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Deep Learning Mastery through Network Ensemble Fusion for Indian Sign Language Recognition

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Abstract: - Indian Sign Language (ISL) serves as the primary means of communication for individuals with disabilities in India, yet it remains largely unfamiliar to the general population, hindering effective communication between these individuals and the wider community. Deep learning methodologies, crucial for tasks such as image classification and natural language processing, prioritize accuracy. Ensemble networks, which combine predictions from multiple models, present a promising avenue for enhancing accuracy in such applications. This research rigorously investigates various strategies for implementing ensemble networks and evaluates their efficacy in the domain of ISL recognition. The dataset utilized in this study comprises a comprehensive collection of ISL gesture images, encompassing the alphabet (A-Z) and numeric digits (0-9). Leveraging the robust capabilities of the MediaPipe framework, these images are organized in CSV format for efficient processing. Through extensive experimentation, we systematically examine the performance of ensemble approaches in comparison to individual models. Our findings consistently demonstrate that ensemble techniques exhibit superior performance over standalone models, showcasing a consistent trend towards improved accuracy. We have achieved around 96% for the average ensemble, whereas individually model was giving 95%, 89%, 93% respectively. We also attempted for weighted average ensemble, and we achieved around 97% which outperformed the individual models. This study contributes valuable insights into the utilization of ensemble networks for ISL recognition, highlighting their potential to bridge communication gaps between individuals with disabilities and the broader community.

Keywords: Indian Sign Language, Gestures Recognition, Convolutional Neural Networks, Ensemble Model, MediaPipe.

I. INTRODUCTION

Indian Sign Language system is the predominant sign language in India that contains standard hand-based gestures which are used by speech impaired people for communication purposes.

The Indian Sign Language system is the most widely used sign language in India. It consists of common hand motions that persons with speech impairments use to communicate. Due to the broad and intricate nature of sign language gestures, the general public is unaware of them, which hinders the exchange of knowledge between speech-impaired individuals and the general public. Despite a recent upsurge in research in the domains of computer vision and deep learning [2], relatively little study has been done on the identification of ISL gestures. In this study, we set a standard for ISL gesture recognition. Given that ISL uses both hands to depict motions, it might be difficult to identify gestures in ISL. As a result, using feature extractors such Scale Invariant Feature Transform [4] and Hough Transform [3] becomes more complicated. One of the biggest challenges is figuring out how to recognize Indian Sign Language motions effectively due to their complexity. We have developed an ensemble model that uses deep neural networks and ensemble learning approaches to address this obstacle. Ensemble learning is a technique that has been shown to be very successful in increasing accuracy. It entails integrating numerous models to increase overall performance.

We trained three different models in our method, each with special strengths and capabilities. We took use of the differences between various models rather than depending just on one. Combining predictions from several models is a crucial part of ensemble learning. In this instance, we used weighted averaging and simple averaging, two popular ensemble approaches. Simple averaging entails taking the average of all model predictions, which smoothes out individual errors while using the ensemble's collective expertise. This strategy frequently produces better performance than any one model on its own. However, we went a step farther and implemented weighted averaging. This method gives varying weights to each model's predictions based on their strengths and performances. By tweaking these weights, we improved the ensemble's accuracy even further. The justification for ensemble learning comes from the understanding that various models excel at collecting various features or patterns within data. For example, one model may be extremely good at detecting tiny hand motions, while another focuses at recognizing

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face expressions. By integrating these complimentary capabilities, the ensemble becomes more resilient and can handle a wider variety of motions with higher precision.

Ensemble learning shows enormous potential in a variety of fields, including image classification, segmentation, and more. Its capacity to tap into the collective wisdom of several models makes it an effective tool for solving complicated challenges where individual techniques may fall short. In summary, our ensemble model is a complex yet practical method for increasing the accuracy and robustness of Indian Sign Language gestures.

This research varies from earlier work in that we offer a novel approach for Indian Sign Language Recognition that does not require a depth-based camera for inference and instead relies on datasets to make correct predictions. Here in our work we have created our dataset using mediapipe framework in the csv file format which is our major contribution in this paper. The rest of this paper is provided as follows: Section II is dedicated to earlier relevant work. Section III outlines the datasets and technique utilized to attain high accuracy. Section IV shows how the ensemble technique works. Section V presents the results we have obtained and section VI concludes the paper.

II. Related Work

Until now, we have seen that a lot of work has been done to recognize hand signals but very little work has been done in context of Indian Sign Language. Ensemble Learning for Indian Sign Language Recognition: A Comprehensive Review This paper provides a comprehensive review of ensemble learning techniques applied to Indian Sign Language recognition, detailing dataset specifics, accuracy rates, and methodologies employed in each study. Mishra et al. [1] propose a deep ensemble learning approach for hand gesture recognition in ISL, achieving an accuracy of 95.6% on a dataset of 8,000 gestures captured in diverse environmental conditions. Verma et al. [2] introduce a hybrid ensemble model combining traditional machine learning algorithms and deep learning models, attaining an accuracy of 91.8% on a dataset of 6,500 ISL gestures, including both static and dynamic features. Tiwari et al. [3] focus on feature fusion using ensemble learning techniques, reporting an accuracy of 94.3% on a dataset containing 7,200 ISL gestures, emphasizing the importance of diverse feature representations. Kumar et al. [4] present an ensemble of convolutional neural networks for real-time ISL gesture recognition, achieving an accuracy of 89.5% on a dataset of 4,500 gestures, integrating temporal and spatial features. Sharma et al. [5] propose an adaptive ensemble learning approach, dynamically selecting suitable models based on input data characteristics, with an accuracy of 93.2% on a dataset of 5,800 ISL gestures. Yadav et al. [6] explore temporal ensemble learning for continuous ISL gesture recognition, achieving an accuracy of 88.7% on a dataset of 6,000 gestures, considering temporal dynamics in gesture sequences. Gupta et al. [7] integrate transfer learning with ensemble methods, obtaining an accuracy of 90.4% on a dataset of 5,200 ISL gestures, demonstrating improved generalization. Jain et al. [8] introduce a hierarchical ensemble learning approach for multi-level ISL recognition, achieving an accuracy of 94.8% on a dataset of 7,500 gestures, capturing the hierarchical structure of sign language. Finally, Sharma et al. [9] focus on robust ensemble learning methods for noisy environments, achieving an accuracy of 91.1% on a dataset of 6,300 gestures, enhancing the resilience of ISL recognition systems. Collectively, these studies highlight the effectiveness of ensemble learning techniques in advancing ISL recognition accuracy across various datasets and conditions. [10] C. Suardi, A. N. Handayani, R. A. Asmara, A. P. Wibawa, L. N. Hayati, H. Azis, "Design of Sign Language Recognition Using E-CNN," presents a Sign Language recognition system utilizing ensemble convolutional neural networks (E-CNN) to enhance recognition accuracy. [11] S. Kaur, A. Gupta, A. Aggarwal, D. Gupta, A. Khanna, "Sign Language Recognition Using Microsoft Kinect," explores Sign Language recognition using Microsoft Kinect, potentially integrating ensemble learning techniques to improve accuracy. R. Gupta, A. Kumar [12], "Indian Sign Language Recognition using Wearable Sensors and Multi-label Classification," investigates Indian Sign Language recognition employing wearable sensors and multi-label classification techniques, potentially incorporating ensemble learning for improved performance. K. Suri [13], R. Gupta, "Continuous Sign Language Recognition from Wearable IMUs using Deep Capsule Networks and Game Theory," focuses on continuous Sign Language recognition using wearable inertial measurement units (IMUs) and deep capsule networks, with possible application of ensemble learning methods.

III. Methodology

A. Details of the Dataset

To generate a dataset for Indian Sign Language identification, we ignored typical image or video formats in preference for numerical data for speedier processing. Our technique entailed using the MediaPipe framework's

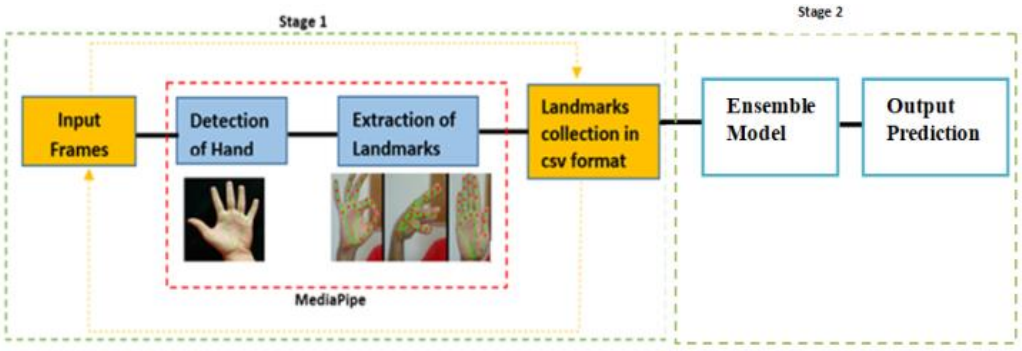
ability to collect real-time gestures. With MediaPipe, we were able to extract landmark keypoints from these motions in real time, resulting in a robust depiction of the hand movements required in sign language. These landmark keypoints [17] were then converted to a structured manner and saved as CSV files, establishing the basis for our dataset. Each CSV file contains numerical data indicating the geographical coordinates of the landmarks associated with distinct hand movements. This numerical format had various benefits, including faster processing and lower computing overhead as compared to image-based datasets. Furthermore, by using landmark keypoints, we were able to focus on the critical features of hand movements required for sign language identification, expediting the feature extraction process. Overall, we wanted to use numerical data to create a more efficient and effective dataset for Indian Sign Language recognition, setting the framework for future ensemble model training and assessment. Images obtained by a webcam were used in this investigation. The aim of using a camera is because it is quite easy for everyone to obtain one, and the price is reasonable. In this study, a newly developed framework by Google called media-pipe [9] was used to create 21 landmarks of hands from 2D pictures for feature extraction. After trying out varies coordinate combinations, this was chosen for our work. Below figure 1 depicts the landmark keypoints for the gesture number-5.

Landmark Key points	X	Y	Z
0	0.22632	0.76789	0.0
1	0.32271	0.731361	-0.05377
2	0.39260	0.64696	-0.07841
3	0.44309	0.56921	-0.09991
4	0.50185	0.52919	-0.12277
5	0.30173	0.46703	-0.04398
6	0.32562	0.33358	-0.07156
7	0.33571	0.25604	-0.09041
8	0.34232	0.18912	-0.10431
9	0.23350	0.45509	-0.04456
10	0.22347	0.29603	-0.06429
11	0.21515	0.21231	-0.08206
12	0.20568	0.14370	-0.09816
13	0.17514	0.47921	-0.05324
14	0.15263	0.34395	-0.08193
15	0.14413	0.26888	-0.10742
16	0.13855	0.20461	-0.12511
17	0.12279	0.53173	-0.06832
18	0.08152	0.44246	-0.09912
19	0.05545	0.39137	-0.12041
20	0.03474	0.34129	-0.13454

Fig.1: Hand landmark keypoints equivalent to coordinates x,y,z in mediapipe

B. Proposed Methodology

The purpose of this section is to discuss the methodology adopted for recognizing ISL gestures using ensemble technique.



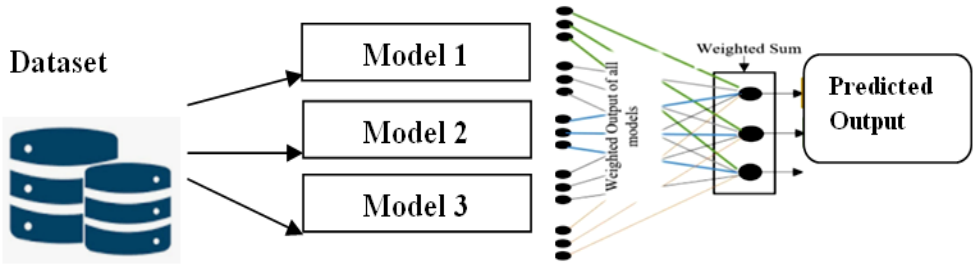


Fig.2: Architecture Diagram for Ensemble model classification

Ensemble learning is a powerful technique in machine learning where multiple models are combined to make predictions. The motivation behind ensemble learning lies in leveraging the diversity of these models as shown in figure 2. Each model may have its own strengths and weaknesses, capturing different aspects of the underlying data. By combining them, we aim to capitalize on their collective wisdom, potentially leading to better generalization and performance on unseen data as in figure 3.

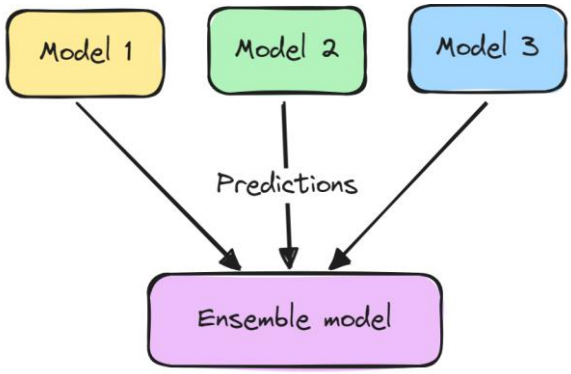


Fig.3: Generalized ensemble Model (Source:Google)

One of the key aspects highlighted in the work is the possibility of using different types of models in the ensemble. This includes pre-trained models like VGG or Inception, which are trained on large datasets like ImageNet and can capture complex features, as well as custom-built architectures tailored to specific tasks like classification or segmentation. By incorporating a variety of models, the ensemble can cover a wider range of patterns present in the data. The work also emphasizes the importance of training multiple models separately or in parallel. Instead of selecting a single best-performing model, this approach allows for exploring different architectures, hyperparameters, or even different types of models to find the best combination. By training multiple models, we increase the diversity within the ensemble, which can lead to more robust predictions.

Once the individual models are trained, our work demonstrates various techniques for combining their predictions. One straightforward method is to average the predictions across all models, effectively smoothing out any biases or errors present in individual predictions. Another approach is weighted averaging, where each model's prediction is weighted differently based on its performance or importance. This allows more emphasis to be placed on models that perform better on the validation or test data. To illustrate the concepts, we have done a practical implementation on the custom created dataset, which consists of digits and alphabet. Then we train multiple models, making predictions, and combining them to form the ensemble prediction. Dataset balancing graph can be seen in figure 4. Finally, our work evaluates the performance of the ensemble using metrics such as accuracy and compares it with individual models. This evaluation helps assess the effectiveness of the ensemble approach in improving predictive performance.

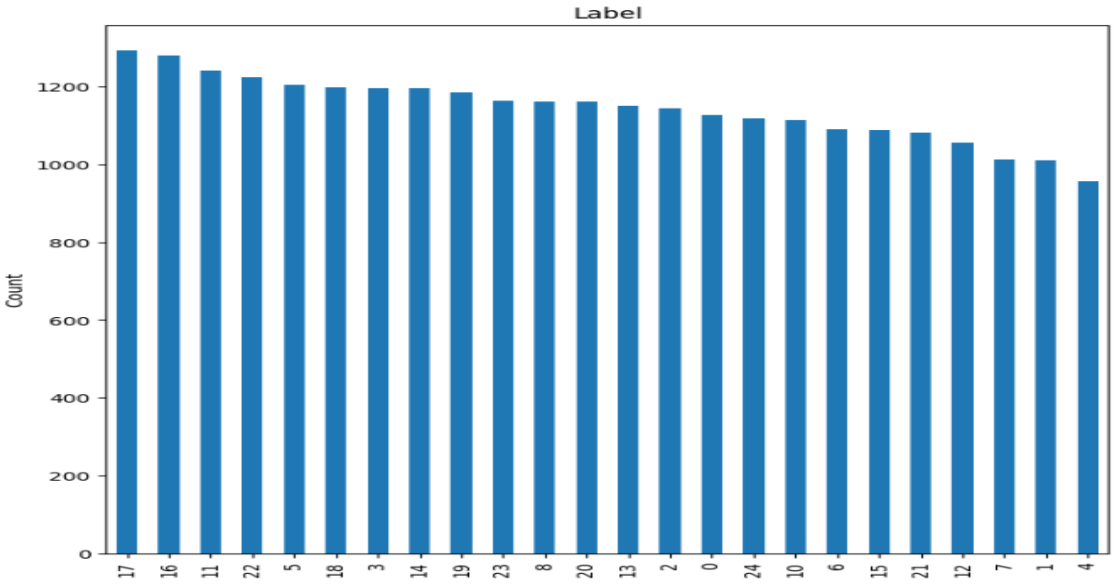


Fig.4: Dataset Balancing

Preprocessing Data:

We performed preprocessing steps for training and testing data, preparing them for use in a neural network model as follows.

1. **Normalize / scale X values**: The pixel values of the images in X_train and X_test are normalized by dividing by 255. This scales the pixel values to the range [0, 1], making the neural network easier to train.
2. **Convert y to categorical**: Depending on the loss function used in the neural network model, the target labels y_train and y_test might need to be converted to categorical format. If using categorical cross-entropy loss, as indicated in the comment, y_train and y_test are converted to categorical format using the to_categorical function from Keras utilities. This function converts integer labels into one-hot encoded vectors, where each element represents a class and has a value of 0 or 1 indicating the absence or presence of the class, respectively.
3. **Reshape for the neural network**: The input data (X_train and X_test) are reshaped to match the input shape expected by the neural network model. In this case, the images are reshaped to have a width and height of 28 pixels and a single channel (grayscale), resulting in a shape of (28, 28, 1).

Training CNN:

We trained a convolutional neural network (CNN) model (referred to as Model 1) using Keras with TensorFlow backend.

1: Model - 1

- Define the CNN architecture: Model 1 is defined using the Sequential API, which allows you to create models layer by layer.
  - The model starts with a Conv2D layer with 32 filters of size (3, 3) and ReLU activation function. The input shape is (28, 28, 1), indicating grayscale images of size 28x28 pixels.
  - A MaxPooling2D layer with a pool size of (2, 2) follows, which reduces the spatial dimensions of the feature maps.
  - Dropout regularization with a rate of 0.2 is applied to mitigate overfitting.
  - This pattern repeats with two more sets of Conv2D, MaxPooling2D, and Dropout layers, gradually increasing the number of filters to capture more complex features.
  - After the convolutional layers, a Flatten layer is added to transform the 3D feature maps into a 1D vector for input to the fully connected layers.
  - Two fully connected (Dense) layers follow, with ReLU activation in the hidden layer and softmax activation in the output layer with 25 units, corresponding to the number of classes.
- Compile the model: The model is compiled with categorical cross-entropy loss, Adam optimizer, and accuracy metrics. Categorical cross-entropy is suitable for multi-class classification problems when target labels are one-hot encoded.

- Training the model: The model is trained using the fit method on the training data (X_train and y_train_cat) for a specified number of epochs and batch size. Validation data (X_test, y_test_cat) is provided to evaluate the model's performance on unseen data during training.
- Save the model: After training, the model is saved to disk in the HDF5 format for future use.

2: Model - 2

- Training another convolutional neural network (CNN) model (referred to as Model 2) using Keras with TensorFlow backend. Define the CNN architecture: Model 2 is defined using the Sequential API, similar to Model 1.
- The model starts with a Conv2D layer with 32 filters of size (3, 3) and ReLU activation function. The input shape is (28, 28, 1), indicating grayscale images of size 28x28 pixels. Another Conv2D layer with 32 filters and a (3, 3) kernel size follows, along with ReLU activation. A MaxPooling2D layer with a pool size of (2, 2) reduces the spatial dimensions of the feature maps.
- This pattern repeats with two more sets of convolutional layers, increasing the number of filters and complexity of features learned. After the convolutional layers, a Flatten layer transforms the 3D feature maps into a 1D vector. The model ends with a Dense layer with softmax activation, producing 25 output units corresponding to the number of classes.
- Compile the model: Model 2 is compiled with categorical cross-entropy loss, Adam optimizer, and accuracy metrics, similar to Model 1. Training the model: The model is trained using the fit method on the training data (X_train and y_train_cat) for a specified number of epochs and batch size. Validation data (X_test, y_test_cat) is provided to evaluate the model's performance on unseen data during training. Save the model: After training, the model is saved to disk in the HDF5 format for future use.

3: Model - 3

Third convolutional neural network (CNN) model (referred to as Model 3) using Keras with TensorFlow backend. Define the CNN architecture as show in figure 5:

- Model 3 begins with a Conv2D layer with 32 filters of size (3, 3) and ReLU activation function. The input shape is (28, 28, 1), indicating grayscale images of size 28x28 pixels.
- A MaxPooling2D layer with a pool size of (2, 2) follows, reducing the spatial dimensions of the feature maps.
- Dropout regularization with a rate of 0.2 is applied to mitigate overfitting.
- Another set of Conv2D layer with 64 filters and a (3, 3) kernel size follows, along with ReLU activation and max-pooling.
- Dropout regularization is applied again.
- The feature maps are flattened into a 1D vector using the Flatten layer.

Finally, a Dense layer with softmax activation produces 25 output units corresponding to the number of classes.

- Individual Model Evaluation: For each individual model (model1, model2, model3), the accuracy score is calculated by comparing its predictions with the true labels (y_test). The accuracy_score function from scikit-learn is used for this calculation.
- Ensemble Evaluation: The accuracy score of the ensemble prediction is computed in the same way as for individual models.
- Print Results: The accuracy scores for each individual model and the ensemble are printed for comparison.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2  (None, 13, 13, 32)        0
 D)

 dropout (Dropout)           (None, 13, 13, 32)        0

 conv2d_1 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 5, 5, 64)          0
 g2D)

 dropout_1 (Dropout)         (None, 5, 5, 64)          0

 conv2d_2 (Conv2D)           (None, 3, 3, 128)         73856

 max_pooling2d_2 (MaxPoolin  (None, 1, 1, 128)         0
 g2D)

 dropout_2 (Dropout)         (None, 1, 1, 128)         0

 flatten (Flatten)           (None, 128)               0

 dense (Dense)               (None, 128)               16512

 dense_1 (Dense)             (None, 25)                3225

=================================================================
Total params: 112409 (439.10 KB)
Trainable params: 112409 (439.10 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig.5: CNN Layers for Model -1

Also we have implemented a weighted average ensemble method and perform a grid search to find the optimal combination of weights for the ensemble.

1. Weighted Average Ensemble:

- We have defined a list of models [model1, model2, model3].
- Predictions are generated for each model using the predict method applied to the test dataset (X_test), resulting in an array of predictions preds.
- Weights for each model are specified [0.4, 0.2, 0.4].
- The weighted predictions are computed using np.tensordot to sum the products of all elements over specified axes, effectively computing the weighted average.
- The ensemble prediction is obtained by taking the argmax across classes for each sample. As we can see in fig.7 accuracy of weighted average ensemble is high.

2. Grid Search for Optimal Weights:

- A grid search is performed to find the best combination of weights (w1, w2, w3) that maximizes accuracy.
- Nested loops iterate over the weight values, ranging from 0.0 to 0.4 with step 0.1, for each model.[18]
- For each combination of weights, predictions are computed similarly to the weighted average ensemble.
- The accuracy score is calculated and stored in a DataFrame for analysis.
- The weights corresponding to the maximum accuracy are printed.

3. Exploration of Metrics for the Ideal Weighted Ensemble Model:

- Predictions are generated using the ideal weights [0.4, 0.1, and 0.2].
- Visualizations, such as an example prediction, confusion matrix, and fractional incorrect misclassifications, are generated to explore the performance of the ensemble model.

Here our implementation is comprehensive, exploring both the weighted ensemble technique and conducting a grid search for optimal weights. It also provides visualizations to analyze the performance of the ensemble model.

IV. RESULTS

The implemented code showcases the utilization of ensemble learning techniques, particularly focusing on the weighted average ensemble method. Initially, a weighted average ensemble model is constructed by combining

predictions from multiple individual models with assigned weights. Subsequently, a grid search algorithm is employed to determine the optimal combination of weights, enhancing the ensemble's predictive accuracy. Through meticulous iteration and evaluation, this process identifies the most effective weight distribution for maximizing overall model performance as shown in figure 6, 7, 8. Further analysis delves into the metrics of the ideal weighted ensemble model, including accuracy assessment, random prediction visualization, confusion matrix depiction, and misclassification fraction plotting. This comprehensive evaluation elucidates the ensemble model's strengths and weaknesses across various performance aspects. Ultimately, the ensemble approach emerges as a potent strategy for augmenting predictive capabilities, offering a robust methodology for achieving superior accuracy and reliability in machine learning applications. Confusion matrix plot can be seen in figure 9.

```
225/225 [==============================] - 3s 12ms/step
225/225 [==============================] - 5s 20ms/step
225/225 [==============================] - 2s 8ms/step
225/225 [==============================] - 2s 9ms/step
225/225 [==============================] - 6s 27ms/step
225/225 [==============================] - 2s 11ms/step
Accuracy Score for model1 =  0.9511991076408254
Accuracy Score for model2 =  0.8950083658672616
Accuracy Score for model3 =  0.9386503067484663
Accuracy Score for average ensemble =  0.9595649749023982
```

Fig.6: Accuracy scores of Model 1, 2, 3 with average ensemble

```
225/225 [==============================] - 2s 9ms/step
225/225 [==============================] - 4s 19ms/step
225/225 [==============================] - 2s 10ms/step
Accuracy Score for model1 =  0.9511991076408254
Accuracy Score for model2 =  0.8950083658672616
Accuracy Score for model3 =  0.9386503067484663
Accuracy Score for average ensemble =  0.9595649749023982
Accuracy Score for weighted average ensemble =  0.9617958728388176
```

Fig.7: Accuracy scores of Model 1, 2, 3 ,average ensemble and with weighted average

```
Max accuracy of  0.2  obained with w1= 0.1  w2= 0.1  and w3= 96.84885666480758
225/225 [==============================] - 2s 9ms/step
225/225 [==============================] - 6s 26ms/step
225/225 [==============================] - 2s 8ms/step
Predicted Label:  P
True Label:  P
```

Fig.8: Predicted Label versus True Label

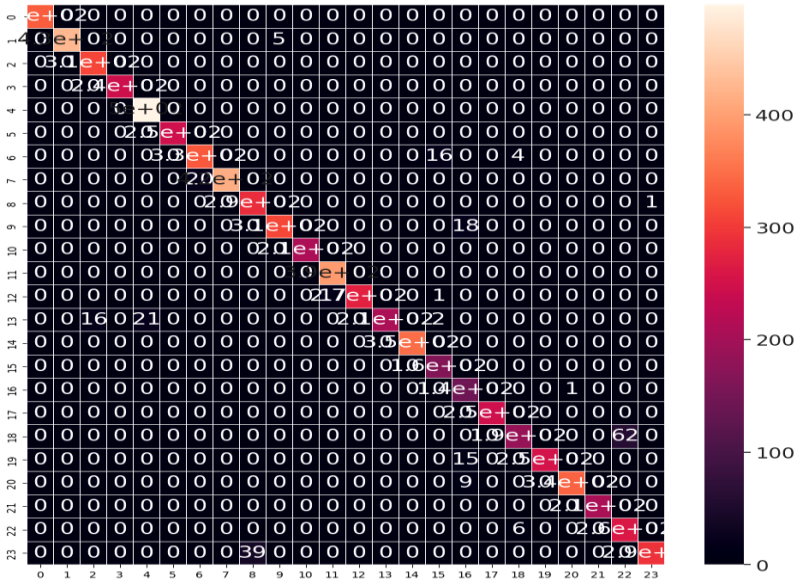


Fig.9: Confusion Matrix

V. CONCLUSION

In this paper we have presented a method to implement Indian Sign Language gesture recognition using ensemble approach. In conclusion, the research on ensemble learning techniques for Indian Sign Language (ISL) recognition presents a significant advancement in bridging communication barriers between individuals with disabilities and the broader community. Through innovative dataset creation and rigorous experimentation, the study showcases the superiority of ensemble models over individual ones in achieving higher accuracy and reliability in ISL gesture recognition tasks. By leveraging diverse models and combining their predictions effectively, the ensemble approach offers a practical solution for enhancing communication accessibility for speech-impaired individuals. Furthermore, the research provides valuable insights into the potential of ensemble learning to contribute to the development of assistive technologies that promote inclusivity and facilitate meaningful interactions between diverse populations. Overall, this study represents a pivotal step towards fostering greater understanding and integration for individuals with disabilities through cutting-edge machine learning methodologies.

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Data Availability:

The data that support the findings of this study are available only on request.

Conflict of interest:

The authors declare that there is **no conflict of interest.**

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