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***Abstract*—The sign language, considered as the main language for deaf and hard of hearing, uses manual communication and body language to convey expressions and plays a major role in developing an identity. Nowadays, sign language recognition is an emerging field of research to improve interaction with the deaf community. The automatic recognition of American, British, and French sign languages with high accuracy has been reported in the literature. Even though, Bangla is one of the mostly spoken languages in the world, no significant research on Bangla sign language recognition can be found in the literature. The main reason for this lagging might be due to the unavailability of a Bangla sign language dataset. In this study, we have presented a large dataset of Bangla sign language consisting of both alphabets and numerals. The dataset was composed of 7052 samples representing 10 numerals and 23864 samples correspond to the 35 basic characters of the alphabet. Finally, the performance of a convolutional neural network in the recognition of numerals and alphabet separately, and in mixing of them, has been evaluated on the developed dataset using 10-fold cross-validation. The proposed method provided an average recognition accuracy of 99.83%, 100%, and 99.80%, respectively for basic characters, numerals, and for their combined usage.**

***Index Terms*—Bangla sign language, convolutional neural network, recognition, dataset**

I. Introduction

Language is the way of human communication, either spoken, written or symbolic, consisting of the use of words or signs in a structured and conventional way. People use language to communicate with each other. In our society, some people are unfortunately impaired due to the limitations to their speaking and listening capabilities. As they impossibilitated or limited in using spoken languages, they have to use special signs to communicate and to express their feelings. According to the definition of sign language found in the English dictionary "Sign language is a system of hand and body movements representing words, used by and to people who cannot hear or talk".

Sing language is the basic way of communicating between listening and hearing impaired people using hand and symbolic gesture instead of sound or spoken language, while the general people do not use it. It is very hard for the general people to communicate with the speaking and listening impaired people because the sign language is not understandable for them.

Sign language has no international form. Interestingly, the American and British sign languages (BSL) are not same, even though English is the spoken languages of both countries. Some other sign languages are Banglai sign language (BdSL), Japanese sign language (JSL), and Indian sign language, Frence sign language, etc. All of the sign languages have been originated independently and dissimilar. In modern society, people are trying to develop the lifestyle of the hearing impaired community by providing alternative ways for communication, education, cultural and sports. These people possess in fact some extraordinary talent. The automatic recognition of sign language (ARSL) can play a vital role to establish instant communication between a normal and a hearing impaired individual. Besides this, since sign language has no international form, the ARSL can act implicitly as an instant interface between speaking or listening impaired people and general people of different languages if it is combined with an appropriate language translator. Thus, today's researchers of natural language processing and artificial intelligence, are trying to develop an automatic recognition system for sign language. The advancement of automatic recognition of some sign languages such as ASL, BSL, and JSL has been performed with high accuracy (more than 99%) [19].

Bangla is the sixth mostly spoken language in the World and an official language of Bangladesh [10]. It is also the spoken language of some states of India. About 2.4 million deaf people live in Bangladesh [24]. However, the research on BdSL recognition did not progress compared to other sign

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languages [4], [7], [23]. Recently, a few research works on the recognition of BdSL have been reported in the literature [2], [18], [21].

Md. Uddin *et al.,* [21] proposed a framework using Support Vector Machine (SVM) to recognize BdSL. They used the RGB image and Gabor filters which produced a high dimensional feature vector. Then, kernel principal component analysis (PCA) technique was used to reduce the dimensionality. Finally, SVM was used for classification of candidate features. They obtained 97.7% accuracy for recognition of BdSL from 4800 images. Rahman *et al.,* [18] provided a system for BdSL recognition from video. In their system, the hue and saturation values from human skin color were considered to represent hand sign. Hence after the normalization, it converts binary image and a K-nearest neighbors (KNN) classifier was used for recognition. The system achieved an average recognition accuracy of 96.46% from 7200 images.

Neural network is another method to recognize sign languages. The procedure proposed in [24] provided a system that uses linear discriminant analyzer (LDA) and artificial neural network (ANN) to recognize the two-handed hand gesture recognition for BdSL. Ayshee *et al.* [2] proposed a hand gesture recognition system for Bangla characters based on fuzzy rules. The system can operate as an interpreter among the BdSL and the spoken language. Karmokar *et al.* [11] proposed a BdSL recognizer (BdSLR), which adopts inputs of BdSL by webcam and performs identification by neural network ensemble (NNE). Thus, the works found in the literature on BdSL recognition used either shallow neural network, SVM or LDA.

To the best of our knowledge, nobody in the literature has reported the use of deep neural network on a large dataset, even though they (e.g. convolutional neural network) [6], [15] have been used for pattern recognition, computer vision, and image processing with more accuracy than that reported using traditional shallow neural network or support vector machines. One major advantage of convolutional neural network (CNN) is that the training of CNN does not depend on manual feature extraction. It extracts itself high intensity features with more details and provides often better performance than traditional shallow neural network.

Although, some researchers recently have started to work on BdSL recognition and reported good accuracy. However, the research on BdSL recognition did not progress as compared to other sign languages. In our opinion, this is also due to the lack of publicly available, reliable, and large datasets. The objective of this study was i) to collect a large set of the alphabet of BdSL, ii) to observe the performance of a CNN on the developed data, and iii) to improve the performance of BdSLrecognition to human acceptance level.

II. Dataset

In this paper, we have developed a BdSL dataset of 30916 samples (basic characters: 23864 and numerals: 7052). The dataset was collected from 25 students of age 18-26 years (all are boys), who suffer from speaking or hearing disabilities. To collect the data, they were trained by the trainer/teacher of Sweet Dream School (i.e., a school for teaching deaf and dumb) at Kushtia, Bangladesh. The signs are collected from the posters which are derived from the "BdSL dictionary", released by the ministry of social welfare of the people's republic of Bangladesh and Bangladesh national federation of the deaf in 1994. The images of hand gestures (signs) were collected using a NIKON D3200 professional camera. The volunteers were informed about the purpose of collecting the dataset, and written consent was taken before collecting the data. All images were stored as 256 color level in a SD memory card. A few samples from the database are shown in Fig. 1.

Fig. 1. **10 numerals (or digits) and 35 characters of Bangla sign language are shown in this figure. The first 10 images (from left to right) represented in the top two rows of the figure are samples of 10 numerals of the number system of BdSl, and the remaining 35 images correspond to the characters of the BdSL alphabet.**

III. Proposed Method

The major steps involved in the proposed method for BdSL recognition have been summarized by the block diagram in Fig. 2.

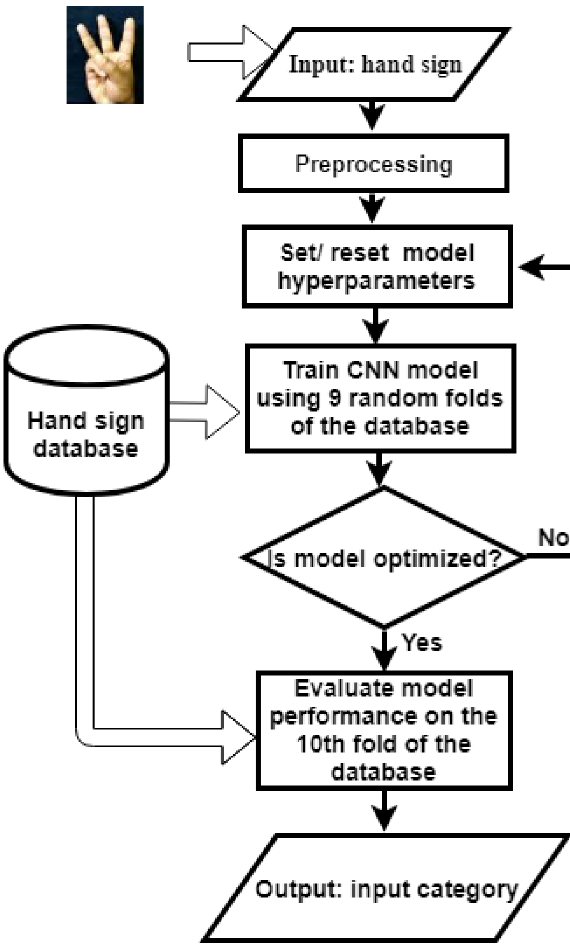

Fig. 2. The block diagram of the proposed BdSL recognition system. The wide and narrow solid arrows,respectively, represent the data flow and flow of control. The input to the system is hand sign image and the final output of the system is the category (or class) of the input hand sign.

A. Data Preprocessing

In this work, first the images were converted to gray scale. Then, the grayscale images were normalized by dividing the gray level pixels by the highest gray level (255). We resized the hand sign images to 64×64 pixels for exploration.

B. Convolutional Neural Network

A CNN [22] is comprised of convolutional layers followed by one or more fully connected layers as in a standard multi-layer shallow neural network . In CNN, each convolutional layer learns features from ithe input data making this architecture well suited to process images. CNNs manipulate multiples hidden layers for learning to capture different features from input data. The complexity of the learned data features may increase for every hidden layer. For instance, the foremost hidden layer could learn how to discover edges in terms of image, and the last learns how to find out more complex shapes of the object which we are attempting to classify.

The performance of CNN model relies on the architecture design with a proper choice of convolution layer and numbers of neuron. There is no universal rule to choose the number of convolution layers and neurons. In this work, the proposed network comprises of six convolution layers, 3 pooling layers and two fully connected layers with one input and one output layer. The structure of the proposed method for Bangla hand sign language recognition has been described by the block diagram in Fig. 3. A brief description of the layers of the model is given here:

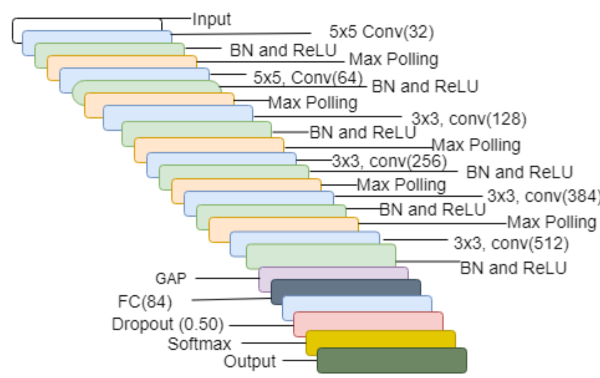

Fig. 3. Architecture of the proposed model for BdSL recognition. In this diagram, the terms Conv, BN, ReLU, GAP, and FC stand for convolutional layer, batch normalization, Rectified Linear Unit activation function, global average pooling, and fully connected layer, respectively.

- Input Layer: The pre-processed images are readily fed into the network with the help of the input layer. The input layer contains 4096 nodes for images of size 64×64 pixels.
- Convolutional Layer: A Convolution layer passes the input image, yielding a feature map with the help of an arbitrary number of learnable kernels (filters) which slide along the width and height of the input image. A kernel can be regarded as an array of numbers often termed as weights. The kernel size, we selected for the convolution layer was 5×5 and 3×3. Every convolution layer is followed by batch normalization [8] which is mainly responsible for reducing internal covariate shift and accelerating the training process.
- Activation Function: Activation functions play a cardinal role in every CNN architecture that susceptible to seek out which node should be fired. In our CNN, we apply ReLU [1] activation functions. ReLUs are several times faster [14] than their alternatives (sigmoid, tanh) in training and can mitigate the vanishing gradient problem. Mathematically, the function ReLU can be expressed as:

$$ReLU(x) = max(0, x) \tag{1}$$

where, x denotes the input to a neuron.

- Pooling Layer: Our network adopts max-pooling operation. Max-pooling operation diminishes the computational burden present in the input feature vector by decreasing the number of links between convolutional layers. It accelerates the training process and helps to reduce the amount of memory taken by the network. The window size, we selected for the max-pooling strategy was 2×2. To avoid overlapping, the pooling stride size was fixed to 2. The output dimension (N_{out}) of the max-pooling operation can be calculated according to (2)

$$N_{out} = floor(\frac{N_{in} - F}{S}) + 1 \qquad (2)$$

  where N_{in}, F and S denote the dimension of the input image, the filter size, and the stride size, respectively.
- Global Average Pooling Layer: The global average pooling (GAP) layer is analogous to max-pooling, except that instead of replacing entire areas with the maximum value, it replaces with the average value. GAP layers execute a significant type of dimensionality reduction, where a tensor with dimensions height×width×depth is decreased in size to have dimensions 1×1×depth.
- Fully Connected Layer: At the end of a CNN, the output of the GAP layer acts as input to the fully connected (FC) layer. The FC layer can be considered as convolution layer with a 1×1 filter size. The previous layers (convolution, pooling) hold information regarding local features in the input image such as edges, blobs, shapes, etc. These features (matrix, tensor) are flattened into a vector which fed into the FC layer. In the FC layer, every neuron in one layer is linked to every neuron in another layer. It performs classification based on the features extracted by the previous layers. The FC layer is followed by a dropout [13], [17] for reducing the over-fitting problem and increasing the performance of the model.
- Output Layer: The output layer of a CNN is responsible for yielding the probability of each class (sign) given the input image. To attain these probabilities, we set out our utmost FC layer to hold the same number of neurons as there are classes. The softmax activation function processes the output of the utmost FC layer and maps to a vector whose elements are sum up to one.

$$\sigma(X)_j = \frac{e^{Xj}}{\sum_{k=1}^{N} e^{X_k}}, \qquad (3)$$

  for $j = 1, 2, 3, ..., N$. Where, X_j are the inputs from the previous fully-connected layer used to each Softmax layer node, and N is the number of utmost FC layer nodes (i.e., the number of classes)

C. Training Details

- Data Augmentation: In terms of images, data augmentation means increasing the number of images in the dataset. In principle, the more the data, the better our models will be able to generalize. But every data collection process is associated with a cost. This cost can be in terms of dollars, human efforts, computational resources and of course time consumed in the process. Therefore, we may need to augment existing data to increase the data size that we feed our classifiers for improving the model's ability to generalize and correctly recognize images and to compensate for the cost involved in further data collection. The conventional methods of data augmentation [5], [20] comprised of changing the rotation, scaling, shifting or flipping the image. From these, we were only interested in the augmentation by randomly varying angles between -10 degrees to 10 degrees, zooming 10%, shifting by 10% on both axis. These values were selected by trial and error (which provided maximum accuracy). To decrease the risk of over-fitting the augmentation work is taken into account for increasing the diversity of the training data.
- Training and Evaluation: There were no separate train and test sets. So, the total data were randomly divided into K (K=10) folds. Nine folds were used for training the network, and the remaining one was used for evaluating the network. The training process was repeated for 10 times, and finally their average was considered as the overall accuracy of the network. In our work, we used a cross-entropy function [16] as a cost function. To minimize the cost function, a gradient descent-based Adam optimization [12] with learning rate 0.001 was used. We trained our model for up to 200 epochs with the batch size: 128 and steps per epoch: 64. The learning rate was updated to 75% of its value if our model validation accuracy did not improve for six consecutive epochs. We included early stopping, to define that we wanted to monitor the validation accuracy at each epoch and after the validation loss has not improved after thirty epochs, training is interrupted. The weights of the network were randomly initialized with small numbers from a normal distribution and we used weight decay 1×10^{-6}. The experiments were carried out on a PC with an Intel core i7 3.90 GHz CPU and NVIDIA Titan XP Pro GTX1080Ti 12 GB GPU, 1 TB HDD and 8 GB RAM. In every epoch, the inference time of our model was around 1 second. After completion of training of the model, it's performance was evaluated by the remaining fold of dataset that has not been used for training.

IV. Results and Discussion

We developed a new dataset of BdSL consisting of 30916 samples (basic characters: 23864 and numerals: 7052). The dataset will be made available (on request) for doing further research. In our proposed model, we observed 100% testing accuracy on numerals, 99.83% testing accuracy for the recognition of the charcaters of Bangla sign language alphabet. We obtained 99.80% accuracy, when both characters and numerals are mixed. The more details about our proposed model have been described in Table II. The accuracy of the proposed model are shown in Fig. 4.

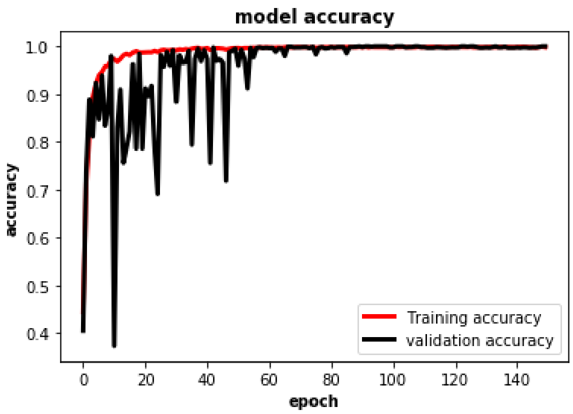

Fig. 4. Performance curve of the proposed model for recognition of the numerals of Bangla sign language.

True label a numeral										
0	120	0	0	0	0	0	0	0	0	0
1	0	63	0	0	0	0	0	0	0	0
2	0	0	85	0	0	0	0	0	0	0
3	0	0	0	84	0	0	0	0	0	0
4	0	0	0	0	76	0	0	0	0	0
5	0	0	0	0	0	80	0	0	0	0
6	0	0	0	0	0	0	48	0	0	0
7	0	0	0	0	0	0	0	46	0	0
8	0	0	0	0	0	0	0	0	48	0
9	0	0	0	0	0	0	0	0	0	49
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	Predicted label of the numeral									

Fig. 5. Confusion matrix of the classification performance on the numerals of Bangla hand sign language. Columns and rows correspond to the true and predicated label, respectively. The number of samples of classes is not equal, the maximum (120) samples of digit zero (0) present in the test set. The classifier recognize all samples of each class with 100% accuracy

In our model, we have incorporated some extra layers like batch normalization, dropout and favorable selection of the number of convolution layer, maxpooling layer, and filter number that may boosted up the classification performance by a significant margin.

The highest accuracy was reported for numerals (digits) recognition, this might due to the fact of a small number of classes or less confusion among the digits. The recognition of the characters is still very high (more than 99%). The recognition accuracy of the proposed system slightly reduced from 100% to 99.80%, when the digits are mixed with the characters. This might be due to the fact that their mixing adds confusions in intra classess of the symbols. The performance of the classifier confirms the validity of the dataset.

TABLE I
PERFORMANCE OF THE PROPOSED MODEL

Data set	Training Acc. (%)	Test Acc. (%)
Characters	99.85	99.83
Digit	99.96	100
Combined	99.65	99.80

TABLE II
COMPARISON BETWEEN EXISTING AND PROPOSED SYSTEMS

Model	Data set size	Accuracy(%)
PCA [3]	2020	76.9
LDA [9]	2000	88.55
KNN [18]	7200	96.46
SVM [21]	4800	97.7
Proposed (CNN)	**30916**	**99.80**

The recognition accuracy of the proposed model for each numeral of BdSL is shown in figure 5. It is observed from figure 5 that the model recognize all numerals precisely with recognition rate 100%.

The comparison of perfomance (accuracy) obtained for the proposed method and the methods reported in the literature has been represented in Table II. It is clearly seen from the table that the proposed method outperformed the previously reported methods for BdSL recognition. Besides this, we also compared the efficiency of the proposed CNN model with one of the popular models of CNN i.e., LeNet-5 for the recognition of Bangla sign language. The use of LeNet-5 architecure provided 98.73% and 99% accuracy, respectively for Bangla numerals and alphabet of Bangla sign language. While the trainig of the proposed model takes 18 mins and 9 mins , respectively for alphabet and numerals, the training of LeNet-5 requires only 11 mins, and 6 mins on the architecture, we considered. Thus, the proposed model provided better results than the equivalent LeNet-5 model. However, this training takes a few mins more than the LeNet-5 architecture which is very simple. Our target was to improve the accuracy. The dataset has been validated by the proposed method, and the model provided about 100% accuracy of Bangla sign language. The recognition accuracy of alphabet is little less than that of numerals, this might be due to the larger number of classess and the similarity of the signs of some characters, which caused interclass confusion to the classifier. The use of an improved model might improve the recognition of alphabet also.

V. Conclusions

A complete dataset for Bangla sign language has been developed and validated using CNN. This work manifests that convolutional neural networks can be used to precisely recognize different signs of the BdSL It is troublesome for most of the people who are not acquainted with the BdSL to communicate without an interpreter. In this work, we have built the first step of automatic interpreter from the static image of BdSL to spoken language with greater accuracy. The generalization capacity of CNN can contribute to the broader research field on automatic BdSL recognition.

In this study, we have evaluated the performance of the proposed model on the newly developed dataset. The development of this dataset and the public distribution of it might reduce the limitations of future research on it. In future, we will compare the performance of the proposed method with existing methods on the same dataset in large scale.

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REFERENCES

[1] A. F. Agarap, "Deep learning using rectified linear units (relu)," *arXiv:1803.08375*, 2018. [Online]. Available: https://arxiv.org/pdf/1803.08375.pdf

[2] T. F. Ayshee, S. A. Raka, Q. R. Hasib, M. Hossain, and R. M. Rahman, "Fuzzy rule-based hand gesture recognition for bengali characters," in *IEEE International Advance Computing Conference (IACC)*, 2014, pp. 484–489.

[3] S. Begum and M. Hasanuzzaman, "Computer vision-based bangladeshi sign language recognition system," in *12th International Conference on Computers and Information Technology*, 2009, pp. 414–419.

[4] H. Birk, T. B. Moeslund, and C. B. Madsen, "Real-time recognition of hand alphabet gestures using principal component analysis," in *Proceedings of the Scandinavian conference on image analysis*, vol. 1, 1997, pp. 261–268.

[5] X. Cui, V. Goel, and B. Kingsbury, "Data augmentation for deep convolutional neural network acoustic modeling," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015, pp. 4545–4549.

[6] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural computation*, vol. 18, no. 7, pp. 1527–1554, 2006.

[7] E.-j. Holden, R. Owens, G. G. Roy *et al.*, "Adaptive fuzzy expert system for sign recognition," in *Proceedings of the International Conference on Signal and Image Processing SIP'2000. 1999: Las Vegas*, 1999.

[8] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," *arXiv:1502.03167*, 2015. [Online]. Available: http://arxiv.org/abs/1502.03167

[9] M. Jasim and M. Hasanuzzaman, "Sign language interpretation using linear discriminant analysis and local binary patterns," in *International Conference on Informatics, Electronics & Vision (ICIEV)*, 2014, pp. 1–5.

[10] M. Karim, M. Kaykobad, and M. Morshed, *Technical challenges and design issues in Bangla language processing*. IGI Global, 701 E Chocolate Avenue, Hershey PA, 17033, USA, 2013.

[11] B. C. Karmokar, Kazi, R. Alam, and M. K. Siddiquee, "Bangladeshi sign language recognition employing neural network ensemble," *International Journal of Computer Applications*, vol. 58, no. 16, pp. 43–46, 2012.

[12] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Conference Track proceedings of the 3rd International Conference on Learning Representations, San Diego, CA, USA, May 7-9, 2015*, 2015.

[13] B. Ko, H.-G. Kim, K.-J. Oh, and H.-J. Choi, "Controlled dropout: A different approach to using dropout on deep neural network," in *IEEE International Conference on Big Data and Smart Computing (BigComp)*, 2017, pp. 358–362.

[14] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097–1105.

[15] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, no. 11, pp. 2278–2324, 1998.

[16] S. Mannor, D. Peleg, and R. Rubinstein, "The cross entropy method for classification," in *Proceedings of the 22nd international conference on Machine learning*, 2005, pp. 561–568.

[17] S. Park and N. Kwak, "Analysis on the dropout effect in convolutional neural networks," in *Asian Conference on Computer Vision*, 2016, pp. 189–204.

[18] M. A. Rahaman, M. Jasim, M. H. Ali, and M. Hasanuzzaman, "Real-time computer vision-based bengali sign language recognition," in *17th International Conference on Computer and Information Technology (ICCIT)*, 2014, pp. 192–197.

[19] W. Tao, M. C. Leu, and Z. Yin, "American sign language alphabet recognition using convolutional neural networks with multiview augmentation and inference fusion," *Engineering Applications of Artificial Intelligence*, vol. 76, pp. 202–213, 2018.

[20] L. Taylor and G. Nitschke, "Improving deep learning using generic data augmentation," *arXiv:1708.06020*, 2017. [Online]. Available: https://arxiv.org/abs/1708.06020

[21] M. A. Uddin and S. A. Chowdhury, "Hand sign language recognition for bangla alphabet using support vector machine," in *International Conference on Innovations in Science, Engineering and Technology (ICISET)*, 2016, pp. 1–4.

[22] R. Vaillant, C. Monrocq, and Y. Le Cun, "Original approach for the localisation of objects in images," *Proceedings of Vision, Image and Signal Processing*, vol. 141, no. 4, pp. 245–250, 1994.

[23] C. Vogler and D. Metaxas, "Adapting hidden markov models for asl recognition by using three-dimensional computer vision methods," in *IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*, vol. 1, 1997, pp. 156–161.

[24] R. Yasir and R. A. Khan, "Two-handed hand gesture recognition for bangla sign language using lda and ann," in *8th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)*, 2014, pp. 1–5.