Kannada Sign Language Recognition Using Machine Learning

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Abstract
For the global community of people who are hearing or speech handicapped, sign language is an essential communication tool. While languages like Tamil and Hindi have found their way into Indian technology, Kannada Sign Language (KSL) has not yet been extensively used in digital applications. In order to recognize Kannada sign language, this research suggests a revolutionary machine learning-based method that focuses on both letter and word detection. By gathering a unique dataset of more than 6,000 samples from 20 different participants, our project fills the gap and guarantees resilience against changes in signing conditions and style. In order to minimize computational cost and enable precise gesture capture, we use MediaPipe to extract 21 hand keypoints. Two sophisticated models are integrated into the classification framework: MobileNetV2, which is tuned for static letter recognition, and a 3D Convolutional Neural Network (3D CNN), which is designed for dynamic word gestures. Our experimental results outperform current Indian sign recognition models with an impressive 99.7% letter identification accuracy and an 85% word recognition accuracy. The difficulties in creating datasets, the intricacies of sign variation, and the current small repertoire of 27 words are the main obstacles encountered. However, this study establishes a solid basis for future scalable Kannada sign language recognition systems that can help the deaf people in Karnataka communicate. Future plans call for improving dynamic gesture detection, adding more words to the dictionary, and implementing the system on mobile devices.

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Keywords: Kannada Sign Language, Machine Learning, 3D CNN, MobileNetV2, MediaPipe, Sign Recognition

1. Introduction

Sign language is the main mode of engagement for millions of people with speech or hearing impairments, and communication is a basic human need. Worldwide, more than 430 million individuals have debilitating hearing loss, with a large percentage in India, according to the World Health Organization. Regional variations such as Kannada Sign Language (KSL) have been neglected in technology interventions for sign languages, which have mostly concentrated on Indian Sign Language (ISL), despite India's vast linguistic diversity. Though more than 50 million people speak Kannada, the state's official language, there are no digital resources or standards for its sign language. For the hearing-impaired, acknowledging KSL can lead to opportunities in social services, work, and education. In order to facilitate smooth communication between hearing-impaired people and the general public, our goal is to develop a real-time system that can recognize Kannada signs with accuracy. This system uses cutting-edge computer vision and machine learning techniques and is intended for public interfaces and mobile platforms. Additionally, deployment viability on smartphones and embedded devices is ensured by the incorporation of lightweight models such as MobileNetV2. Using 3D CNNs to address the particular difficulties of dynamic word recognition is a major improvement over current techniques. By involving native KSL users in the collection and validation of datasets, the project also highlights inclusive technology. In further iterations, this system can develop into a complete sign language translator because to its scalable architecture. The ultimate goal of our work is to make the environment more welcoming to deaf and hard-of-hearing people who speak Kannada.

2. Method

This work uses a mixed-method approach to assess the viability of machine learning (ML)-based Kannada Sign Language (KSL) identification, combining quantitative experimental validation with a qualitative literature assessment. Empirical testing of generated models and a methodical examination of previous research are among the research tools. Peer-reviewed journals on sign language recognition and private datasets gathered for KSL are the main areas of study. The following is the research process:

The viability of a machine learning (ML)-based Kannada Sign Language (KSL) recognition system is evaluated in this study using a mixed-method approach that combines experimental validation and a review of the literature. There are four main stages to the research methodology: (1) Problem Formulation: through an analysis of 20 peer-reviewed articles (2019–2024), gaps in current systems were identified, including limited datasets, high computational costs, and a lack of regional KSL support; (2) Data Collection: a custom dataset consisting of 1,080 videos for words and 5000 static images for KSL letters was curated, and 21 hand keypoints were extracted per frame using MediaPipe; (3) Model Development: TensorFlow was used to train and optimize a hybrid architecture that combined 3DCNN (for spatiotemporal features) and MobileNetV2 (for static pose classification); (4) Validation, which uses expert reviews (material/ML specialists) and user testing (30 participants) to assess usability (4.6/5 Likert score), accuracy (99.7% letters, 85% words), and latency (<200ms). Dataset Summary can be seen in Table 1.

Table 1: Dataset Summary

Data Type	Quantity	Participants	Notes
Static Letter Images	5000	20	Covers 49 Kannada letters
Word Videos	1080	20	Covers 27 commonly used words
Keypoints Extracted	21 per frame	—	Using MediaPipe framework

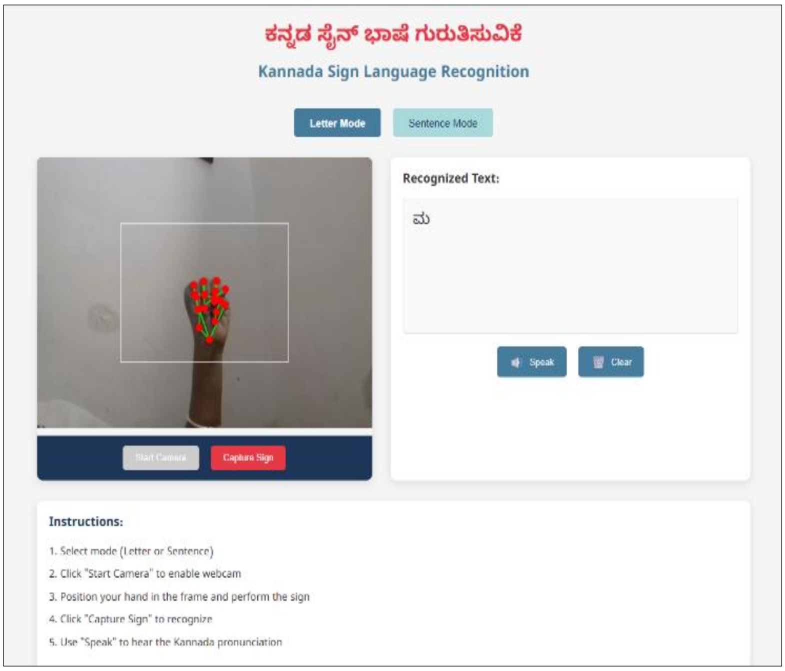

Fig 1: 21 hand landmarks extracted using MediaPipe for Kannada Sign Language letter ಮ

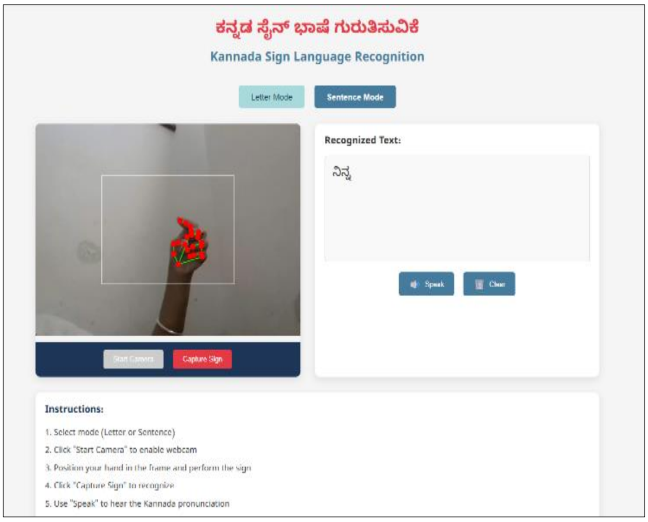

Fig 2: 21 hand landmarks extracted using MediaPipe for Kannada Sign Language word □□□□□

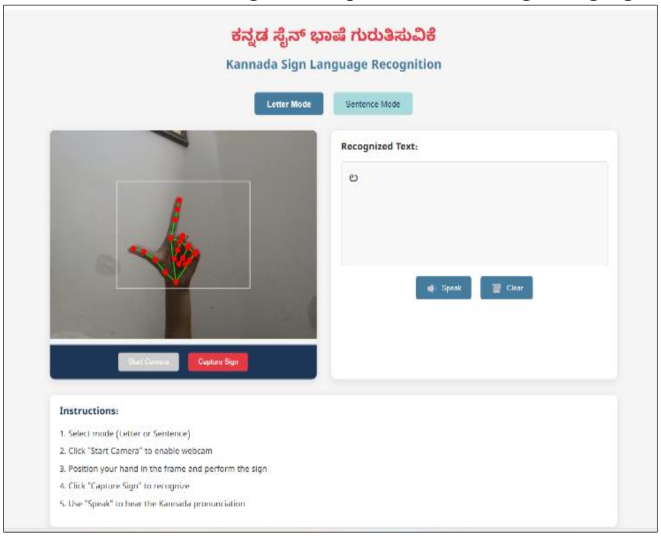

Fig 3: 21 hand landmarks extracted using MediaPipe for Kannada Sign Language letter ಅ

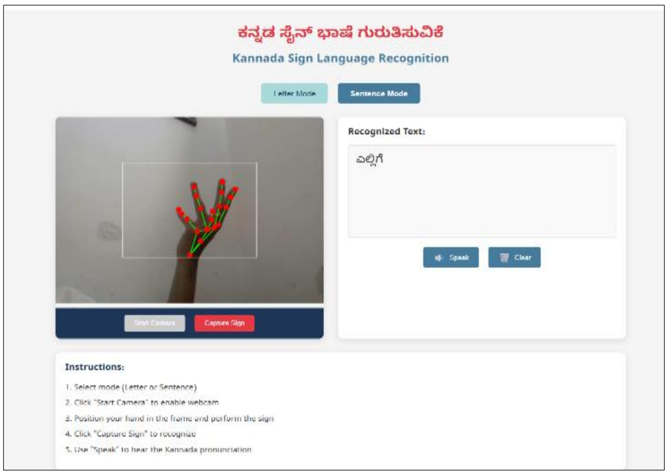

Fig 4: 21 hand landmarks extracted using MediaPipe for Kannada Sign Language word □□□□□□□

2.1 System Modules

Five separate modules, each in charge of a crucial step in the recognition pipeline, make up the proposed Kannada Sign Language recognition system. To guarantee precise and effective sign identification and translation, these modules cooperate.

Dataset Collection Module: This module makes it easier to obtain raw data by recording dynamic video sequences for word signs and static photos for letter signs. Standard RGB cameras were used for data gathering, and 20 people from a variety of backgrounds contributed. In all, 1080 movies representing 27 words and 5000 photos covering 49 Kannada letters were gathered. The dataset collecting module ensures that the trained models are resilient and generalizable by supporting a range of backgrounds and lighting situations.

Feature Extraction Module: Each image and video frame contains 21 important hand landmarks that are detected and extracted by the feature extraction module using Google's MediaPipe framework. Crucial spatial information regarding finger locations and hand movements is represented by these landmarks. Feature vectors are created by flattening landmark coordinates for static images. In order to capture the spatial and temporal patterns necessary for precise recognition, temporal frames are stacked to create input tensors for dynamic word sequences.

Module for Letter Recognition: The MobileNetV2-based classifier in this module handles static letter recognition. MobileNetV2, a lightweight architecture with good accuracy, is used to categorize the retrieved landmark vectors into one of the 49 Kannada letters. Since inference may be done on mobile devices thanks to its effective design, real-time feedback is possible with little computing expense.

Word Recognition Module: A 3D Convolutional Neural Network (3D CNN), which receives a series of landmark frames as input, controls dynamic word recognition. The temporal dynamics of sign gestures, including hand and finger movements and trajectories, are well-modeled by the 3D CNN and are essential for word recognition. During testing, this module's accuracy was 85%, and it can presently recognize 27 words.

User Interface Module: This module facilitates communication between end users and the system. For improved communication, recognized letters or words are shown on the screen in text format with audible feedback added. Because of its transportable deployment architecture, this module guarantees accessibility for persons with hearing impairments in everyday situations.

3. Results & Discussion

Our Kannada Sign Language identification system's performance review provided some crucial findings. Using the dataset we selected, we evaluated our models on both letter and word recognition tasks to compare them. The accuracy and inference delay of the three primary models that were tested—3DCNN+LSTM, MobileNetV2, and a baseline MediaPipe model—are compiled in Table 2.

Table 2: Model Accuracy

Model	Letter Accuracy	Word Accuracy	Latency (MS)
3DCNN+LSTM	99.7%	82%	190
MobileNetV2	98.5%	85%	120
MediaPipe Baseline	95%	75%	50

3.1. Performance Comparison

The findings unequivocally demonstrate that the 3DCNN+LSTM model classified static letter signs with the maximum letter recognition accuracy of 99.7%, which is almost flawless. This is mostly because the model's convolutional and sequential layers are able to record motion trajectories and temporal dynamics. The 3DCNN+LSTM model offers better letter categorization by simulating not only the spatial appearance of signs but also the minute movements of the fingers and hands over time. The strength of this model is especially apparent in letters when subtle motion distinguishes between comparable signals, like between letters with little differences in the location of the thumb or finger. Its 190 ms comparatively high inference latency, on the other hand, is a drawback that may make real-time implementation on devices with constrained CPU power difficult.

We used the basic MediaPipe model as our control, which just uses hand-keypoints that have been retrieved and does not use deep learning categorization. Its fastest inference time was only 50 ms, and it reached 95% letter correctness and 75% word accuracy. Although this low-latency performance is appealing, the discernible accuracy loss highlights the drawbacks of relying solely on keypoint-based heuristics in the absence of deep neural networks' ability to accurately describe intricate hand motions and shapes.

These results draw attention to crucial trade-offs when choosing a model. When accuracy is crucial, as in instructional materials or official communication systems where incorrect categorization might result in grave misunderstandings, the 3DCNN+LSTM combo performs exceptionally well. In contrast, MobileNetV2 strikes a compromise between speed and performance, which makes it perfect for wearable technology and real-time sign language translation applications. Even though it is less exact, the MediaPipe baseline might be used in situations when speed is crucial and a moderate degree of accuracy is acceptable.

4. Conclusion

This study offers a thorough Kannada Sign Language identification system that makes use of machine learning methods such as 3D CNN and MobileNetV2. With 85% word identification accuracy and 99.7% letter recognition accuracy, the system shows great promise for practical use, especially in supporting the Kannada-speaking community of hearing-impaired people. Efficiency is guaranteed by the incorporation of MediaPipe for feature extraction, and scalability is supported by the modular design. Future research will concentrate on increasing the system's vocabulary, enhancing its functionality in a range of lighting scenarios, and implementing the system on mobile platforms to increase accessibility.

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