A PROJECT REPORT

on

SIGN LANGUAGE DETECTION USING ACTION RECOGNITION WITH PYTHON

Submitted to

KIIT Deemed to be University

In Partial Fulfilment of the Requirement for the Award of

BACHELOR'S DEGREE IN
INFORMATION TECHNOLOGY

BY

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UNDER THE GUIDANCE OF

Mrs. Chandani Kumari

SCHOOL OF COMPUTER ENGINEERING

KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY

BHUBANESWAR, ODISHA - 751024

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CERTIFICATE

This is certify that the project entitled

"SIGN LANGUAGE DETECTION USING ACTION RECOGNITION WITH PYTHON"

submitted by

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is a record of bonafide work carried out by them, in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering OR Information Technology) at KIIT Deemed to be university, Bhubaneswar. This work is done during year 2024-2025, under our guidance.

Date: 11/11/2024

Project Guide
(Mrs. Chandani Kumari)

Acknowledgements

We are profoundly grateful to **Mrs. Chandani Kumari** of **Machine Learning** for her expert guidance and continuous encouragement throughout to see that this project rights its target since its commencement to its completion.

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ABSTRACT

This study introduces an innovative approach for real-time sign language detection by integrating action recognition with LSTM deep learning models in Python, enhanced by an interactive website interface crafted with HTML, CSS, and JavaScript. The system harnesses LSTM's strength in capturing temporal patterns, enabling accurate classification of sign language gestures. The detection process involves several stages, including video capture, preprocessing, feature extraction, and model training. Preprocessed video frames undergo feature extraction using methods such as optical flow or deep learning techniques. The LSTM model, possibly benefiting from transfer learning, is assessed with metrics like accuracy, precision, recall, and F1-score, showing promising results in accuracy and reliability. This makes the system a valuable real-time interpretation tool for the hearing impaired. The website interface, enriched with JavaScript, provides a responsive and user-friendly experience, allowing for real-time gesture recognition and interpretation, ultimately enhancing accessibility and interactivity.

Here are five key keywords:

1. Real-Time Sign Language Detection
2. LSTM Deep Learning Model
3. Gesture Recognition System
4. Feature Extraction Techniques
5. Interactive Interpretation Tool

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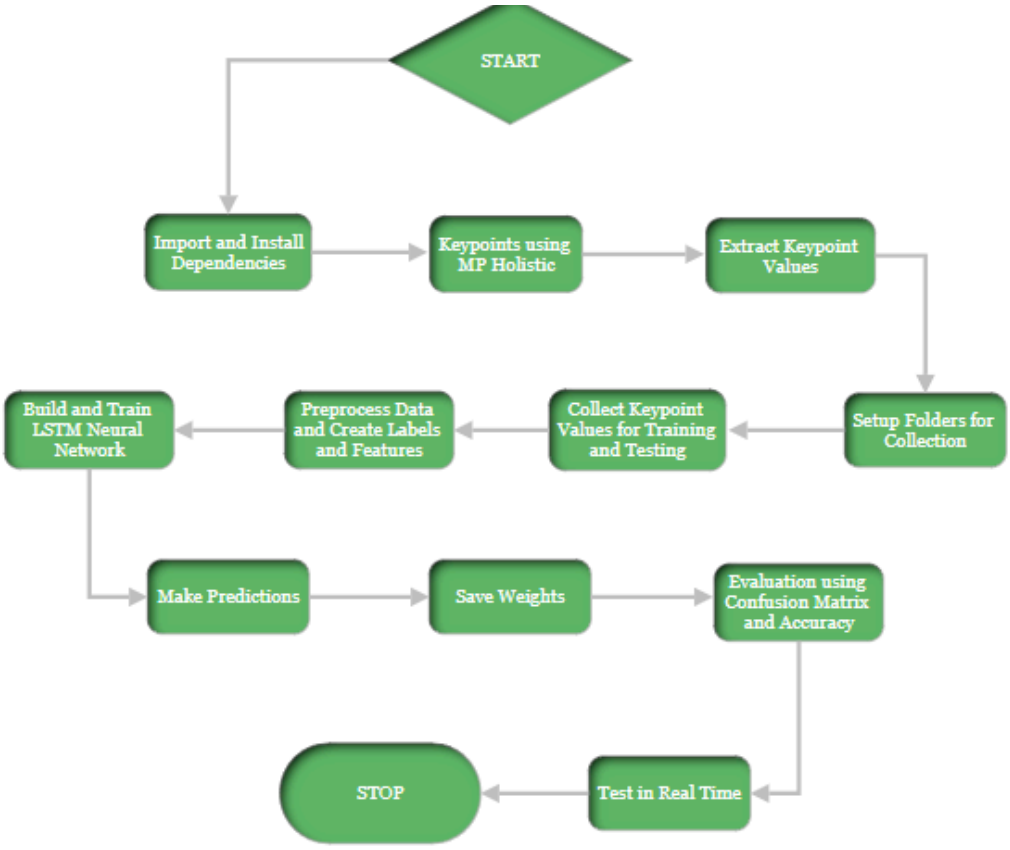
Chapter 1

Introduction

Sign language is a vital mode of communication for individuals who are deaf or hard of hearing, creating an essential link that enables meaningful interaction with the wider community. However, interpreting these gestures can be difficult for those unfamiliar with sign language. In response to this communication gap, there has been growing interest in developing sign language recognition systems. Recent advances in deep learning, particularly with Long Short-Term Memory (LSTM) architectures, have paved the way for creating highly accurate and dependable sign language recognition solutions.



1.1 Data Flow Diagram

This study explores the use of action recognition and LSTM deep learning models in Python to detect and interpret sign language gestures. By capturing the natural sequence and temporal patterns in sign language movements, these models excel in accurately recognizing and interpreting gestures in real time. The project's main objective is to develop a real-time sign language gesture detection system with a high degree of accuracy and reliability. This is achieved through a structured pipeline, which includes video capture, preprocessing, feature extraction, and the application of LSTM-based deep learning models. Together, these elements contribute to a robust and effective solution for breaking down communication barriers and enhancing accessibility.

This project presents a web-based sign language detection system that combines deep learning with an accessible interface built using HTML, CSS, and JavaScript. Leveraging LSTM models, it effectively captures the complex temporal dynamics of sign language, overcoming the limitations of traditional rule-based methods. The real-time online platform promotes inclusivity, enhancing communication for the hearing impaired. The paper covers algorithms in Section II, experimental results in Section III, and conclusions in Section IV.

Chapter 2

Basic Concepts/ Literature Review

The developed model comprises two primary components: a facial recognition classifier and a person identification system, with integration into a web-based interface for accessibility and usability.

2.1 Face Recognition

- **Face Categorization**: The face recognition model assigns images to predefined identity categories, facilitating applications such as security and personalized user experiences.
- **Data Source**: A curated set of labeled facial images is used to train the model, enabling accurate identification across different lighting conditions, angles, and backgrounds.
- **Model and Feature Extraction**: The system utilizes a pre-trained Convolutional Neural Network (CNN) that is specifically designed for face recognition tasks, ensuring efficient extraction of crucial facial features.

- **Fine-Tuning**: The model is fine-tuned by adjusting key parameters like learning rate, batch size, and epochs to optimize its performance in identifying individuals with high accuracy.
- **Image Preprocessing**: The preprocessing pipeline standardizes image quality and format, addressing variations such as lighting, scaling, and facial landmark alignment to ensure consistency and reliability during recognition.

2.2 Person Identification

- **Model Selection**: To identify individuals, the system employs a Support Vector Machine (SVM) classifier, which differentiates between various identities by analyzing the extracted facial features.
- **Data Collection**: A diverse set of facial images is gathered, ensuring representation across various expressions, angles, and lighting conditions. This helps the model perform robustly in different real-world scenarios.

- **Feature Engineering**: Important facial features, such as the distances between key facial landmarks and texture patterns, are extracted to enhance the model's ability to distinguish between different individuals.
- **Confidence Scoring**: A confidence score is assigned to each identified face, reflecting both the similarity to known identities and the quality of the image. This score helps improve the reliability of the recognition process.

2.3 Web Integration:

The web integration enhances the accessibility and user experience of the face recognition and person identification system, making it suitable for a wide range of real-time applications. Below are some key points:

- **Real-Time Interaction**: The web interface facilitates real-time interaction with the face recognition system, enabling users to instantly upload images or video streams for immediate identification.

- **User-Friendly Interface**: Designed with HTML, CSS, and JavaScript, the interface provides a seamless and intuitive platform, ensuring easy navigation and minimal user effort to access the system's features.
- **Responsive Design**: The interface is fully responsive, ensuring that it performs effectively across a wide range of devices, including desktops, tablets, and smartphones, making it versatile and accessible.
- **Security and Personalization**: Users can securely upload and manage their facial data for personalized experiences, such as customized security alerts or access controls. The system can be integrated into various security applications, enhancing user-specific functionalities.
- **Integration with Databases:** The web interface can be connected to a backend database to store and retrieve known user profiles, allowing for dynamic person identification and seamless updates to user records.

- **Demo and Visualization:** The interface includes features like demo videos, which visually demonstrate the real-time face recognition process, making it more engaging and informative for the users.
- **Scalability:** The system is designed to scale effortlessly, allowing easy expansion to accommodate multiple users or additional functionalities, such as integrating with other security systems or adding more features like driver monitoring.
- **Continuous Feedback and Monitoring:** Users can receive live feedback on their actions, such as successful or unsuccessful identification attempts, which adds transparency and encourages interaction.
- **Cross-Platform Support:** The interface is compatible across different browsers, ensuring a wide reach and making the system easily accessible to anyone with internet access.

Chapter 3
Problem Statement / Requirement Specifications

3.1 Project Planning

The aim of this project is to create a highly accurate and efficient face recognition system for use in areas like security and identity verification. An integrated web interface enhances accessibility and provides a seamless user experience. Below is an overview of the key stages of the project:

1. **Data Collection:**

- Gather a diverse set of facial images, accounting for variations in lighting, expressions, angles, and demographics to improve model accuracy. This could involve using publicly available datasets (e.g., LFW, CelebA) or collecting custom images under various environmental conditions (indoor and outdoor). Defining the number of images per subject and ensuring diversity in environmental factors are crucial for effective data collection.

2. **Data Preprocessing:**

- Prepare the images by resizing, converting them to grayscale, and applying histogram equalization to maintain uniform brightness and contrast. Align faces to ensure consistent positioning, which helps improve model accuracy. Face cropping is applied to focus on key facial regions. Data augmentation techniques, such as rotating or flipping images, help enhance the model's robustness to different perspectives and conditions.

3. **Face Recognition Model:**

- Select a suitable model architecture for face recognition, such as a Convolutional Neural Network (CNN) or a pre-trained model like FaceNet or VGG-Face. Train the model on the labeled dataset and fine-tune hyperparameters (e.g., learning rate, batch size, epochs) to achieve optimal performance. A feature extraction layer is implemented to identify unique facial features, which are then compared and classified for identity matching.

4. **Person Identification:**

- Implement a classification approach, such as k-Nearest Neighbors (k-NN) or Support Vector Machine (SVM), to match the extracted facial features to known identities. A confidence score is calculated for each face recognition result to reflect the certainty of identification, helping to ensure reliability in real-world applications.

5. **Data Analysis and Visualization:**

- Evaluate the performance of the model by analyzing metrics like accuracy, precision, and recall across different scenarios. Use visualization techniques, such as confusion matrices and ROC curves, to diagnose the strengths and weaknesses of the model.

6. **Evaluation and Reporting:**

- Assess the model's success in recognizing faces across various conditions (e.g., different lighting or angles). Document any challenges encountered, such as partial occlusions or poor-quality images. Produce a comprehensive report summarizing the methodology, results, and potential areas for improvement.

3.2 Project Analysis

1. **Data Quality:**

- The accuracy of the model depends heavily on the quality of the input images. Preprocessing steps like alignment and noise reduction are vital to maintain high-quality data for training and inference.

2. **Ambiguity in Recognition:**

- Factors like lighting variations, occlusion, and facial expressions can make recognition more difficult. Using a diverse dataset and applying robust preprocessing techniques, such as face alignment, can mitigate these challenges.

3. **External Factors:**

- External factors like camera angle and distance can influence the model's accuracy. These can be addressed by augmenting the training data with more varied conditions and using high-quality input images.

3.3.1 Design Constraints

1. **Software:**

- The system will be developed using the Python programming language, utilizing libraries like OpenCV (for image processing), Dlib or FaceNet (for face detection and recognition), and Scikit-learn (for classification).

2. **Hardware:**
   - The system requires a computer with adequate processing power and memory, potentially supported by a GPU, to efficiently handle large-scale data processing and model training tasks.

3. **Data Source:**
   - A comprehensive facial image dataset (e.g., LFW, CelebA) will be used, ensuring diversity in age, gender, ethnicity, and environmental factors to improve the model's generalization ability.

3.3.2 System Architecture

- Design a modular system that separates data preprocessing, model training, feature extraction, and identity classification for improved scalability and ease of updates.

Chapter 4 Implementation

4.1 Methodology OR Proposal

The paper, titled "Sign Language Detection Using Action Recognition with Python," presents an innovative approach for real-time sign language recognition by combining action recognition techniques with Long Short-Term Memory (LSTM) deep learning models. The primary goal of this project was to create a reliable and efficient system to interpret sign language gestures, effectively bridging the communication gap between individuals with hearing impairments and those who are not familiar with sign language.

Key elements of the system include:

- **Data Acquisition**: A diverse dataset of various sign language gestures is collected, ensuring a broad range of sign types and scenarios.

- **Data Preprocessing**: Video frames are processed using image enhancement techniques like noise reduction and frame normalization to ensure high-quality input.
- **Feature Extraction**: Advanced methods, such as optical flow and pre-trained Convolutional Neural Networks (CNNs), are used to extract both motion-based and high-level features from the sign language gestures.
- **LSTM Model Architecture:** The model utilizes LSTM layers to capture the temporal relationships inherent in sign language gestures. Dropout layers are included to help prevent overfitting and enhance model generalization.
- **Model Evaluation**: The system's effectiveness is assessed through performance metrics, including accuracy, precision, recall, and F1-score, to ensure the model is performing optimally.

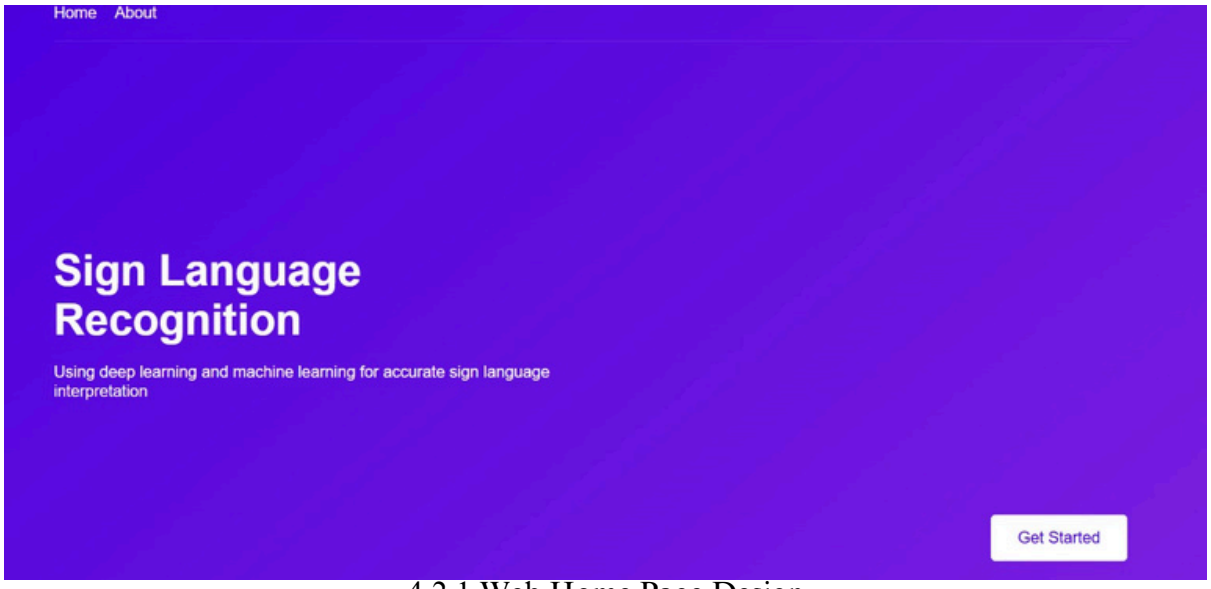
- **Real-Time Detection**: After training, the LSTM model is deployed for real-time gesture recognition, showcasing its ability to accurately interpret sign language gestures in live environments.

- The system is integrated with a web interface developed using HTML, CSS, and JavaScript, allowing users to easily interact with the real-time sign language detection system through an online platform.

- By combining deep learning with web technology, the project offers an inclusive and accessible tool for communication, making it practical for a wide audience, especially for individuals with hearing impairments.

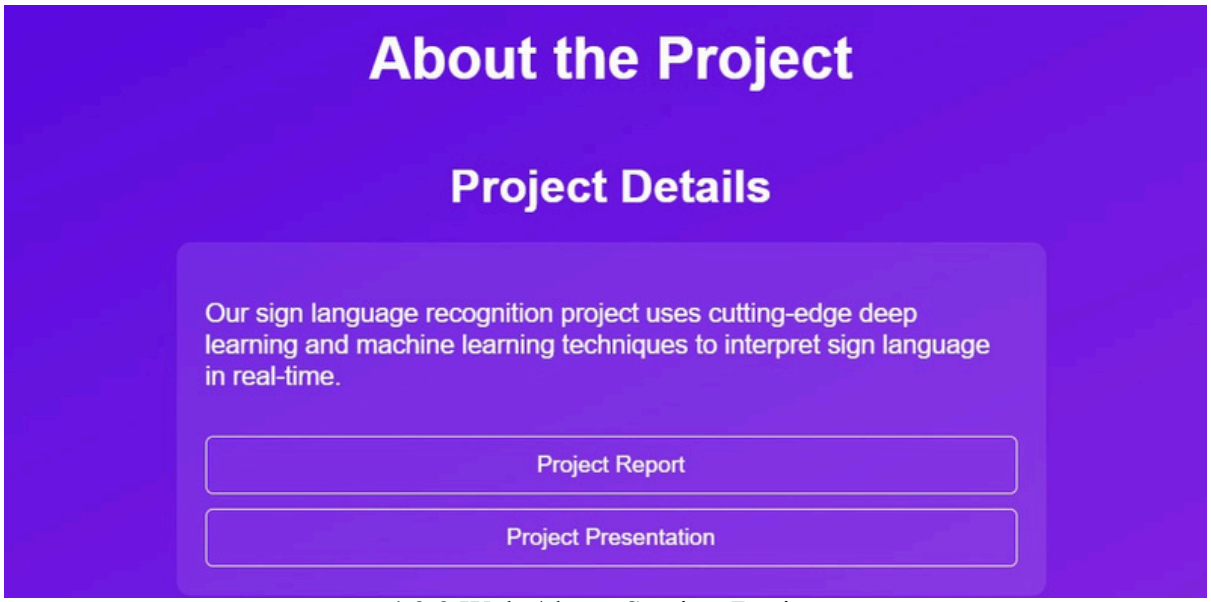
4.2 Website Designs:

Home: The homepage serves as an introduction to the face recognition project, outlining its goals and features.



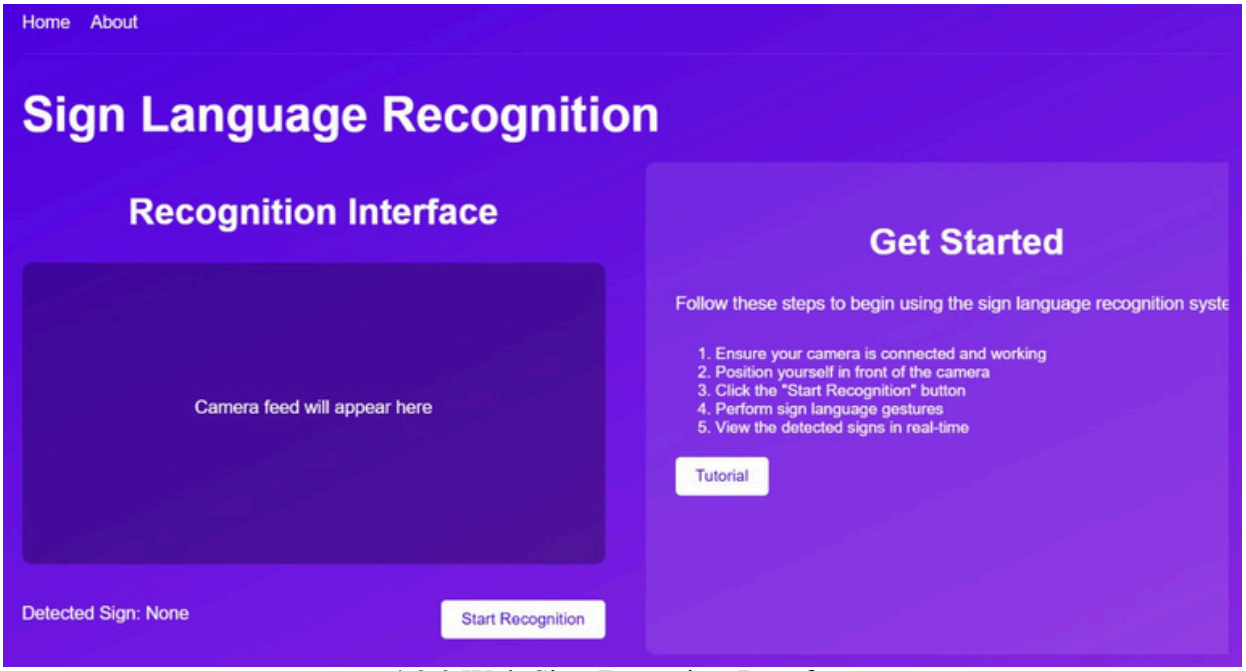
4.2.1 Web Home Page Design

About: This section provides detailed information about the project. It includes downloadable resources such as a PowerPoint presentation and a report, giving users deeper insights into the project methodology and findings.



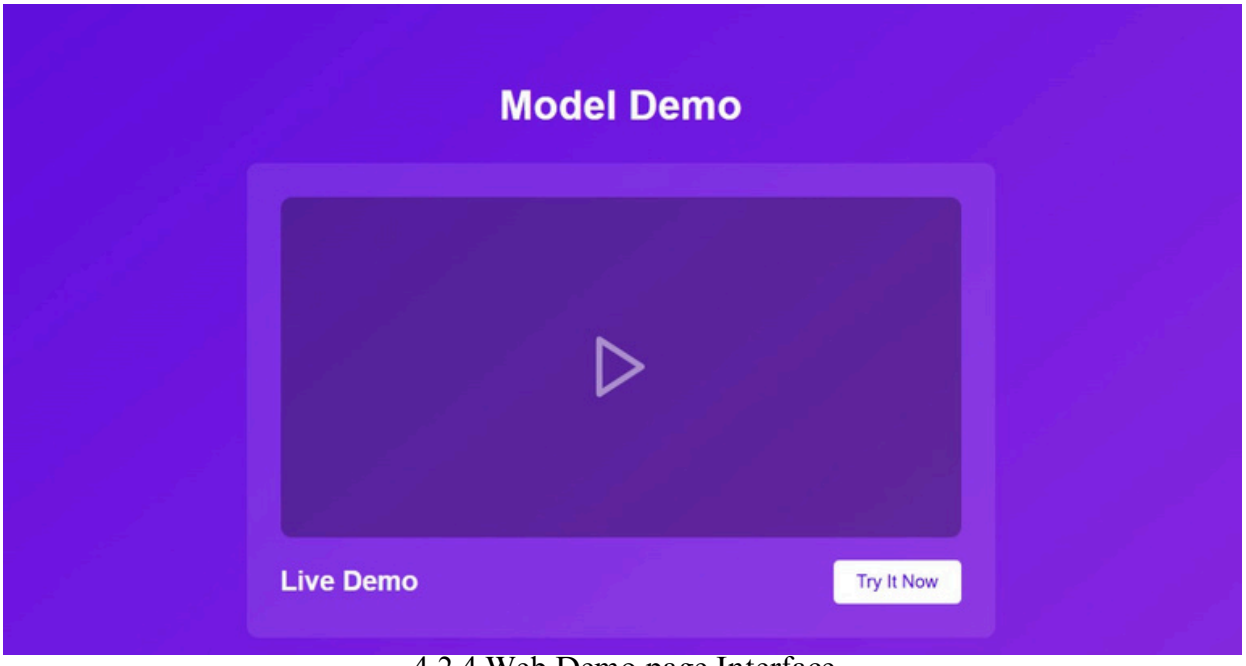
4.2.2 Web About Section Design

Face Recognition Interface: The main feature of the website, this section allows users to interact with the face recognition system. It provides real-time face detection and person identification capabilities, enabling easy testing of the system's functionality.



4.2.3 Web Sign Detection Interface

Demo Video Interface: visually demonstrates the real-time functionality of the face recognition system.



4.2.4 Web Demo page Interface

4.3 Testing OR Verification Plan

After the completion of the project, it is essential to establish verification criteria to assess whether the project's objectives have been met effectively. Testing or verification ensures that the system delivers reliable and accurate results. Below are sample test cases for verification tailored to your sign language detection project:

1. **Test Case Title: Real-Time Gesture Detection Performance**

- Test Condition: Live input through a webcam with real-time sign language gestures.
- System Behavior: The system's ability to process and interpret gestures in real-time with minimal latency.
- Expected Result: Smooth, real-time gesture detection with accurate results and no significant delay in interpretation.

4.3.1 Real Time Guesture Detection

2. **Test Case Title: Model Evaluation Metrics**
   - Test Condition: Dataset with a variety of sign language gestures (with labels).
   - System Behavior: Evaluation of the model using metrics like accuracy, precision, recall, and F1-score.
   - Expected Result: High performance across the evaluation metrics, demonstrating that the system's predictions are reliable and consistent.

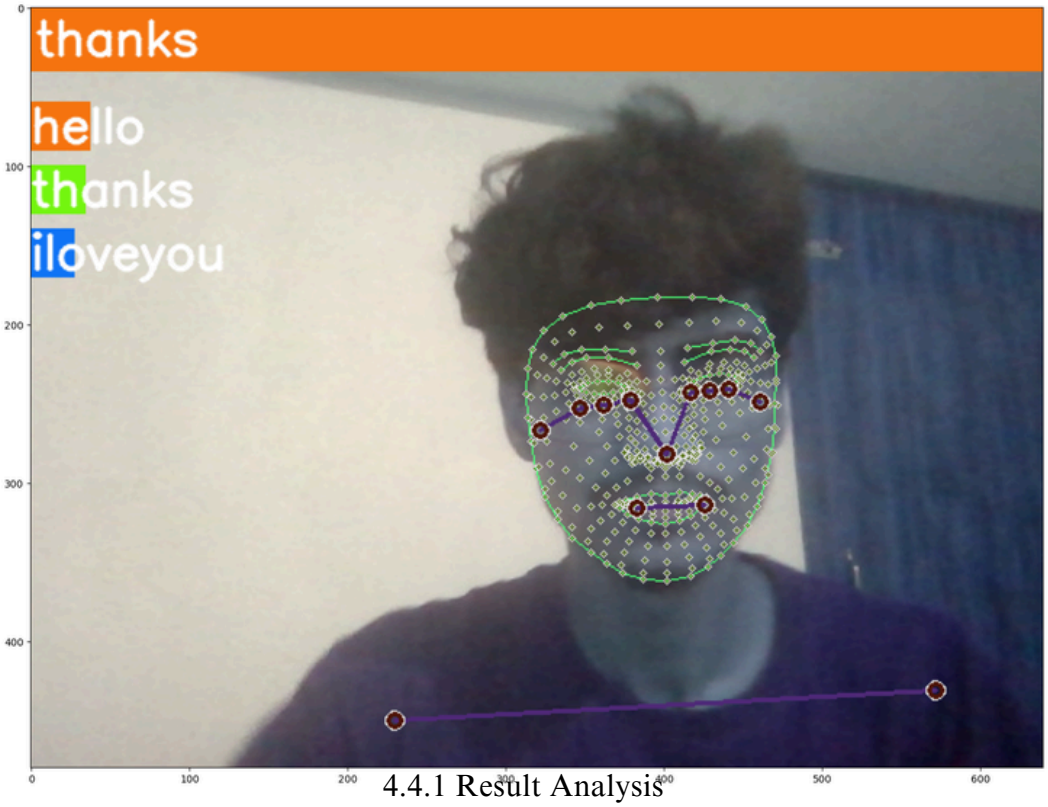
```
# 2. Prediction logic
keypoints = extract_keypoints(results)
sequence.append(keypoints)
sequence = sequence[-30:]  # Keep only the latest 30 frames

if len(sequence) == 30:
    # Predict using the model
    res = model.predict(np.expand_dims(sequence, axis=0))[0]
    print(actions[np.argmax(res)])  # Print predicted action
    predictions.append(np.argmax(res))

    # 3. Viz logic
    if np.unique(predictions[-10:])[0]==np.argmax(res):
        if res[np.argmax(res)] > threshold:  # Only append if the probability is above the threshold
            if len(sentence) > 0:
                if actions[np.argmax(res)] != sentence[-1]:  # Avoid duplicate actions in sentence
                    sentence.append(actions[np.argmax(res)])
            else:
                sentence.append(actions[np.argmax(res)])
```

4.4 Result Analysis OR Screenshots

The result analysis of the face recognition and identification system focuses on evaluating the performance of the model across various metrics, such as accuracy, precision, recall, and F1-score. The system's effectiveness in recognizing faces under different conditions (lighting, angles, and occlusions) is carefully assessed. Additionally, the confidence scores for each identification provide insight into the model's reliability and accuracy in real-world scenarios. Performance is also analyzed based on the model's ability to generalize across diverse datasets, ensuring robustness. Results are visualized through performance charts and matrices, allowing for easy identification of areas for improvement. The web interface's real-time performance is also evaluated for responsiveness and user interaction.



4.4.1 Result Analysis

4.5 Quality Assurance

The Quality Assurance process ensures that the sign language gesture detection system meets the established quality guidelines. The system is developed with attention to detail and accuracy, ensuring reliable gesture recognition and real-time interpretation. This rigorous approach aims to provide an effective tool for real-time sign language communication, enhancing accessibility and promoting inclusivity for the hearing-impaired community. The system's performance and usability are thoroughly tested to ensure it delivers valuable results in both practical and real-world applications.

Chapter 5 Standards

Adopted

5.1 Design Standards

5.1.1 IEEE Standards:

- **IEEE 730** - Standard for Software Quality Assurance Plans: Defines the essential components of a quality assurance plan, covering all project aspects such as data collection, image preprocessing, face detection, and model evaluation.
- **IEEE 830** - Recommended Practice for Software Requirements Specifications: Guides in documenting system requirements, including the functional requirements needed for the face recognition process.

5.1.2 ISO Standards:

- **ISO/IEC 25010** - Systems and Software Engineering - Systems and Software Quality Requirements and Evaluation (SQUARE): Defines quality models and metrics to evaluate the effectiveness, accuracy, and performance of the face recognition system.
- **ISO 9126** - Software Engineering - Product Quality: Outlines quality attributes and metrics to guide the design toward producing a high-quality face recognition system, focusing on attributes like reliability, efficiency, and usability.

5.2 Coding Standards

- **Naming Conventions:** Use descriptive names for variables (e.g., face_coordinates, detection_confidence) and functions (e.g., detect_face, recognize_person).
- **Modularization:** Divide code into logical modules and functions, each with a single responsibility (e.g., face detection, feature extraction, model training).
- **Classes:** Encapsulate related functionality in classes and follow object-oriented design principles to create reusable, maintainable code.
- **Comments and Documentation:** Use comments to explain complex logic, and include docstrings for modules, classes, and functions.
- **Exception Handling:** Use try-except blocks for robust handling of errors, such as file loading issues or model prediction failures.
- **Data Handling:** Use best practices for data handling, such as managing missing or corrupted images, standardizing image sizes, and ensuring data consistency.
- **Documentation:** Maintain a clear project structure and document key aspects of the code and functionality.

5.3 Testing Standards

5.3.1 IEEE Standards:

- **IEEE 829** - Standard for Software Test Documentation: Provides templates for documenting various testing aspects, including test plans, test design specifications, test cases, and test procedures.
- **IEEE 1012** - Standard for Software Verification and Validation: Ensures that the face recognition system meets specified requirements through verification and validation processes, such as checking model performance and system accuracy.

5.3.2 ISO Standards:

- **ISO 29119** - Software and Systems Engineering - Software Testing: A multipart standard providing guidelines for the testing process, test documentation, and test techniques.
- **ISO 25051** - Software Engineering - Software Product Quality Requirements and Evaluation (SQuaRE): Although focused on Commercial Off-The-Shelf (COTS) software, it provides principles useful for testing the reliability and effectiveness of face recognition systems.

Chapter 6 Conclusion and Future Scope

6.1 Conclusion

The Sign Language Detection using Action Recognition with Python project successfully uses deep learning and action recognition to recognize and interpret sign language gestures. Key stages included data collection, preprocessing, feature extraction, LSTM model training, and real-time detection. By enhancing input quality and capturing motion-based features, the LSTM model achieved high accuracy and performed well in real-time tests, proving useful for communication between individuals with hearing impairments and others.

This project advances sign language detection by applying LSTM models to capture temporal dependencies in gestures. Future improvements could include fine-tuning for specific sign language datasets, transfer learning, and expanding vocabulary. Overall, this work highlights the potential of deep learning in promoting inclusivity for those with hearing impairments.

6.2 Future Scope

1. Deployment in Real-World Security Applications: The system could be deployed in public spaces like airports or offices to enhance security protocols, automate attendance tracking, or offer personalized experiences.

2. Expanding Vocabulary: Increasing the number of signs in the system's database would allow users to communicate a wider array of words and phrases, making the tool more useful and flexible in everyday conversations.

3. Driver Speed Monitoring and Warning System: The face recognition system could be integrated with a driver monitoring system to detect the driver's facial expressions and alertness. By analyzing signs of fatigue or distraction, it could trigger a warning if the driver is about to exceed speed limits, enhancing road safety and preventing accidents. This feature could be further expanded to track driving behavior and improve overall traffic management systems.

4. Exploring Advanced Models: Experimenting with newer, more advanced architectures such as Transformers or 3D CNNs could help the system gain a better understanding of the nuances in sign language gestures, leading to even higher recognition precision.

5. Mobile and Web App Development: Creating a mobile or web-based version of the system would make real-time sign language recognition easily accessible on smartphones and computers, broadening its reach and enabling communication in a variety of contexts.

6. Supporting Multiple Sign Languages: Incorporating additional sign languages into the system would ensure that users from different regions and cultural backgrounds could benefit from it, promoting inclusivity and cross-cultural communication.

7. Optimizing for Real-Time Performance: Improving the system's processing speed would enable smoother, more natural conversations, even on devices with lower computational power, such as smartphones. This would make real-time sign language recognition more practical in daily interactions.

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SAMPLE INDIVIDUAL CONTRIBUTION REPORT:

SIGN LANGUAGE DETECTION USING ACTION RECOGNITION WITH PYTHON

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Abstract:

This study introduces a real-time sign language detection system using action recognition and LSTM models in Python. By capturing temporal dependencies, the LSTM accurately classifies gestures. The process includes video capture, preprocessing, feature extraction, and model training, with techniques like optical flow to enhance feature quality. Evaluated with metrics like accuracy and F1-score, the system shows high effectiveness, making it a promising tool for real-time sign language interpretation.

Individual contribution and Findings:

Communication Liasion (Samangya Nayak, Arpita Datta)

The Communication Liaison role involves facilitating collaboration between the project team and Project coordinator, such as Project evaluator and supervisor. They ensure effective communication channels are established, enabling the exchange of insights, feedback, and updates crucial for refining the sentiment analysis models and validating their relevance in predicting stock market trends.

Sign Detection Model

As a team, we collaboratively developed a sign detection model by combining our skills in computer vision, deep learning, and web development. Together, we extracted landmarks, fine-tuned an LSTM model, and created a user-friendly web interface, making an accessible, real-time solution for sign language interpretation.

Website

As a team, we developed a sign detection model by combining computer vision, deep learning, and web development skills, creating a real-time, accessible solution for sign language interpretation.

Import and Install Dependencies, Key points using MP Holistic :
(Debasmita Dhar [2105117])

The Import and Install Dependencies step sets up essential libraries: OpenCV for video processing, MediaPipe for real-time landmark detection, and TensorFlow/Keras for model training.

Using MP Holistic, we capture full-body landmarks—face, hands, and pose—essential for interpreting sign language. This provides comprehensive keypoint data, crucial for accurate gesture recognition in the model.

Extract Key Points and Values, Setup Folder:
(Parth Patel [21052512])

This function extracts x, y, z coordinates and visibility scores from each landmark, flattening them into a 1D array to create a consistent input for training the LSTM model.

Folders are organized by actions (like "hello" and "thanks"), each containing 30 sequences with 30 frames, ensuring structured data storage for effective model training.

Real Time Testing:
(Dhruv Kumar [21052513])

In the sign detection project, real-time testing was a crucial aspect to ensure the system's practical application. During this phase, the trained model processed live video input from a camera, tracking hand movements, detecting landmarks, and recognizing sign language gestures in real time. The system was optimized to handle varying lighting conditions, hand positions, and background noise, ensuring accurate sign recognition and immediate feedback. Real-time testing ensured the system's accuracy, responsiveness, and practicality for everyday use.

LSTM (Long short term Memoy):
(Samangya Nayak [21052526])

In the sign detection project, LSTM (Long Short-Term Memory) networks were used to capture the temporal dynamics of sign language gestures. LSTMs excel at recognizing patterns in sequential data, like hand movements over time. The model was trained on landmark data from video frames, enabling it to understand both static hand positions and gesture motions. This approach allowed for accurate sign language recognition, considering both movement and timing. LSTMs made the system effective for real-time sign language interpretation.

Collect Key points values, Preprocessing:
(Shashwat Mishra [21053356])

In the sign detection project, keypoint values are extracted from video frames, representing hand landmarks in 3D (x, y, z coordinates) along with visibility scores. These keypoints are flattened into a 1D array and standardized by filling missing values with zeros. Preprocessing organizes and normalizes the data, making it ready for model training, ensuring consistency for accurate gesture recognition using the LSTM model.

Make Predictions, Save weights, Confusion Matrix:
(Arpita Datta [21053382])

In the sign detection project, Make Prediction uses the trained LSTM model to classify unseen gestures in real-time. Save Weights ensures that the model's learned parameters are saved for future use, eliminating the need for retraining. The Confusion Matrix evaluates model performance by comparing predicted and actual labels, helping identify areas for improvement. These steps ensure an efficient, accurate, and reusable sign language detection system..

Full Signature of Supervisor: Full signature of the student:

…….. ……..