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# Sign language emotion and alphabet recognition with hand gestures using convolution neural network

**Varsha K. Patil[1], Vijaya R. Pawar[2], Aditya Patil[3], Vinayak Bairagi[1]**
[1]Department of Electronics and Telecommunication Engineering, AISSMS Institute of Information Technology, Pune, India
[2]Department of Electronics and Telecommunication Engineering, Bharati Vidyapeeth College of Engineering for Women, Pune, India
[3]Department of Electronics and Communication Engineering, BITS Pilani Goa Campus, Sancoale, India

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**ABSTRACT**

American sign language (ASL) is a special means of interaction for hard-of-hearing individuals and has precise conventional rules. Since the general public does not know these sign language protocols, there is a need to have an efficient automatic sign-emotion recognition system. The objective of this paper is, to develop a framework that recognizes standard hand gestures. The gesture represents emotions and alphabet. This paper covers the methodology, results and performance factors, for experimentations. This experimentation of ASL-based alphabet and emotion recognition is novel as till now many efforts of alphabets categorization are done but this is the new direction of research where emotions, such as together', 'happy', 'peace, 'sad', 'confused', and 'love' are captured and automatically classified with hand signs. We mention our approach to increase 'accuracy', wherein we capture images and regions of interest (ROI). In this article, a specifically designed convolution neural network (CNN), is used to identify emotions from hand gestures and the addition of ROI enhances accuracy. The captured hand gesture dataset of the size of 94,000 images. "peace" sign emotion has the highest recognition rate ('98.95%'). Alphabet's "P" and "Q" sign ASL alphabets have the maximum recognition rate of signs. In all, very impressive accuracy of "92%" and above is detected. The limits of the experimentation are as mentioned i) there is no repeatability of accuracy for the same hand gesture; ii) The distance and angle of hand gestures with camera are crucial factors for an experiment; and iii) the alphabet recognition system is not working for the alphabets "J" and "Z".



***Corresponding Author:***

Varsha K. Patil
Department of Electronics and Telecommunication Engineering, AISSMS Institute of Information Technology
Pune, India
Email: varshapatil101@gmail.com

## 1. INTRODUCTION

Nonverbal communication [1] is when individuals say many things without speaking. The message in nonverbal communication is sent by making and moving faces or poses to form movements of body parts. These movements are called gestures [2]. When hard-of-hearing people interact with each other, they use a well-structured form of communication called sign language. The American sign language (ASL) is one of the popular sign languages, where emotions and characters are expressed with the movements of hands. These movements are done with a set of rules. To understand sign language communication, a trained person who has acquired sign skills is required. To make the social interactions among hard of hearing and people with good audacity, there is a technical implementation need for recognizing emotions automatically.

This paper brings the methods, performance factors, and successful results for automatically recognizing ASL. The secret of communication lies in understanding the hand gestures involved. This article aims to automatically recognize emotions and the alphabet via standardized hand gestures and positions. The highlight of this work is, that it is the first article that shows the method to recognize happy, love, sad, peace, confused, and together emotions with 92% and more accuracy.

## 2. LITERATURE SURVEY

This section is divided into two parts. The first part discusses about the broad domain of signal processing of ASL. The second part deals with methodology to increase the accuracy for sign language.

### 2.1. Literature survey of American sign language signal processing

To begin hand recognition with image processing, Baca *et al.* [3] provides basics of hand geometry capturing hand positions and related mathematical background. Ko *et al.* [4] have worked on deep learning, the recurrent neural network methodologies for realizing the important key landmarks of the human body. The hidden Markov model (HMM) [5] method is used by Starner *et al*. [5] for tracking the subject's hands. The sign language, and the universal facial expressions of sign language were discussed by Sandler [6]. Deep neural networks [7] were used to classify nonsearchable signs from the entire Dutch and Flemish sign-based language. The 2D convolutional neural network (CNN) approch was considered by Pigou *et al*. [7]. Emotion classification with audio and video was considered by Wang *et al*. [8]. An approch for using virtual signers "sign language" was used by Kipp *et al.* [9]. For the video frames the CNN method [10] provided" 98.981% "accuracy. Al-Qurishi *et al.* [11] provided the significance of input modalities. The comparison of the unimodal recognition and combination of methods was documented in [11]. The HMM was used by Li *et al.* [12]. Kothadiya *et al.* [13] demonstrated Indian sign language (ISL) based deep-learning model video frames. CNN for hand movement detection are considered in the article [14] with single shot detection, shows that methods are employed for Arabic sign language recognition with long short-term memory (LSTM) and CNN is the main aim of the paper [15]. Sign language recognition review as in [16]. Subramanian *et al.* [17] uses a media pipe-based methodology that integrates with the optimized gated recurrent unit. Jiang *et al.* [18] uses fingerspelling recognition in Chinese sign language. According to Zahid *et al*. [19], sign languages are translated using TensorFlow and linear regression with the method's accuracy of 97%. Table 1, provides methods in literature for recognizing sign language.

### 2.2. Literature for methods for incrementing the accuracy-related to ASL processing

For this part, the approach of listing the methods for incrementing the accuracy related to ASL processing is considered. Table 1 lists and briefly describes different strategies for improving the automatic ASL processing methods' accuracy. Table 1 summarizes different approaches by the various authors for incrementing the accuracy of ASL-related sign languages. Table 1 experiments for accuracy increments include the use of a large dataset, utilizing techniques such as deep learning or glove-based methods.

Table 1. Methods for incrementing the accuracy related to ASL processing

| Sr No. | Method for incrementing the accuracy | Remarks |
|---|---|---|
| 1 | "Finger spelling, a" datasets [10] | Utilizing large, diverse sign language datasets of videos (with added corresponding emotional labels), which have images of different sizes, orientations, and complex backgrounds for increasing accuracy. |
| 2 | Using deep learning [11] | Exploring different architectures and training strategies to enhance the accuracy of deep learning models [11]. |
| 3 | Cross-lingual recognition and real-world Glove sensor-based /recognition of the real-time gestures [12] | It is related to develop techniques to create cross-lingual models that recognize emotions across different sign languages. Using a device with sensors, such as accelerometers flex sensors, and infrared cameras placed on body parts the fingers, and hands. |
| 4 | Real-world applications [13], [19], [20] | Communication aids, and educational tools [13], HSV colour space [19] models, converting hand gestures into written words and audible speech [20] are some of the real time applications |
| 5 | Edge detection [21] | Image processing techniques such as edge detection |
| 6 | Transfer learning [22] | "VGG16", "ResNet50", "MobileNetV2", "InceptionV3", and "CNN", these are the examples of transfer learning methods |
| 7 | Studying review articles [23] | A review of sign language with facial expression, hand gestures, and glove sensor technology is considered |
| 8 | Robotic glove movement [24] | The glove movement with the robotic principle, represents4emotions and 4 numbers in ASL. |
| 9 | Static hand gesture images [25] | Some deep learning methods worked on static hand gesture images [25]. |
| 10 | Sign language day celebration [26] | Sign language day celebration is one of the ways to accelerate the process of advancements in the sign language field. |

## 3. METHOD

From the literature survey in the previous section, the general steps of automatic sign language recognition start with capturing hand gesture images, followed by preprocessing steps. After preprocessing there is the crucial step of core algorithms. Algorithms like transfer learning, and deep learning are used, in literature. In this article, the method used is the CNNs. To interpret the meaning of hand gesture frames from the input video, we have utilized three steps for implementing sign recognition namely i) dataset creation, ii) real-time data capturing and feature extraction by the CNN method, and iii) training and testing.

Figure 1 summarizes these steps with a block diagram consisting of preprocessing, feature extraction, training, and testing. The output is expressed in terms of performance parameters such as confusion matrix, score, and accuracy. The other form of the system output is the classification of emotions and alphabets. The system shown in Figure 1 works for confusion, love, together, sad, peace, confused, and happy emotions. The steps of implementation of the proposed system are shown in Figure 1 and are elaborated as follows.

Step 1: dataset creation: Initially, the input hand gesture images are captured as per the ASL a teachable machine is used for data capturing and augmentation. The emotion dataset contains 18,000 hand gesture images categorized into 6 emotion classes. The dataset is created by using a teachable machine. The alphabet hand gesture image dataset consists of 94,000 images. In the case of each alphabet, 3,000 images are captured. The main concern of dataset creation is that we have followed ASL guidelines for representing the alphabet with hand gestures. The total size of the dataset created is 94,000 images, out of these 18,000 images are related to 6 emotions. The remaining 76,000 images in the dataset are related to the English alphabet. The alphabet and emotions are kept in separate folders for processing.

Each class that we created contains 3,000 images alphabets. There are subfolders in the emotion folder, sad, happy, together, peace, and love. The labeled data in the alphabets folder is of 24 Engish alphabets except J and Z. To mitigate the limitations of this dataset size, we utilized data augmentation techniques through Keras's ImageDataGenerator, incorporating a width shift range of 0.1, height shift range of 0.1, a zoom range of 0.2, shear range of 0.1, and a rotation range of 10 degrees. These augmentations enhance the diversity of the dataset and improve model generalization, with augmented image batches generated at a size of 20. These preprocessing methods effectively address the dataset size constraints and bolster the model's robustness. The data is labeled into folders containing emotions and This way we have created our own data set.

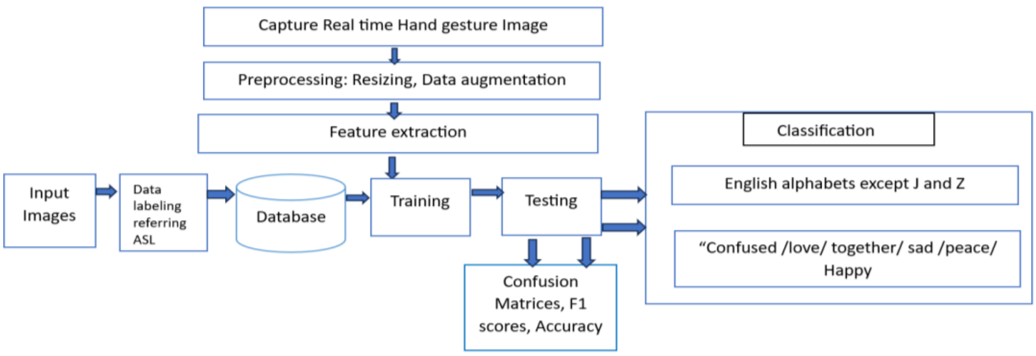


Figure 1. Block diagram for emotions and alphabet recognition

Step 2: real-time data capturing and feature extraction by CNN method: the hand gestures indicating signs of the alphabet and emotions are captured from the live video feed. The image preprocessing tasks such as resizing, and zooming are done. Then the features are extracted by the CNN. A dataset of 94,000 images (captured and processed by us) is used as a reference. The dataset creation band preprocessing process is already explained in step 1. Figure 2 shows a representative picture of the proposed system for identifying hand gestures where the input of a preprocessed image is provided to the CNN network, the output image shows the emotion recognition of peace expressed with of 98.95% accuracy.

As shown in Figure 2, we have designed three layered CNN for sign language, which has inputs from real-time hand gestures. Our system preprocesses the input image by resizing and edge processing. The output image shows the" Peace" emotion demonstrated by hand gestures. indicated with a and the output of emotions. identification experiment shows a bounding box (region of interest (ROI)). A high accuracy of 98.56% is observed for this experimentation.

The CNN processes input images with filters of size 32×32 pixels with 3 color channels. The pre-processing step is to import and convert the label "optimizer" from the dataset. CNN has three convolutional layers: the first two layers use 32 filters per 3×3 pixel size and ReLU activation, followed by a layer of 64 filters per 3×3 pixel size. CNN has three convolutional layers: the first two layers use 32 filters per 3×3 pixel size and ReLU activation, followed by a layer of 64 filters per 3×3 pixel size.

MaxPooling2D layers have a pool size of 2×2 pixels and are put after the second convolutional layer, This reduces the dimensionality of the image map and avoids overfitting. The model includes pooling layers and convolutional. There is a Dense layer with 512 units and a ReLU activation function. These layers are preceded by an output-dense layer having SoftMax activation). The network is classified with the Adam optimizer of learning rate of 0.001 and categorical cross-entropy loss function. Dropout layers with a rate of 0.25 are applied after the second convolutional layer to enhance generalization. A sequential kernel size of 3 with ReLU activation and a dropout of 0.2 is used. Flattening the model, and adding a dense layer with ReLU activation and dropout, followed by a SoftMax layer are the significant design steps to get the best results by adding nonlinearity. These steps are represented in Figures 3 and 4.

Our proposed model's general and specific features are seen in Figures 3 and 4. The steps are to import the libraries, design the CNN with different layers, and use the feature extensions. As shown in Figure 3, the general areas of signal processing in image processing are manual localization, segmentation, morphology, and signal processing in image extraction. We used the TensorFlow platform for sign language recognition using the CNN approach. In our experiments, using TensorFlow for hand signals, the following parameters ar e used for detection.

Step 3: training and testing: with hand gesture images, our model is trained for alphabet and emotion recognition. There are two types of results offered by models. The performance factors like classification parameters of confusion matrix, accuracy. The g splits with a ratio of 80:20 is used for training and testing. For training purposes 2,400 images and 600 images for testing.

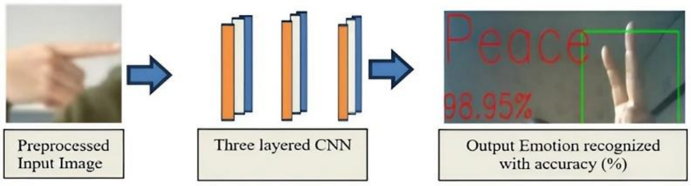


Figure 2. CNN based ASL for emotion recognition

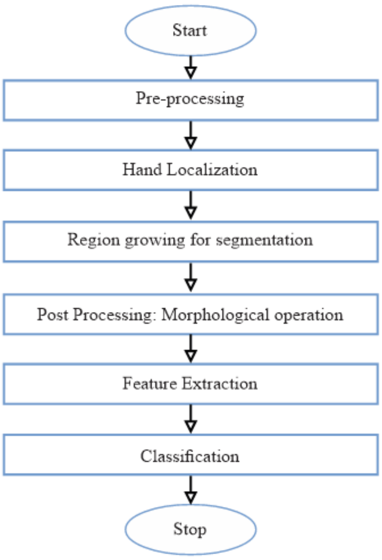


Figure 3. General steps flowchart for sign language approch

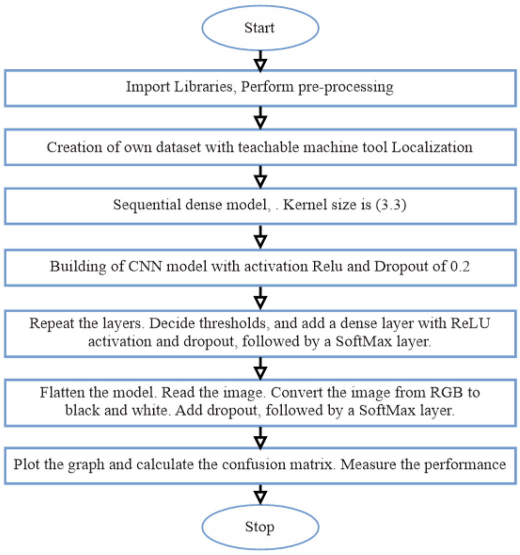


Figure 4. Flowchart for CNN-based emotion recognition with sign language approach

## 4. RESULTS

The next subsections focus on two key aspects: onscreen results and the confusion matrix. This subsection highlights the impact of the ROI and epoch on performance. Multiple graphs illustrate their effects on accuracy and loss metrics. These visualizations provide insights into model evaluation.

### 4.1. Emotion recognition and confusion matrix

This section contains the results of the experimentation related to emotion recognition. As shown in the Figure 5, our system recognizes emotions. The related confusion matrix is in Figure 6. The emotions identified are "peace (98.95%)" "happy (94.96%)" "together"(94.03%).

Figure 5. Emotions like "happy" (94.45%) "together" (94.05%) are recognized from hand gestures

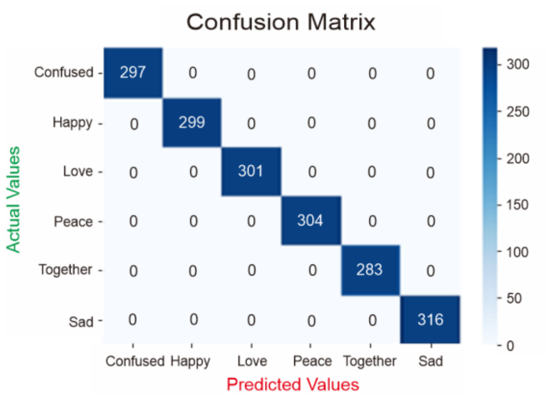


Figure 6. Confusion matrix for emotions

### 4.2. Graphs of epoch vs loss and epoch vs accuracy

While training and testing emotion and alphabet models, there are the graphs of epochs vs loss and accuracy as shown in Figure 7. We have allocated the right part of the figure for the alphabet recognition graph. The left column of the figure is allocated for emotion recognition graphs, The accuracy increases with the number of epochs and loss decreases.

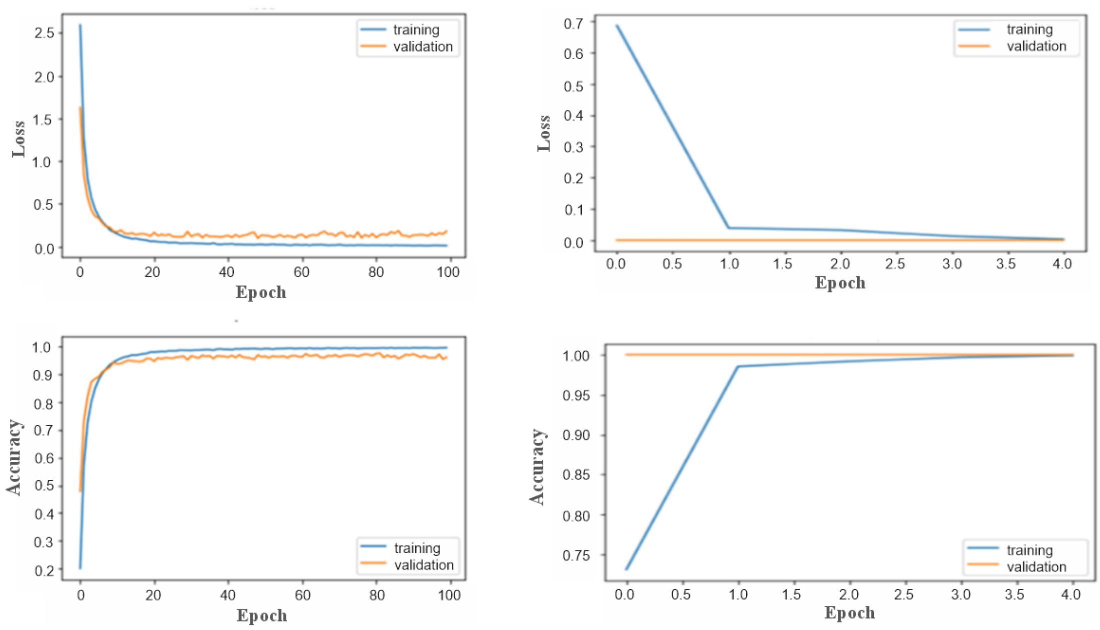


Figure 7. Graphs for alphabet and emotion for epoch vs loss and epoch vs accuracy

### 4.3. Effects of region of interest

The automatic hand gesture recognition system is designed in steps. Dataset generation, CNN design, and training and testing phases are the three steps of implementation of our methodology. The sign recognition is done by creating a green-colored bounding box called as ROI on the images. The addition of the ROI on images ensures maximum accuracy and less loss.

To generate maximum accuracy and less loss of the trained datasets, we have created a ROI. The ROI is a small green-colored box around the sign. The data is to be recognized with signal processing logic. The ROI logic contains grayscale and Gaussian blur effect image processing algorithm implementation for maximal data prediction.

Figures 8 and 9 show increased accuracy by introducing the ROI for sign language-based alphabet and emotion recognition. Figure 8 shows sign recognition for alphabets. Accuracy increases with the ROI. ROI is shown for 24 alphabets. (“J” and “Z” Alphabets are not recognized). Representation of the effect of ROI on the accuracy of each emotion Performance matrices shows that all emotions are more accurately recognized with ROI shown in Figure 9.

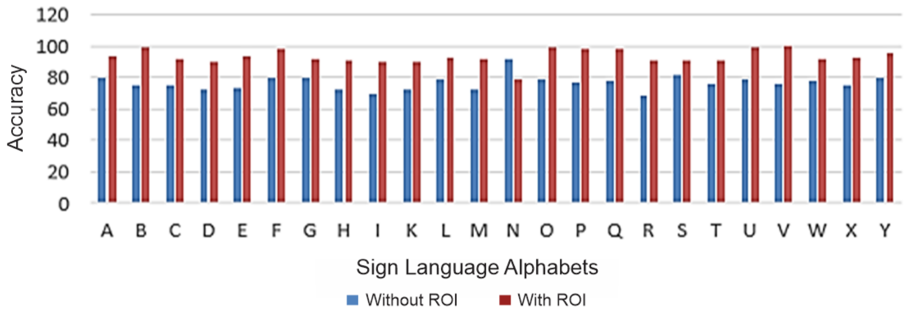


Figure 8. Alphabet’s sign: accuracy increases with the ROI for 24 alphabets

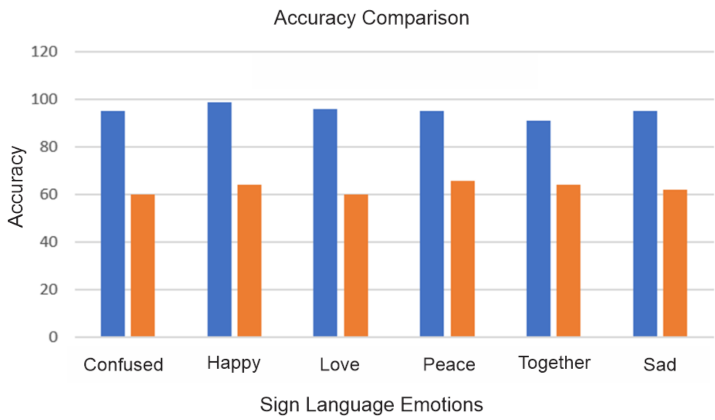


Figure 9. Emotion sign recognition: accuracy comparison with and without ROI

### 4.4. Alphabet recognition: performance parameters

The ASL-based hand gestures and their interpretation in terms of emotions and the alphabets are recognized by our system. The results for the letters “R”, “W”, and “Q” Alphabets recognized are shown in Figure 10. The noteworthy part is in the lab environment the “Q” letter has 100 percentage of accuracy. For 24 alphabets (except J and Z), the precision, F1 score, and confusion matrix are presented.

The performance parameters results are shown in Figures 11 and 12. Figure 11 shows the performance parameters for 24 “alphabets”. The system shows robustness in identifying the hand gestures of letters mentioned in Figure 12. Letters “E”, “S”, “I”, and “Y” show the best performance parameters. However, our system has limitations in that the letters “J” and “Z” are not recognized. Hence Figure 11 includes figures of performance parameters like precision, accuracy, and F1 score for only 24 letters. Figure 12 shows the confusion matrix for alphabets.


Figure 10. “R”, “W”, and “Q” alphabets recognized (e.g. “W” accuracy is 99.89%)

| Letter | Precision | Recall Score | F1 Score | Support |
|---|---|---|---|---|
| A | 0.97 | 1 | 0.90 | 331 |
| B | 1 | 0.96 | 0.98 | 432 |
| C | 0.90 | 0.93 | 0.92 | 310 |
| D | 1 | 0.97 | 0.98 | 245 |
| E | 1 | 1 | 1 | 468 |
| F | 0.97 | 1 | 0.98 | 247 |
| G | 0.92 | 0.93 | 0.93 | 348 |
| H | 0.96 | 0.96 | 0.96 | 438 |
| I | 1 | 1 | 1 | 268 |
| K | 1 | 0.95 | 0.97 | 331 |
| L | 1 | 1 | 1 | 209 |
| M | 1 | 0.99 | 1 | 194 |
| N | 1 | 0.95 | 0.96 | 291 |
| O | 0.91 | 0.83 | 0.87 | 246 |
| P | 1 | 0.99 | 0.99 | 347 |
| Q | 0.96 | 1 | 0.99 | 164 |
| R | 0.87 | 1 | 0.99 | 144 |
| S | 1 | 1 | 1 | 246 |
| T | 0.96 | 0.92 | 0.96 | 248 |
| U | 0.94 | 1 | 0.97 | 266 |
| V | 1 | 0.95 | 0.97 | 346 |
| W | 1 | 1 | 0.96 | 206 |
| X | 0.90 | 1 | 0.95 | 267 |
| Y | 1 | 1 | 1 | 332 |

Figure 11. Performance parameters for recognition of alphabets by hand gestures

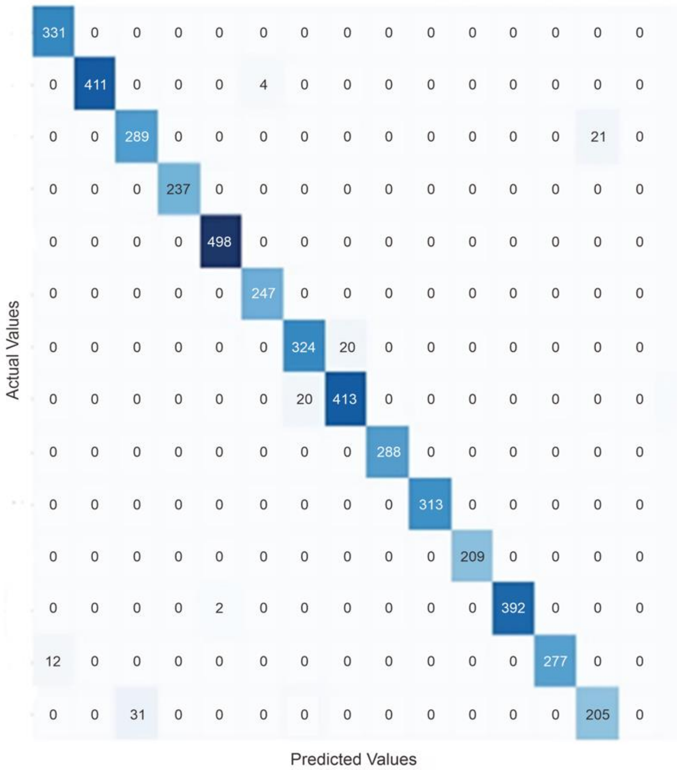


Figure 12. Confusion matrix for recognition of alphabets shown by hand gesture

## 5. DISCUSSION

We conducted a study using a self-created dataset comprising 94,000 hand gesture images to advance the recognition of sign language alphabets and emotions. This dataset was processed using CNN. While many studies focus on alphabet recognition, few address emotion recognition via sign language, making this research a pioneering effort in the field. Our system analyzes six emotions-confused, happy, sad, love, peace, and together-evaluating accuracy with and without ROI application. Results show that incorporating ROI improves accuracy up to 100%, while its absence reduces accuracy to as low as 60%. For alphabet recognition, 24 letters (excluding "J" and "Z") were analyzed, with ROI significantly enhancing performance. Recognition accuracy exceeded 95% for "P" and "Q", whereas it dropped to about 75% for "D" and "K".

The system achieved overall accuracy rates of 96%-98% for alphabets and 97%-99.8% for emotions. However, limitations include dependency on factors such as camera angle, distance, and sign presentation consistency. Future work could involve integrating non-invasive communication methods and advanced signal processing to further optimize system efficiency and broaden its applicability in diverse real-world scenarios.

## 6. CONCLUSION

ASL, can be understood by trained/skilled individuals. However, the ASL emotions and alphabets are not recognized by the layman. Hence there is a gap in the automatic recognition of the English alphabet using ASL. In this article, the hand gestures, and movement are recognized with CNN. The main contribution of this work is, that our system is capable of identifying emotions such as peace, togetherness, love, and happy are identified with significant confidence (greater than 91%). We have added the ROI to increase the accuracy. Graphical, tabular output is presented for sign language-based emotion recognition. The ROI is a signal processing and localization technique with abounding box around the hand. However, the system has limitations on the repeatability of the readings. The very same accuracy is not observed after repeated readings. The image characteristics are the influencing factors for the sequence and content of the sign language processing steps. Additionally, the quality of the segmentation may depend on factors such as lighting conditions, camera angle, and the complexity of the hand gesture being performed. Besides these odd limitations, our system provides an average accuracy greater than 91% of accuracy.

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**Varsha K. Patil** an M.Tech. electronics in the year 2009 from the Government College of Engineering Pune. She has filed 02 patents and 1 copyright in the technical field. She has published more than 25 papers. She has been invited as a resource person for 10 faculty development programs. Her areas of interest are image processing, AIoT, the internet of things, and electronics in agriculture. She has worked to establish the Center of Excellence of Texas Innovation Lab and IEEE Affordable Agriculture Lab. She has worked on two research grant-funded projects and one QIP Grant. She is a life member of ISTE and IETE. She can be contacted at email: varshapatil101@gmail.com.

**Vijaya R. Pawar** has completed M.E. in electronics in 2002 from Shivaji University Kolhapur, Bharati Vidyapeeth Deemed University, Pune has awarded her a Ph.D. degree in electronics engineering in 2015. She has teaching experience of 28 years and research experience of 10 years. She has filed 02 patents and 2 copyrights in the technical field. She has published more than 47 papers, of which 28 papers are in international journals. Her 25 papers are indexed in Scopus and 12 papers are indexed in SCI. She was invited as session chair for 12 national and international conferences. She has also been invited as a resource person by 06 colleges as a resource person for delivering a session on, "Digital signal processing" and "Biomedical signal processing". She has received one research grant and 08 development grants. She is a life member of ISTE, IEI, and IETE. She can be contacted at email: pawarvr74@gmail.com.

**Aditya K. Patil** is graduated B.Tech. in electronics and communication engineering from Birla Institute of Technology and Sciences, Goa Campus in 2024. His research interests include nanoelectronics, circuit design, and applications of machine learning in related fields. Currently, he is working as at texas instruments. He can be contacted at email: patiladitya101@gmail.com.

**Vinayak Bairagi** has completed M.E. in electronic in 2007. The University of Pune has awarded him a Ph.D. degree in Engineering in 2013. He has teaching experience of 17 years and research experience of 12 years. He has filed 12 patents and 5 copyrights in the technical field. He has published more than 81 papers, of which 38 papers are in international journals. His 71 papers are indexed in Scopus and 32 papers are indexed in SCI. He was invited as session chair for 21 national and international conferences. He has also been invited as a resource person by 31 colleges for invited talk. He has received four research grants. He was Chair of the IEEE Signal Processing Society Pune chapter (2020-23). He can be contacted at email: bairagi1@gmail.com.