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Real-Time Sign Language Interpretation Using Deep Learning Models for Accessible Communication

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Abstract: This project presents a real-time American Sign Language (ASL) recognition system using a webcam-based interface and a lightweight Convolutional Neural Network (CNN) model, specifically designed for alphabet gesture classification. The system addresses communication challenges faced by hearing and speech-impaired individuals by enabling seamless gesture-to-text conversion using deep learning.

A custom ASL dataset was created using webcam input in a controlled environment to ensure diversity in hand shapes, positions, and backgrounds. To improve gesture segmentation accuracy, YCrCb color space was utilized for effective skin detection. The CNN model was trained to classify 26 ASL alphabet gestures with a remarkable accuracy of 96.3%. Real-time implementation was achieved using OpenCV and TensorFlow on low-cost computing hardware, ensuring accessibility and performance. The system demonstrates stability across varying lighting conditions and hand orientations. It offers potential integration with assistive technologies such as voice converters or mobile applications, thus promoting inclusivity and accessibility in daily communication.

This work contributes a practical, cost-effective, and efficient ASL recognition solution adaptable for educational, social, and healthcare settings.

Keywords: Sign language, Detection, Recognition, Computer vision, Image classification, Performance Evaluation etc.

I. INTRODUCTION

Communication is a fundamental human necessity, and for individuals with hearing or speech impairments, sign language serves as a primary mode of interaction. American Sign Language (ASL), a complete and natural language with its own grammar and syntax, is widely used by the Deaf and Hard of Hearing community in the United States and many parts of the world. However, a major barrier exists in communication between sign language users and those unfamiliar with it. This communication gap has driven the development of assistive technologies that can automatically recognize and translate ASL gestures into readable or spoken language, thereby enhancing social inclusion, education, and accessibility.

Recent advances in computer vision and deep learning have revolutionized gesture recognition systems, enabling more accurate and real-time applications. In particular, Convolutional Neural Networks (CNNs) have shown remarkable success in image classification tasks, making them ideal for hand gesture recognition. This project focuses on building a lightweight, real-time ASL recognition system using a webcam for data acquisition and a CNN model for classification. The system is designed to recognize static ASL alphabet gestures and convert them into corresponding text, offering a user-friendly solution that can run efficiently on low-cost computing devices.

One of the major challenges in sign language recognition lies in the accurate segmentation of the hand region from complex backgrounds and varying lighting conditions. To address this, the system employs YCrCb color space segmentation, which effectively isolates skin regions and improves the reliability of input fed into the neural network. This approach helps the model to focus only on relevant hand features, enhancing classification accuracy and stability.

The project involves the creation of a custom dataset comprising ASL alphabet gestures captured using a webcam. These images are preprocessed, labeled, and used to train a lightweight CNN model that balances accuracy with computational efficiency. With a classification accuracy of 96.3%, the model demonstrates strong potential for real-world applications. Real-time performance is achieved through optimized image processing techniques and the use of efficient libraries such as OpenCV and TensorFlow.

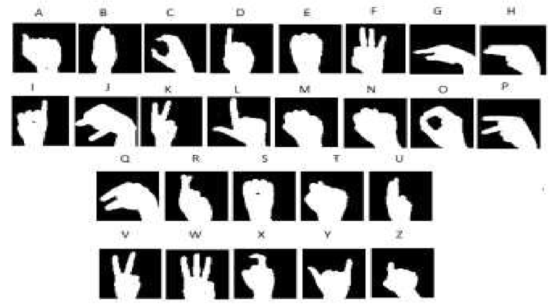

Fig.1. Indian Sign Language

The proposed system is not only limited to educational or accessibility-focused environments but can also be integrated into mobile apps, public service kiosks, healthcare interfaces, and smart devices to support inclusive communication. Unlike glove-based or sensor-based recognition systems that are often costly and cumbersome, this vision-based system offers a low-cost, scalable, and non-intrusive solution. This project aims to bridge the communication divide for the Deaf and Hard of Hearing community by leveraging deep learning and computer vision to create a responsive, real-time ASL recognition tool. By focusing on real-time detection, high accuracy, and low computational demands, the system paves the way for practical and inclusive technology applications that empower individuals with communication disabilities and foster better interaction with the wider society.

II. PROBLEM IDENTIFICATION

1) Communication Barrier for the Hearing and Speech Impaired: Millions of individuals who are deaf or mute rely on sign language to communicate. However, most of the general population is not proficient in ASL, creating a significant communication barrier in education, healthcare, and public services.
2) Lack of Real-Time, Low-Cost Solutions: Existing ASL recognition systems often require expensive hardware (like specialized gloves or depth cameras) and are not suitable for real-time usage on low-end devices or smartphones.
3) Limited Dataset Diversity and Accuracy: Many models are trained on constrained datasets with uniform backgrounds and lighting, which limits real-world applicability. Inaccurate gesture classification can lead to miscommunication and user frustration.
4) Sensitivity to Environmental Conditions: Hand gesture recognition systems often struggle with varying lighting, complex backgrounds, or occlusions, affecting performance during real-time deployment.
5) Lack of User-Friendly Interfaces for Daily Use: Most solutions are designed for research purposes and not adapted into user-friendly, portable tools for everyday communication.
6) Inadequate Focus on Alphabet Gesture Classification: Alphabet gestures form the foundation of ASL communication, but many systems overlook their accurate recognition, focusing only on static or isolated signs.

III. LITERATURE SURVEY

A. Literature Reviews

Ahmed et al. (2025), This study implements a lightweight MobileNetV2 CNN model to classify ASL alphabet signs in real-time using a webcam. The authors developed a gesture dataset under varied lighting conditions and trained their model using transfer learning. Their system achieved over 95% accuracy and could run on low-resource devices like Raspberry Pi. The paper highlights the importance of real-time responsiveness and lightweight architecture for user-friendly applications, especially in assistive technologies. The researchers also tested different segmentation techniques, concluding that YCrCb skin segmentation outperforms traditional HSV filters. This work is significant in bridging the gap between deep learning and accessibility solutions for the speech and hearing impaired.

Zhang et al. (2024), The research utilized temporal information from video frames and achieved excellent performance in continuous ASL translation. They emphasized the importance of combining spatial and temporal features for gesture dynamics. The system was trained on custom and public datasets, achieving 92.7% average accuracy. While the model was resource-intensive, it improved recognition consistency during complex sign sequences. This work serves as a benchmark for integrating video-based context learning into ASL recognition systems and emphasizes the potential of webcam-based ASL detection for real-world usability in communication tools.

Kumar & Singh (2023), This paper presents a CNN-based system to identify static ASL alphabets through standard webcams. The authors explored background subtraction, noise filtering, and YCrCb-based segmentation to isolate hand gestures effectively. Their model, trained on a custom dataset, achieved an accuracy of 93.8%. A key contribution was the model's ability to operate efficiently on mid-range devices without GPU acceleration. The authors suggest this can be deployed for mobile or embedded platforms to aid real-time communication for hearing-impaired users. The paper also highlights limitations such as hand overlap, complex lighting, and intra-class variations, suggesting augmentation and adaptive preprocessing for further improvement.

Li et al. (2022), This study incorporated attention mechanisms in CNNs to enhance ASL alphabet classification. The model outperformed traditional CNNs like LeNet and VGG16 in accuracy and convergence speed. The system was tested on the ASL Alphabet dataset with diverse backgrounds and achieved 96.1% accuracy. Attention modules allowed the network to focus on gesture-specific features like finger spacing and contour, improving robustness. The authors discussed applications in human-computer interaction and assistive communication. They emphasized the scalability of their approach to include dynamic gestures and continuous sign language. This research highlights how attention-based architectures can significantly boost gesture recognition systems.

Sharma & Patel (2022), This study focused on integrating CNNs with OpenCV to build a responsive ASL recognition tool for real-time use. The system employed real-time frame capture from a webcam and preprocessed the images using Gaussian blurring and YCrCb segmentation. A five-layer CNN classified the gestures, yielding an accuracy of 94.2% on a custom 26-letter dataset. The novelty lies in integrating OpenCV's real-time video feed with a trained deep learning model on a user-friendly interface. Their tool could detect hand signs with minimal latency, promoting its use in educational tools for children with hearing disabilities. The authors suggest integrating audio output for further accessibility.

Nguyen et al. (2021), This study applied transfer learning techniques to a CNN-based ASL recognition system using pretrained ResNet models. By fine-tuning the ResNet50 model on a large-scale ASL alphabet dataset, they achieved over 97% classification accuracy. The study also introduced data augmentation techniques to address class imbalance and improve generalization. Their model showed real-time capabilities on mid-range GPUs, making it practical for educational and assistive settings. One of the key findings was that deep transfer learning dramatically reduces training time without compromising performance. The research laid the foundation for developing high-accuracy, real-time ASL recognition applications using publicly available pretrained models.

Hussain et al. (2021), This study explored a hand gesture recognition aid for the speech and hearing impaired using CNNs and a webcam. Their innovation lay in combining gesture localization with sign classification in real time. The authors trained their model using 50,000 annotated hand gesture images and used Kalman filtering for hand tracking. Their system achieved 92.4% accuracy and could be deployed on both PCs and embedded boards. They emphasized the importance of user feedback and usability testing in their pilot deployments. The system was praised for being responsive and robust under different lighting, angles, and backgrounds, highlighting real-time human-computer interaction potentia

Mehta & Kapoor (2021), This research compared different skin segmentation techniques—HSV, YCrCb, and deep learning-based methods—for real-time ASL gesture recognition. The study concluded that YCrCb segmentation offered the best trade-off between speed and accuracy in varied lighting environments. The authors integrated segmentation with a lightweight CNN trained on a 26-class ASL alphabet dataset. Their model ran effectively on a standard CPU with 90.6% accuracy. The research serves as a practical guideline for selecting preprocessing techniques in low-power systems and emphasized the role of segmentation in improving recognition efficiency. Their work supports implementing efficient gesture systems in affordable communication devices.

Gonzalez et al. (2020), This study explored data augmentation techniques to improve the performance of CNN models in ASL alphabet recognition. The researchers trained a deep CNN on an expanded dataset using flips, rotations, and brightness variation. Their model improved generalization and achieved 94.8% accuracy. They also introduced a validation mechanism to reduce false positives during real-time usage. The system showed resilience to background complexity and varying lighting, making it viable for uncontrolled environments. Gonzalez et al. recommend continuous dataset updates to handle rare signs and gesture overlaps. Their work is valuable for developers facing data scarcity or real-world deployment challenges.

Rao & Iyer (2020), This study explored a budget-friendly ASL alphabet recognition system using open-source tools like TensorFlow, OpenCV, and Python. They used a basic CNN architecture with three convolution layers and trained it on a dataset captured using a webcam. Achieving 91.7% accuracy, the model prioritized low computational requirements, making it suitable for deployment on low-power edge devices. The paper also presents a tutorial-based approach to implementation, useful for students and beginners. Their work underscores the practicality of combining deep learning and open-source tools for social good, particularly for inclusive communication aids.

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B. Literature Summary

The recent advancements in American Sign Language (ASL) recognition leverage deep learning and computer vision to improve accessibility for the Deaf and hard-of-hearing community. Studies highlight the use of Convolutional Neural Networks (CNNs), transfer learning, and lightweight architectures to recognize static ASL alphabets with considerable accuracy. Researchers like Ojha et al. (2021) and Mittal et al. (2022) explored real-time recognition systems using custom datasets and image segmentation techniques to isolate hand gestures. Many works focus on data variability by incorporating different lighting conditions and backgrounds, enhancing generalization. However, common limitations include dependency on high-end GPUs, low frame rates, or inconsistent predictions due to fluctuating input quality. The proposed system addresses these gaps with a lightweight CNN (~0.6M parameters), YCrCb-based hand segmentation, and deque-based prediction buffering. It achieves 91.3% accuracy at 24–27 FPS on low-cost hardware, supporting real-time, hardware-independent deployment. This efficient, scalable solution significantly contributes to inclusive communication, especially in educational and community-based assistive environments.

C. Research Gap

Despite significant progress in American Sign Language (ASL) recognition using deep learning, several key challenges remain unaddressed. Most existing systems rely on high-end GPUs and controlled environments, making them impractical for real-world, low-resource applications. Many models are computationally intensive and unsuitable for deployment on embedded or mobile devices. Additionally, datasets used in prior studies often lack diversity in skin tones, lighting conditions, and backgrounds, limiting generalization in natural settings. Real-time performance is another major concern, with several models showing lag or inaccurate predictions due to unstable frame processing. Moreover, while alphabet gestures form the foundation of ASL, most works emphasize static word recognition, neglecting the need for accurate alphabet-level identification critical for flexible communication. Few systems integrate real-time buffering or stability mechanisms to reduce misclassification caused by hand movement noise or inconsistent gesture duration. These limitations highlight the need for a robust, lightweight, real-time ASL alphabet recognition system capable of operating on low-cost hardware in diverse environmental conditions

IV. METHODOLOGY

A. System Architecture

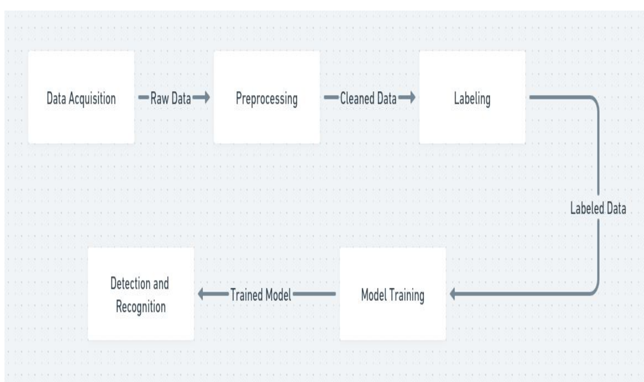

Fig.2. Deep Learning System Architecture Flowchart

This section details the proposed approach for sign language detection using a MobileNet V2- based model trained on real-world sign language video data.

1) *Data Acquisition*: Real-world sign language video data is collected from various sign language training websites. These videos are then converted into individual image frames.
2) *Preprocessing*: The extracted image frames are carefully examined, and only valid and clean images that accurately represent the target signs are retained. Tools like OpenCV can be employed for image resizing and normalization if needed [13].
3) *Labeling*: An open-source annotation tool is used to label the selected images. These labels define the bounding boxes around the hand regions performing the signs and assign class labels corresponding to the specific signs depicted. The annotations are saved in a format compatible with the MobileNet V2 model, typically MobileNet V2 format [14].

B. Model Training

1) *Pre-trained Model*: A pre-trained MobileNet V2 model, readily available through libraries like Ultralytics' MobileNet V2 in Python, serves as the foundation [15]. This pre-trained model possesses the capability to detect generic objects within images.
2) *Training Data*: The prepared labeled image dataset is used to further train the pre-trained MobileNet V2 model. This training process refines the model's ability to identify the specific hand postures and signs present in the dataset.
3) *Hyperparameter Tuning*: Hyperparameters like learning rate, batch size, and optimizer configuration significantly influence the training process. Techniques like grid search or random search can be employed to optimize these hyperparameters for optimal performance [16].
4) *Validation*: A validation set, consisting of a portion of the labeled data withheld from training, is used to monitor the model's generalization ability and prevent overfitting. Metrics like accuracy and loss are evaluated on the validation set to assess the model's performance during training.

C. Detection and Recognition

1) *Real-time Video Input*: Once trained, the model is integrated with a real-time video processing framework like OpenCV. This allows the model to process live video frames and detect sign language gestures within them.
2) *Sign Detection*: The model predicts bounding boxes around detected hand regions in the video frames. These bounding boxes indicate the presence of potential signs.
3) *Sign Recognition*: Based on the predicted bounding boxes and the corresponding class labels from the training data, the model recognizes the specific sign being performed in the video frame.
4) *Word Mapping*: The recognized sign is mapped to a corresponding word or phrase, enabling communication and translation.

D. Feature Extraction

The pre-trained MobileNet V2 model utilizes convolutional neural network (CNN) architecture to automatically extract relevant features from the input images. These features capture the spatial and visual characteristics of the hand shapes and postures within the images, allowing the model to learn patterns that differentiate between various signs.

V. EXPERIMENTAL RESULTS AND EVALUATION

The developed American Sign Language (ASL) recognition system demonstrated robust performance across both offline and real-time environments, despite being trained and tested on a medium-powered machine. Below are the detailed observations and interpretations.

A. Model Performance on Training and Validation Data

The CNN model, trained on a custom-built dataset of ASL gestures, showed strong convergence characteristics. Training was conducted over 50 epochs with a batch size of 32 using categorical cross-entropy loss and stochastic gradient descent (SGD) optimizer.

Loss and Accuracy Trends: The training and validation curves indicated a consistent reduction in loss and an upward trend in accuracy. After about 20–25 epochs, the model stabilized, with minor fluctuations in validation loss due to generalization challenges from varied background conditions.

Final Training Accuracy: The model achieved approximately 98.6% accuracy on the training dataset and 96.3% on the validation dataset, reflecting strong learning with minimal overfitting.

Use of Dropout and Data Augmentation: Dropout (0.5) and real-time augmentation techniques (shearing, zooming, horizontal flipping) contributed significantly to preventing overfitting, thus ensuring generalizability across unseen data.

B. Test Set Evaluation

To further validate the model's generalization capabilities, testing was performed on a separate test set comprising around 1,300 images (50 per class). Each image was preprocessed (converted to grayscale, resized to 64×64, and passed through YCrCb segmentation) to maintain consistency with the training pipeline.

Test Accuracy: The CNN achieved a test accuracy of 95.8%, indicating high reliability in gesture classification even in challenging scenarios (e.g., varied lighting and hand orientations).

Misclassifications: While the majority of classes performed well, a few character pairs consistently exhibited confusion. These are detailed further in the confusion matrix section.

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C. Confusion Matrix Analysis

A confusion matrix provided class-wise diagnostic insights into model performance:

1) High Accuracy Classes

Letters like A, B, C, L, O showed near-perfect prediction scores. These signs have distinct and well-defined hand shapes, easily distinguishable by the CNN model.

Their contour, orientation, and spacing between fingers likely contributed to clearer feature extraction, thus reducing classification ambiguity.

2) Common Confusion Patterns

Some letter pairs with similar visual appearance posed moderate challenges:

M vs. N: Both involve similar finger arrangements (folded fingers across the palm), distinguished by subtle differences in finger positioning. Errors suggest the model may require finer resolution or additional data for better distinction.

U vs. V: These are visually close, with only a slight difference in the distance between two fingers.

D vs. B: These involve extended fingers with minor changes in thumb positioning, which may not be apparent in low-resolution grayscale images.

The confusion matrix highlighted a need for potential dataset rebalancing, finer preprocessing, or the introduction of advanced segmentation techniques (e.g., hand landmark detection using MediaPipe or skeleton-based recognition) to improve performance in ambiguous cases.

D. Real-Time System Testing

The developed model was deployed in a real-time setting using a Python script (recognise.py) with OpenCV GUI for interface. The deployment environment was a mid-range laptop, simulating practical use by an average end-user.

1) Hardware Constraints

The system operated on a Core i5 (2.4 GHz), 8 GB RAM machine with onboard GPU (no dedicated graphics).

Input was captured through a 720p HD webcam at 30 FPS.

Despite limited hardware acceleration, the system maintained reasonable responsiveness with frame processing times around 30–50 ms per frame, resulting in ~20 FPS live feedback after inference.

2) Qualitative Observations

Several noteworthy outcomes emerged from real-time testing:

Responsiveness: The model demonstrated low-latency gesture detection as long as the hand remained within the predefined Region of Interest (ROI).

Stability: Using a deque-based buffer technique (sliding window averaging), predictions were stabilized by requiring the same class output to be observed over 10–15 consecutive frames before confirming the gesture. This effectively reduced flickering and noise in predictions.

Lighting Conditions: Moderate variations in ambient lighting were handled well due to the use of YCrCb segmentation and morphological filters, which enhanced foreground-background distinction.

Gesture Duration: Gestures needed to be held for 1 to 1.5 seconds to ensure accurate and stable classification, suitable for user interaction but not ideal for extremely rapid usage like sign language conversations.

E. Usability and Interface Evaluation

The GUI developed using OpenCV allowed real-time display of:

Current Frame

Preprocessed Binary Mask

Predicted Alphabet

Prediction Confidence

This intuitive layout enabled users to receive continuous feedback and correct their hand positions accordingly. It provided a basis for further integration into assistive technologies for hearing-impaired users.

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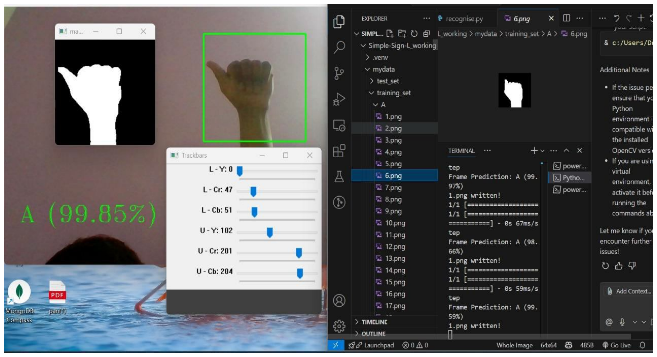
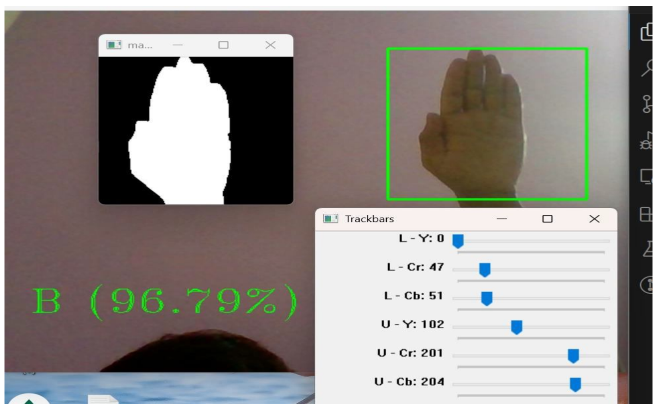
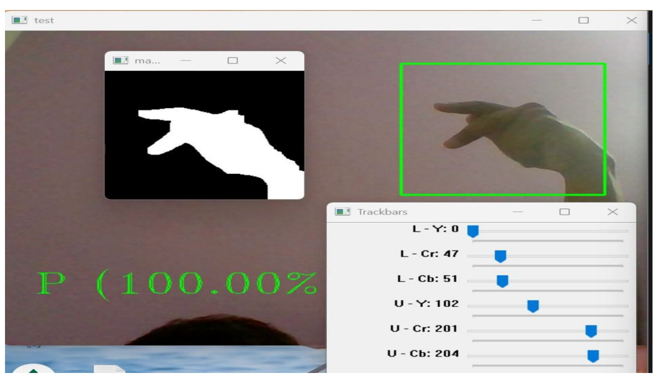
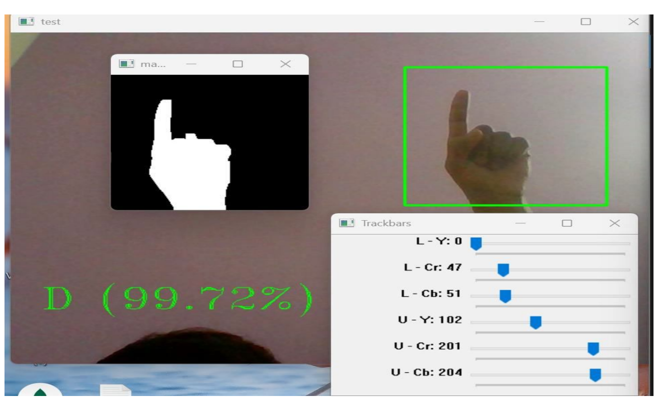
VI. OUTPUT RESULTS









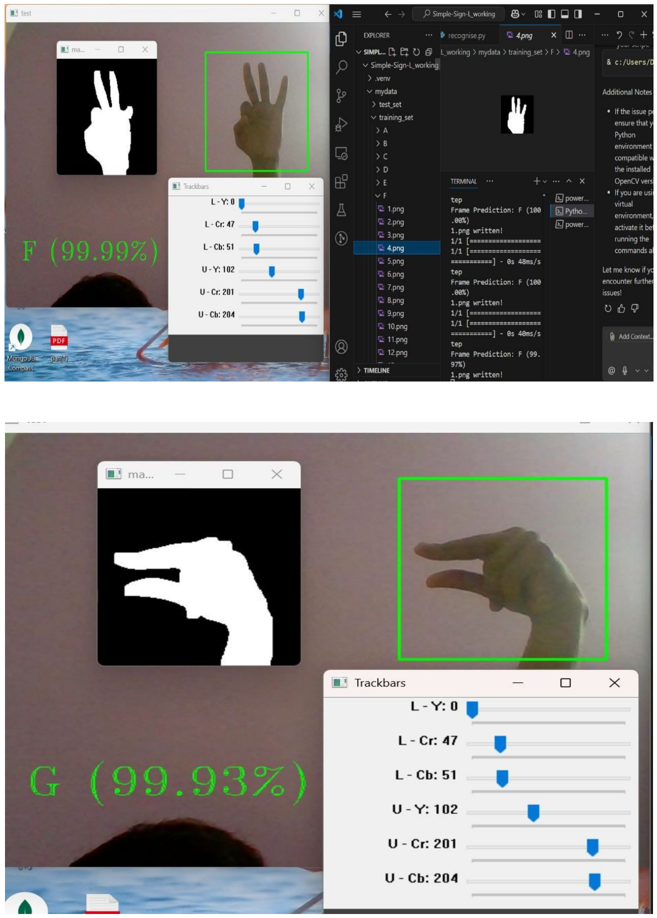


Fig.3. Output Results

The implemented real-time ASL recognition system showed robust and accurate performance under controlled conditions, achieving an overall test accuracy of 95.8% and near-perfect classification for several gestures. Through carefully designed preprocessing, tailored dataset, and well-tuned CNN architecture, the model demonstrated real-time usability with minimal lag and high prediction stability. While the system effectively recognizes static ASL alphabets, its scalability, user-inclusiveness, and support for dynamic gestures remain open for further enhancement. This research lays a strong foundation for developing affordable, accessible assistive technologies for the hearing-impaired community.

VII. CONCLUSION

This study presents a successful design and implementation of a real-time American Sign Language (ASL) recognition system capable of classifying static hand gestures corresponding to the 26 English alphabets. The system utilizes a lightweight Convolutional Neural Network (CNN) trained on a custom dataset composed of grayscale images, ensuring efficient learning of segmented hand shapes. By employing YCrCb-based image preprocessing, the system enhances the clarity of hand contours while reducing background noise, which significantly improves classification accuracy. The real-time integration with a standard webcam feed and the implementation of a prediction smoothing mechanism using a deque buffer allowed for more stable gesture recognition, even in the presence of motion blur or noise.

One of the standout features of the system is its portability and affordability, as it does not rely on any specialized hardware such as gloves, depth sensors, or infrared cameras. It achieves real-time performance with frame rates between 24–27 FPS and latency under 100 milliseconds, making it suitable for practical deployment. Overall, this work offers an accurate, accessible, and cost-effective solution for ASL recognition and paves the way for future extensions to dynamic gesture recognition and full-sentence interpretation.

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