Liquid Propulsion Systems Center (LPSC)
Valaimala, Thiruvananthapuram, Kerala - 695547

Internship Report

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Real-Time Dynamic Sign Language Recognition Using LSTM Networks

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Acknowledgment

I would like to express my heartfelt gratitude to all those who have supported and guided me throughout my internship and the preparation of this report.

First and foremost, I am deeply grateful to **Mr. Manusubramanian S** (Sci./Engr-SF, DDH, CND/CISDG, LPSC/ISRO) for his invaluable guidance, insightful suggestions, and unwavering encouragement throughout the course of my project. His expertise and mentorship have been pivotal in shaping the direction and outcome of this work.

I would also like to extend my sincere thanks to my academic institution, **JNEC, MGM University**, for providing me with the opportunity to intern at such a prestigious organization. Their support and encouragement throughout my academic journey have been integral to my success.

Furthermore, I wish to express my profound appreciation to **LPSC, ISRO** for accepting my application and granting me the privilege of interning at their esteemed institution. The knowledge and experience I have gained during this internship have been truly invaluable and will serve as a strong foundation for my future professional endeavors.

Finally, I am grateful to all my colleagues, faculty members, and family who have continuously motivated and supported me throughout this journey.

Once again, I thank everyone who has contributed to the success of this internship and the completion of this report.

Certificate

This is to certify that the project titled **“Real-Time Dynamic Sign Language Recognition Using LSTM Networks”**, submitted to the **Human Resource Development Division (HRDD), Liquid Propulsion Systems Centre (LPSC), Valiamala**, is a bonafide record of work carried out by **Pratik Ashok Salve**, a student of **Jawaharlal Nehru Engineering College, MGM University**. The project was undertaken under my guidance and supervision from **2nd December 2024 to 15th January 2025** at the **Computer Infrastructure and Software Development Group**, Liquid Propulsion Systems Centre, ISRO, Valiamala.

During this internship, the candidate explored advanced techniques in **dynamic sign language recognition**, focusing on the integration of **LSTM networks** with cutting-edge deep learning approaches. The work emphasized improving the real-time recognition of dynamic hand gestures, contributing to the development of innovative, efficient, and accurate solutions for sign language communication.

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About LPSC

Liquid Propulsion Systems Centre (LPSC) is the lead Centre for development and realization of earth-to-orbit advanced propulsion stages for Launch Vehicles and also the in-space propulsion systems for Spacecrafts. The LPSC activities and facilities are spread across its two campuses viz., LPSC Headquarters and Design Offices at Valiamala/Thiruvananthapuram, and Spacecraft Propulsion Systems Activities at LPSC, Bengaluru/Karnataka.

LPSC is vested with the responsibility of design, development and system engineering of high-performance Space Propulsion Systems employing Earth Storable and Cryogenic Propellants for ISRO's Launch Vehicles and Satellites. Development of fluid control valves, transducers, propellant management devices and other key components of Liquid Propulsion Systems are also under the purview of LPSC.

LPSC Valiamala is the Centre Headquarters, responsible for R & D, System Design/Engineering and Project Management functions. The Fluid Control Components Entity and the Materials & Mechanical Engineering Entity are located here apart from the Earth Storable & Cryogenic Propulsion Entities, handling the core tasks of the Centre.

LPSC Bengaluru focuses on satellite propulsion. Design & Realisation of Propulsion Systems, integration of spacecraft propulsion systems for Remote Sensing and Communication satellites, Development and production of transducers / sensors are other major activities at LPSC, Bengaluru. Fabrication of launch vehicle stage tanks and structure at ASD/HAL is also coordinated and managed by LHWC at Bengaluru.

Abstract

Sign language recognition is a critical tool for bridging communication gaps between individuals with Hearing / Speech challenged and the rest of society. This study focuses on the recognition of dynamic Indian Sign Language (ISL) gestures commonly used in emergency scenarios. The dataset, provided by the Central University of Kerala, consists of video recordings of six gestures: ‘Accident,’ ‘Call,’ ‘Doctor,’ ‘Help,’ ‘Hot,’ and ‘Pain.’ These dynamic gestures were recorded in controlled indoor settings and processed using advanced computer vision and deep learning techniques.

The research employs a pipeline that includes preprocessing, feature extraction using the ‘MediaPipe Holistic model’, and gesture classification using a ‘Long Short-Term Memory (LSTM)’ deep learning model. Each video was segmented into 45 frames, and keypoints representing hand landmarks were extracted to capture temporal dependencies. The LSTM architecture, designed for sequential data, effectively models these dependencies, enabling accurate gesture recognition.

Experimental results reveal an overall accuracy of 100%, 100% accuracy on test dataset and a generalization accuracy of 98% (in controlled environment), demonstrating robust performance on unseen data for the six ISL gestures, demonstrating the system's robustness and potential for real-time applications. The proposed system offers a practical solution for assistive technologies, facilitating communication in emergency situations. Future directions include expanding the dataset, incorporating advanced models such as transformers, and enhancing system scalability for broader deployment.

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5. Introduction

Communication is a fundamental aspect of human interaction, and for individuals with Hearing / Speech challenges, sign language serves as a vital medium of expression. Indian Sign Language (ISL), a predominant form of sign language used in India, plays a significant role in empowering millions of people by facilitating effective communication. However, in emergency scenarios where timely assistance is crucial, the inability to understand ISL gestures can pose significant challenges for first responders and the general population. This highlights the importance of dynamic sign language recognition systems capable of interpreting gestures in real-time.

Dynamic sign language recognition focuses on gestures that evolve over time, requiring an understanding of both spatial and temporal features. Unlike static gestures that involve fixed hand positions, dynamic gestures encompass motion patterns of the hands gestures.

This Project aims to develop a system for recognizing six dynamic ISL gestures commonly associated with emergency contexts: ‘Accident,’ ‘Call,’ ‘Doctor,’ ‘Help,’ ‘Hot,’ and ‘Pain.’ The dataset used for this research consists of video recordings provided by the Central University of Kerala, captured under controlled indoor settings. To ensure accurate and efficient recognition, the proposed approach utilizes a pipeline comprising preprocessing, feature extraction using the ‘MediaPipe Holistic’ framework, and classification using a ‘Long Short-Term Memory (LSTM)’ neural network.

‘MediaPipe Holistic’, a state-of-the-art pose estimation tool, extracts keypoints representing the hands, body, and face from video frames. These keypoints capture the intricate motion patterns of ISL gestures, serving as inputs to the ‘LSTM’ model. ‘LSTM’, a deep learning architecture designed for sequential data, is well-suited for modelling the temporal dependencies inherent in dynamic gestures.

6. Algorithm Implemented

A. **Data preprocessing:** This study leverages a dataset provided by the Central University of Kerala, comprising video recordings of eight dynamic Indian Sign Language (ISL) gestures frequently used in emergency scenarios: accident, call, doctor, help, hot, pain. Each video is segmented into 45 frames to ensure consistency in temporal resolution across the dataset. The frames undergo preprocessing to enhance visual quality, including noise reduction, contrast enhancement, and normalization. This step ensures that the extracted features are both high-quality and suitable for input into the deep learning model.

B. **Feature Extraction:** To extract meaningful features, the MediaPipe Holistic model is applied to each frame. This model detects and extracts keypoints representing body landmarks, with a specific focus on hand gestures using the MediaPipe Holistic Hand Module. The resulting keypoints, encapsulating spatial relationships critical for understanding dynamic gestures, are stored as NumPy arrays for efficient processing. This structured feature representation forms the basis for capturing the temporal and spatial dependencies inherent in sign language gestures.

C. **Learning the LSTM Model:** The extracted features are passed through a deep learning architecture designed for temporal sequence modeling. The model comprises two Bidirectional LSTM layers, a single LSTM layer, and three Dense layers, allowing it to learn temporal dependencies and spatial patterns effectively. The dataset is divided into training, validation, and testing subsets to ensure robust evaluation and prevent overfitting. The model training process employs the Adam optimizer, ensuring dynamic adjustment of learning rates for efficient convergence.

D. **Model Evaluation:** The trained model's performance is evaluated on the testing set using comprehensive metrics such as accuracy, precision, recall. These metrics highlight the model's ability to accurately classify dynamic Indian Sign Language (ISL) gestures. Experimental results demonstrate the model’s ability to recognize gestures with high accuracy, showcasing its potential for real-time applications in emergency communication scenarios.

E. **Real Time Sign Language Detection:** The trained LSTM model is deployed in a real-time environment to recognize sign language gestures from a live video stream. Each incoming frame from the video stream undergoes the same preprocessing steps as during training. The preprocessed frames are then passed through the LSTM model to generate predictions. The model outputs probabilities or class labels, which are interpreted to recognize and understand the sign language gestures in real time. This deployment enables dynamic gesture recognition, facilitating seamless communication in live scenarios.

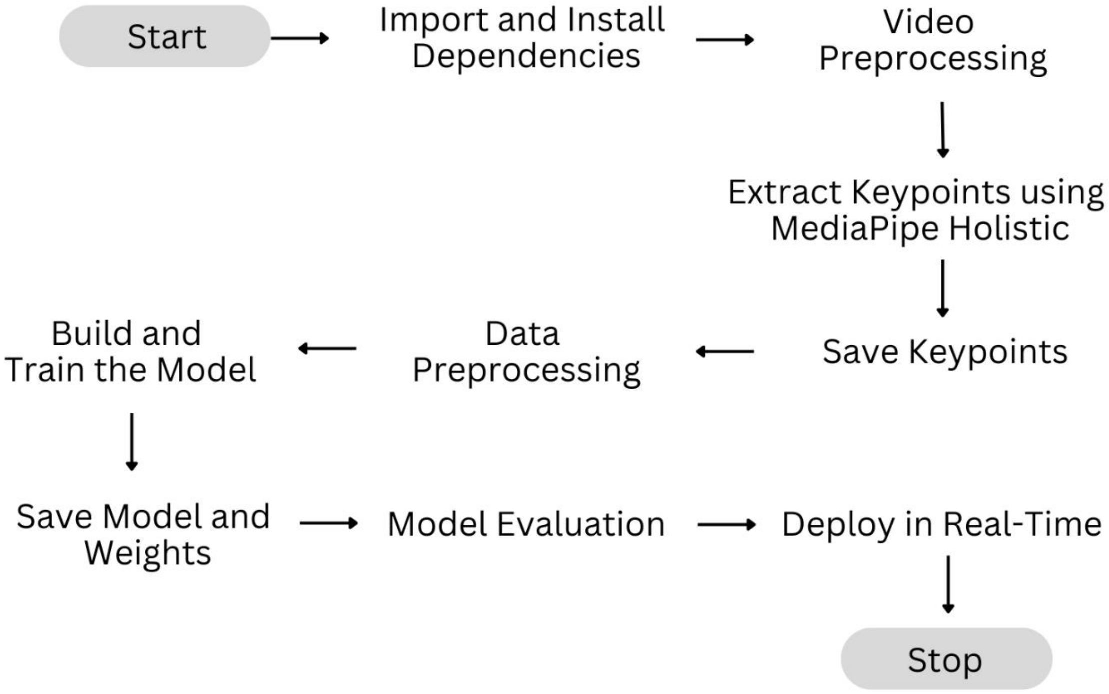


Fig1: Flow Chart

7. LSTM Architecture for Sign Language Recognition

1. **Input Layer:**
    - **Shape:** The input is a 2D tensor with the shape (sequence_length, num_features) where:
        - sequence_length is the number of frames per video (e.g., 45 frames).
        - num_features is the number of features per frame (e.g., 126 features extracted from MediaPipe Holistic Hand landmarks 63 features per hand).
2. **Bidirectional LSTM Layers:**
    - **First Bidirectional LSTM Layer**
        - units = 64 (adjustable based on model size).
        - return_sequences=True to preserve sequence information for the next layer.
        - **Activation:** tanh (default for LSTM cells).
        - **Dropout rate:** 0.2 to mitigate overfitting.
    - **Second Bidirectional LSTM Layer:**
        - units = 128 to capture more complex temporal dependencies.
        - return_sequences=True (as the next layer also expects a sequence).
        - **Activation:** tanh.
        - **Dropout rate:** 0.2 to further regularize the model.
3. **LSTM Layer:**
    - **Third LSTM Layer:**
        - units = 64 to reduce dimensionality.
        - return_sequences=False (since it's the last LSTM layer before the Dense layers).
        - **Activation:** tanh.

4. **Fully Connected (Dense) Layers:**
    - **First Dense Layer:**
        - units = 64.
        - **Activation:** ReLU (non-linear activation to learn complex patterns).
        - **Dropout rate:** 0.2 for regularization.

- **Second Dense Layer:**
  - units = 32 to further refine learned features.
  - **Activation:** ReLU.

5. **Output Layer:**
   - **Dense Layer:**
     - units = 6 (one unit for each gesture class: ‘Accident’, ‘Call’, ‘Doctor’, ‘Help’, ‘Hot’, and ‘Pain’).
     - **Activation:** Softmax to predict probabilities for each class.

6. **Optimization and Regularization:**
   - **Dropout:** Added with a rate of 0.2 after LSTM and Dense layers to reduce overfitting.
   - **Optimizer:** Adam optimizer with a learning rate of 0.001 is used for sequence models.
   - **Loss Function:** Categorical cross-entropy to compute the loss for multi-class classification tasks.

7. **Activation Functions:**
   - **ReLU:** Used in Dense layers to introduce non-linearity, allowing the model to learn complex representations of the data.
   - **Tanh:** Used in LSTM cells to regulate temporal dependencies and ensure smooth gradients.
   - **Softmax:** Used in the output layer to convert logits into class probabilities.

8. **Model Outputs:**
   - **Class Prediction:** The model outputs the class with the highest probability, corresponding to one of the six gesture classes.

9. **Evaluation Metrics:**
   - **Accuracy:** Monitors the model's overall performance during training.
   - **Loss:** Cross-entropy loss to measure the difference between predicted and actual class probabilities.

8. Dataset Description

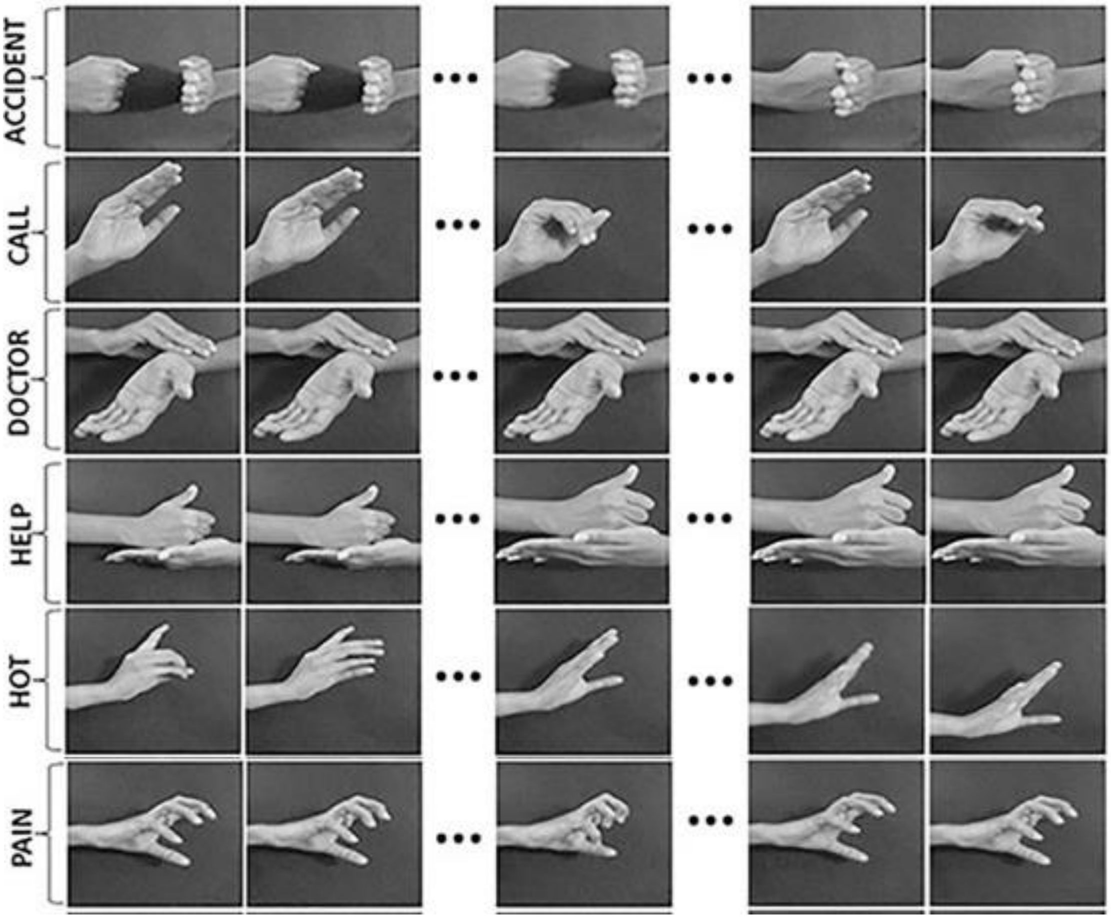


Fig2: Data Set

The dataset comprises video recordings of hand gestures representing eight words from Indian Sign Language (ISL): '*Accident'*, '*Call'*, '*Doctor'*, '*Help'*, '*Hot' and* '*Pain'*. These gestures are commonly used in emergency communication scenarios. The dataset is particularly valuable for researchers working on vision-based automatic sign language recognition and hand gesture recognition.

Among the included words, all except *doctor* involve dynamic hand gestures. The videos were recorded with participants standing comfortably behind a black backdrop to ensure clear gesture visibility. A Sony Cyber-shot DSC-W810 digital camera, featuring a 20.1-megapixel resolution, was used to capture the videos.

The dataset includes recordings from 26 participants, consisting of 12 males and 14 females, aged between 22 and 26 years. Each participant contributed two sample videos, recorded in an indoor environment under normal lighting conditions. The camera was positioned at a fixed distance during all recordings to maintain consistency.

The dataset is organized into two folders: one contains the original raw video sequences, and the other provides cropped and downsampled versions of the same videos, optimized for analysis.

Reason for Selecting the Dataset

This dataset was selected due to its relevance to the project's focus on dynamic sign language recognition, particularly in emergency scenarios. Its inclusion of diverse participants ensures robustness in recognizing gestures across individuals with varying hand shapes, sizes, and movement styles. Furthermore, the dataset's structured format, with both raw and preprocessed videos, aligns well with the requirements for feature extraction and deep learning-based analysis. The emphasis on ISL also makes the dataset culturally and contextually significant for addressing communication challenges in Indian settings.

9. Different Approaches for Dynamic Sign Language Detection

1. Sign Language Recognition using Mediapipe Holistic and LSTM Deep Neural Network

Approach Overview:

- **Mediapipe Holistic**: This is a powerful solution for body, hand, and face pose estimation, providing 3D landmarks of key points in the body, face, and hands. These points serve as the primary input features for the model.
- **LSTM**: Long Short-Term Memory networks are ideal for capturing temporal dependencies, which is crucial for sign language recognition where the gesture sequence is important for understanding.

Methodology:

- Mediapipe extracts 3D coordinates (features) for each frame in a sign language video, including joint coordinates of the body, hands, and face.
- These features are passed to an LSTM network, which processes the sequential nature of sign language to predict the corresponding gesture label.
- The LSTM model can be bidirectional to enhance the ability to capture context from both past and future timesteps.

Strengths:

- Effective for capturing sequential dependencies in dynamic sign language gestures.
- Uses pre-trained Mediapipe models, reducing the need for extensive data preprocessing.
- Can work in real-time with minimal computational overhead.

Weaknesses:

- Mediapipe’s accuracy is dependent on the quality of the input video (e.g., lighting and angle of the person performing the sign).
- LSTM may struggle with long sequences or complex sign language gestures that require more detailed modeling of long-term dependencies.

2. Transformer-based 3D CNN with Pose Estimation

Approach Overview:

- **3D Convolutional Neural Networks (CNNs)**: These are used to process spatial and temporal information simultaneously by operating on 3D video input data (height, width, and time).
- **Transformer-based**: Transformers are designed to capture long-range dependencies and contextual information better than RNNs or LSTMs, making them useful in sequence prediction tasks like sign language recognition.

Methodology:

- The input is typically a sequence of 3D data, possibly extracted from a pose estimation model (like OpenPose or Mediapipe).
- The 3D CNN processes spatial features (e.g., from multiple frames or multi-camera setups), while transformers model the temporal dependencies between frames in the sequence.
- Pose estimation ensures that the spatial information is captured accurately before passing it to the model.

Strengths:

- Transformers allow better context understanding across long sequences, handling complex sign language gestures.
- 3D CNNs capture both spatial and temporal patterns effectively, improving accuracy in dynamic gesture recognition.

Weaknesses:

- Computationally expensive, requiring high performance hardware (e.g., GPUs) for real-time processing.
- Transformer models can be complex to train and may need large datasets.

3. Gesture Recognition with Two-stream CNN

Approach Overview:

- **Two-stream CNN**: This method involves using two distinct CNNs that learn complementary features from different data streams. In the context of gesture recognition, the two streams typically consist of:
  - One stream for appearance-based features (spatial feature)
  - Another stream for motion-based features (temporal feature)

Methodology:

- Each stream processes different inputs, and their outputs are fused (usually by concatenating the feature maps) before being passed to the final classifier.
- The appearance stream focuses on the static shape and structure of the gesture, while the motion stream models the temporal changes or hand movement across frames.

Strengths:

- Effective for gesture recognition since it captures both static and dynamic features simultaneously.
- Can work well even with noisy or incomplete data, as the motion stream compensates for appearance-based ambiguities.

Weaknesses:

- Requires dual CNN architectures, which can be computationally demanding.
- The fusion process may introduce challenges if the two streams are not well-aligned in terms of temporal features.

4. Skeleton-based Gesture Recognition with Graph Neural Networks (GNN)

Approach Overview:

- **Skeleton-based recognition** uses joint or keypoint data extracted from human body pose estimation models (e.g., OpenPose or Mediapipe).
- **Graph Neural Networks** (GNNs) treat these joints as nodes in a graph, where edges represent the relationships between them (e.g., the bones or limbs connecting the joints).

Methodology:

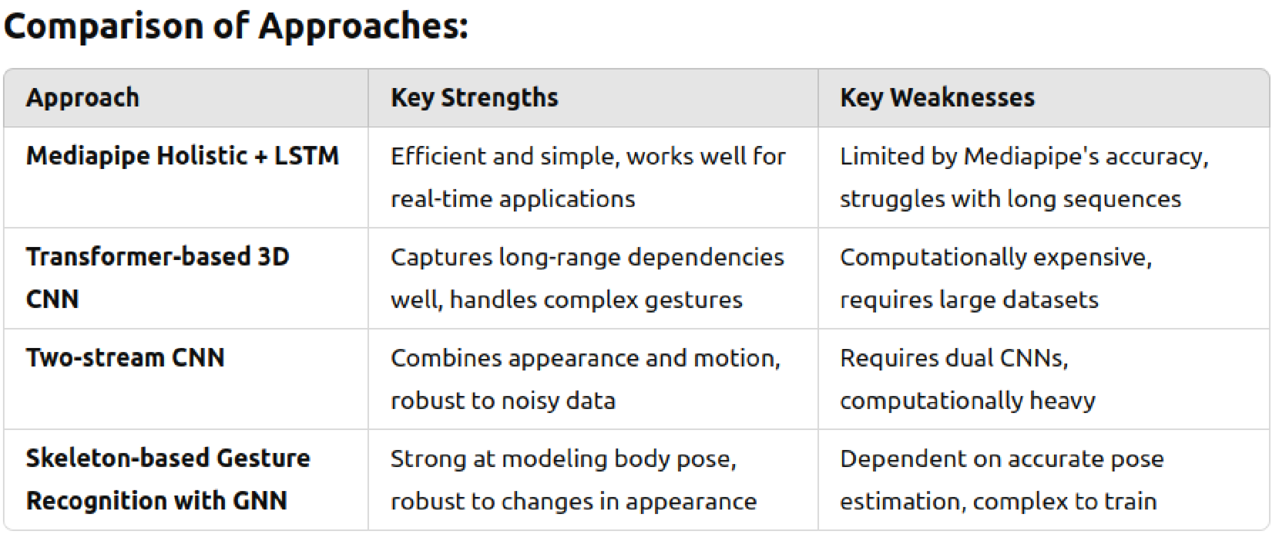
- The skeleton data (i.e., the 2D/3D joint positions) is modeled as a graph, where each frame is represented as a graph.
- A GNN is then used to capture the spatial and temporal relationships between these joints across frames, enabling the model to understand complex gestures.
- Temporal dependencies can be modeled using GNNs or additional models like GRU/LSTM.

Strengths:

- GNNs can naturally capture the spatial relationships between different body parts, making them well-suited for skeleton-based tasks.
- More robust to changes in appearance, background, and noise, since they focus on body pose rather than pixel values.

Weaknesses:

- GNNs can be computationally intensive, especially for larger graphs (many joints).
- Requires accurate pose estimation for good performance; errors in pose estimation can severely affect the model’s accuracy.



Comparison of Approaches:

Approach	Key Strengths	Key Weaknesses
Mediapipe Holistic + LSTM	Efficient and simple, works well for real-time applications	Limited by Mediapipe's accuracy, struggles with long sequences
Transformer-based 3D CNN	Captures long-range dependencies well, handles complex gestures	Computationally expensive, requires large datasets
Two-stream CNN	Combines appearance and motion, robust to noisy data	Requires dual CNNs, computationally heavy
Skeleton-based Gesture Recognition with GNN	Strong at modeling body pose, robust to changes in appearance	Dependent on accurate pose estimation, complex to train

Table1: Comparison Chart

Why We Chose 'Mediapipe Holistic + LSTM'

The '**Mediapipe Holistic + LSTM'** model was selected for this project due to its efficiency, simplicity, and suitability for real-time applications. 'Mediapipe Holistic' provides a comprehensive pipeline for extracting keypoints from the face, hands, and body, which are critical features for sign language recognition. When combined with 'LSTM (Long Short-Term Memory)', a recurrent neural network capable of learning temporal dependencies, the model becomes effective at recognizing dynamic gestures from sequential data.

Key reasons for this choice include:

1. **Real-Time Capability**: The model is lightweight and performs well in real-time scenarios, making it ideal for applications requiring immediate feedback, such as sign language interpretation.

2. **Ease of Implementation**: 'Mediapipe Holistic' simplifies the feature extraction process by directly providing accurate keypoints, reducing the complexity of preprocessing.

3. **Adaptability to Noise**: The model is robust enough to handle slight variations in gesture performance among participants, ensuring reliable recognition across different individuals.

10. Selection of Neural Network Architecture and Components

1. Architecture Selection:

The architecture was chosen based on its ability to effectively model **temporal dependencies** inherent in dynamic hand gestures. Bidirectional LSTMs (BiLSTMs) and LSTMs are widely reported in the literature as effective for sequential data tasks, including dynamic gesture recognition, due to their capability to learn patterns from both past and future frames. This makes them ideal for dynamic sign language recognition where understanding the motion trajectory is crucial.

2. Key Components and Reasons for Selection:

Bidirectional LSTM Layers:

- **Why Bidirectional?** BiLSTMs process input sequences in both forward and reverse directions, allowing the network to capture context from the entire sequence. This enhances the model's ability to understand complex motion patterns in gestures.
- **Number of Units (64, 128):** The choice of 64 and 128 units was guided by the dataset's size and complexity. Using a smaller first layer helps extract initial temporal features, while a larger second layer captures more intricate dependencies.

Dropout Layers (0.2):

- Dropout is used to prevent overfitting, especially since deep LSTM architectures can easily memorize training data. A rate of 0.2 was found to balance regularization without underutilizing the network's capacity.

Dense Layers:

- **64 and 32 Units:** These layers help transform high-dimensional sequential outputs into features suitable for classification. The smaller size ensures efficient computation while retaining performance.
- **ReLU Activation:** ReLU is widely used due to its simplicity and efficiency in avoiding vanishing gradients, which are common in deep networks.

Final Dense Layer with Softmax:

- The softmax activation function is standard for multi-class classification tasks, as it outputs probabilities for each gesture class.

Input Shape (45, 126):

- **45 Frames:** Represents the temporal dimension of input, chosen to capture sufficient gesture information without unnecessary redundancy.
- **126 Features:** Represents the total keypoints extracted by MediaPipe Holistic for hands, face, and pose.

Loss Function (Categorical Cross-Entropy):

- This is the most suitable loss function for multi-class classification, ensuring proper penalization for incorrect predictions based on their probabilities.

Optimizer (Adam):

- Adam is widely preferred due to its efficiency and adaptability, making it well-suited for tasks involving sequential data.

3. Literature and Practical Considerations:

- This architecture aligns with approaches highlighted in the literature for tasks like dynamic hand gesture and action recognition. Similar configurations have been reported to achieve strong performance in sequential modeling tasks.

11.Results and Discussions

The proposed ‘Mediapipe Holistic + LSTM’ model was trained for 100 epochs on the Hand Gestures for Emergency Situations dataset. This model achieved an exceptional accuracy of 100% on the test dataset, as demonstrated in the confusion matrix. All six gesture categories ‘Accident’, ‘Call’, ‘Doctor’, ‘Help’, ‘Hot’, and ‘Pain’ were accurately classified, with no misclassifications observed. The confusion matrix, combined with the test accuracy score and low loss value of 0.026, validates the model’s capability to perform precise gesture recognition. Experimental results reveal an overall accuracy of 100% and a generalization accuracy of 98% (in controlled environment), demonstrating robust performance on unseen data for the six ISL gestures. This underscores the system's robustness and potential for real-time applications. The proposed system offers a practical solution for assistive technologies, facilitating communication in emergency situations.

This high level of performance is largely attributed to the **controlled environment** of the dataset, which reduced variability in lighting, backgrounds, and noise. As a result, **Mediapipe Holistic** was able to extract high-quality pose, face, and hand keypoints, serving as a robust input for the LSTM model. The LSTM architecture proved effective in capturing the **temporal dependencies** inherent in dynamic gestures, such as **‘Help’** and **‘Hot’**, while also distinguishing static gestures like **‘Doctor’**. By leveraging the temporal sequence information, the model successfully recognized complex patterns in gesture transitions.

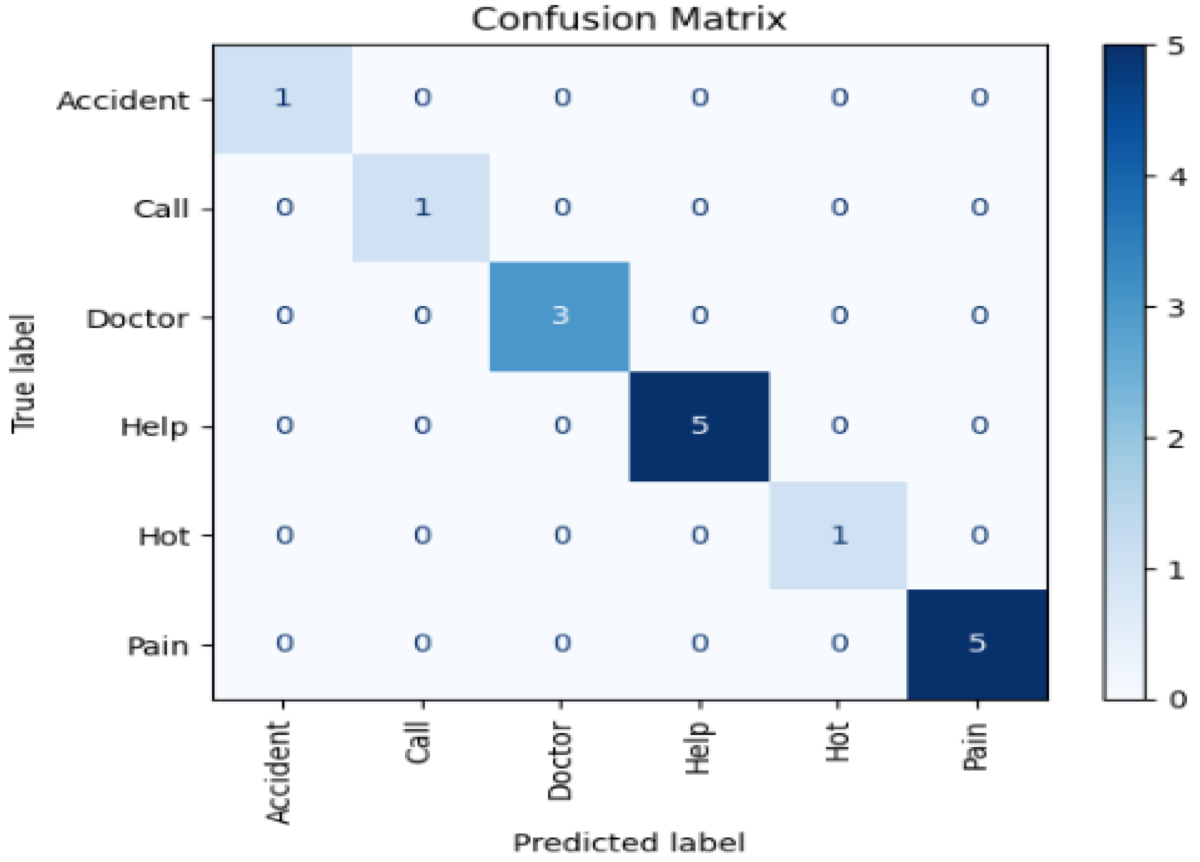
The smooth learning curves observed during training further reinforce the model's reliability. The training accuracy consistently increased, while the training loss steadily decreased across the epochs. This indicates that the model efficiently learned the underlying patterns in the dataset without encountering challenges like overfitting or underfitting. The absence of fluctuations in the learning process highlights a well-tuned learning rate and an appropriate model architecture for the task. The alignment between the final training and test accuracies demonstrates the robustness and generalizability of the model.

Despite the controlled dataset contributing to the model’s success, it is important to address potential challenges in real-world scenarios. Factors such as **dynamic lighting conditions, cluttered backgrounds, occlusions, and diverse signer characteristics** could introduce variability and reduce accuracy. To enhance the model's robustness, future work could involve:

1. **Data augmentation techniques** to simulate real-world variations, including random changes in lighting, rotation, scaling, and occlusions.
2. Expanding the dataset to include **different signers, environments, and noise levels** for better generalization.

Additionally, integrating the model into a **real-time gesture recognition system** was evaluated using a 720p camera, analyzing the last 45 frames for prediction. The system demonstrated reliable performance, highlighting its feasibility for real-world applications. However, further optimization in terms of inference speed and resource efficiency could improve usability on edge devices.

In conclusion, the **'Mediapipe Holistic + LSTM'** approach has proven to be an effective framework for dynamic sign language recognition in controlled environments. Its success underscores the importance of leveraging accurate keypoint extraction and temporal modeling for dynamic gestures.



	Accident	Call	Doctor	Help	Hot	Pain
Accident	1	0	0	0	0	0
Call	0	1	0	0	0	0
Doctor	0	0	3	0	0	0
Help	0	0	0	5	0	0
Hot	0	0	0	0	1	0
Pain	0	0	0	0	0	5

Fig3: Confusion Matrix for Test set

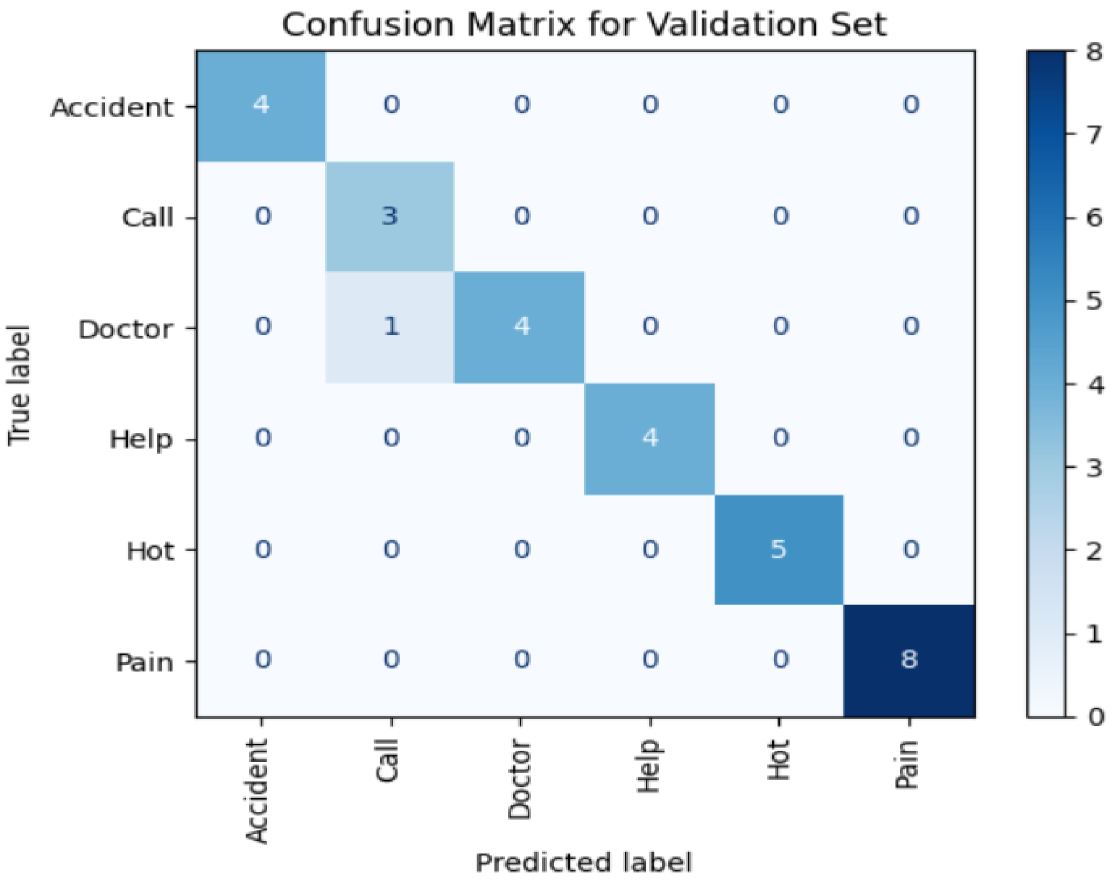


Fig4. Confusion Matrix for validation set

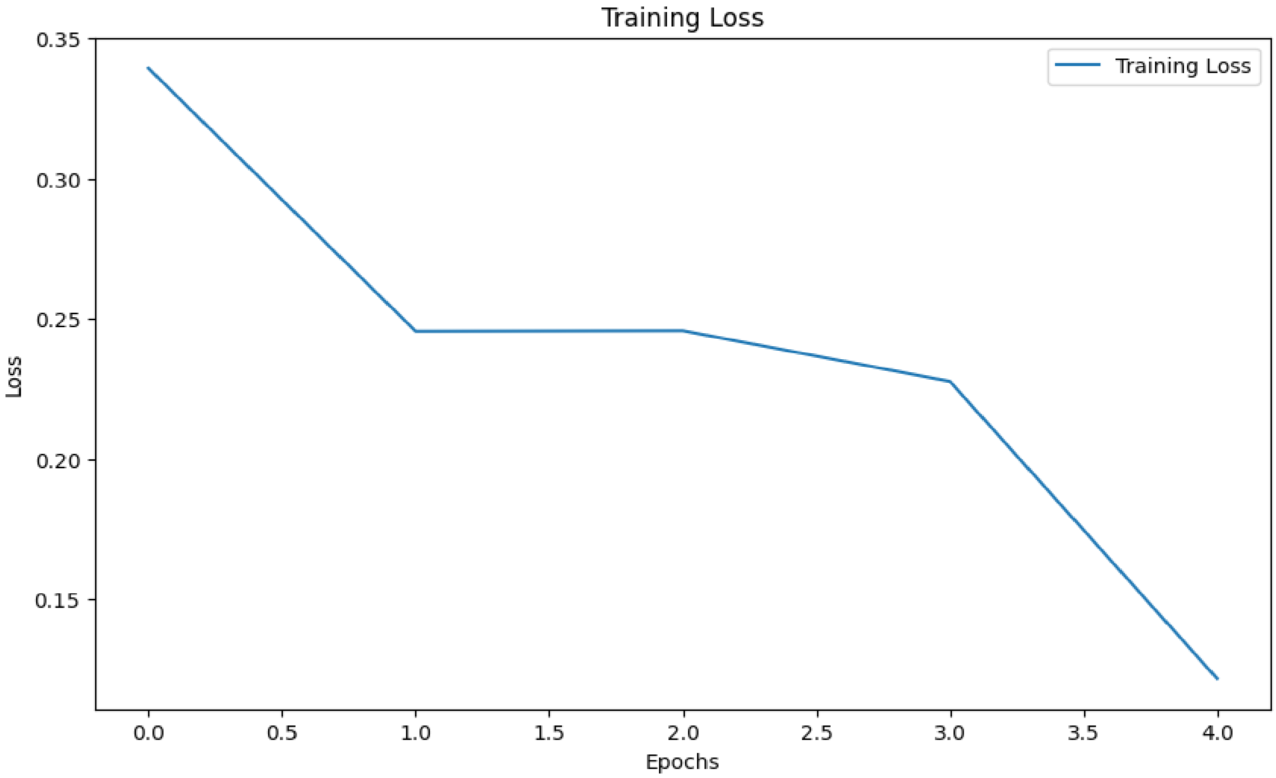


Fig5: Training Loss Graph

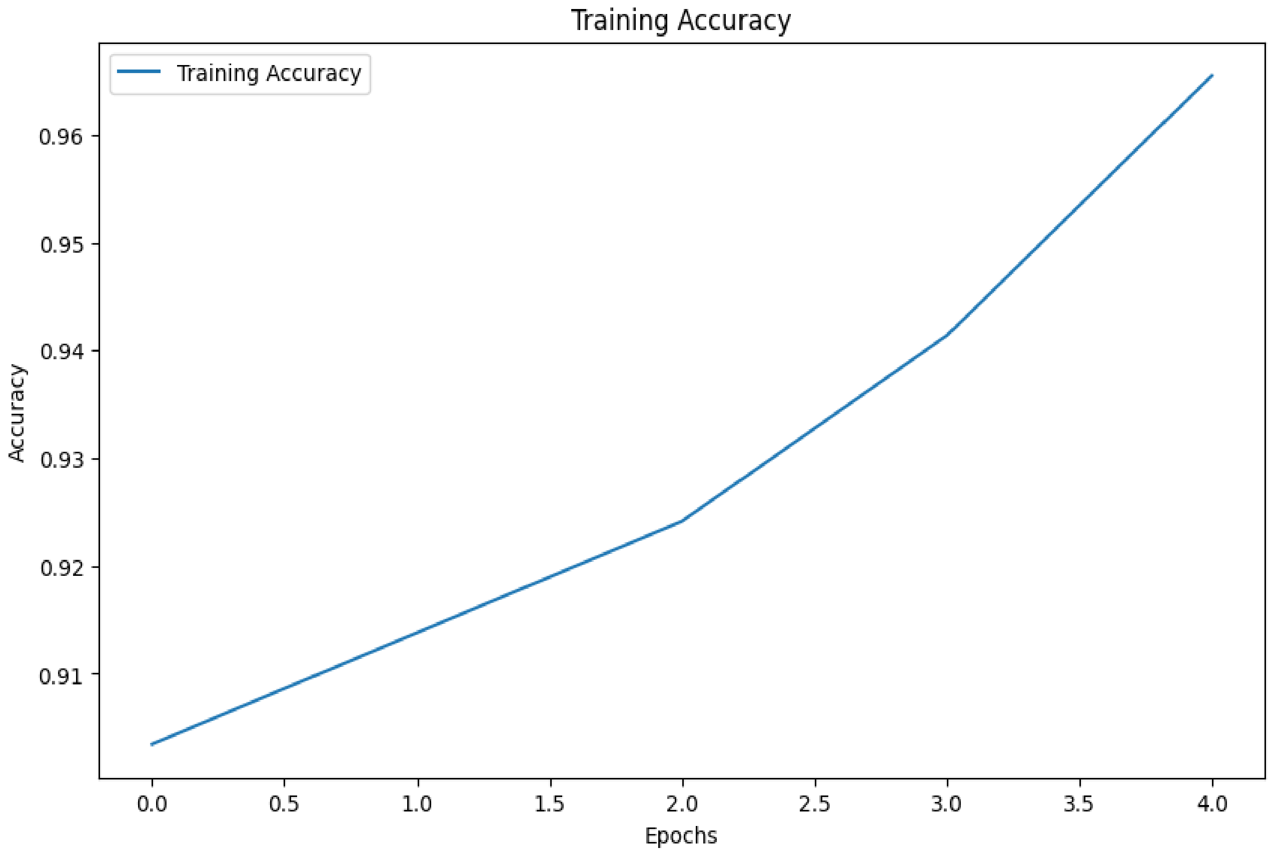
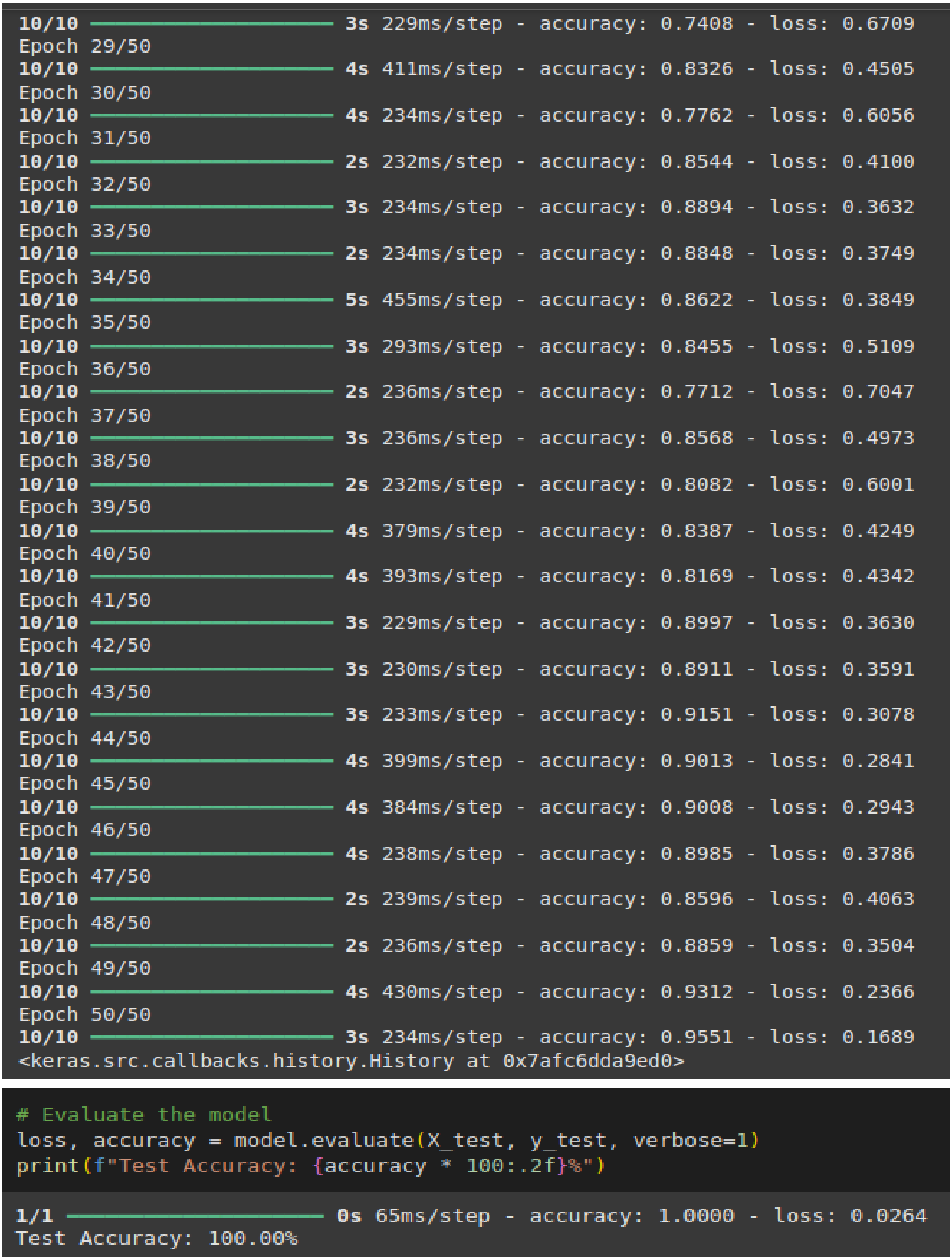


Fig6: Training Accuracy Graph



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10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 229ms/step - accuracy: 0.7408 - loss: 0.6709
Epoch 29/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 411ms/step - accuracy: 0.8326 - loss: 0.4505
Epoch 30/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 234ms/step - accuracy: 0.7762 - loss: 0.6056
Epoch 31/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 232ms/step - accuracy: 0.8544 - loss: 0.4100
Epoch 32/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 234ms/step - accuracy: 0.8894 - loss: 0.3632
Epoch 33/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 234ms/step - accuracy: 0.8848 - loss: 0.3749
Epoch 34/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 5s 455ms/step - accuracy: 0.8622 - loss: 0.3849
Epoch 35/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 293ms/step - accuracy: 0.8455 - loss: 0.5109
Epoch 36/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 236ms/step - accuracy: 0.7712 - loss: 0.7047
Epoch 37/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 236ms/step - accuracy: 0.8568 - loss: 0.4973
Epoch 38/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 232ms/step - accuracy: 0.8082 - loss: 0.6001
Epoch 39/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 379ms/step - accuracy: 0.8387 - loss: 0.4249
Epoch 40/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 393ms/step - accuracy: 0.8169 - loss: 0.4342
Epoch 41/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 229ms/step - accuracy: 0.8997 - loss: 0.3630
Epoch 42/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 230ms/step - accuracy: 0.8911 - loss: 0.3591
Epoch 43/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 233ms/step - accuracy: 0.9151 - loss: 0.3078
Epoch 44/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 399ms/step - accuracy: 0.9013 - loss: 0.2841
Epoch 45/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 384ms/step - accuracy: 0.9008 - loss: 0.2943
Epoch 46/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 238ms/step - accuracy: 0.8985 - loss: 0.3786
Epoch 47/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 239ms/step - accuracy: 0.8596 - loss: 0.4063
Epoch 48/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 2s 236ms/step - accuracy: 0.8859 - loss: 0.3504
Epoch 49/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 4s 430ms/step - accuracy: 0.9312 - loss: 0.2366
Epoch 50/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 234ms/step - accuracy: 0.9551 - loss: 0.1689
<keras.src.callbacks.history.History at 0x7afc6dda9ed0>
```

```
# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test, verbose=1)
print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 65ms/step - accuracy: 1.0000 - loss: 0.0264
Test Accuracy: 100.00%
```

Fig6: Some Model Training Screenshots

12. Real-Time Implementation

The system setup for **real-time testing** involved a well-defined pipeline to ensure smooth, accurate, and responsive gesture recognition. The steps included the following:

1. **Webcam Configuration:** A standard built-in 720p resolution webcam was configured to capture live video streams. The frame rate was adjusted to ensure smooth video capture, optimizing the performance for real-time processing without causing delays.

2. **Preprocessing Pipeline:** The captured frames underwent a real-time preprocessing pipeline to prepare the data for gesture recognition:
    - **Frame Capture and Enhancement**: Frames were captured in real-time using 'OpenCV' and subjected to basic preprocessing steps, such as resizing and color normalization, to enhance visual quality.
    - **Feature Extraction with 'MediaPipe Holistic'**: Each frame was processed through '**MediaPipe Holistic'**, a powerful pose estimation framework, to extract keypoints representing the face, hands, and body pose. These keypoints were normalized and scaled to ensure consistent input across varying signer positions and distances.

3. **Gesture Recognition:** The gesture recognition module utilized a trained 'LSTM' model to classify gestures in real-time:
    - **Input Preparation**: The system maintained a sliding window of the last 45 frames, capturing the temporal progression of gestures. This approach ensured that the input sequence encompassed the key motion elements required for dynamic gesture recognition.
    - **Temporal Analysis with LSTM**: The extracted keypoints from the 45 frames were fed into the LSTM model. The model leveraged its ability to capture temporal dependencies and sequential patterns, analyzing the dynamic motion of gestures over time.
    - **Real-Time Predictions**: Based on the processed input, the LSTM model generated a prediction for the gesture class.

To evaluate the practicality of the system in real-world scenarios, the model was tested with six different subjects. Each subject performed the gestures for all six categories: 'Accident', 'Call', 'Doctor', 'Help', 'Hot', and 'Pain'. The system successfully recognized the correct hand gestures for all participants, demonstrating its robustness and effectiveness in real-time conditions.

Here are the following screenshots showcasing the real-time implementation and the corresponding gesture recognition results for each subject:

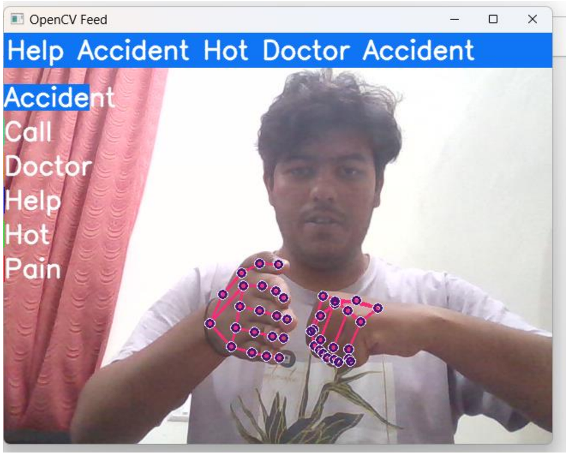


Fig1: 'Accident' hand sign recognized in real-time by subject 1

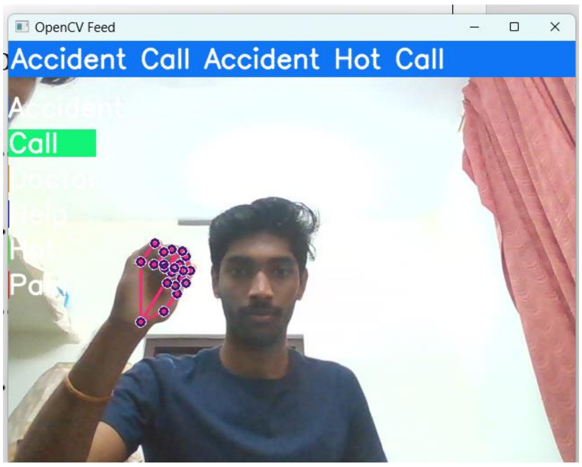


Fig2: 'Call' hand sign recognized in real-time by subject 2

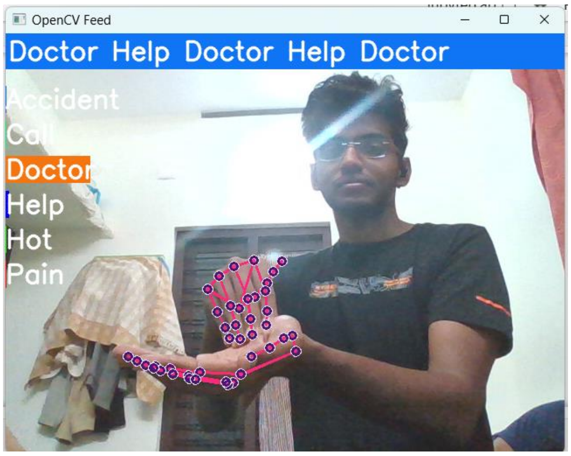


Fig3: 'Doctor' hand sign recognized in real-time by subject 3

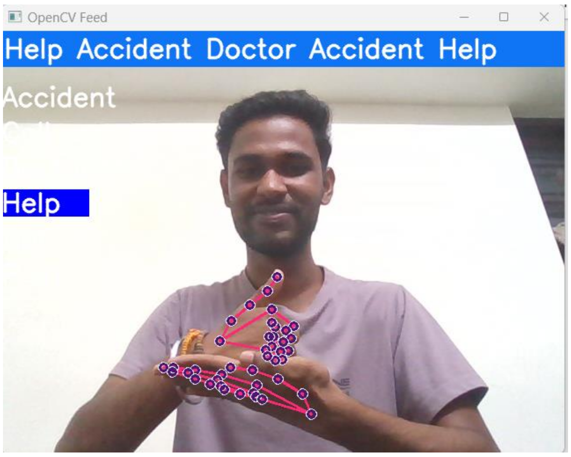


Fig4: 'Help' hand sign recognized in real-time by subject 4

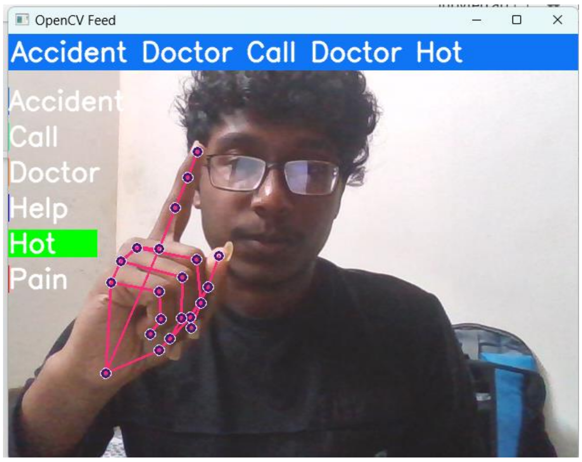


Fig5: 'Hot' hand sign recognized in real-time by subject 5

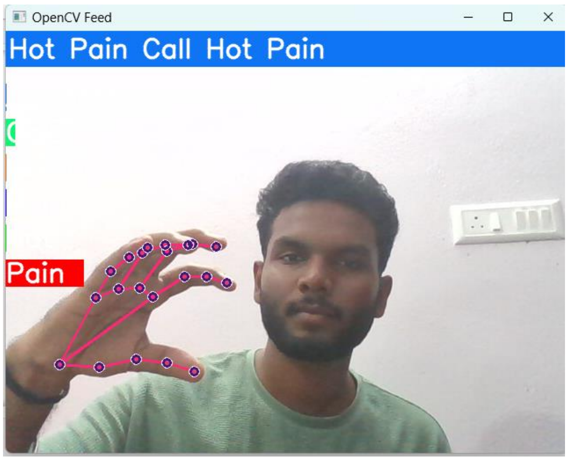
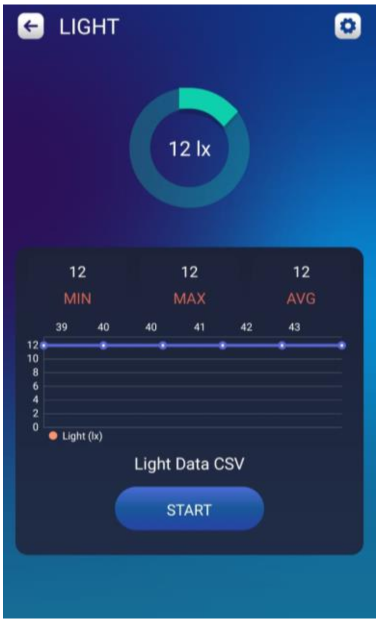


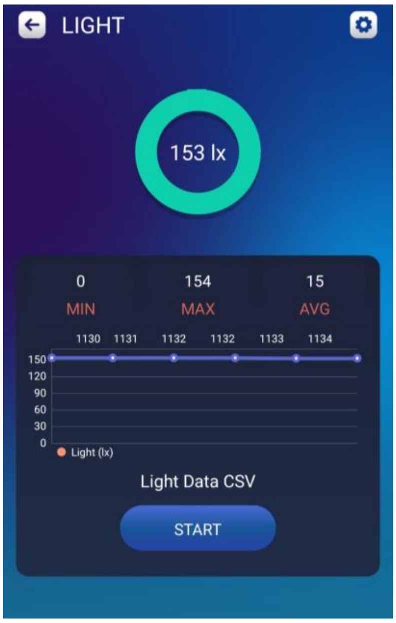
Fig6: 'Pain' hand sign recognized in real-time by subject 6

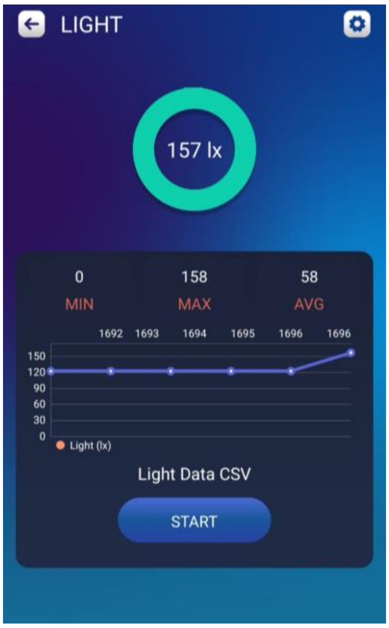
13.Visual Analysis of Lighting Conditions

To analyse the effect of lighting on gesture recognition, screenshots of each category were captured under three different lighting conditions:

1. **Dim light (Bulb only):** 12 lux.
2. **Bright light (Tube light only):** 153 lux.
3. **Well-lit environment (Both lights):** 157 lux.







1. Dim light (Bulb only): 12lux

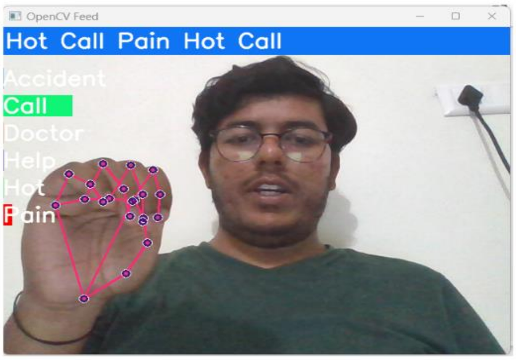


fig1. Subject showing 'Call' handsign in dim light condition

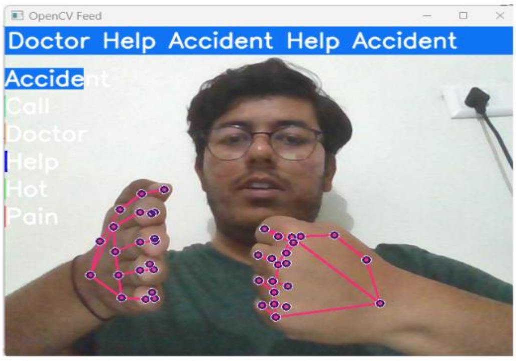


fig2. Subject showing 'Accident' handsign in dim light condition

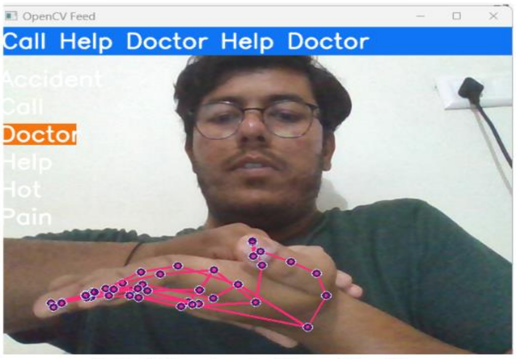


fig3. Subject showing 'Doctor' handsign in dim light condition

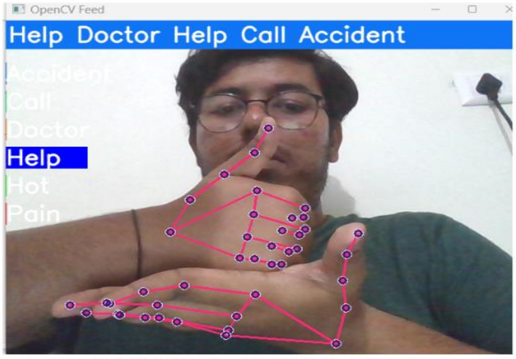


fig4. Subject showing 'Help' handsign in dim light condition

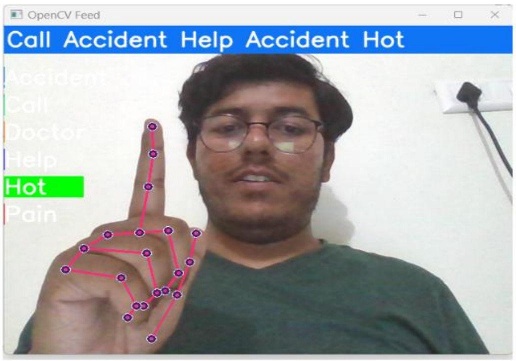


fig5. Subject showing 'Hot' handsign in dim light condition

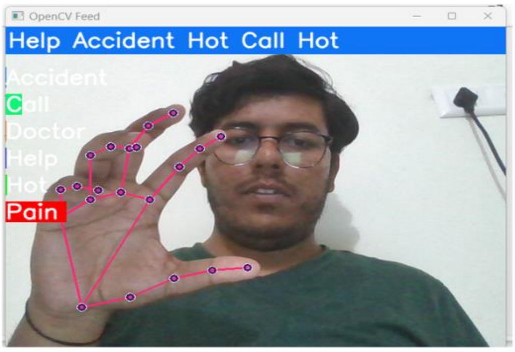
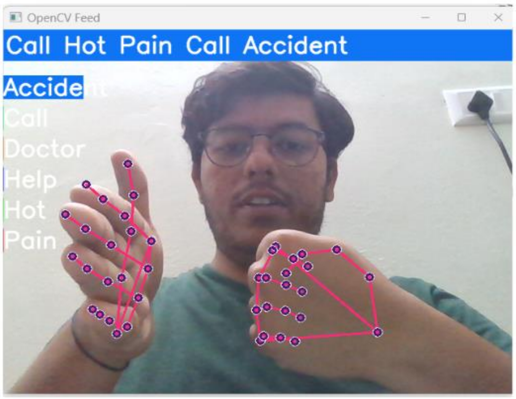


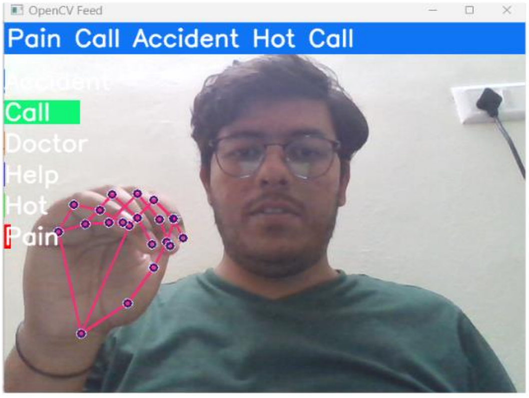
fig6. Subject showing 'Pain' handsign in dim light condition

2. Bright light (Tube light only): 153 lux



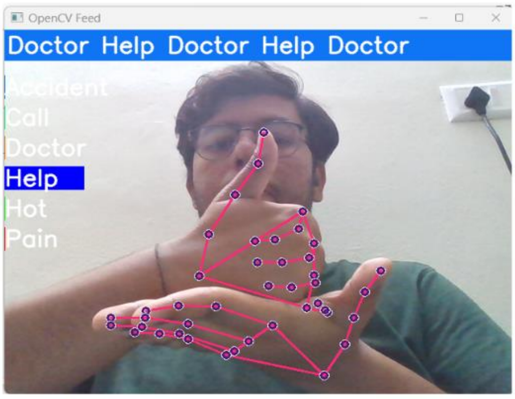
Call Hot Pain Call Accident

fig1. Subject showing 'Accident' handsign in bright light condition



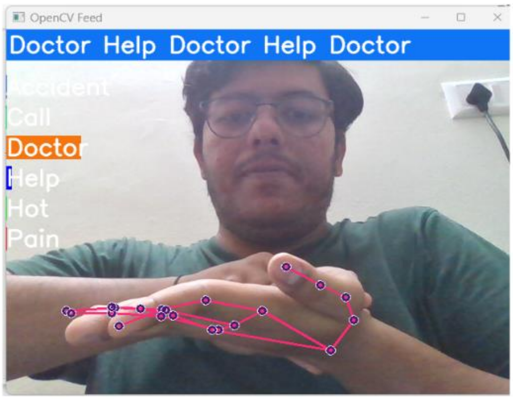
Pain Call Accident Hot Call

fig2. Subject showing 'Call' handsign in bright light condition



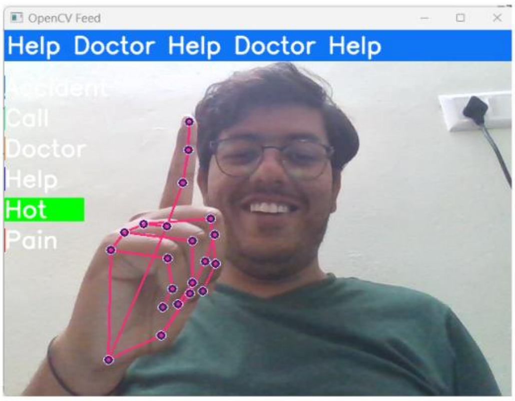
Doctor Help Doctor Help Doctor

fig3. Subject showing 'Help' handsign in bright light condition



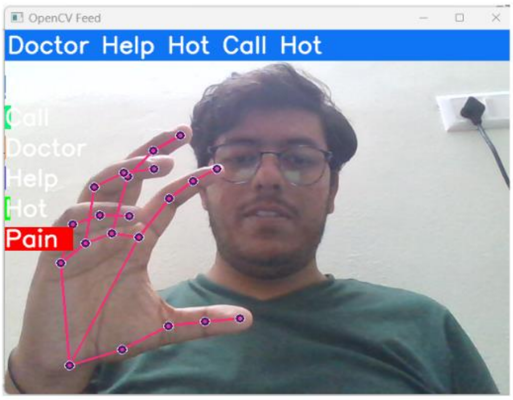
Doctor Help Doctor Help Doctor

fig4. Subject showing 'Doctor' handsign in bright light condition



Help Doctor Help Doctor Help

fig5. Subject showing 'Hot' handsign in bright light condition



Doctor Help Hot Call Hot

fig6. Subject showing 'Pain' handsign in bright light condition

3. Well-lit environment (both light): 157 lux

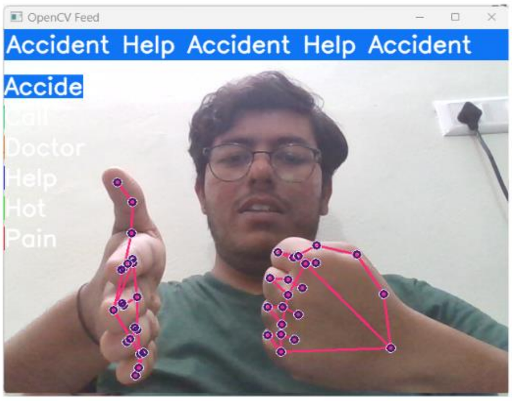

Accident Help Accident Help Accident

fig1. Subject showing 'Accident' handsign in well-lit light condition

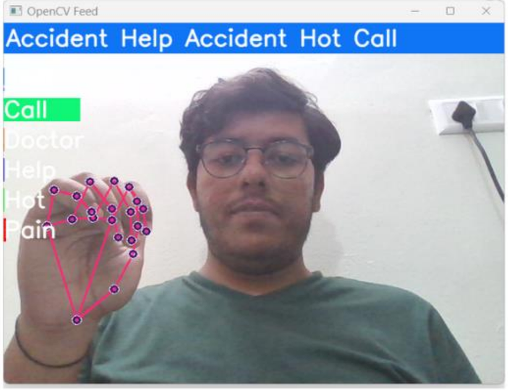

Accident Help Accident Hot Call

fig2. Subject showing 'Call' handsign in well-lit light condition

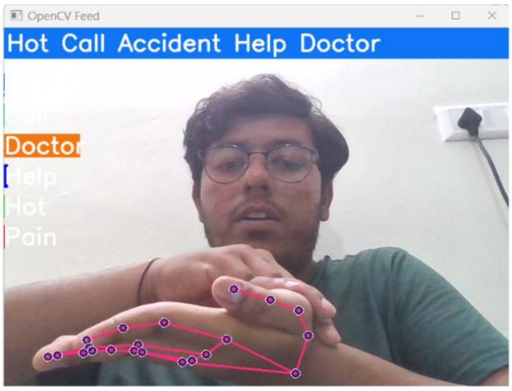

Hot Call Accident Help Doctor

fig3. Subject showing 'Doctor' handsign in well-lit light condition

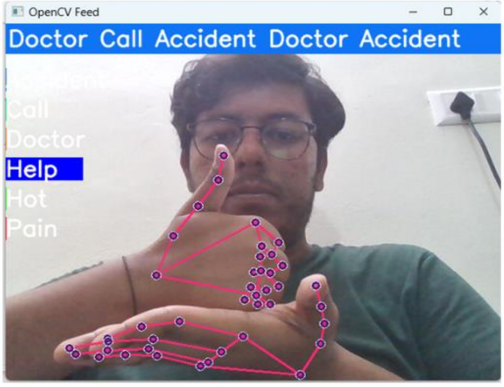

Doctor Call Accident Doctor Accident

fig4. Subject showing 'Help' handsign in well-lit light condition

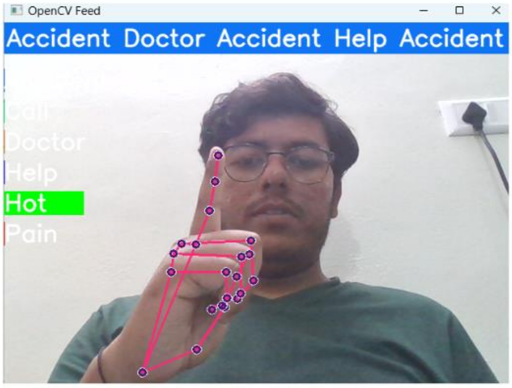

Accident Doctor Accident Help Accident

fig5. Subject showing 'Hot' handsign in well-lit light condition

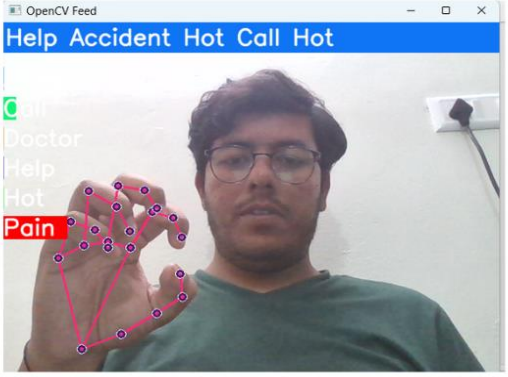

Help Accident Hot Call Hot

fig6. Subject showing 'Pain' handsign in well-lit light condition

14. Future Work

Several potential improvements could be made to enhance the performance and scope of the sign language recognition system:

1. **Dataset Expansion:** Integrating additional datasets, such as INCLUDE, along with the current dataset from the Central University of Kerala, would provide a more diverse set of samples. This could help increase the dataset's size for each category and improve the overall accuracy and robustness of the model across different gesture types.
2. **Transfer Learning with Pre-trained Models:** Exploring pre-trained models like VGG19, ResNet, and EfficientNet for transfer learning could potentially improve the system’s performance. These models, trained on large image datasets, may be better at feature extraction and could outperform the current model by providing more generalized features.
3. **Model Enhancement with Transformer Architectures:** Investigating the use of transformer-based models, such as ‘Vision Transformers (ViT)’ or hybrid models combining ‘CNNs’ with ‘transformers’, could help in better capturing spatial-temporal dependencies, potentially improving accuracy in recognizing dynamic gestures.

14. Conclusion

My report presents a **Dynamic Sign Language Recognition System** for **Indian Sign Language (ISL)** gestures specifically designed for **emergency situations**. The system utilizes a **dataset from the Central University of Kerala**, consisting of six ISL gestures: **‘Accident’, ‘Call’, ‘Doctor’, ‘Help’, ‘Hot’, and ‘Pain’**. The proposed pipeline integrates **video preprocessing**, **feature extraction using ‘MediaPipe Holistic’**, and **gesture classification with a ‘Long Short-Term Memory (LSTM)’ model**, offering a **robust solution** for recognizing dynamic gestures.

The system effectively captures **temporal dependencies in dynamic gestures** by leveraging the sequential modeling capabilities of **LSTM**, distinguishing between complex motion patterns. The experimental results validate the system's **high accuracy** and **low loss values**, achieving an **overall accuracy of 100%**, **100% accuracy on the test dataset**, and a **generalization accuracy of 98%** (in controlled environment). This performance demonstrates the model's potential to handle **emergency ISL gestures** with **exceptional reliability**.

Additionally, the system is optimized for **real-time performance**, leveraging a **720p webcam** for live video capture and processing the **last 45 frames of input** in a **sliding window approach**. The integration of **‘MediaPipe Holistic’** ensures **high-quality keypoint extraction**, while the efficient design of the **preprocessing and recognition pipeline** enables **seamless and responsive predictions**. These features make the system suitable for deployment in **assistive devices** aimed at improving **communication in emergencies**.