80 percent of the total dataset was utilized, while the remaining 20 percent of the data collection is used for research. 60 percent of the 80 percent data collection reserved for testing is used for testing, while 40 percent is used for validation. Z-score normalization was used for signal scaling during simulation, and the Gauussian activation function was used for testing.

We trained the framework with 150 epochs as well. Figure 5.4 demonstrates the performances obtained for accuracy and loss function, and table 5.5 demonstrates model simulation results. Loss function value obtained during training was 0.0568. Loss function value is 0.1541 for the validation data collected, and 0.12037 for test dataset. And the accuracy value of test dataset is 96.30 percent.

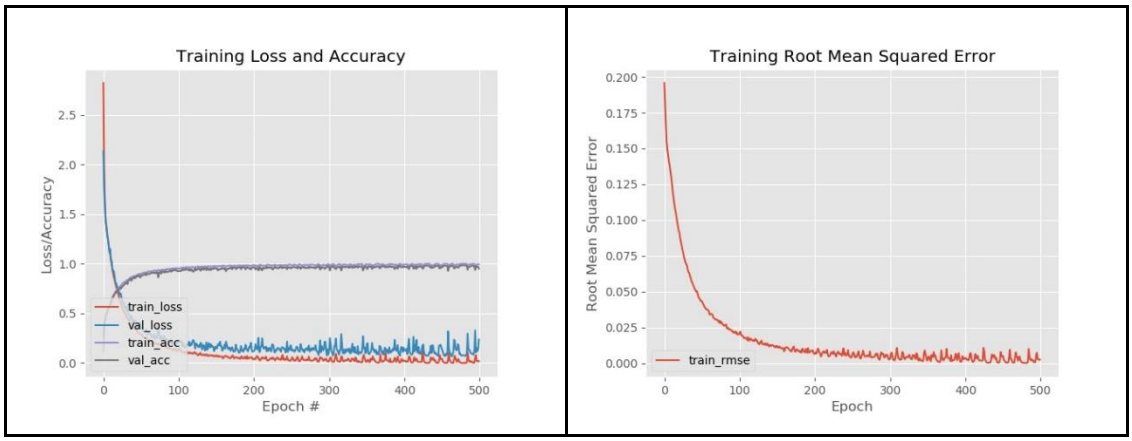

Figure 5.4: HOG plus NN simulation results obtained for loss function, accuracy and RMSE

Table 5.5: HOG plus NN simulation results

Partitions	Loss Function	Accuracy (%)	AUC (%)	RMSR (%)
Training	0.0568	97.92	99.99	0.0098
Validation	0.1541	95.04	99.77	0.0164
Testing	0.12037	96.30	99.63	0.0141

5.3.3 Simulation using HOG plus SVM

In this simulation, by combining the HOG module plus SVM module, a hybrid model is formed for the design of the translation system. But here, the HOG module is utilized for data pre-processing and feature extraction, while the SVM module is used to classify the extracted features into ASL. Table 5.5 and Figure 5.6 depict a classification report and confusion matrix, respectively.

As seen in the results, miss-classification is low leading to high accuracy. The performances in this section were obtained utilizing cross-validation approach as described at simulation phase of the hybrid system. LinearSVC learning algorithm is also utilized in the design of the model. Training of the model is performed using 150 epochs. At test phase, obtained accuracy rate is 99.28% and the error is 0.5981.

Letters	Precision	Recall	F1-score	Support
a	1.00	1.00	1.00	168
b	0.99	1.00	1.00	166
k	0.99	1.00	1.00	163
l	1.00	1.00	1.00	155
m	0.99	0.97	0.98	172
n	0.97	0.96	0.97	147
o	1.00	1.00	1.00	134
p	1.00	1.00	1.00	133
q	1.00	1.00	1.00	157
r	1.00	0.99	1.00	130
s	0.99	1.00	1.00	161
t	0.99	1.00	1.00	147
c	1.00	1.00	1.00	148
u	0.99	0.98	0.98	155
v	0.99	0.95	0.97	147
w	0.96	0.99	0.98	154
x	1.00	0.99	1.00	135
y	1.00	1.00	1.00	136
d	0.97	1.00	0.99	146
e	0.99	1.00	1.00	182
f	1.00	1.00	1.00	135
g	1.00	1.00	1.00	139
h	1.00	1.00	1.00	177
i	0.98	1.00	0.99	139

Figure 5.5: Classification report for HOG plus SVM

```
Labels:    a   b  k   l  m  n  o  p  q  r  s  t  c  u  v  w  x  y  d  e  f  g  h  i
[[168   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0 166   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0 163   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0 155   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0 166   3   0   0   0   0   0   1   0   0   0   0   0   0   1   0   0   0   0   1]
 [  0   0   0   0   0 142   0   0   0   0   1   0   0   1   0   0   0   0   0   1   0   0   0   2]
 [  0   0   0   0   0   0 134   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0 133   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0 157   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0 129   0   0   0   0   0   0   0   0   1   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0 161   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0 147   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0 148   0   0   0   0   0   0   0   0   0   0   0]
 [  0   1   1   0   0   0   0   0   0   0   0   0   0 152   0   0   0   0   1   0   0   0   0   0]
 [  0   0   0   0   1   1   0   0   0   0   0   0   0   0 141   4   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   1 153   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 134   0   1   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 136   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 146   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 182   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 135   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 139   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 177   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 139]]
```

Figure 5.6: Confusion matrix for HOG plus SVM

5.4 Comparative Results of Different Models

Results of performances of some of the highly competitive frameworks used for sign language translation are listed in Table 5.6. Research works that depicted accuracy rate were considered. Simulations were carried out utilizing different dataset selected by the respective researchers. Majority of the researches utilize ASL data, some of them Indian Sign Language data, some-Indonesian Sign Language data. The literature review of these researches is demonstrated in section 1 (introduction).

Table 5.6: Different models comparative results

Authors (year)	**Methods and Dataset**	**Accuracy (%)**
Jalal et al. (2018)	Capsule-Based Deep Neural Network (Kaggle ASL Letter)	99.74
Rastgoo et al. (2018)	Restricted Boltzmann Machine (Massey University Gesture Dataset 2012, etc)	98.13
Lahamy and Lichti (2012)	Real-Time and Rotation-Invariant (Self-generated Dataset)	93.88
Vaitkevičius et al. (2019)	Hidden Markov classification (Self-generated Dataset Using Leap Motion Device)	86.10
Atwood et al. (2012)	Neural network and principal component analysis (Self-generated Dataset Using Matlab Sofware)	96.10
Bheda & Radpour (2017)	deep CNN (Self-generated Dataset)	82.50
Dong et al. (2015)	Microsoft Kinect (Self-generated Dataset)	90.00
Kacper and Urszula (2018)	Snapshot learning (Surrey University and Massey University ASL Dataset)	93.30
Current research	HOG + SVM (Kaggle ASL Fingerspelling)	99.28
Current research	HOG + NN (Kaggle ASL Fingerspelling)	96.30

Current research	CNN (Kaggle ASL Fingerspelling)	92.21
Propose hybrid model	SSD + incept v3 + SVM (Kaggle ASL Fingerspelling)	99.90

In the course of SLT design, we tested the learning technique of several deep structures so as to choose the best model for the task (sign language translation). Some of the tested deep structures include: YOLO, SSD, Inception v3, Faster R-CNN, AlexNet, GoogleNet, ResNet-50, SSD+ResNet-50+SVM, SSD+AlexNet+SVM, SDD+YOLO+SVM and SSD+Inception v3+SVM. The performances of these deep structures are depicted in Table 5.7.

Table 5.7: Other tested deep structures

Methods	**Accuracy (%)**
YOLO	92.83
SDD	95.97
Inception v3	93.68
Faster R-CNN	90.10
AlexNet	86.25
GoogleNet	88.50
ResNet-50	89.36
SSD+Inception v3+SVM	99.90
SSD+YOLO+SVM	94.62
SDD+AlexNet+SVM	90.89
SSD+ResNet-50+SVM	93.19

Extensive comparison of object detection methods is provided in (Liu et al., 2016) as well as (Zhao et al., 2019). From these papers, SSD model achieve higher accuracy as compared to the rest methods. In our investigation, utilizing extraction of feature and classification methods, we designe different models for comparative purposes. These models are based on HOG-SVM, HOG-NN, CNN-fully connected network (FCM), inception V3-SVM. Tables 5.6 and 5.7 include the performances of the models used for translation of ASL. In the proposed SLT, we carry out transfer learning here, we reuse pre-trained SSD with Inception V3 frameworks, and concatenated them to SVM network in order carry out translation on our original data. As shown, SLT (SSD + Inception v3 + SVM) achieve the best result as depicted in Tables 5.6 and 5.7.

Inclusion of SSD for hand detection in the first module makes extraction of the features simpler and faster for the inception v3. The presented model is examined practically and is very effective in translating real-time hand gestures into one of the 24 signs in the American Sign Language. The fragments of experiments about real-time implementation of the propose model are provided in the web pages Https://www.youtube.com/watch?v=FRUvbRRfZMw with Https://www.youtube.com/watch?v=TzwfcW3Ufts. Real-time experiments of SLT are repeated ten times. In each case, the recognition system is run to recognize all the 24 signs presented on-line. The accuracy rate of SLT in real-time experiment was obtained as 96%. As shown in real-time, we got accuracy rate less than the accuracy rate obtained with ASL data set as depicted in Tabls 5.6 and 5.7. This low accuracy is due to inaccurate representation of some signs by the user's hand. This can be corrected by changing hand orientation and clearer representation of signs, after this correction, we got the same result (99.90%) as shown in Tables 5.6 and 5.7. The result obtained depicts high convergence in learning as well as performance. Surely, the comparative results show the effectiveness of SLT over the other systems intended to perform the same task.

CHAPTER 6

CONCLUSION

Analysis of existing research studies on sign language translation based on image processing techniques has shown that these research works are basically using object detection, feature extraction and classification modules. For each module, different algorithms were implemented for solving the stated problems. However, the systems based on these methods have disadvantages related to computation accuracy and speed of the system. In the thesis, sign language translation-based deep structure is proposed.

The proposed system allows the increase of speed and precision of the designed system. The structure of a Sign Language Translation System based on CNNs was proposed. This system uses SSD for object detection, Inception 3 module for extraction of feature, and Support Vector Machine for classification of image. Using integration of SSD, inception V3 and SVM, vision-base American SLT is implemented.

Construction of the model includes training and on-line stages. The hybrid system training is performed utilizing the cross-validation technique and validated using a Monte Carlo estimator. The results obtained from these two experiments show the effectiveness of the cross-validation approach over the Monte Carlo method. The design of the proposed hybrid system is implemented using the ASL fingerspelling dataset. For simulations, using a cross-validation approach, the recorded rate of accuracy is 99.9%, and RMSE is 0.0126.

The major advantage of the model is its simplified structure that seamlessly integrates detection of object, extraction of features as well as classification modules in the body of SLT structure without ambiguities. This designed system could automatically detect hands from camera images and classify the detected object into one of the 24 American Sign Language symbols/sign. This designed model can improve information communication between people, particularly between deaf individuals and people who have some speaking difficulties. The great results of SLT shows the robustness of the three learning techniques combined to form the compact model. But more specifically, in our automated training process, these modules are combined to robustly learn the

features in the given images. Using these modules which were automatically trained, the hybrid SLT was able to detect the associated symbols in the new dataset.

Future directions intended to be implemented includes the training of the hybrid model on real-world sign language literature (text and sentences translations) for deaf TV broadcasts. This can be accomplished by introducing algorithms that track face and hand for computer vision so as to remove vectors from signer's news recordings. Finally, the proposed framework will be built as a mobile app to be used by the affected population.

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APPENDIX 1

SOURCE CODES

- **Dataset Building**

```
# python build_dataset.py

# import the necessary packages
from researchcenter import config
from imutils import paths
import shutil
import os

# loop over the data splits
for split in (config.TRAIN, config.TEST, config.VAL):
  # grab all image paths in the current split
  print("[INFO] processing '{} split'...".format(split))
  p = os.path.sep.join([config.ORIG_INPUT_DATASET, split])
  imagePaths = list(paths.list_images(p))

  # loop over the image paths
  for imagePath in imagePaths:
    # extract class label from the filename
    filename = imagePath.split(os.path.sep)[-1]
    label = config.CLASSES[int(filename.split("_")[0])]

    # construct the path to the output directory
    dirPath = os.path.sep.join([config.BASE_PATH, split, label])

    # if the output directory does not exist, create it
    if not os.path.exists(dirPath):
      os.makedirs(dirPath)

    # construct the path to the output image file and copy it
    p = os.path.sep.join([dirPath, filename])
    shutil.copy2(imagePath, p)
```

- **Feature Extraction**

```
# python extract_features.py

# import the necessary packages
from sklearn.preprocessing import LabelEncoder
```

```
from keras.applications import InceptionV3
from keras.applications import imagenet_utils
from keras.preprocessing.image import img_to_array
from keras.preprocessing.image import load_img
from researchcenter import config
from imutils import paths
import numpy as np
import pickle
import random
import os

# load the InceptionV3 network and initialize the label encoder
print("[INFO] loading network...")
model =InceptionV3(weights="imagenet", include_top=False)
le = None

# loop over the data splits
for split in (config.TRAIN, config.TEST, config.VAL):
  # grab all image paths in the current split
  print("[INFO] processing '{} split'...".format(split))
  p = os.path.sep.join([config.BASE_PATH, split])
  imagePaths = list(paths.list_images(p))

  # randomly shuffle the image paths and then extract the class
  # labels from the file paths
  random.shuffle(imagePaths)
  labels = [p.split(os.path.sep)[-2] for p in imagePaths]

  # if the label encoder is None, create it
  if le is None:
    le = LabelEncoder()
    le.fit(labels)

  # open the output CSV file for writing
  csvPath = os.path.sep.join([config.BASE_CSV_PATH,
    "{}.csv".format(split)])
  csv = open(csvPath, "w")

  # loop over the images in batches
  for (b, i) in enumerate(range(0, len(imagePaths), config.BATCH_SIZE)):
    # extract the batch of images and labels, then initialize the
    # list of actual images that will be passed through the network
    # for feature extraction
    print("[INFO] processing batch {}/{}".format(b + 1,
      int(np.ceil(len(imagePaths) / float(config.BATCH_SIZE)))))
    batchPaths = imagePaths[i:i + config.BATCH_SIZE]
```

```
    batchLabels = le.transform(labels[i:i + config.BATCH_SIZE])
    batchImages = []

    # loop over the images and labels in the current batch
    for imagePath in batchPaths:
      # load the input image using the Keras helper utility
      # while ensuring the image is resized to 299x299 pixels
      image = load_img(imagePath, target_size=(299, 299))
      image = img_to_array(image)

      # preprocess the image by (1) expanding the dimensions and
      # (2) subtracting the mean RGB pixel intensity from the
      # ImageNet dataset
      image = np.expand_dims(image, axis=0)
      image = imagenet_utils.preprocess_input(image)

      # add the image to the batch
      batchImages.append(image)

    # pass the images through the network and use the outputs as
    # our actual features, then reshape the features into a
    # flattened volume
    batchImages = np.vstack(batchImages)
    features = model.predict(batchImages, batch_size=config.BATCH_SIZE)
    features = features.reshape((features.shape[0], 7 * 7 * 512))

    # loop over the class labels and extracted features
    for (label, vec) in zip(batchLabels, features):
      # construct a row that exists of the class label and
      # extracted features
      vec = ",".join([str(v) for v in vec])
      csv.write("{},{}\n".format(label, vec))

  # close the CSV file
  csv.close()

# serialize the label encoder to disk
f = open(config.LE_PATH, "wb")
f.write(pickle.dumps(le))
f.close()
```

- **Training and Classification**

```
# python train.py
```

```
# import the necessary packages
from sklearn.svm_model import LinearSVC
from sklearn.metrics import classification_report
from researchcenter import config
import numpy as np
import pickle
import os

def load_data_split(splitPath):
  # initialize the data and labels
  data = []
  labels = []

  # loop over the rows in the data split file
  for row in open(splitPath):
    # extract the class label and features from the row
    row = row.strip().split(",")
    label = row[0]
    features = np.array(row[1:], dtype="float")

    # update the data and label lists
    data.append(features)
    labels.append(label)

  # convert the data and labels to NumPy arrays
  data = np.array(data)
  labels = np.array(labels)

  # return a tuple of the data and labels
  return (data, labels)

# derive the paths to the training and testing CSV files
trainingPath = os.path.sep.join([config.BASE_CSV_PATH,
  "{}.csv".format(config.TRAIN)])
testingPath = os.path.sep.join([config.BASE_CSV_PATH,
  "{}.csv".format(config.TEST)])

# load the data from disk
print("[INFO] loading data...")
(trainX, trainY) = load_data_split(trainingPath)
(testX, testY) = load_data_split(testingPath)

# load the label encoder from disk
le = pickle.loads(open(config.LE_PATH, "rb").read())

# train the model
```

```
print("[INFO] training model...")
model = LinearSVC(svm="rbf", multi_class="auto")
model.fit(trainX, trainY)

# evaluate the model
print("[INFO] evaluating...")
preds = model.predict(testX)
print(classification_report(testY, preds, target_names=le.classes_))

# serialize the model to disk
print("[INFO] saving model...")
f = open(config.MODEL_PATH, "wb")
f.write(pickle.dumps(model))
f.close()
```

APPENDIX 2

CURRICULUM VITEA

JOHN BUSH IDOKO

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SKILLS

Scientific research, deep learning/machine learning modeling, computer network administration, system analysis, academic counseling, motivational speech

PERSONAL DETAILS

Nationality:	Nigeria
State of Origin:	Benue
Date of Birth:	22/05/1989
Marital Status:	Single
Sex	Male

ACADEMIC QUALIFICATION

2017-2020 Near East University, North Cyprus
- Ph.D. Computer Engineering (First Class)

2015-2017 Near East University, North Cyprus
- M.Sc. Computer Engineering (First Class)

2005-2010 Benue State University Makurdi
- B.Sc. Computer Science (Second Class Division)

1997-2003 Emmanuel Secondary School Ugbokolo
- Senior Secondary School Certificate (S.S.C.E)

ACADEMIC ACHIEVEMENTS

- Reviewer at International Journal of Intelligent Computing and Cybernetics
- Reviewer at International Journal of Advances in Fuzzy Systems
- Reviewer at International Journal of Applied Biochemistry and Biotechnology
- Reviewer at KSII Transactions on Internet and Information Systems
- Reviewer at International Research Journal of Medicine and Medical Sciences (IRJMMS)
- Reviewer at International Journal of Neurology, Neurological Science and Disorders
- Reviewer at International Journal of Annals of Robotics and Automation
- Reviewer at International Journal of Mathematics and Computer Science
- Organizing Committee Member of several international conferences
- Member, International Association of Engineers (IAENG)
- Member, Near East University Center for Applied Artificial Intelligence Research

LIST OF PUBLICATIONS

- Research URL: https://scholar.google.com/citations?user=eVqc6HkAAAAJ&hl=en&oi=ao
- Abiyev, R.; Arslan, M.; Bush Idoko, J.; Sekeroglu, B.; Ilhan, A. Identification of Epileptic EEG Signals Using Convolutional Neural Networks. Appl. Sci. 2020, 10, 4089.
- Abiyev, R. H., Arslan, M., & Idoko, J. B. (2020). Sign Language Translation Using Deep Convolutional Neural Networks. *KSII Transactions on Internet & Information Systems*, *14*(2).
- Idoko, John Bush; Abiyev, Rahib; Arslan, Murat. Impact of machine learning techniques on hand gesture recognition. Journal of Intelligent & Fuzzy Systems. DOI: 10.3233/JIFS-190353, 2019.
- Abiyev, R. H., & Idoko, J. B., Arslan, M. Reconstruction of Convolutional Neural Network for Sign Language Recognition. Proc. of the 2nd International Conference on Electrical, Communication and Computer Engineering (ICECCE). 12-13 June 2020, Istanbul Turkey. IEEE.
- Ikenna, U., Ugochukwu, G.I., Idoko, J.B., and Shaban, I.A. Traffic Warning System for Wildlife Road Crossing Accidents Using Artificial Intelligence. International Conference on Transportation and Development, USA 2020
- Idoko JB, Arslan M, Abiyev R. Fuzzy Neural System Application to Differential Diagnosis of Erythemato-Squamous Diseases. Cyprus J Med Sci 2018; 3: 90-7.
- Idoko John Bush, Rahib Abiyev, Mohammad Ma'aitah Khaheel and Hamit Altiparmak. Integrated Artificial Intelligence Algorithm for Skin Detection. ITM Web of Conferences 16, 02004, 2018.
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- Abdulkader Helwan, Dilber Uzun Ozsahin, Rahib Abiyev, John Bush, One-Year Survival Prediction of Myocardial Infarction. International Journal of Advanced Computer Science and Applications, Vol. 8, No. 6, 2017 173-178.
- Mohammad Khaleel Sallam Ma'aitah, Rahib Abiyev and Idoko John Bush, Intelligent Classification of Liver Disorder using Fuzzy Neural System, International Journal of Advanced Computer Science and Applications, Vol. 8, No. 12, 2017.
- Idoko John Bush, Murat Arslan, Abiyev Rahib. (2019) Intensive Investigation in Differential Diagnosis of Erythemato-Squamous Diseases. ICAFS-2018. DOI: 10.1007/978-3-030-04164-9_21.
- Abdulkader Helwan, John Bush Idoko, Rahib H Abiyev, Machine learning techniques for classification of breast tissue, Procedia Computer Science, 2017, 120:402-410. Elsevier.
- J.B. Idoko, R.H. Abiyev, and M.K. Ma'aitah, Intelligent machine learning algorithms for colour segmentation, WSEAS Transactions on Signal Processing, 2017.
- K. Dimililer, J.B. Idoko, Automated classification of fruits: pawpaw fruit as a case study, International Conference on Man–Machine Interactions, 2017, 365-374.

WORK EXPERIENCE

Near East University ----------Feb, 2016 – Date
Lefkosa-Cyprus
Position: Research Assistant
Responsibilities:

- Courses Lectured: System programing (ECC406), engineering management (ECC427), automata theory (COM344), object-oriented programming (COM210), discrete structures (ECC104), c programming lab (ECC106), data communication and networking lab (ECC303)
- Supervises undergraduate projects/research
- Installation/maintenance of software applications as well as network equipment
- Weekly routine check of systems in the laboratories.

First Bank of Nigeria Ltd ----------Dec, 2012 – Sept, 2015
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Position: IT/Help Desk Support
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- Provided first level Technical and operational Support to branches
- Supervise the activities of outsourced service providers (ISP, CCTV, etc. vendors)
- Installation and Configuration of Western Union Money Transfer (WUMT)/MoneyGram.
- Installation, Configuration and Maintenance of Devices and Network Infrastructures.
- Hardware handling/Service Desk duties and Provision of first-tier ATM support.
- Monitoring and escalation procedures relative to appropriates SLAs.
- LAN Installations in branches and Installation of Banks applications.
- Configuration and IP Address leasing on DHCP Servers, repairs and reset of password on Exchange server.

Government Secondary School ----------Nov, 2011-Oct, 2012
Keffi, Nasarawa State
Position: NYSC (Computer Education/Mathematics Teacher)
Job Description:

- Delivered Computer Education and Mathematics lessons to students.
- NYSC Community Development Service (CDS).

Ace Telecoms International ----------Sept, 2008- July, 2009
Bolton White Apartment, Zone 7-Abuja
Position: Industrial Trainee (Network Optimization Team)
Job Description:

- Site Audit and Optimization
- Antenna Orientation on Towers and Roof Tops without height phobia
- Tilt Adjustment (Mechanical and Electrical) and Adjustment of Azimuth
- Snags and Swap Detection and Correction.

HOBBIES: Travelling, Reading and Football

REFEREE

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Chairman of Automotive Engineering Department
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APPENDIX 3:

ETHICAL APPROVAL REPORT

NEAR EAST UNIVERSITY

ETHICAL APPROVAL DOCUMENT

Date: 18/09/2020

To the Graduate School of Applied Sciences

For the thesis topic entitled “Deep Learning-Based Sign Language Translation System” the researchers declare that they did not collect any data from human/animal or any other subjects. Therefore, this thesis does not need to go through the ethics committee evaluation.

Title: Prof. Dr.

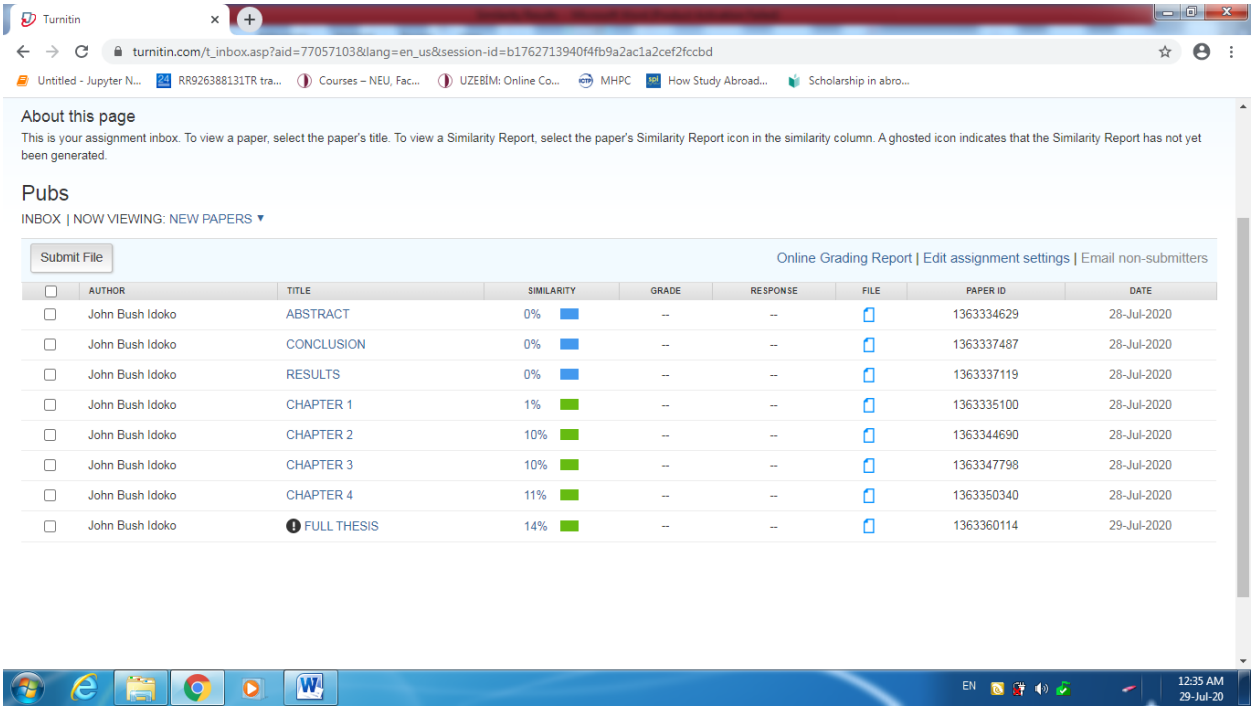
Name Surname: Rahib Abiyev

Signature: 

Role in the Thesis Research: Supervisor

APPENDIX 4

SIMILARITY REPORT



Title: Prof. Dr.

Name Surname: Rahib Abiyev

Signature: 

Role in the Thesis Research: Supervisor