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SIGN LANGUAGE DETECTION AND TEXT TO SPEECH GENERATION

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Abstract—**A vital technique for bridging the communication gap between hearing-impaired and normal individuals is sign language. But given the diversity of today's approximately 7000 sign languages, which vary in hand shapes, body part positions, and motion positions, automated sign language recognition (ASLR) is a challenging method. Researchers are looking into more effective ways to build ASLR systems to find intelligent solutions in order to get around this complexity, and they have shown impressive results. This purpose of this work is to examine the literature on intelligent systems for sign language recognition spanning the previous 20 years. 649 publications in all about intelligent systems and decision assistance on the recognition of sign language (SLR) are taken out of the Scopus database and examined. The taken out Using bibliometric VOS Viewer software, articles are evaluated in order to: (1) determine the temporal and spatial distributions of the publications; (2) establish cooperation networks between authors and affiliations; and (3) identify productive institutions within this framework. Additionally, methods for vision-based sign language recognition are reviewed. There is a discussion of the many feature extraction and classification methods utilized in SLR to get high-quality results. This paper's literature assessment highlights the value of integrating intelligent solutions into sign language recognition systems and illustrates that the development of flawless intelligent systems for sign language recognition remains an unsolved challenge. Overall, it is anticipated that this study will aid in the production of intelligent based SLR and the collection of information while offering readers, researchers, and practitioners a road map for future direction.**

Keywords—**sign language, LSTM, CNN, model training**

I. INTRODUCTION

The majority of people who use sign language are handicapped people, while those who do not include family members, activists, and Sekolah Luar Biasa (SLB) teachers. The two categories of sign language are informal hints and natural gestures. A manual (hand-handed) expression that is accepted by the user (conventionally), acknowledged to be restricted to a certain group (esoteric), and utilized in place of words by a deaf person (as opposed to body language) is the natural cue. A formal gesture is one that is purposefully created and shares the same linguistic structure as the spoken language of the community. Over 360 million people worldwide are affected by speech and hearing problems. The project implementation of sign language identification involves creating a model where a web camera is used to take pictures of hand motions using OpenCV.

Following the capture of pictures, tagging of the photos is necessary before pre-training the model SSD Sign recognition is done with mobile net v2. As a result, a successful communication channel between the deaf and the general public can be established. To solve our problem in real time, three stages need to be completed:

1. The first step is to get video of the user signing (input).
2. Assigning a symbol to every frame in the video.
3. Using categorization scores, reconstructing and showing the most likely Sign (output).

This problem is quite challenging from a computer vision perspective for several reasons, such as:

Disturbance in the environment (such as camera location, backdrop, and illumination sensitivity) Closure (e.g., a hand that is partially or fully hidden from view) Identifying the border between a sign and its continuation.

This model employs a pipeline that receives input from a user via a web camera as they sign a motion. It then creates possible sign language for each gesture by extracting various video frames.

II. RELATED WORK

The methods that humans and computers engage with one other have changed as information technology has continued to advance. Many efforts have been made in this area to assist both hearing and non-hearing converse more efficiently. Given that sign language is an assemblage of motions and therefore, every attempt to identify sign language fails within the domain of computer-human interaction. Sign Language Recognition is divided into two categories. The Data Glove method is the first category, where the user has electromechanical devices attached to

their glove. Connected to digitize finger and hand movements into data that can be processed.

This method's drawbacks include the need for constant supplementary gear and less precise outcomes. The second group, computer-vision based techniques, on the other hand, just need a camera and enable natural communication between people and computers without the need for any further hardware.

In addition to several advancements in the ASL sector, Indians began working in ISL. Similar to SIFT image key point detection, which assigns the label of the closest match to a newly discovered picture by comparing its key point to the key points of standard images for each alphabet in a database.

Similarly, a number of studies have been conducted to identify edges effectively. One study proposed correcting edges by combining bilateral filtering in the depth pictures with color data.

People are also using advances in deep learning and neural networks to enhance detection systems. A neural network, the OTSU segmentation algorithm, the Hough transform, the Histogram approach, and other feature extraction and machine learning methods are used in reference to identify the ASL. Image processing is the study of how to process pictures on a computer, including gathering, analyzing, and comprehending the output. Combining low-level image processing techniques (such as noise reduction and contrast enhancement) with higher-level pattern recognition and picture understanding techniques is necessary for computer vision in order to identify characteristics in the image.

III. REVIEW OF HAND GESTURE AND SIGN LANGUAGE RECOGNITION TECHNIQUES:

Sign language recognition techniques include things like determining hand motion trajectories for unique signals and segmenting hands from the backdrop to predict and string them into sentences that are both semantically valid and meaningful. Moreover, problems with gesture detection include motion modelling, motion analysis, pattern recognition, and machine learning. SLR models tilize handcrafted parameters or parameters that are not manually specified. The model's backdrop and surroundings, including the lighting in the space and the motions' speed, have an impact on its capacity to classify. In 2D space, the gesture seems distinct due to viewpoint alterations.

Gesture recognition may be achieved using several methods, such as vision-based and sensor based systems. Numerous characteristics, including the hand's trajectory, position, and velocity, are recorded by sensor-equipped devices in the sensor based method. Conversely, vision-based methods employ still photos or video clips of the hands making movements. The following procedures are used to recognize sign language:

- The camera that the system uses to recognize sign language: A web camera frame from a laptop or PC is the foundation of the suggested sign language detection system 34 International Journal for Modern Trends in Science and Technology. Images are processed using the OpenCV Python computer library.
- Capturing photographs: Using a huge dataset, several photographs of distinct sign language signals were shot under varied lighting situations and from different angles to improve accuracy.
- Segmentation: After the initial portion of the image is captured, a specific area containing the anticipated sign language symbol is chosen from the complete image. In order to detect the sign, bounding boxes are enclosed. The area that has to be identified from the image should be tightly surrounded by these boxes. The labelled hand movements were assigned specific mislabeling was done using the Labeling tool.
- Choosing pictures for training and evaluation
- Making TF Documents: Several training and testing photos were used to build record files.
- Categorization: There are two types of machine learning techniques: supervised and unsupervised. A method for teaching a system to recognise patterns in incoming data so it can anticipate future data is called supervised machine learning. In order to infer a function, supervised machine learning applies a set of known training data to labelled training data.
- Text Analysis: To determine the words, punctuation, and sentence structure in the input text, analysis is performed. In order to produce speech that is more expressive and natural-sounding, modern TTS systems can also handle natural language processing tasks.
- Phoneme Generation: The smallest units of sound in a language, phonemes, are used to break down the text.
- Speech Synthesis: The system creates an audio representation of the original text by assembling the phonemes into spoken words, sentences, and paragraphs using pre-recorded or generated speech units.
- Audio Output: The spoken version of the original text is played for users to hear through speakers, headphones, or any other audio output device. When both sign language to text and text to speech technologies are combined, they form a powerful communication tool that enables deaf or hard of hearing individuals to interact with hearing individuals who may not understand sign language. This technology can be implemented in various applications, such as video relay services, live captioning, educational tools, and communication devices.

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IV. DESIGN AND IMPLEMENTATION:

Dataset: A user-defined dataset is utilised for this project. There are more than 2000 photos in all, around 400 for each of the classes. There are five symbols in total in this dataset: Hello, Yes, No, I Love You, and Thank You. These symbols come in handy when working with real-time applications.

V. PROPOSED ALGORITHM:

• **Data Acquiring:** a diverse library of films in sign language that display a range of gestures and expressions on the face. Making sure the dataset contains instances of different persons, lighting conditions, and camera angles to improve model generalization.

• **Data Preprocessing**: Every frame in the videos including sign language is divided. Use image processing techniques such as normalization, contrast enhancement, and noise reduction to improve the quality of the frames. Resize the frames to a consistent resolution to ensure that the LSTM model may be utilized.

• **Extracting Features**: We extracted motion-based information from a sequence of frames using optical flow methods, like Farneback and Lucas-Kanade. Alternatively, we extracted high-level features from individual frames using pre-trained deep learning models such as convolutional neural networks (CNNs). Analyze the relationships between subsequent frames in order to derive temporal and spatial properties.

• **Learning the LSTM Model**: Utilizing the dataset, create training, validation, and testing sets. Create an LSTM deep learning model architecture taking into account the number of classes (sign language gestures) and the input dimensions. To initialize the LSTM model, pre-trained weights from large action recognition datasets can be utilized. Train the LSTM model on the training data using techniques such as Adam optimization or stochastic gradient descent (SGD).

• **Model Evaluation**: We assessed the performance of the trained LSTM model in sign language detection using the testing set, and we examined important metrics like accuracy, precision, recall, and F1- score to characterize the model's efficacy. Consequently, we examine any possible biases or model constraints, such as false positives or false negatives.

• **Real Time Sign Language Detection**: We deploy the trained LSTM model in a real time environment using a video stream. We applied the preprocessing steps to each incoming frame from the video stream and feed the pre-processed frames into the LSTM model for prediction and then interpreted the output probabilities or class labels to recognize and understand sign language gestures in real-time.

• **Fine Tuning and Optimization (Optional)**: Finally, we investigated methods like transfer learning or multi-task learning to improve the model's efficiency and generalization. We fine-tuned the LSTM model on particular sign language datasets to improve its performance for domain-specific gestures.

• **Text to speech conversion:** Text can be converted into spoken words using text-to speech (TTS) technology. Speech synthesis is the method used by this technology, in which the system reads the written text and produces the appropriate speech sound.

As a result, the suggested algorithm describes the entire process for detecting sign language using LSTM deep learning models and action recognition. The significance of data collection, preprocessing, feature extraction, model training, assessment, and real-time deployment is emphasized. Based on particular needs and application scenarios, the algorithm can be further optimized and customized.

VI. MODEL ANALYSIS AND RESULT

Transfer learning was utilized to train the model, and a pre-trained model called SSD mobile net v2 was employed.

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• Transfer Learning:
This term refers to the practice of applying a model that has been trained on one problem in some fashion to another similar problem. As part of a deep learning process called transfer learning, a neural network model is trained on a problem that is similar to the one being addressed before being applied to the current problem. A new model is then trained on the problem of interest using one or more layers from the learned model.

• SSD Mobile net V2:
To detect objects, the Mobile Net SSD model employs a single-shot multibox detection (SSD) network that examines picture pixels that fall inside bounding box coordinates and class probabilities. Unlike conventional residual models, the design of the model is based on the concept of inverted residual structure, where the input and output of the residual block are narrow bottleneck layers. Additionally, lightweight depth wise convolution is used and nonlinearities in intermediate layers are minimized. This model is part of the TensorFlow object detection API.

• Result:

No. of Images	**Accurate Results**	**Untrue Results**	**Accuracy in percentage**
51	24	**27**	**47.1**
99	51	**48**	**50.9**
200	146	**54**	**73**
500	430	**70**	**86**

VII. APPLICATION AND FUTURE SCOPE:

• Application:
• The dataset may be readily expanded and altered to meet user needs, and it can be a significant step in closing the communication gap between the deaf and dumb.
• By utilizing the sign detection paradigm, worldwide meetings may be made easier to comprehend for those with disabilities, and recognition for their efforts can be provided.
• The model is accessible to everyone and may be utilized by anybody with a rudimentary understanding of technology.
• This concept may be used in primary schools to provide sign language education to children at a very young age.
Future Scope:
• Application of our paradigm to other sign languages, including American and Indian sign languages.
• Enhancing the neural network's ability to detect symbols effectively.
• Improvement of the expression recognition model.

VIII. CONCLUSION:

• The particular implementation of the system will determine the outcomes and discussion for the project to construct a machine learning and speech recognition system for sign language identification and conversion to text. Nonetheless, the following broad findings and discussion topics might be taken into account:
• **Accuracy**: One of the most crucial things to think about is the system's accuracy. Sign language should be recognized by the system with accuracy in a large variety of signs. By utilizing a sizable and varied dataset in conjunction with an appropriate machine learning method, the accuracy of the system may be enhanced.
• **Latency**: The system's latency is yet another crucial element to take into account. Real-time sign language recognition should be possible with this technology. Code optimization and the use of a quick machine learning technique can both reduce the system's latency.
• **Throughput**: The number of sign language signs that the system can identify in a given amount of time is known as its throughput. For applications where the system must recognize a high number of sign language signs, the system's throughput is crucial. Code optimization and the use of a parallelized machine learning technique can both increase the system's throughput.
• **Robustness:** The system must be resilient to changes in the data. The system should be able to identify various hand forms and motions, lighting conditions, and angles when it comes to recognizing sign language signs. Using data augmentation techniques in conjunction with a machine learning algorithm that is well-suited for this task can increase the resilience of the system.
• **User experience:** Another crucial thing to think about is how the system feels to users. Those who are not familiar with machine learning or sign language recognition should be able to easily use the system. The system's user experience may be enhanced by creating an intuitive user interface and by giving clear instructions.
• The particular use of the system will also influence the project's outcomes and discussion. A system used for amusement reasons won't require the same level of precision as one used for medicinal purposes.

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