Modified CNN Model for Hand Gesture Recognition Using Sign Language

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Abstract: In this article an enhanced accuracy of hand gesture recognition using data augmentation is presented. The proposed model has base on the CNN with data augmentation to recognize static hand gestures. The model has tested on 7172 images after being trained on 27,455 images. The accuracy of the model using supplemented data was 99.76%, which is nearly greater than the accuracy of the CNN model without augmentation (86.87%).

Keywords: Neural Network, Static Hand Gestures Recognition, Data Augmentation and Sign Language

INTRODUCTION

Dumb people struggle to communicate since normal people rarely learn Sign Language (SL) [1]. If there is no silent person in their social circle or if it is not necessary for their profession, individuals typically do not learn it. Communication with a soundless individual can be challenging and time-consuming. The purpose of the study is to examine a Convolutional Neural Network (CNN) [2] recognition capacity and conversion of ASL pictures of hand gestures into text format. The main focus of the study is on letters and numerical symbols in American sign language (ASL). Gestures (J and Z) are eliminated because they require movement to be executed. In general, people use hand gestures more frequently for communication than other body parts. Nonverbal communication takes place while two people are conversing which expresses the meaning of the speech through hand and body motions. Several advanced sensor techniques are available to capture hand gestures. Bobick and Wilson [3], claimed that a gesture is a movement of the body designed to communicate with other agents. Most researchers suggest the Gesture Recognition method for creating user-friendly interfaces. People who are deaf or dumb can also communicate via sign language, which uses well-known gestures or body language to convey meaning rather than utilizing sound [4]. A symbol enables hearing-impaired people to communicate with one another by linking spoken language letters, words, and phrases to understand hand gestures and body language. Hand gesture recognition has recently been utilized to take the place of commonly used human-computer interactive devices like joysticks, keyboards, and mice [5]. The sign of the alphabet is represented by Fig1.

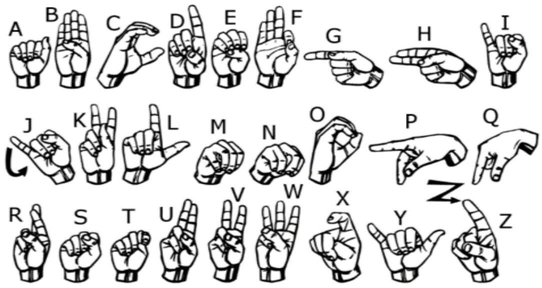

Fig1: Sign of alphabets

Various deep-learning techniques are available for sign language recognition using the CNN approach. Most of the techniques show good performance and better recognition capabilities but there needs an improved model for enhanced recognition accuracy and low time complexity. Using a boundary histogram, [6] showed rotation-invariant postures. The input image was captured using a camera, and then a skin color detection filter, clustering, and a standard contour-tracking technique were used to determine the boundaries of each group in the clustered image. The boundaries have been adjusted and the image has been divided into grids. The border was represented as a chord-size chain that was employed as a histogram by dividing the image into N radially spaced areas, each with a different angle. Neural Networks MLP and Dynamic Programming DP matching were employed in the classification procedure. 26 static postures from American Sign Language were used in the trials, which were executed on several feature formats and varied chord sizes for the histogram and FFT. The results showed DP matching and MLP at 94% and 98.8 respectively. The method TDSEP (Temporal Decomposition Source Separation BSS (blind source separation) together with the neural network) was presented by [7] and successfully employed to classify small muscle activity for distinguishing modest hand action. It was suggested by [8-10] .

A convolution neural network is used in this study.[11] to recognize hand gestures using data from the Kinect sensor. It uses 5 people and 8 different types of gestures, and its accuracy is 98.52%.The proposed hand gesture recognition system by.[12] was used to recognize the digits 0 through 9. The effectiveness of the two strategies was compared by the authors in this research. The convolutional Neural Network (CNN) approach was used under changeable conditions, such as picture rotation and scaling with constant background, before the contour-SVM-based method. Three datasets of the highest caliber, SLD, ASL, and ASL-FS, were used to test the proposed methodologies. Authors discovered that the contour and draw convex hull in the contour-based approach. SVM was used for classification, and gestures were identified based on the length and angle of the convex hull. CNN relied on a method that divided the digit data into five convolutional layers. To accomplish hand gesture identification, authors used more than 10,000 digital photos from the database for the digits 1 to 10. The original data for this database was gathered from a Creative Senz3D camera with a 320x240 resolution. The proposed technique, according to the authors, obtained an accuracy close to 69% for contour-SVM and 98.31% for the CNN-based approach.[13] introduce CNN in Sign language and find good accuracy in comparison to other machine learning methods currently in use.M Islam and others [14] the impact of data augmentation in deep learning was explored and analyzed by the writers. In this study, the author used a self-contracted dataset using CNN for classification, achieving an accuracy of 98.12% for CNN with augmented reality and 92.87% for CNN without. CNNs were employed for classification in [15] study of static hand gestures. The author used two picture bases comprising 24 movements, certain segmentation techniques, and the CNNs to get a classification accuracy of 96.83%. A deep CNN feature-based static hand motion detection system was proposed by[16]. Deep features are retrieved using fully connected layers of AlexNet) and the redundant features are subsequently minimized using PCA. SVM was then used as a classifier to categorize the poses of hand motions. Using a dataset of 36 gesture poses, the system's performance was assessed. The results showed an average accuracy of 87.83%.The classification of hand gestures based on inaudible sound using convolutional neural networks was explored by.[17] The author used both the CNN-based and STFT approaches, and she was able to identify 8 different hand gestures with 87.75% accuracy. The author was able to create a fused gesture dataset using the spatial fuzzy matching (SFM) approach [18-30] worked on a machine learning model to categorize Twitter posts into positive, negative, and neutral categories. Implemented on "twitter-airline-sentiment" dataset by using Random Forest (RF) Decision Tree (DT), Naive Bayes (NB), and K-nearest neighbors(KNN) and achieved 83% accuracy.[31]introduce a multiscale deep learning model for unconstrained hand detection in still images. Deep learning models, and deep convolutional neural networks(CNNs) on comprehensive datasets collected from several different public image resources. And achieved 81.25% accuracy.[32] are discussed myoelectric control scheme for hand prosthesis leveraging HD-EMG and deep learning and implemented in a fully embedded adaptive gesture recognition system featuring the complete chain from bio-electric sensing through deep learning model training to real-time inference and operation and achieved state-of-the-art offline classification results with 98.2% accuracy.

Ref	Author	Year	Data Set	Detection Technique	Other Characteristics
6	Simei G et al.	2002	ASL	DP matching ,MLP	DP 94%,MLP 98.8%
7	Ganesh R Naik et al.	2007	sEMG	TDSEP	97%
8	hwanHeo et al.	2010	Hand gesture data set	Binary open (Stretching) and close(crooking)	99%
9	Paulo Trigueiros et al.	2012	ASL	k-NN,NaiveBayes,ANN, SVM	95.45,25.87,96.99,91.66
10	Zhi-hua et al.	2014	1300 image	SVM,CRF(Conditional random field	96.69
11	Gongfa Li et al.	2017	2000 hand gesture image	CNN,SVM	98.52
12	PS neetu et al.	2020	200 image hand gesture	CNN classification approach based on CC alogrithms with enhancement technique	96.2
13	PriyankaParvath y et al.	2020	Sebastian Maecel dataset	SVM	96.5
14	Abhishek B.et al.	2020	EGO dataset,Jester dataset	3DCNN	not calculated
15	Adiya V et al.	2021	NUS hand Posturer data set, American Finger spelling dataset	CNN	99.96 for Americal finger spelling
16	abul et al.	2021	ASL	CNN,SVM	99.82

Table 1. Chronological summary of various techniques in the domain

In this section, we present an efficient and effective method for hand gesture recognition and Model using data augmentation for providing better results.

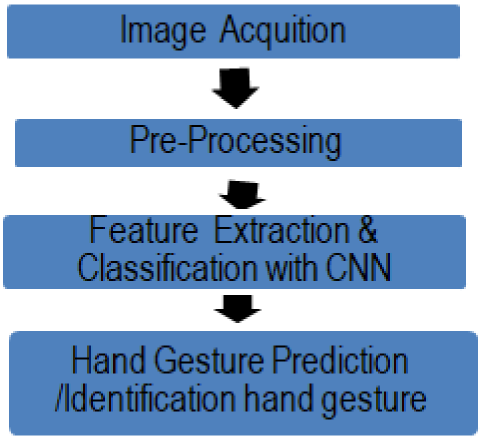

Fig2. Proposed our model

Image Acquisition: Basically camera, even a laptop webcam can be used to acquire the image but in this study take hand gesture image publicly available at Kaggal.

Pre-processing: The most important challenge during the experiments is to find a suitable dataset The dataset consists of various hand gesture images at different conditions as lightning, varied backgrounds, dimensions, and So on. To make a real-time classification, the images are converted to grayscale, i.eThe pre-processing of theimage consists of the conversion of RGB to a greyscale image. as shown in Fig.3 .Thus applying image pre-processing reduces the number of parameters in the first convolutional layer and reduces computational requirements.

Fig3: Image Pre-processing of dataset

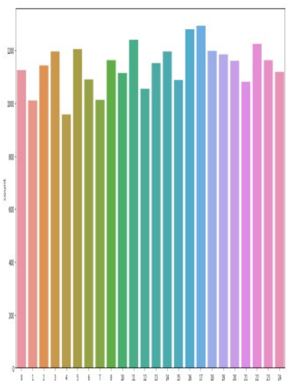

Fig4: sampling

Data Augmentation: With more data available, deep learning neural networks frequently perform better. Data augmentation is a method for faking fresh training data out of old training data. To do this, domain-specific approaches are applied to instances from the training data to produce brand-new and distinctive training examples. The most well-known form of data augmentation, known as "image data augmentation," is transforming images from the training dataset into new copies that are members of the same class as the original image. Rotations flips, zooms, and other image alteration techniques are included in the category of transforms.

DATASET:

The examination of the suggested model in this research makes use of the Sign Language MNIST dataset. Using the URLhttps://www.kaggle.com/datasets/datamunge/sign-language-most, one can get the sign MNIST dataset. This dataset is well-liked and useful for recognizing gestures. It has 24,000 pictures, and 24 different gestures, in it. The dataset consists of two.csv files, sign_mnist_test.csv, and sign_mnist_train.csv, which are used for testing and training the model, respectively. The training data set consists of 27,455 cases (80%), and the test data set has 7172 cases (20%). Available data are for testing and training the model total 34627. The dataset is now accessible in testing and training formats. For targeting output, 784 features are taken into account. The label is the dataset's first column. That is the objective. Label, which has 24 distinct values, will be used as the target parameter. For multiclass problems, it is employed. Our data set is of the imbalance kind. We have 24 classes, but not every class has the same number of classes. According to Figure 4, Sample No. 17 has the highest value and Sample No. 4 has the lowest value.

METHODOLOGY:

In our study, each image in the dataset has a width and height of 28. This data set has been developed to be useful to people with hearing and hearing difficulties. Some of the alphabets in the data set are shown in Fig 4. In this study, Fig 5 shows the typical architecture of CNN. The proposed method we take 28*28 Image Applying this CNN involves the following steps: first, a picture is inputted (which is read as an array of pixels); second, pre-processing is shown in Fig 3 and filtering must be done; and finally, the results are acquired after the classification. shown in Fig5.The proposed CNN framework is designed to obtain the best results for human static hand gesture recognition. The framework architecture is shown in Fig.5 In Convolutional neural networks that take input images and convolve them with filters or kernels to extract features. In this paper, I will consider NxN image is convolved with an fXf filter and this convolution operation learns the same feature on the entire image. The window slides after each operation and the features are learnt by the feature maps.

$$(N \times N) * (f \times f) = N - F + 1 \quad (1)$$

Equation 1 indicates the size of the output matrix with no padding also known as the feature map matrix, in this study image matrix 28*28 map 3*3 filter (28-3+1)=26, i.e. 26*26 is the feature map. Equation 2 presents The size of the output matrix with padding.

$$(NXN) * (fXf) = (N+2P-f)/(s+1) \quad (2)$$

Here p is padding and s is stride. The convolution operation is defined as Conv(m,n) = $I(x,y) \otimes f(x,y)$, where $\otimes$ is convolution operation, $I(x,y)$ is expressing input image matrix, $F(x,y)$ is expressing filter or kernel function. So Convolution is a mathematical technique that accepts two inputs, such as an image matrix and a filter or kernel. The image matrix is a digital representation of picture pixels, and the filter is another matrix used to process it. It can process any aspect of the image because the kernel is significantly smaller than the image. This paper uses 3-by-3 filters. To be employed in a layered architecture with numerous convolutional layers using kernels (or filters) and a Pooling operation, each model must first be trained, followed by testing. Rotation, Width, Height, Shear, and Zoom variables are taken into account for data augmentation. The accuracy of the model is boosted when the proper values for these parameters are filled in. As indicated in Table 2, the CNN model's remapping parameter was deemed false.

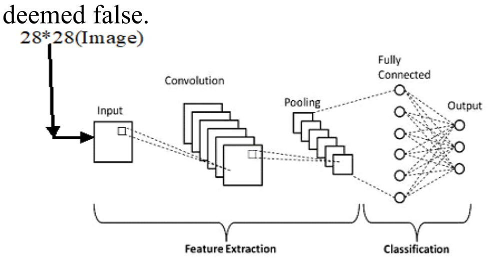

Fig 5: Architecture CNN

We normalize the dataset's features but not the dataset's labels. Feathers values between 0 and 255 normalize to 0. Pixel values are simply divided to 255 for this. Thus, machines can comprehend with ease. When a statistic stops improving, lowers the learning rate. Once learning reaches a plateau, models frequently gain by decreasing the learning rate by a factor of 2–10. This callback keeps track of a quantity, and it slows down learning if there hasn't been any improvement for a predetermined amount of epochs. The proposed CNN Model's layers are depicted in Fig6.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 28, 28, 35)        350

 batch_normalization_2 (Batc  (None, 28, 28, 35)       140
 hNormalization)

 max_pooling2d_2 (MaxPooling  (None, 14, 14, 35)       0
 2D)

 conv2d_3 (Conv2D)           (None, 14, 14, 50)        15800

 dropout_1 (Dropout)         (None, 14, 14, 50)        0

 batch_normalization_3 (Batc  (None, 14, 14, 50)       200
 hNormalization)

 max_pooling2d_3 (MaxPooling  (None, 7, 7, 50)         0
 2D)

 flatten_1 (Flatten)         (None, 2450)              0

 dense_1 (Dense)             (None, 24)                58824

=================================================================
Total params: 75,314
Trainable params: 75,144
Non-trainable params: 170
```

Fig6: Summary of proposed CNN Model.

A specific linear process called a convolution layer is used to extract important information. To reduce the covariance shift and boost neural network stability, batch normalization is performed. By taking the batch mean away and dividing it by the batch standard deviation, it normalizes the output of an earlier activation layer. By offering an abstracted version of the representation, max pooling aids in reducing over-fitting. To avoid overfitting, the Dropout layer randomly sets input units to 0 with a frequency of rate at each step during training. The sum of all inputs is maintained by scaling up non-zero inputs by 1/(1 - rate).

Sr No.	Arguments	Values
1.	Featurewise_center	False
2.	Samplewise_center	False
3.	Featurewise_std_normalization	False
4.	Samplewise_std_normalization	False
5.	zca_whitening	False
6.	Rotation_range	10
7.	Width_shift_range	0.1
8.	Height_shift_range	0.1
9.	Shear_range	0.1
10.	Zoom_range	0.1
11.	Horizontal_flip	False
12.	Vertical_flip	False

Table2:data augmentation argument

Sr No.	Arguments	Values
1	monitor	val_ accuracy
2	patience	2
3	factor	0.5
4	verbose	1
5	min_lr	0.0001

Table3: Learning rate argument

RESULT ANALYSIS:

For analyzing the impact of model precision, recall, F-1 score, and accuracy are to be considered. Precision is a measure of a model's accuracy in classifying a sample as positive. Recall measures the ability to detect positive samples. F1-Score is used to balance precision and recall. Accuracy is how close a given set of observations is to their true value. Table 4 shows the values of these parameters in different situations. The proposed model claims the highest accuracy. parameters in different situations. The proposed model claims the highest accuracy.

S.No	Performance Measure	CNN Without augmentation	CNN with augmentation[29]	CNN with augmentation by proposed model
1	**Precision**	0.9291	0.9718	1.00
2	**F-Measure**	0.9289	0.9715	1.00
3	**Recall**	0.9287	0.9713	1.00
4	**Accuracy**	92.87	97.12	99.76

Table4: Classification Report

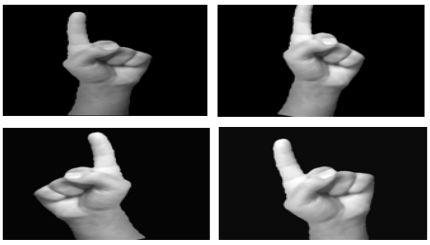

Fig 7: Effect of data Augmentation

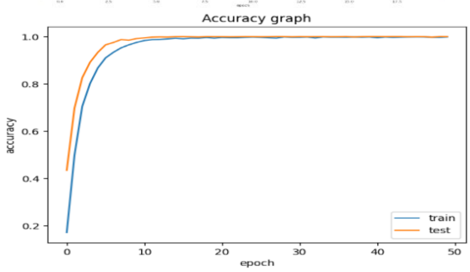

Fig8: Accuracy Graph

Fig 9: CNN with augmentation by proposed model

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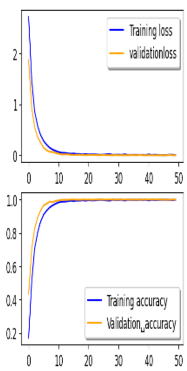


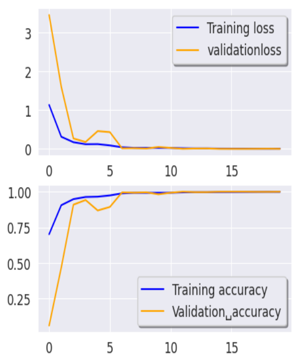
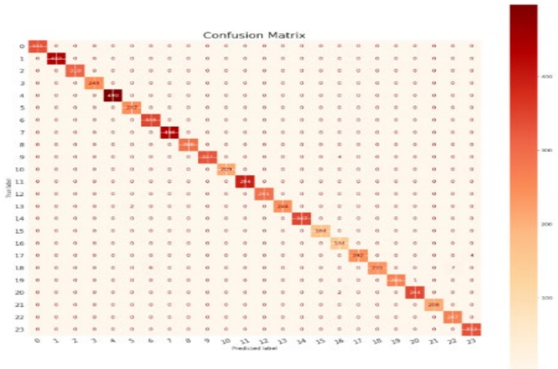


Fig10: Accuracy in Training and validation **Fig 11:**Accuracy in Training and validationof Normal of proposed modelCNN Model

Both the blue and yellow lines depict the accuracy during training and validation, respectively. Fig.8 demonstrates that accuracy is close to 99% after 5 repetitions. The accuracy achieved while applying CNN to the "MNIST dataset" with an 80:20 splitting ratio was 99.76%, demonstrating the flexibility of the suggested approach for various datasets. Fig.11(A) and Fig 11(B) display the confusion matrix obtained from the dataset.



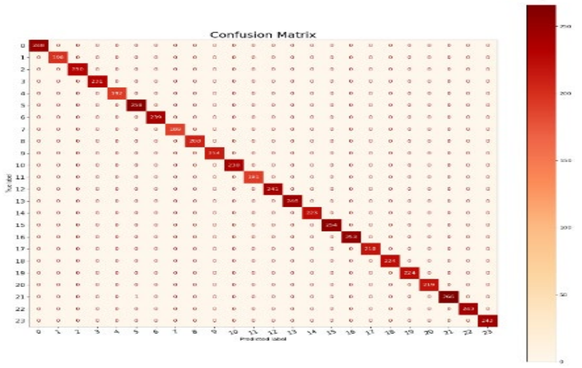


Fig 11(A): Confusion Matrix for Proposed Model**Fig11(B):** Confusion Matrix for CNN Model

Class 18 reports 232 accurately, whereas 16 are errors. Also in the case of 6 with 1 mistake and 348 properly anticipated. The author obtained encouraging results after processing the data using these techniques and the evaluation procedure. Table 4 displays the outcomes for the sign MNIST dataset: using the suggested methods, I achieved good accuracy.

Reference	Model	Accuracy
[30]	Random Forest (RF) and Boosting Algorithms, Decision Tree Algorithm	83%
[31]	AdaBoost Algorithm, SAMME Algorithm, SGD Algorithm, Edgebox Algorithm	81.25%
[29]	Convolutional Neural Networks (CNN) model applied to sign language MNIST dataset	91.41%
[32]	Convolutional neural network (CNN) and myoelectric control scheme	98.2%
Proposed Model	Convolutional Neural Networks (CNN) model applied to sign language MNIST dataset with augmented data	99.76%

Table5: Comparison between proposed and state-of-the-art work

CONCLUSIONS& FUTURE WORK:

This research examines the impact of data augmentation in deep learning to improve human-computer interactions by predicting the correct hand motions of humans. After doing this study, we can conclude that CNN is a data-driven methodology and that data augmentation has a significant impact on deep learning. As a result, this proposed objective can be used to forecast more accurate results in terms of better communication between humans and machines. Convolutional Neural Networks (CNN), which have an accuracy of 99.76%, produce the best outcomes. Random forest findings outperform other standard algorithms, barring CNN, with an accuracy of 84.43%. Deaf and mute people will also become accustomed to that in their everyday conversation, and these data can also be utilized for researchers working in the same field. In the Future for the balancing dataset, upsampling techniques can be used. The imbalance dataset can be transformed into the balance dataset via smoteup sampling. Machines can operate on samples equally when all classes have the same number of values. Since we are now attaining accuracy close to 99%, we are not using this strategy. But in the future, we can use this approach to obtain greater precision

Conflicts of Interest: The authors declare no conflict of interest.

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