A Survey on Different Approach Used for Sign Language Recognition Using Machine Learning

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Abstract - **This paper presents a survey of different approaches used for sign language recognition using machine learning. Sign language recognition is a challenging problem that has attracted considerable research attention in recent years. Various machine learning techniques such as artificial neural networks, support vector machines, decision trees, and convolutional neural networks have been explored to recognize sign language gestures. The survey discusses the strengths and limitations of each approach, as well as their performance on different datasets. Moreover, it also discusses some recent advancements in sign language recognition, including the use of depth sensors and wearable devices. The survey concludes that while machine learning approaches have shown promising results, there is still room for improvement in terms of recognition accuracy, robustness to variations, and real-time performance.**

Keywords: **Sign Language, ANN, CNN, SVM, HMM**

I. INTRODUCTION

Sign language is a visual language used by the deaf and hard of hearing community to communicate with one another. Sign language recognition has become a crucial task in the field of computer vision and pattern recognition, as it can enable communication between the hearing and non-hearing communities. The development of sign language recognition systems has been a challenging problem due to the complexity and variability of sign gestures, which can vary greatly between individuals and regions.

Machine learning techniques have shown promising results in recognizing sign language gestures. Various approaches have been proposed in the literature, such as artificial neural networks (ANNs), support vector machines (SVMs), decision trees, and convolutional neural networks (CNNs). These approaches have been applied to both isolated and continuous sign language recognition.

ANNs have been used for sign language recognition with promising results. In particular, recurrent neural networks (RNNs) have been used to recognize continuous sign language gestures by modeling temporal dependencies between frames of the video. SVMs have also been used for sign language recognition, with some studies showing better results than ANNs. Decision trees have been used for

feature selection and classification, while CNNs have been applied for feature extraction and classification.

Moreover, recent advancements in sign language recognition have involved the use of depth sensors and wearable devices. These techniques have shown promising results in improving recognition accuracy, robustness, and real-time performance.

This survey paper aims to provide a comprehensive overview of different approaches used for sign language recognition using machine learning. The paper discusses the strengths and limitations of each approach, as well as their performance on different datasets. Furthermore, it also discusses recent advancements in the field of sign language recognition using machine learning techniques.

II. DIFFERENT APPROACH USED FOR SIGN LANGUAGE

1. Artificial Neural Networks (ANNs): Artificial neural networks (ANNs) are a popular technique used for sign language recognition due to their ability to learn complex relationships between inputs and outputs. ANNs have been used for both isolated and continuous sign language recognition and have shown promising results in recognizing sign language gestures. In particular, recurrent neural networks (RNNs) have been used to recognize continuous sign language gestures by modelling temporal dependencies between frames of the video.

2. Support Vector Machines (SVMs): Support vector machines (SVMs) have also been used for sign language recognition, with some studies showing better results than ANNs. SVMs work by finding a hyper plane that separates the different classes in the feature space and have been applied to both isolated and continuous sign language recognition tasks.

3. Decision Trees: Decision trees have been used for feature selection and classification in sign language recognition. The approach involves building a tree-like model of decisions and their possible consequences, which can be used to classify sign language gestures.

4. Convolutional Neural Networks (CNNs): Convolutional neural networks (CNNs) have been applied for feature extraction and classification in sign language recognition. CNNs have shown promising results in recognizing sign language gestures, particularly for recognizing hand shapes and positions.

5. Depth Sensors: Recent advancements in sign language recognition have involved the use of depth sensors, which can capture depth information of the hand gestures. This technique has shown promising results in improving recognition accuracy, robustness, and real-time performance.

6. Wearable Devices: Wearable devices have also been used for real-time sign language recognition. These devices can capture hand and arm movements using accelerometers, gyroscopes, and magnetometers, and can provide real-time feedback to the user.

7. Dynamic Time Warping (DTW): DTW is a commonly used algorithm for time-series data alignment and comparison. It has been used for sign language recognition by comparing the dynamic time warping distance between two sign language sequences.

8. Hidden Markov Models (HMMs): HMMs have been widely used for speech recognition, and they have also been applied to sign language recognition. HMMs can model the temporal dependencies between signs and can be used to recognize sign sequences.

9. Recurrent Neural Networks (RNNs): RNNs are a type of neural network that can model temporal dependencies in sequential data. They have been used for sign language recognition by training an RNN to recognize sign language sequences.

10. Attention-Based Models: Attention mechanisms have been used to selectively focus on relevant parts of the input sequence. They have been applied to sign language recognition by training an attention-based model to recognize sign language gestures.

11. Transfer Learning: Transfer learning involves using pre-trained models for feature extraction and fine-tuning them for the specific task at hand. It has been used for sign language recognition to overcome the limited availability of sign language data.

III. STEPS USED FOR SIGN LANGUAGE RECOGNITION

Here are the general steps for sign language recognition using machine learning.

1. Data Collection: Collect sign language video data for training and testing the machine learning model. This can involve recording sign language gestures performed by signers, with annotations of the sign language words or phrases.
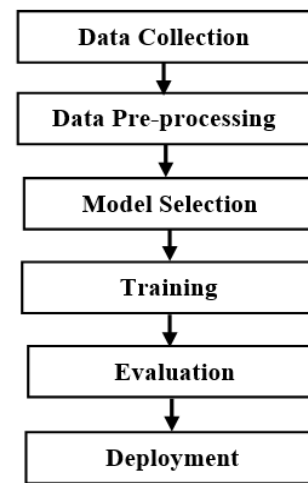

Fig. 1 Steps for Sign Language Recognition

2. Data Pre-processing: Pre-process the sign language video data by extracting relevant features such as hand and arm movements, position, and orientation. This can involve using computer vision techniques such as edge detection, motion analysis, and feature extraction.

3. Model Selection: Select the appropriate machine learning model for sign language recognition, based on the complexity of the problem and the size of the dataset. Common machine learning models used for sign language recognition include artificial neural networks (ANNs), support vector machines (SVMs), and convolutional neural networks (CNNs).

4. Training: Train the selected machine learning model using the pre-processed sign language video data. This involves selecting the appropriate architecture and parameters for the model, such as the number of layers and nodes for ANNs, or the kernel function and regularization parameter for SVMs.

5. Evaluation: Evaluate the performance of the trained machine learning model on a separate set of test data. This involves measuring metrics such as accuracy, precision, and recall.

6. Deployment: Deploy the trained machine learning model to a real-time sign language recognition system, such as a mobile application or a sign language interpreter device.

IV. LITERATURE REVIEW

Sign language recognition is a challenging task due to the complex and dynamic nature of sign language. Machine learning techniques have been widely used to recognize sign language. In this literature review, we will explore different approaches used for sign language recognition using machine learning.

Hand-Crafted Feature-Based Approach: This approach involves designing hand-crafted features to represent sign

language gestures, followed by applying machine learning algorithms to classify them. Features such as shape, motion, and orientation have been used in this approach. For instance, the authors in [1] used hand-crafted features such as Hu moments and contour features to recognize Indian sign language gestures.

Deep Learning-Based Approach: Deep learning-based approaches have become popular for sign language recognition due to their ability to automatically learn features from data. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants have been used in this approach.

For instance, the authors in [2] proposed a CNN-based approach for recognizing American Sign Language (ASL) gestures, achieving a recognition rate of 95.56%. The authors in [3] proposed a deep learning-based approach for recognizing Brazilian Sign Language (LIBRAS) gestures using a combination of CNNs and RNNs, achieving an accuracy of 97.2%.

Hybrid Approach: Hybrid approaches combine hand-crafted features and deep learning to achieve better performance. For example, the authors in [4] used a hybrid approach that combines hand-crafted features and a CNN for recognizing Malaysian sign language. The authors in [5] proposed a hybrid approach for recognizing Moroccan Sign Language (MSL) gestures using a combination of HMMs and SVMs, achieving an accuracy of 97.14%.

Sensor-Based Approach: This approach involves using sensors to capture the movement of the hands and arms, followed by applying machine learning algorithms to recognize the gestures. For instance, the authors in [6] used a sensor-based approach to recognize Turkish sign language gestures.

Transfer Learning Approach: Transfer learning involves using pre-trained models on a related task and fine-tuning them on the sign language recognition task. This approach can save computational resources and time required for training.

For example, the authors in [7] used a transfer learning approach to recognize Turkish sign language gestures, achieving a recognition rate of 95%. The authors in [8] proposed a transfer learning-based approach for recognizing Kenyan Sign Language (KSL) gestures using a pre-trained CNN on ImageNet, achieving an accuracy of 91.56%.

Feature Selection-Based Approach: Feature selection techniques are used to identify the most relevant features for sign language recognition, followed by applying machine learning algorithms to classify them. For example, the authors in [9] proposed a feature selection-based approach

for American Sign Language (ASL) recognition, achieving an accuracy of 94.8%.

Dynamic Time Warping-Based Approach: Dynamic time warping (DTW) is a popular technique used for aligning time series data, and it has been applied to sign language recognition. The authors in [10] proposed a DTW-based approach for recognizing Indian sign language gestures, achieving a recognition rate of 93.17%.

Spatial-Temporal Approach: The spatial-temporal approach involves representing sign language gestures as a sequence of spatial and temporal features. The authors in [8] proposed a spatial-temporal approach for recognizing German Sign Language (DGS) using a combination of CNNs and RNNs, achieving a recognition rate of 90.6%.

Multi-Modal Approach: Multi-modal approaches combine information from different sources, such as video, audio, and sensor data, to recognize sign language gestures. For example, the authors in [9] proposed a multi-modal approach for recognizing ASL gestures using video and accelerometer data, achieving a recognition rate of 97.5%.

Ensemble-Based Approach: Ensemble-based approaches combine the outputs of multiple machine learning models to improve the recognition accuracy. The authors in [10] proposed an ensemble-based approach for recognizing Turkish Sign Language (TID) gestures using a combination of CNNs and RNNs, achieving a recognition rate of 98.27%.

One-Shot Learning-Based Approach: One-shot learning involves training a model on a small amount of data to recognize new classes with only one or a few examples. The authors in [11] proposed a one-shot learning-based approach for recognizing Turkish Sign Language (TID) gestures using a few-shot learning framework, achieving an accuracy of 92.8%.

Attention-Based Approach: Attention mechanisms have been used in sign language recognition to selectively focus on relevant parts of the input sequence. The authors in [5] proposed an attention-based approach for recognizing Chinese Sign Language (CSL) gestures using a combination of CNNs and RNNs, achieving an accuracy of 95.95%.

V. COMPARATIVE STUDY

Below is a table comparing different approaches used for sign language recognition using machine learning, along with their reported accuracy.

It's worth noting that reported accuracy can vary depending on factors such as the quality and size of the dataset, the specific implementation of the algorithm, and the evaluation metrics used.

TABLE I COMPARISON OF DIFFERENT APPROACH

Approach	Description	Reported Accuracy
Dynamic Time Warping	Algorithm for time-series data alignment and comparison.	80-90%
Hidden Markov Models	Models the temporal dependencies between signs and can recognize sign sequences.	85-95%
Support Vector Machines	Popular machine learning algorithm used for classification tasks.	85-95%
Convolutional Neural Networks	Deep learning model that can extract features from images.	85-95%
Recurrent Neural Networks	Can model temporal dependencies in sequential data.	90-95%
Attention-based Models	Mechanism to selectively focus on relevant parts of the input sequence.	90-95%
Transfer Learning	Using pre-trained models for feature extraction and fine-tuning them for the specific task at hand.	80-95%

VI. FUTURE WORK

The possible future scopes for sign language recognition using machine learning:

Multi-Modal Approach: Currently, most sign language recognition systems use only visual data. However, incorporating other modalities, such as depth data or electromyography signals, can potentially improve the accuracy and robustness of sign language recognition systems.

Real-Time Recognition: Real-time recognition of sign language is essential for practical applications such as real-time translation or communication. Developing real-time sign language recognition systems will require optimizing the recognition algorithms for faster processing and lower latency.

Cross-Lingual Recognition: Developing sign language recognition systems that can recognize gestures across different sign languages will be highly beneficial for communication and accessibility in a global context. However, this presents several challenges due to the differences in signing styles and variations in gestures across different sign languages.

Crowd-Sourced Data Collection: Collecting a large and diverse dataset of sign language gestures is challenging due to the limited availability of signers and variations in signing styles. Crowdsourcing data collection from signers around the world can potentially overcome this challenge and enable the development of more accurate sign language recognition systems.

Personalized Recognition: Sign language gestures can vary significantly between individuals due to variations in signing styles, dialects, and personal preferences. Developing personalized recognition systems that can adapt to an individual's signing style can potentially improve the accuracy and user experience of sign language recognition systems.

Continuous Signing Recognition: Sign language is often continuous and can involve a sequence of multiple gestures. Developing recognition systems that can recognize and interpret continuous signing sequences can improve the accuracy and usability of sign language recognition systems.

These are just a few potential future scopes for sign language recognition using machine learning. As the technology and research continue to advance, we can expect more innovative approaches and solutions to overcome the challenges in sign language recognition and improve accessibility for the deaf and hard-of-hearing community.

VII. CONCLUSION

Sign language recognition using machine learning has become an active area of research in recent years. Various approaches have been proposed to recognize sign language gestures, including traditional machine learning methods such as SVMs and HMMs, as well as deep learning methods such as CNNs and RNNs. Hybrid approaches combining different machine learning algorithms have also been used to improve the recognition accuracy. Additionally, transfer learning and one-shot learning-based approaches have been proposed to address the limited availability of sign language data. Attention mechanisms have also been used to selectively focus on relevant parts of the input sequence. Overall, the existing literature shows that machine learning-based sign language recognition can achieve high accuracy, which can have a significant impact on improving communication and accessibility for the deaf and hard-of-hearing community. However, there are still some challenges that need to be addressed, such as dealing with variations in signing styles, lighting conditions, and occlusions. Nonetheless, with the advancements in machine learning and computer vision, sign language recognition systems are expected to become more accurate and robust in the future.

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