A comprehensive Study on Sign Languages Recognition Systems using (SVM, KNN, CNN and ANN)

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ABSTRACT
The needs of communities and the new emerging technologies aspire researchers to come up with new and innovative ways to fulfil these needs. Sign languages are said to be a visual language that is used by the deaf community. Undoubtedly, there is a communication difficulty between the hearing-impaired people and the hearing community. To overcome this impediment between the two communities, various approaches were conducted to develop sign language recognition systems. An evaluation between some of these recent technologies is crucial to compare their methodologies and accuracy of their results. Therefore, this paper provides a comprehensive study on the different approaches and techniques used to develop a sign language study. On systems that were developed based on support vector machine (SVM), K-nearest neighbours (KNN) classifier, deep convolutional neural networks (CNN) and artificial neural networks (ANN).

KEYWORD
Sign language recognition; machine learning; Support Vector Machine (SVM); K-Nearest Neighbour (KNN); Artificial Neural Network (ANN); Convolutional Neural Network (CNN).

1. INTRODUCTION
Considering the current period as the technology era, it is important now more than ever to exploit the use of these innovative technologies to enhance the human life. Especially for people who have hearing disabilities, as they have a hard time interacting with the hearing people. In order for them to communicate they use sign language which not all people can easily understand and contrary to the popular belief, sign language is not a universal language [1]. As in every country a specific and different kind of sign language is used based on the spoken language of that country. In America, the American Sign Language is considered the 3rd language mostly used in the USA [2]. The ASL is mainly used in the United States of America, Canada and in several countries, such as parts of West Africa and Southeast Asia [3]. According to some statistics conducted in 2006 the number of people speaking ASL ranges from 250,000 to 500,000 [4].

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Another research showed that in 2016 the number of hearing-impaired people is approximately 2.8 Million in India [5]. According to the Turkey ministry of National Education, the number of hearing- impaired people is about 400,000 [3]. Sign languages are growing in every other country with each having their own grammar and rules. Nowadays, many researchers try to design and develop interactive systems between human and machine with the help of the new emerging technologies. In the late 90s dealing with automatic sign language recognition systems started in different languages which is very crucial to develop a human-machine interaction system to benefit many people. Previously, the initial works started via electromechanical devices for gesture recognition to affect the signing capabilities of the person [4]. Another work dealt with utilizing coloured gloves providing colour segmentation and extract features to distinguish the signs [4]. Lately, with the constant evolvement there is no need of using any electromechanical devices or even use gloves to develop such a system. As over the past two decades interest in machine learning has boomed. Machine learning can be defined as "Algorithms that parse data, learn from that data, and then apply what they've learned to make informed decisions" [6]. Nowadays, various applications use great amount of data and with this ever-increasing amount of data, automatic techniques are required for smart analysis date. Such analysis can be made with the help of machine learning as it can detect, predict and/or make decisions upon the data [3]. A simple way to understand how a machine learning algorithm works is the example of on-demand music playing service. Here the service needs to decide which next song to recommend or singer according to the listener's preferences. The machine learning algorithm associate these preferences with other subscribers who listen to similar music. Therefore, for a service or a system to be able to perform machine learning, it indicates that it is doing a task with the data provided to it and gets better gradually at that task [6]. Commonly, sign languages recognition systems have three fundamental phases as follows [3]:

1. First Step: Image Pre-processing.
2. Second Step: Tracking.
3. Third Step: Recognition.

The main challenges Sign language recognition faces are: feature extraction of fixed finger position, alteration due to different hand sizes, and fractional occlusion of the hand [7]. While the challenges that can be faced in CNN for sign languages recognition possibly are video trimming and classifying of signs. It can also be sign video background modelling, sign feature depiction and sign extraction [9].
The contribution of this paper can be briefly explained in 1) an overview of four different approaches to develop a sign language recognition system. 2) a brief introduction to the different approaches that are: Support Vector Machine (SVM) [5], K-Nearest Neighbour classifier [7], Deep convolutional

Neural Network (CNN) [9], and Artificial neural networks [3] and [10]. 3) an overview of the results of each approach and how successful each were. 4) a comparison between their methodologies and results. The rest of the paper is arranged as: Section 2 explains the related works that this paper is based on. Section 3 presents the implementation of each approach. Section 4 presents the results and comparisons. Finally, Section 5 is discussing results and concluding the paper.

2. LITERATURE REVIEW

Nowadays, many researchers attempt to extract the complex and constant changing head and hand movements as much accurate as possible. Since it is considered a problematic issue in computer vision as these recognition attempts are done for the sake of developing sign language recognition systems among many other systems. Nevertheless, there are a variety of different techniques that have been developed for hand recognition to develop sign language recognition systems. This section is dedicated to review some of the similar literature and previous techniques to accomplish such a system. Some of those proposed approaches are computer vision-based that incorporate soft computing techniques, others are gloves-based techniques. Some can be classified as sensor based and vision-based systems. All these techniques prove to be efficient and beneficial for the deaf people. In [5] an Indian Sign Language system was developed based on dynamic hand gesture recognition in real-time. The implementation was done by converting the video to HSV colour space for pre-processing after that according to skin pixels, segmentation was done. To obtain more precise results, depth information was utilized in parallel. Furthermore, the extraction of Hu moments and motion trajectory were done from the image frames and then the classification was performed by SVM. The evaluation of their results proved to be (97.5%) exact (out of 80, 78 were classified accurately) for four designated signs of the Indian Sign Language. Another study [7] was implemented a system for American sign language with a finger-spelling recognition method using KNN classifier. When the pattern was denoted by full dimensional characteristics it showed a high percentage (99.8%) for k=3 and their results showed that the KNN classifier is more appropriate for a basic education application for kids to learn the ASL alphabet finger-spelling. In [9] another Indian Sign Language gesture recognition was proposed by exploiting a specific type of artificial intelligence, CNN. The authors of this paper initiated the creation of the first dataset for mobile selfie sign language with 5 various subjects executing 200 signs in different angles with also different background settings. They did the CNN training with 3 samples of different sizes that were of many subject sets and multiple angle views. The other 2 samples were for testing the trained data. They tested their data set on different architectures of CNN to ensure better results. Compared to other classification models tested on that same data set, they obtained a result of 92.88% accuracy of the recognition rate. Another related study that was done for a MSc dissertation [10] and was published [3] was more of a combination of a comparison study and developing a universal sign language recognition system. Where the comparison was done based on a system that was developed based on Hausdorff distance and another based on ANN. Both sign language recognition systems that were proposed in this study were for American, British, and Turkish sign languages. The first system was developed by using feed forward neural network structure and recognition of training the dataset of each sign language using MATLAB. The second system was implemented based on Hausdorff distance algorithm and Hu invariants as the focus of this approach was how to process the different movements of the hand and to recognize the different letters also OpenCV libraries were utilized. The results that were found in this work indicated that the first approach with the use of ANN was higher as it gave 93.4% success rate for the three sign languages while the second one's success rate was 90.9%.

3. MACHINE LEARNING

It is stated that the data that is being observed can be rationalized through a process [11]. Even if the details are not clear of the process for generating the data. As an example; customer behaviour; it is evident that the way they go and buy things are not random and do not choose the items randomly. It can be observed there is a pattern in the items they choose if it is summer they go for cold drinks and ice-cream unlike during winter. However, the entire process might not be explained completely but a good and meaningful estimation can be constructed. This approximation will perceive specific patterns or some consistencies for the data. This is where the function of machine learning come into work and through these patterns predications can be possible. Machine learning has an abundant application area as in science, telecommunication. . . etc. For example; in finance banks, it is important for analysing their old data, so they can create models for fraud detection, stock market.... etc. In industry to learn their models is crucial where optimization and control are necessary features. Nevertheless, machine learning cannot be considered only for database issues. It can also be considered as part of Artificial Intelligence as for systems to be intelligent in a changing surrounding it should have learning capabilities. The advantage of this learning is that the system itself learns and adapts to the various changes, hence there won't be any need for the designer to consider different solutions for all the possible conditions and events. Additionally, machine learning enables the discovery of solutions to numerous problems in areas like vision/speech recognition as well as robotics. Humans can easily and unconsciously recognize a face or a shape even without knowing the underlying process of how the human brain can do this task. However, what is known is that a face image does not consist of random pixels but consists of the structure of the face since it is symmetrical, and the locations of each component is known. The pattern of the combination of the human face is known and analysing a sample of a human face is possible. Therefore, a learning program can capture the pattern particular to that individual and recognize it by checking that exact pattern in an image. Examples of Machine Learning Applications can be learning associations, classification, regression, unsupervised learning, reinforcement learning [11].

3.1 Support Vector Machine

SVM is a discriminative classifier formally and one of the supervised machine learning techniques that produces output from a set of categorized training data [12]. The SVM is a member of the kernel methods and it is used for classification or regression, See figure 1.

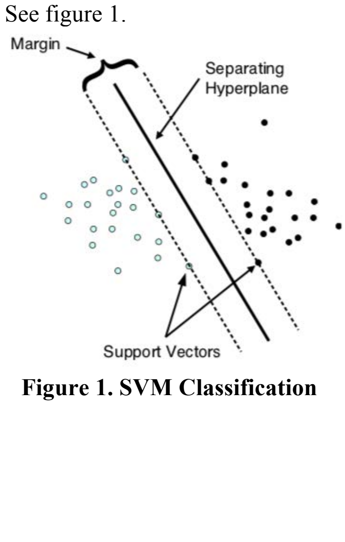

Figure 1. SVM Classification

SVM is built on the idea of decision lines that define decision boundaries. A decision line is used to separates among a group of inputs having different class members. To make the data more separable for classification purposes, if it is compared to the input data a transformation is done to convert it to a higher dimension. Furthermore, the output is generated by depending on the boundaries as well as in regression it disregards any data which is not close to the wanted prediction. SVM is used in many applications in different areas like face recognition, bioinformatics and image processing [12].

3.2 K-Nearest Neighbour

One of the simplest algorithms of machine learning is k-nearest neighbour (KNN) [13]. The nearest neighbour is a non-parametric method used in data classification. It aims to classify how approximately a data point belongs to one class or another depending on what the set of data points closest to it are in. after that it gets a set of points in space and then considers two similar points to be the distance between them in that space in some proper metrics. Then the algorithm works by deciding which of those points of the training set are more alike to be taken into consideration while selecting the class for predicting a new observation is by picking the k nearest data points to that observation and to give the most communal class amongst the classes. Thus, a positive integer is set for k, beside a new sample and then the k entries are chosen in the database that are nearest to the new sample. Then the most common classification among them is found. Finally, this will be the classification that will be given to the new sample [13]. Figure 2 shows example of using the majority votes in kNN to determine the classes in the data set.

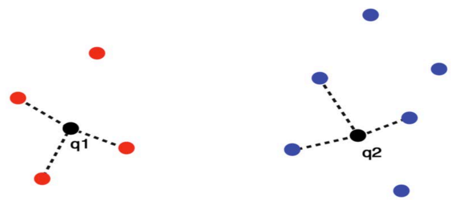

Figure 1. KNN illustrates

3.3 Convolutional Neural Network

Convolutional Neural Networks is a class of deep learning which is mostly used for classifying images, clustering the images by their resemblance as well as executing recognition of objects within the views [14]. CNN consists of neurons that are self-optimized by learning. The architecture of CNN consists of three layers and they are; convolutional layer, pooling layer and fully-connected layer as seen in figure 3.

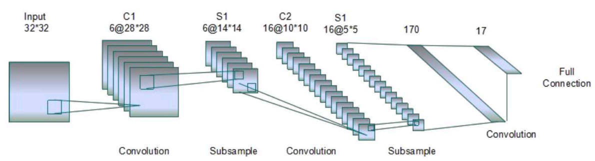

Figure 3. Architecture of CNN

The CNN algorithms have two key processes; they are convolution and sampling. The first process a filter that can be trained is used on the input image and it is convolved and it is a feature image of each layer that is called feature map and then a bias is added to it; this happens in the convolutional layer. This convolutional layer defines the output of neurons that are connected to local regions of the input by calculating the production between their weights and the region connected to the input volume. The rectified linear unit (ReLu) performs an elementwise activation function to the output that is produced by the preceding layer. The pooling layer where the sampling process happens. The fully-connected layer tries to create the class scores from the activations that then can be used for classification [14].

3.4 Artificial Neural Network

One of the common algorithms of machine learning is ANN which has the power to recognize patterns. The ANN is inspired from the biological nervous system of human brain, ANN is built on nerve cells that calls neurons and all these neurons are connected which start from the input neurons until output [15]. These neurons are connected to each other by direct connections, synapses, related to their weights. These weights are used by ANN as they are a form of information. Furthermore, the basic architecture of the system consists of the input layer where an input is loaded onto it as a multidimensional vector, and this will be delivered to the hidden layer and then there is the output layer. The hidden layer is where the decision of recognition happens also if there are multiple hidden layers then it is referred to deep learning [15]. The power of ANN is that it is used for generalizing problems, the system gets the data and train on a set of patterns [3]. This training will continue till finding the right weight values which adjusts the patterns and the system will learn the features of these patterns.

4. IMPLEMENTATIONS OF THE FOUR SL RECOGNITION SYSTEMS

The implementation of each approach is briefly explained in this section:

4.1 Indian Sign Language Recognition using SVM

The implementation of a sign language recognition system using SVM, in [5] the authors followed the below steps that are explained briefly. It is known that SVM cannot handle unlabelled data directly that's why the authors designed the system starting with converting the images to binary and this made SVM handle the unlabelled data.

a) Taking Binary Image: The system need the images to be binary which it controls basic calculation of required features. so that starting with converting the captured video to binary image. The captured video frame is converted into HSV color space, while the hue factor is different from HSV image because of the hue of the skin is unlike from background image. And then applying on calculated of hue value an experimental threshold see figure below which equals to 0.1. the captured video has many objects therefore these will cause noises in converted image, but it will be removed and the selecting the largest linked region.

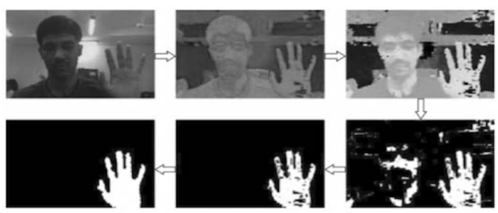

Figure 4. Image pre-processing [5]

b) Feature Extraction: The system is verified for 4 signs with 30 frames. To identify objects in video frame, the figure 4 shows the process of the system. and there are many features were used: Hu moments: The invariant moments are location, shape and angle. For the system only two of hu moments are enough because the tests show that other hu moments are not affected that much on the gesture. Fingertips: can be calculated using many different algorithms like colour based, k-means. But in this system, a spatial domain method was used for detecting the fingers. The steps of the method are: 1- take the binary hand image as centre of circular filter. 2- Calculate the radius. 3- Make new circular filter by taking centre and radius. 4- Remove the wrist of hand if it still there. 5- The results just show fingers as binary images

Trajectory tracking: the next step is extracting the path of the hand the trajectory of hand must be tracked to avoid obstruction between the objects and the hand. This tracking is done by mean shift or Kalman tracking filter.

c) Classification Using SVM: The system used 30 frames and the feature vector after its extracted to classify it multi class SVM linear classifier applied. The dataset comprised of 4 signs that are A, B, C and a word "hello". As well as the length of the signs are fixed to avoid mismatching between the feature vector and testing.

4.2 American Sign Language-Based Finger-spelling Recognition using k-Nearest Neighbours Classifier

The methodology behind the American Sign Language- Based Finger-spelling Recognition system [7] is summarized below; For training a subclass of the dataset that was published one by [8]. They used the motion sensor Microsoft Kinect sensor for capturing the hand and to detect and track the hand of the user the OpenNi+Nite framework were used. As in Kinetic sensor two kinds of images are obtained in this study they have only used colour images for plainness to train the dataset. Their training dataset consists of colour images of hand shape colour taken by Kinect that was placed in front of the user's hand. Which included 5.254 samples of ten ASL finger-spelling alphabets as it can be seen in figure 5 below.

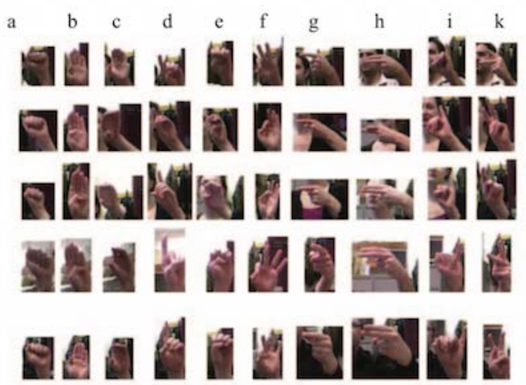

Figure 5. Samples of signs of ASL [7]

After that, the feature extraction step was done and for fast recognition their image patterns were denoted by normalized colour histogram. Hence, each colour channel of RGB were of a 16-bin histogram and these were combined to produce a 48-dimensional vector as it can be seen in figure 6.

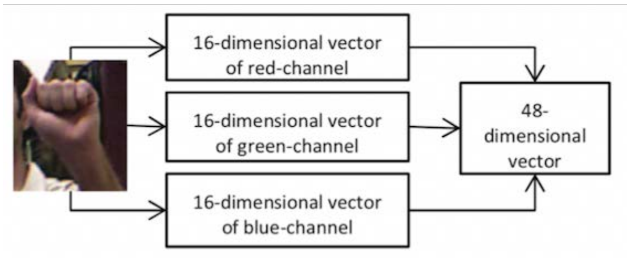

Figure 6. Feature Extraction of the hand [7]

Next, they had to reduce data dimension so Principal Component Analysis (PCA) was used. These Principal components then were chosen based on their Eigenvalues those that were reflecting the variability of the original dataset. In this study, the quantity of principal components used were less than or equal to the quantity of original dimension. Last part of their implementation was using KNN as their classifier for their system. They assumed the 48-dimensional vectors to represent image and be set as x and y to be a categorical variable for each image sample and its value depending on x. Furthermore, they assumed a scalar function which made up an ASL alphabet class. Their dataset was set as T and supposed a hidden data as u. with the use of KNN which basically identifies k samples in a training set that have their variables x closer to u and then using the rule of majority decision in order to categorize that hidden data u. in this study, the Euclidean distance was used to measure the likeness between x and u. Additionally, in KNN choosing the value for k can be quite difficult thus, in this work, they have tried different values for k.

4.3 Deep Convolutional Neural Networks for Sign Language Recognition

In [9] the architecture they proposed for their model consisted of an input layer as seen in figure 7, this architecture 4 convolutional layers of different sizes [16x16, 9x9, 5x5 and 5x5] are used for the window, followed by 5 activation functions (ReLu). Two stochastic pooling layers were used for feature representation in order not to lose important feature information, they found stochastic pooling to be suitable for their work after testing two other types of pooling as mean and max pooling. Their classification phase consisted of fully connected layers which also were followed by activation function of SoftMax.

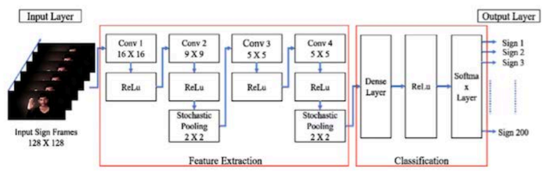

Figure 7. Designed Deep CNN Architecture [9]

The size of the input video frames to their system was 640x480 the first step was to pre-process the input video frames into 128:128x3 by resizing them. The output of this step would have more computational ability as it helped in the training part of CNN which used high performance computing. The total dataset is 5000 signs for 200 signs and done by five Indian sign language users with five different angles of view, with 60 frames per second. The activation functions were used to recognize the input video frames accurately in order to know the feature representation learned by their proposed CNN system.

4.4 Real-Time Sign Languages Recognition based on Hausdorff distance, Hu invariants and Neural Network

In [3] artificial neural network was used for their second approach. The architecture was based on feed forward algorithm consisted of two layers with principal component analysis been applied. To train the dataset the author used 10 samples of each letter a total of 810 samples for the designated three sign languages. For training a sample of the image was taken then it was cropped then scaling and improvements were done on the image's contrast and then the sample was changed to binary. The trained samples were put into a single column vector. Additionally, two user interfaces were developed one for training and one for recognition so that the user can train the system. The first UI, trainer UI, worked by first starting video stream and then generating an object from the recorded video and turn the frame grey from RGB frame. After that, it saves the images as data vector and then it goes to the training part where it is done by feed forward algorithm as mentioned earlier and save the trained results for recognition purposes in the latter UI which is the tester UI. In the tester UI, the trained dataset was loaded then the camera would track the hand [10]. This process can be seen in a flow chart below in figure 8. Moreover, using multi-layer propagation feed-forward algorithm the recognition phase starts and then the letter is predicted.

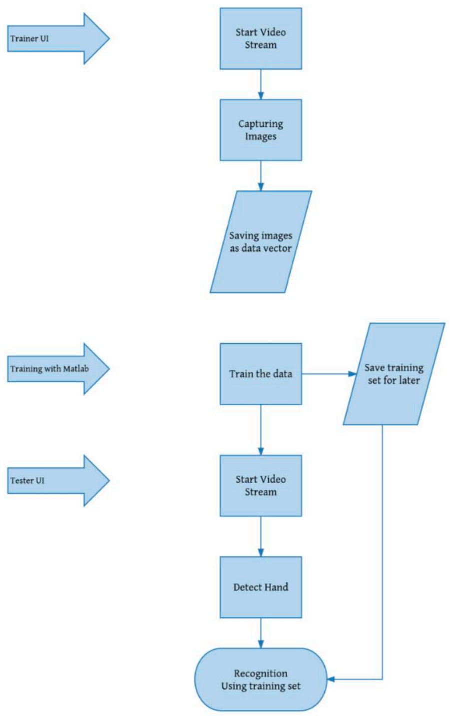

Figure 8. Flow chart of the designed ANN [10].

5. RESULTS & CONCLUSION

In conclusion, Sign language is the only communication way between deaf people as well as with the hearing communities. SL is different from one country to another as mentioned before. This paper has discussed four different approaches and works; Support Vector Machine (SVM), k-Nearest Neighbour classifier, Deep convolutional Neural Network (CNN), and Artificial neural networks (ANN) for implementing a sign language recognition system. The works were on recognizing different sign languages as Indian, American, British and Turkish sign languages. The implementation of these approaches was briefly discussed and the difference between them were illustrated. As well as the paper shows the main advantages and disadvantages of implemented approaches that were compared with other works. The results provided exhibits that there is no best choice for such a system using machine learning approaches because it depends on the requirements of the system needed to design.

Using different datasets and sign languages can change the results and performance of different algorithms in this section the light is shed on the advantages and disadvantages with the results for the aforementioned methods which is illustrated in table 1.

Table 1. Comparison between the different approaches and algorithms for detecting different Sign Languages

The proposed method	Success rate	The sign language	The signs	The work compared with	Mentioned advantages	Mentioned disadvantages
SVM	97.5%	Indian sign languages	"A","B","C" and "hello"	NA		Just 2 of 7 Hu moments used
KNN	99.8%	American sign language	Results just shows A B C D E F G H I J K	[16]	- k-NN is often categorized as a "lazy learning"	- hard to find covariance matrix - simplest invariance could not be captured - interpreting the results of dimension reduction analysis
CNN	92.8%	Indian sign languages	200 signs as mentioned contains words and letters	[17] [18] [19] [20]	Used 3 sets for training 2 for testing	The results were limited to 46 signs among 200.
ANN	95.2%	American sign language	A B C D E F G H I J K L M N O P Q R S T U V W X Y Z	[21]:84% [22]:91.7% [23]:90.1% [24]:94% [25]:92.85 [26]:60%	In Hausdorff X, Z did not work well	
	90.3%	British sign language	A B C D E F G H I J K L M N O P Q R S T U V W X Y Z		Better than Hausdorff due to conflicts in (A and Z), (E, O, S and U), (L, M, N, R and V).	
	94.6%	Turkish sign language	A B C D E F G H I J K L M N O P R S T U V Y Z		Better than Hausdorff due to conflicts in (A-H) and (U-V-Y)	Does not include: Ç Ğ İ Ö Ş Ü

As shown in table 1, even a simple algorithm like KNN can recognise symbols of a small sample accurately. However, this small sample cannot easily be scaled up to a larger and more practical sample without sacrificing a lot of efficiency and accuracy of the trained algorithm. Although the SVM uses a simple set of alphabets and a single word, its accuracy scored worse than KNN, this might be due to the underlying used data-set as they tried to use unlabelled data to train the system. While using methods of ANN and CNN, the success rate has slightly dropped but, on the other hand, in [9] and [10] more extensive and realistic sets of signs were used. Hence larger data sets with a much harder task to start with. Moreover, using deep neural networks eliminates the need of Hausdorff distance which might cause some conflicts between the letters [10]. These conflicts decrease the ability of the model to identify characters successfully.

The main advantages of the SVM is that it is suitable for using it on data that are labelled, works fine with different types of data like images or texts, the ability to solve complex problems by having a strong kernel trick, has fewer overfitting risks. While the disadvantages of SVM are that choosing a good function is hard, and it take extended periods of time for training [5]. KNN is often considered as a “lazy learning” classifier as it accepts calculation until it receives a request to classify an unlabelled data [7]. This characteristic makes it adaptive to new dataset. Nevertheless, k-NN creates high computation because it reruns the computation for all dataset for each new unseen data. The main advantages of the KNN is its simplicity which makes it, is easy implementation. Designing models is inexpensive, flexible categorization, suitable for several modal classes as well as with numerous class labels. Whilst the shortcomings for this technique are that it is expensive for classifying unidentified data, the precision can be affected with the noise or unrelated features.CNN the advantages are; it is faster and better to recognize texts but the drawback for CNN is the difficulty to determine the window size [9]. In ANN [3], these conflicted letters in the test occurred due to the converted image to foreground mask in Hausdorff distance and seem like the rest as it is in black and white. While this problem does not happen in the neural network technique as it is using RGB. The advantages of ANN are that it performs tasks that linear programs cannot solve, if any element fails, the system continues. ANN learns, no need to reprograming and it can be implemented in any application. Whereas, the disadvantage is it needs time for training as well as the need for extended periods of time for processing in large applications.

6. References

[1] L. Pigou, S. Dieleman, P. Kindermans and B. Schrauwen, ”Sign Language Recognition using Convolutional Neural Networks”, 2015.

[2] R. Mitchell, T. Young, B. Bachleda and M. Karchmer, ”How Many People Use ASL in the United States? Why Estimates Need Updating”, Sign Language Studies, vol. 6, no. 3, pp. 306-335, 2006.

[3] S. Ozbay and M. Safar, ”Real-time sign languages recognition based on hausdorff distance, Hu invariants and neural network”, 2017 International Conference on Engineering and Technology (ICET), 2017.

[4] P. Mekala, Y. Gao, J. Fan and A. Davari, ”Real-time sign language recognition based on neural network architecture”, 2011 IEEE 43rd Southeastern Symposium on System Theory, 2011.

[5] J. Raheja, A. Mishra and A. Chaudhary, ”Indian sign language recognition using SVM”, Pattern Recognition and Image Analysis, vol. 26, no. 2, pp. 434-441, 2016.

[6] B. Grossfeld, ”A simple way to understand machine learning vs deep learning - Zendesk”, Zendesk, 2017. [Online]. Available: https://www.zendesk.com/blog/machine-learning-and-deep-learning/. [Accessed: 26- May- 2018].

[7] D. Aryanie and Y. Heryadi, ”American sign language-based finger- spelling recognition using k-Nearest Neighbors classifier”, 2015 3rd International Conference on Information and Communication Technology (ICoICT), 2015.

[8] Pugeault, N., and Bowden, R. “Spelling It Out: Real-Time ASL Fingerspelling Recognition,” In Proceedings of the 1st IEEE Workshop on Consumer Depth Cameras for Computer Vision, jointly with ICCV’2011, 2011.

[9] G. Rao, K. Syamala, P. Kishore and A. Sastry, ”Deep convolutional neural networks for sign language recognition”, 2018 Conference on Signal Processing And Communication Engineering Systems (SPACES), 2018.

[10] M. SAFAR, ”REAL-TIME SIGN LANGUAGES RECOGNITION BY ARTIFICIAL NEURAL NETWORKS”, M. Sc. Thesis in Electrical and Electronics Engineering, UNIVERSITY OF GAZIANTEP, 2017.

[11] E. Alpaydin, Introduction to Machine learning, 2nd ed. London, England: The MIT Press Cambridge, Massachusetts.

[12] L. Wang, Support Vector Machines: Theory and Applications. Berlin Heidelberg: Springer-Verlag., 2005.

[13] O. Sutton, ”Introduction to k Nearest Neighbour Classification and Condensed Nearest Neighbour Data Reduction”, 2012.

[14] T.Liu,S.Fang,Y.Zhao,P.Wang,J.Zhang,Implementationof Training Convolutional Neural Networks, 2015.

[15] K.TeiloO’SheaandR.Nash,”AnIntroductiontoConvolutionalNeural Networks”, 2015.

[16] Pugeault, N., and Bowden, R. “Spelling It Out: Real-Time ASL Fingerspelling Recognition,” In Proceedings of the 1st IEEE Workshop on Consumer Depth Cameras for Computer Vision, jointly with ICCV’2011, 2011.

[17] G Ananth Rao and PVV Kishore. “Sign language recognition system simulated for video captured with smart phone front camera”. International Journal of Electrical and Computer Engineering, 6(5):2176, 2016.

[18] G Anantha Rao, PVV Kishore, D Anil Kumar, and ASCS Sastry. “Neural network classifier for continuous sign language recognition with selfie video”. Far East Journal of Electronics and Communications, 17(1):49, 2017.

[19] KVV Kumar, PVV Kishore, and D Anil Kumar. “Indian classical dance classification with adaboost multiclass classifier on multifeature fusion”. Mathematical Problems in Engineering, 2017, 2017.

[20] G Ananth Rao and PVV Kishore. “Selfie video based continuous Indian sign language recognition system”. Ain Shams Engineering Journal, 2017.

[21] S. Dogic, G. Karli, ”Sign language recognition using neural networks”, TEM Journal, vol. 3, no. 4, pp. 296-301, 2014.

[22] L. Pigou, S. Dieleman, P. Kindermans and B. Schrauwen, ”Sign Language Recognition Using Convolutional Neural Networks”, Computer Vision - ECCV 2014 Workshops, pp. 572-578, 2015.

[23] J. R. Pansare, S. H. Gawande, M. Ingle, ”Real-time static hand gesture recognition for American Sign Language (ASL) in complex background”, Journal of Signal and Information Processing, vol. 3, pp. 364-367, 2012.

[24] L. Vargas, L. Barba, C. Torres and L. Mattos, ”Sign Language Recognition System using Neural Network for Digital Hardware Implementation”, 2011.

[25] M. Paulraj, S. Yaacob, M. bin Zanar Azalan and R. Palaniappan, ”A phoneme based sign language recognition system using skin color segmentation - IEEE Conference Publication”, Ieeexplore.ieee.org, 2010. [Online]. Available: http://ieeexplore.ieee.org/document/5545253/. [Accessed: 13- Dec- 2017].

[26] D. Sharma, R. Giri and S. Taunk, ”Static Gesture Recognition of Devnagari Sign Language using Feed-Forward Neural Network”, Ijarcet.org, 2014.