Design and Implementation of Multilingual Hand Gestures Recognition System for Dumb and Deaf.

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Abstract- The Multilingual Sign Language Recognition System addresses communication barriers faced by the hearing and speech-impaired community, especially in multilingual contexts. Sign language serves as the principal means of communication for millions of Deaf and mute individuals globally, providing a comprehensive and organized visual language for interaction. However, due to the scarcity of interpreters and the limited awareness among the general public, individuals relying on sign language often face significant challenges in communication. These barriers lead to social isolation and hinder equal access to essential services such as education, healthcare, and employment opportunities. Sign Language Recognition (SLR) systems are designed to bridge this gap by automatically translating sign language into text or speech, fostering inclusive and accessible communication. These systems hold immense potential to improve interactions between the Deaf and dumb within the society thereby creating enabling seamless integration in public, professional, and personal domains. By leveraging advanced deep learning techniques, the YOLO algorithm for real-time gesture detection and Tensorflow for classification was adopted for this study. This system focused on recognizing hand gestures across multiple sign languages such as ASL and BSL. The study achieved a detection accuracy of 99%. Despite limitations like dependency on high-performance hardware and exclusion of facial expressions, the project demonstrated significant potential as an assistive technology.

Index Terms- *Detection, hand gesture, Multilingual, Recognition, TensorFlow*

I. Introduction

Communication is an essential human necessity, and language serves as its medium. The majority of individuals has the capacity to listen and talk, utilizing several languages such as Yoruba, Hausa, Igbo, French, and English for communication. But for the deaf and dumb people, the case is different. They use signs to communicate and person that do not know sign language will face difficulties in dealing or communicating with them. In this paper we try to develop a system that can convert sign into English text for communication between signers and non-signers. The main objective is to facilitate a large population of hearing-impaired persons and making them an integral part of the society. The system will convert the predefined text in the application into their respective sign language along with the text's audio. The detection system works by taking images of user making particular sign through webcam and uses skeletal tracking combined with machine learning to detect what sign they are making. A deaf person is a person that cannot hear normally as someone with normal hearing. Whose hearing thresholds in both ears is loss. This may be mild, moderate, severe, or profound, they rarely communicate in the public for fear of being intimidated and these people are part of the community which need to be benefited from hearing aids.

Gestures can be defined as a sort of nonverbal communication where observable body movements convey significant signals, as a substitute for speech or vocal expressions. Gestures encompass movements of the hands, face, or other bodily regions (Khaskheli, 2022). So here gesture is used for deaf people they used gesture in the form of input to convey their message whatever it will be and the given gesture translated into text for the hearing people. Gesture-based communication is the most significant and centered approach of communication for deaf and dumb individuals. The gesture based communication structure can be preferred for cooperation between individuals with hearing hardships to avoid the creation of language boundary (Vaidhya & Deiva Preetha, 2022). Despite the percentage rate of the world's population interaction, individuals with hearing and speech impairments frequently encounter systemic communication difficulties (Bo hacek *et la.,* 2022), the primary mode of interaction for this group remains sign language. This language system relies on dynamic combinations of hand gestures, facial expressions, and body movements to convey alphabets, numbers, and complex phrases (Athira *et al*., (2022). However, the diversity of sign languages globally adds complexity to the development of SLR systems. Countries such as the United States, the United Kingdom, and India, for example, each have their own distinct sign languages like American Sign Language (ASL), British Sign Language (BSL), and Indian Sign Language (ISL), respectively. In an increasingly globalized and interconnected world, the demand for technology that transcends linguistic and cultural barriers has become more pressing. Multilingual SLR systems are especially crucial, as they enable cross-cultural communication by supporting multiple sign languages within a unified framework. Recent advancements in artificial intelligence (AI), machine learning, and computer vision have provided the tools necessary to develop such systems. These technologies enable real-time processing of gestures, facilitating practical applications in scenarios ranging from education to customer service.

However, building multilingual SLR systems requires addressing challenges such as variability in hand shapes, motion speed, and contextual interpretation of gestures. These systems must also account for regional nuances and cultural differences embedded in various sign languages. By integrating deep learning algorithms like YOLO (You Only Look Once), researchers are now capable of achieving higher accuracy and efficiency in detecting and interpreting sign gestures in diverse linguistic contexts.

The development of a multilingual sign language recognition system is not just a technological achievement, it is a step toward creating a more inclusive society where communication barriers are minimized, and individuals with hearing and speech impairments can participate fully in all aspects of life.

A. Statement of the Problem

The Deaf community faces unique challenges due to language barriers in various social interactions, education, healthcare, and employment. While SLR systems have been developed for such languages, usually, systems cannot generalize across multiple languages, and often, the scale is limited. The identified issues are:

- **Limited Language Support:** Existing SLR systems often focus on one sign language, which limits accessibility for users from different linguistic backgrounds. They are designed to recognize a single sign language, typically chosen based on the regional or demographic focus of the system's developers (e.g., American Sign Language for U.S.-based applications or British Sign Language for U.K.-based ones). However, this narrow focus restricts the accessibility and utility of these systems in a global context, as sign languages vary significantly across regions and cultures. Each language has its own syntax, vocabulary, and grammar rules, meaning that the gestures, hand shapes, and movements unique to one sign language often differ from those in another.
- **Variability and Complexity of Gestures:** Sign language involves a complex variation in the movement of the hands, face, and body, further complicating recognition as the movements differ among different languages.
- **Limited Data Availability:** Most of the sign languages do not have sufficient data required for training a recognition system since there are languages that have less research done on them.
- **Real-Time Recognition Constraints:** Real-time recognition is crucial for practical Sign Language Recognition (SLR) systems, as delays in translation can disrupt the natural flow of communication. Achieving low latency in real-time SLR is challenging due to the high computational demands involved in processing gestures, facial expressions, and body movements in quick succession. These systems should ideally be able to identify, analyse, and translate each gesture in a very negligible fraction of time without delay for seamless and uninterrupted communication between users. That is to say, speed and accuracy have to be balanced. For complex gestures, especially in multilingual contexts, far more robust algorithms will be needed to analyses minute details of movements within milliseconds. YOLO is such an algorithm that works for real-time object detection and hence can be promising for fast gesture recognition. Even with optimized models, real-time processing requires substantial computational power because of great differences among multiple sign language gesture sets.

B. Purpose of the Study

The purpose of this project is to design and implement a multilingual sign language recognition system able recognize and translate signs from various languages into text or speech output. This system aims to enhance better communication between Deaf individuals with non-signers making it easier for Deaf individuals to interact with others in public, educational, and professional spheres. The project will explore real-time recognition using YOLO (You Only Look Once) to ensure quick and accurate translation of signs.

C. Objectives of the Study

The primary objectives of this study are:

1. To develop a real-time hand gesture recognition system using YOLO and TensorFlow.
2. To train the system to recognize gestures from multiple sign languages.
3. To evaluate the performance of the system under varying environmental conditions.

II. MULTILINGUAL SIGN LANGUAGE RECOGNITION SYSTEM

Sign Language Recognition (SLR) systems play a crucial role in bridging communication gaps for the deaf and dumb communities. This system leverage advancements in machine learning, computer vision, and natural language processing to translate processing to translate sign language into spoken language vice versa. Multilingual SLR systems are particularly significant as they cater to a global audience by recognizing and translating multiple sign languages, such as American Sign Language (ASL), British Sign Language (BSL), an Indian Sign Language (ISL) (Najib, 2024).

The development of multilingual SLR systems addresses the unique challenges posed by the diversity of sign languages. Each sign language has its own grammar, gestures, and regional dialects, making it essential for SLR systems to support multiple languages to ensure inclusivity and accessibility (Najib, 2024). Recent technological advancements in real-time processing and computer vision have set the stage for the creation of effective multilingual SLR systems.

One of the key technologies enabling multilingual SLR is deep learning, particularly convolutional neural networks (CNNs) for visual gesture detection, paired with NLP models for language interpretation and translation. These systems process video or image data to detect hand movements, facial expressions, and body postures, which are essential components of sign language communication. Real-time recognition capabilities, such as those provided by the YOLO (You Only Look Once) algorithm, allow for the efficient processing of gestures, making it possible to deliver accurate translations promptly.

The impact of multilingual SLR systems extends across various sectors, including education, healthcare, public services, and customer support, where the ability to communicate effectively with Deaf individuals is crucial. In educational settings, for example, these systems can provide real-time translations, allowing Deaf students to follow along in classrooms. In healthcare, they can bridge communication gaps between Deaf patients and medical professionals, ensuring clarity and accuracy in care delivery.

Developing an effective multilingual SLR system presents technical challenges, such as the need for large, annotated datasets across multiple languages, handling variations in gestures and expressions, and achieving real-time processing within the constraints of available hardware. Nonetheless, the development of multilingual SLR systems holds the potential to create a more inclusive world, where Deaf individuals can access communication services in their preferred sign language, fostering greater independence and social integration. Recent technological advancements in real-time processing and computer vision have set the stage for the creation of effective multilingual SLR systems.

A. Features of Multilingual Sign Language Recognition System

- Real-time Processing: Real-time performance gives way to meaningful and interactive communication. To this effect, there exists a gamut of computers combining machines with intelligent algorithms to perform real-time hand gesture recognition and translation into text or speech, such as the Multi-lingual Sign Languages Interpreter, MSLI.
- Multilingual Capability: Successful SLR needs to identify and then distinguish between different sign languages. Training on diverse datasets comprising different sign languages with dialectal variations provides a model with excellent generalization across languages, preserving the characteristic gestures and grammatical rules of each language.
- Accurateness and Precision: The high precision with which it is recognized, therefore, yields reliable translations. In enhancing precision, some strategies include making use of deep learning models that are implemented with huge and different datasets, the application of pre-trained models for transfer learning, and refinement techniques on the recognition results carried out as post-processing.
- Scalability and Flexibility: A successful SLR system should be scalable, which means it can handle new additions of languages or dialects without being completely retrained. Modular neural networks, or architectures like transformers, can be adapted to support multiple languages and extended functionality.
- Computer Vision and Deep Learning: Computer vision techniques, mainly convolutional neural networks, take into consideration the analysis of images or video frames to detect hand gesture, facial expression, and body movement1. Deep learning models, such as Long Short-Term Memory, are put into use for continuous sign language recognition.
- NLP: The signs are translated into coherent sentences in one of the spoken languages by the various NLP techniques. Either sequence-to-sequence model-based or transformer-based neural architectures interpret the recognized gestures and thereby convert them into natural spoken language (Kuznetsova et al., 2013).

B. Theoretical Framework of Multilingual Sign Language Recognition Systems

This section will outline the theoretical basis for SLR systems, covering the core technologies that enable gesture recognition and language translation:

- Computer Vision: This is a fundamental technology in Sign Language Recognition (SLR) systems, enabling the analysis of images or video frames to detect hand gestures, facial expressions, and body movements, Central to computer vision is the use of Convolutional Neural Network (CNNs). CNNs are particularly effective for image processing tasks due to their ability to capture spatial hierarchies in visual data. These networks consist of multiple layers that apply convolutional filters to the input image, extracting features such as edges, textures, and shapes. This makes CNNs ideal for gesture recognition, where the intricate details of hand movement and facial expressions are critical for accurate interpretation (Kim, 2016)
- YOLO Algorithm: The YOLO (You only Look Once) algorithm is a single-stage object detection system known for its real-time processing capabilities. Unlike traditional object detection methods that perform region proposal and classification separately, YOLO divides the input image into grid and predicts bounding boxes and class probabilities within each cell. This simultaneous detection and classification make YOLO exceptionally fast, which is crucial for real-time application like SLR. YOLO's trade-offs between speed and accuracy make it well-suited for detecting complex hand movements and gestures in SLR systems. YOLO's ability to handle multiple objects (gestures) in a single frame further enhances its suitability for real-time sign language recognition (Redmon *et la*, 2016).
- Natural Language Processing (NLP): Natural Language Processing (NLP) are critical for translating recognized signs into coherent sentences in various spoken languages. In the context of multilingual SLR, sequence-to-sequence models or transformer-based

architectures, such BERT or GPT, are employed to interpret the recognized gestures and convert them into natural language. These models handle the complexities of language translation, ensuring that the output is contextually appropriate and grammatically correct. However, adapting NLP models for SLR poses challenges, as gesture sequences may vary significantly by language and cultural nuances. Ensuring accurate contextual understanding requires extensive training on diverse datasets to capture these variations (Devl in et al., 2018)

C. Related Works

Lawal et al. (2024) evaluate the efficacy of a mobile application titled "Hausar Kurma" in instructing English to Hausa-speaking students with hearing impairments at Nigerian special education institutions. A solitary participant was employed to assess the effects of the application. Evidence-based methodologies were utilized to evaluate the efficacy of the educational instrument and to guarantee adherence to the gold standard. Multiple single-subject design methodologies, such as the celeration line, binomial test, and Wilcoxon signed-rank test, were employed. The results demonstrated a substantial Cohen's big impact classification and an increased acceptance rate of the program among users. This study's findings validate the app's effectiveness and advocate for its adoption in special schools to improve English language education for Hausa-speaking pupils with hearing impairments and those who are hard of hearing. The study was restricted to individuals who are hard of hearing and speak Hausa exclusively. Alam et al. (2024) conducted a survey of research papers on speech disorders, published from 2012 to 2023. A comprehensive search and systematic approach for organizing the literature, along by a clearly defined theoretical framework for outcomes and findings, was established. The study primarily consisted of a review. Shaban & Elsheweikh, (2024) developed an intelligent Android system for the automatic recognition of Arabic and American sign languages to facilitate teaching and learning. The system comprises the Sensory Smart Glove, utilizing Internet of Things technology for automatic sign language recognition. It features a smart glove with five flex sensors that assess finger bending corresponding to executed gestures, along with an MPU-6050 accelerometer sensor to monitor hand position across three axes (X, Y, Z). The sensed data are analyzed by an Arduino Nano microcontroller, and the recognized gesture's text is transmitted via the HC-05 Bluetooth module to an Android phone. This phone exhibits text and transforms it into audible speech via an Android application. The findings exhibited elevated recognition accuracy rates for Arabic and American Sign Languages. The study was intended solely for the specified languages. Yousaf et al., (2018) proposed application, termed Vocalizer to Mute (V2M), employs automated speech recognition (ASR) techniques to interpret the speech of Deaf-mute individuals and transform it into a comprehensible form of speech for hearing individuals. Mel frequency cepstral coefficients (MFCC) characteristics were retrieved for each training and testing sample of deaf-mute speech. The Hidden Markov Model Toolkit (HTK) was utilized for speech recognition processes. The application used a 3D avatar to offer visualization assistance, tasked with executing sign language on behalf of an individual unfamiliar with Deaf-mute society. The trial results indicate that mobile technology intervention enhances face-to-face socialization among Deaf-mute individuals. Vaidhya & Deiva Preetha, (2022) worked on motion based communication for the people with hearing and speaking impairments. He came up with the fact that communication through signs is a successful choice rather than talking with the impairments. Text comprehension study tasks was suggested for hearing impaired localities using Sign Language Recognition. Baktash *et al*., (2021) developed a method to facilitate numerous sign language translations via a sensor-equipped glove and an Android smartphone, aimed at enhancing communication for individuals with speech impairments. The hand talking system (HTS) was developed using several sensors and an efficient sewing controller (Lilypad). The system comprised flex sensors, an Arduino, a smartphone, and an accelerometer. The HTS employs an Android application designed to hold many languages in a SQLite database, facilitating user interaction with the system. The technology facilitates communication using letter-formed words or by employing the most commonly used terms in daily interactions via hand gestures. Saleem *et al*., (2023) made a comparison between three different sign languages; American Sign Language (ASL), Pakistani Sign Language (PSL), and Spanish Sign Language (SSL). The system was able to detect the sign language and converts it into an audio message for the ND-M. The hand gesture data of D-M individuals was acquired using an LMD device and processed using a Convolutional Neural Network (CNN) algorithm. A supervised ML algorithm completes the processing and converts the hand gesture data into speech.

III. METHODOLOGY

A. Research Design

This chapter outlines the research methodology used in developing the multilingual sign language recognition system, focusing on hand gesture detection and classification. The system employs the Yolo (you only look once) algorithm for object detection and Tensorflow for model training. Tensorflow's solution for mobile and embedded devices helps to run machine-learned models on mobile devices with low latency, and this can be used to do classification, regression or any other thing without necessarily incurring a round trip to a server. It's presently supported on Android and iOS via a C++ API, as well as having a Java Wrapper for Android Developers. The processing required data collection, data preprocessing, model training, and performance evaluation. This approach ensures a systematic process for achieving accurate and reliable hand gesture recognition.

B. System Design

The architecture of the Multilingual Sign Language Recognition System is designed to facilitate efficient detection and classification of hand gestures. The main components include:

i. **Input Module:** Captures video frames of hand gestures in real time or from pre-recorded datasets.

Prepossesses input frames by resizing and normalizing them for compatibility with the YOLO model.

ii. **Detection Module:** Utilizes the YOLO algorithm to detect hand gestures within the frames. Outputs bounding boxes around detected gestures along with confidence scores.

iii. **Classification Module:** Employs TensorFlow to train and classify detected gestures into corresponding sign language classes.

iv. **Evaluation Module:** Measures model performance using metrics such as accuracy, precision, recall, and F1 score. Analyzes error cases for potential improvements.

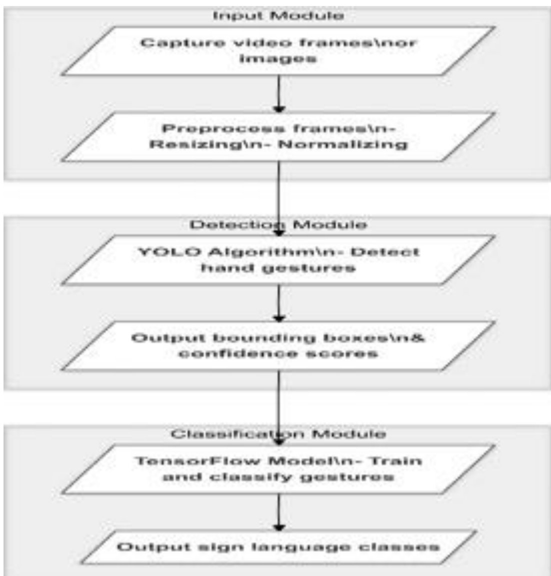

Figure 1: System Architecture

C. Research Design

The research adopts an experimental approach to test the system's accuracy and robustness. Data Collection and Annotation was carried out by Collecting gesture images and videos for multiple sign languages and annotated datasets with bounding boxes and corresponding gesture labels using LabelImg tool. The data were reprocessed by normalizing image data to enhance model training and augmenting data to improve model generalization. The Model was trained using YOLO for gesture detection and fine-tuned by classification layers using TensorFlow to differentiate between gestures of various languages. The model was evaluated and the results were compared across different lighting conditions, backgrounds, and hand sizes.

IV. RESULTS AND IMPLEMENTATION

The Multilingual Sign Language Recognition System was implemented using YOLO for detection and TensorFlow for classification. GPU resources were leveraged for training, ensuring efficient processing. The implementation process included model training, testing, and evaluation on diverse datasets.

A. System Testing Setup

System testing is a critical phase in the development of the multilingual sign language recognition system, ensuring the functionality, reliability, and performance of the model. The testing was conducted in controlled environments using annotated gesture datasets, with an emphasis on maintaining reproducibility and precision. This section outlines the steps involved in the testing setup

B. Dataset Preparation

The annotated gesture datasets collected during the earlier phases of the project were systematically prepared for testing. The preparation involved dataset being segmented into two 70% for the training and 30% for testing and validation. In order to optimize the testing process, the system was set up in an environment tailored for high-performance computation:

Hardware Setup: The testing was conducted using Google Colab, a cloud-based platform that provides free access to GPU resources. This allowed for efficient computation and scalability without the need for physical hardware.

Software Configuration: The environment was configured to run TensorFlow frameworks and integrate the YOLO algorithm. All dependencies, libraries, and packages were installed and tested for compatibility.

Detection and Classification Accuracy: The model's ability to correctly identify and classify hand gestures was measured using standard metrics such as precision, recall, F1-score, and overall accuracy.

Processing Speed: Real-time capability was assessed by measuring the system's frame rate in frames per second (FPS) during inference.

C. Results

The system demonstrated the following performance metrics in American Sign Language (ASL) and British Sign Language (BSL) for different signs such as No, Hello and thank you as shown in the figure below.

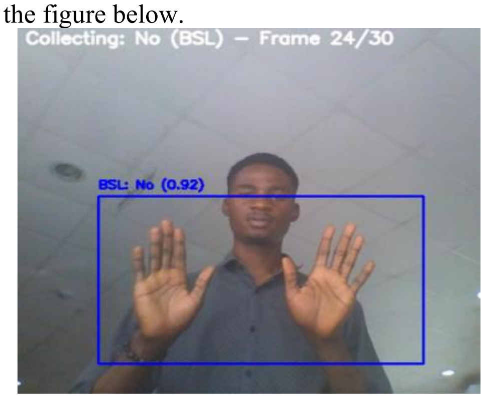

Figure 2: NO Detection Gesture for BSL.

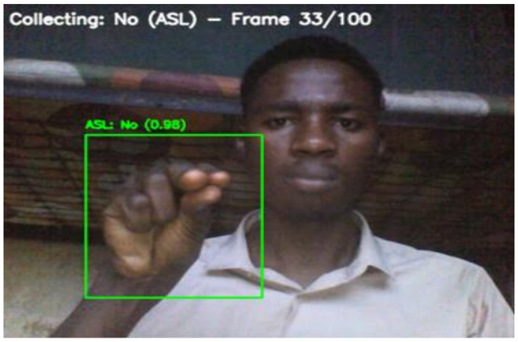

Figure 3: NO Detection Gesture for ASL

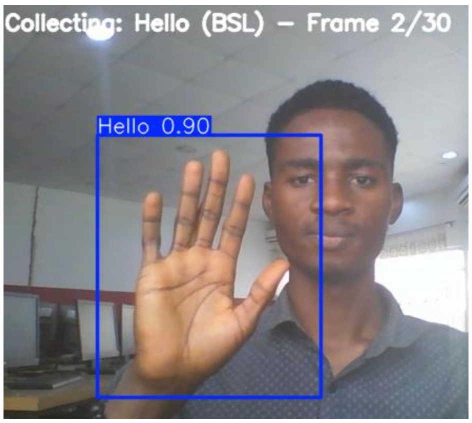

Figure 4: Hello Detection Gesture for BSL

Figure 5: Hello Detection Gesture for ASL

Figure 6: Thank you detection gesture for BSL

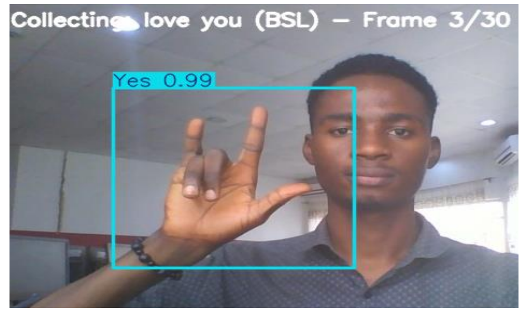

Figure7: Love you detection gesture for BSL

Above images indicated with a bounding box shown the detected gesture of the same word in different languages.

Table 1: Comparison for the sign detection in ASL and BSL.

SIGNS	ASL	BSL
NO	0.90	0.92
LOVE	0.74	0.99
THANK YOU	0.82	0.94
HELLO	0.99	0.90

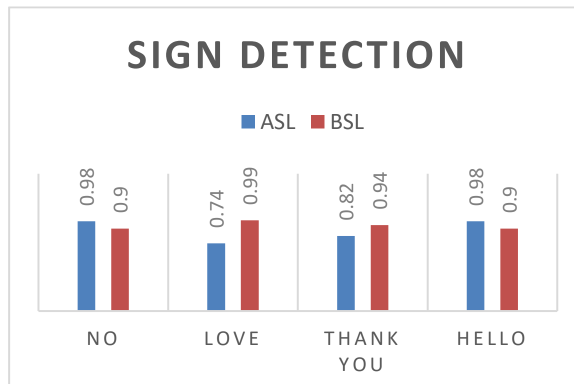

Figure 8: Graph for the Comparison detection rate.

D. DISCUSSION

The results of the system testing provided valuable insights into the performance, strengths, and areas for improvement in the multilingual sign language recognition system. The discussion focuses on the effectiveness of the methodologies employed, the integration of key technologies, and the challenges encountered during the development and testing process.

The YOLO (You Only Look Once) algorithm demonstrated significant effectiveness in detecting and recognizing hand gestures in real-time. The results from the table1 and figure 8 above indicated that the developed model detected signs for LOVE, NO, THANK YOU and LOVE differently with high confidence rate. Its ability to process frames quickly without compromising accuracy was a critical factor in achieving high detection rates. The model successfully identified and localized hand gestures within frames, even under moderate variations in hand position and orientation. However, its performance slightly degraded in scenarios with complex overlapping gestures or inconsistent lighting, highlighting potential areas for refinement. TensorFlow proved instrumental in enabling the classification of detected gestures. Its flexibility and support for neural network architectures allowed seamless integration with the YOLO algorithm. However, fine-tuning the model required iterative adjustments to hyper parameters, such as learning rates and batch sizes, to optimize classification accuracy. These adjustments, though time-intensive, were essential for improving the overall performance of the system. While the system performed well under controlled conditions, several challenges were encountered such as low-light conditions which made the model struggled to maintain accuracy in environments with inadequate lighting, leading to reduced detection rates and occasional misclassifications. Also an overlapping gestures which made the system sometimes failed to distinguish between multiple gestures when it overlapped or perfumed in quick succession.

V. SUMMARY

This project developed a Multilingual Sign Language Recognition System focusing on the detection and classification of hand gestures using YOLO and TensorFlow. The system achieved high detection and classification accuracy, demonstrating its potential as an assistive tool for the deaf and dumb impaired community. High accuracy in detecting and classifying hand gestures across multiple sign languages and efficient processing speed, achieving real-time analysis capabilities.

VI. CONCLUSION

The Multilingual Sign Language Recognition System represents a significant step toward bridging communication barriers for the deaf and dumb impaired community. By addressing current limitations and building on the findings of this study, future developments can pave way for more inclusive and effective communication technologies.

It is recommended that the datasets can be expanded to include more sign languages, variations in hand gestures, and environmental conditions to validate system performance and robustness for further studies.

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CONFLICTS OF INTEREST/ COMPETING INTERESTS:

Based on our understanding, this article has no conflicts of interest.

ETHICAL APPROVAL AND CONSENT TO PARTICIPATE

The data provided in this article is exempt from the requirement for ethical approval or participant consent.

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