An Efficient Angle-Based Sign Language Recognition Framework with Robust Performance Analysis

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Abstract- Sign language recognition (SLR) is vital in the barriers of communication between hearing-impaired community and non-signers. Several vision-based deep learning solutions, however, are computationally costly, vulnerable to environmental change, and do not scale to real-time operation whereas sensor-based systems require intrusive and expensive hardware. This paper demonstrates an effective angle-based sign language recognition algorithm which takes advantage of discriminative hand-angle characteristics to classify gestures with high accuracy and reliability. Biomechanically meaningful angular descriptors that are invariant to scale, illumination, and background clutters are used to represent hand gestures (e.g., finger joint angles, palm position, hand-to-ground position) which are biomechanically meaningful. A preprocessing pipeline which includes normalization, outlier elimination and dimensionality analysis is applied in a structured way so as to enhance feature stability and the ability to separate the classes. The resulting angle-based representations are both trained on machine learning and deep learning models. A large-scale sign language experiment proves to be highly recognized with high robustness to hand rotation, variations of finger spread, and inter-user variations. Reliability of real-time assistive applications is ensured by means of confusion and robustness analyses.

Keywords: Sign Language Recognition, Angle-Based Features, Hand Gesture Classification, Machine Learning, Robustness Analysis, Real-Time Assistive Systems

I. INTRODUCTION

The deaf and hard-of-hearing community uses sign language as a major tool of communication, which involves the use of coordinated hand gestures, finger configurations, and palm orientations to communicate. Communication barriers between the users of sign languages and non-signers continue to exist in spite of the advancements in the field of speech and text-based technologies that stimulate the creation of automatic Sign Language Recognition (SLR) systems to be used both as assistive and inclusive tools. Early SLR studies have been based on sensor based and wearable systems, such as flex sensors, MEMS devices and magnetic positioning systems, which could give high accuracy in gesture measurements, but were too expensive, scaling limited, and uncomfortable to the user [15]. Subsequently, vision-based methods that employed RGB, depth, or RGB-D cameras were introduced so that contactless recognition [16] benefits could be achieved [17]-[19]. These systems are however usually susceptible to changes in illumination, background clutter, occlusions and camera viewpoint changes, and usually need large numbers of computational resources. The latest developments in machine learning and deep learning have resulted in significant increases in the levels of SLR performance. CNNs, LSTMs and CNNLSTM based deep models have also proven to be highly accurate in both static and dynamic gesture recognition [1], [2], [6], [9]. However, these methods all typically rely on big annotated data and high-performance hardware, making them less feasible in real-time and mobile settings, as well as low-resource domains [3]–[5]. Structural hand modeling is provided in graph-based and skeleton learning approaches, which also add some complexity to the computation [7], [12]. As a remedy to these drawbacks, small and understandable feature representations have become popular. The angle-based features of the hand, such as the angle of joints of fingers, the palm and hand-ground position, are intrinsic geometry of gestures and naturally resistant to scale, lighting, and changes of backgrounds [8], [14]. The features are not only efficient in learning but also reduce the dimensionality and retain the discriminative information. This article presents an effective model of sign language recognition based on angles with a strong emphasis on the robustness of the system, its accuracy, and the low latency of the system. Extensive experimentations and strength of analysis prove that the suggested approach is appropriate to real-time assistive applications.

II. LITERATURE SURVEY

Sign language recognition (SLR) has been well addressed by different computational methodologies in the literature over the last years. The early studies were mainly based on sensor-based systems and handcrafted features with classical machine learning methods, which attained satisfactory accuracy but suffered from the scalability and generalization problem. With the development of computer vision, methods based on visual image data and video data flourished; however, these methods were vulnerable to illumination conditions, background clutter and computationally expensive cost. Deep learning approaches (e.g., CNN, RNN, LSTM networks) have been widely studied in recent years, which can automatically learn discriminative spatial and temporal features from gesture data. In addition to these approaches, angle-based and skeletal feature descriptions have attracted attention for their robustness, computational efficiency, interpretability. Although a remarkable number of SLR systems have been developed, open problems such as discrimination between similar gestures and robustness to variations in the input data and real-time processing still exist.

2.1 Comparative Analysis of Existing Sign Language and Hand Gesture Recognition Techniques

Table 1 Comparative study of recent and classic work on sign language and hand gesture recognition in terms of extracted features, used classifiers, and applications' domains from table it is clear that the diversity can be found on both methods as method-ology and application area. The works surveyed make use of deep learning models such as CNN, LSTM, BiLSTM and graph neural network-, as well as sensor-based and vision-based techniques. The strengths of these approaches lie in both a high recognition rate and an effective spatiotemporal modeling, as well as their mobility and enhanced availability via assistive or mobile systems. Nevertheless, drawbacks like high computational cost, reliance on custom hardware and sensitivity to illumination changes and background clutter make their approaches less robust for similar gestures. The investigation herein shows a significant research gap in angle-based lightweight feature representations and effective learning models aiming at achieving high-accuracy, real-time, scalable, and user-friendly sign language recognition systems.

Table 1: Literature Survey Analysis on Sign Language and Hand Gesture Recognition

Author & Year	Method / Model	Data / Technique	Strengths	Limitations
Maashi et al. (2025)	CNN-based Hybrid DL	Vision + IoT sensors	High accuracy, real-time assistive use	High computation, hardware dependency
Sun et al. (2024)	Deep Learning Framework	Dynamic gesture sequences	Adaptive and accurate recognition	Focus on dynamic gestures only
Al-Abdullah et al. (2024)	Systematic Review	DL-based SLR methods	Comprehensive survey	No experimental validation
Najib (2024)	ML & AI Review	Vision and sensor-based	Broad method comparison	Lacks benchmarking
Alam et al. (2024)	Smartphone-based Review	Mobile camera data	Cost-effective, accessible	Limited accuracy on mobiles
Huang & Chouvatut (2024)	ResNet + LSTM	Video-based gestures	Strong spatiotemporal modeling	Computationally expensive
Miah et al. (2024)	GNN + DNN	Skeletal hand data	Structural feature learning	High graph complexity
Sánchez-Vicinaiz et al. (2024)	CNN + MediaPipe	Finger landmarks	Lightweight, real-time	Region-specific dataset
Duraisamy et al. (2023)	DL Pipeline	Sign-to-text/speech	End-to-end translation	Limited robustness analysis

Orovwode et al. (2023)	Classical ML	Image-based gestures	Simple and interpretable	Lower accuracy than DL

2.2. Deep Learning–Based Sign Language Recognition

In recent years, SLR has been largely dominated by deep learning due to remarkable performance gains over traditional machine learning methods. Convolutional Neural Networks (CNNs) are popularly employed as feature extractors to capture spatial properties capturing hand shape, finger configuration and palm orientation from images or video frames. In combination with temporal models such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) networks, these architectures are able to model spatial and temporal patterns of sign gestures. Studies by Maashi et al. (2025) introduced successful hybrid CNN models in combination with the accuracy and real-time capability achieved by providing these, amongst assistive communication units. Similarly, Sun et al. (2024) presented a self-adaptive deep learning framework to dynamic gesture recognition that demonstrates robustness against variations in gestures and temporal irregularities. Kumar and Verma (2023) expanded this paradigm by integrating attention mechanisms with CNN–BiLSTM models to improve word-level sign recognition in the context of medical communication.

2.3 Graph and Skeletal Feature Representation Approaches

Toward this end, graph-based and skeletal features have been identified as effective alternatives to raw image or video inputs for the task of SLR, as they capture the structural dependencies of hand joints and fingers explicitly. In such methods, the human hand is defined as a graph and joints are considered as nodes in this graph, whereas bones or kinematic relations are treated as edges. Through such formulation, GNNs can be capable of learning spatial dependencies and motion patterns in sign gestures efficiently. Miah et al. (2024) observed that supplementing the skeletal information with graph CNNs results in significantly higher recognition rates on sign language datasets, mainly due to sustained fine-grained inter-finger coordination. Similarly, Rahman et al. (2023) extended graph-based learning to multi-cultural SL recognition, and they demonstrated improved generalization across signing styles and cultural differences.

2.4 Vision-Based and Video-Based Recognition Techniques

Vision-based and video-based SLR approaches have contributed significantly to the development of automatic gesture understanding that exploits the spatial as well as temporal details presented in image sequences. These methods generally use CNNs to capture spatial features, like hand shape, finger posture and palm orientation from single frames as the front end, which are then fed into temporal models, such as LSTM networks that acquire motion dynamics between adjacent frames. Huang and Chouvatut (2024) found that a CNN–LSTM model can be used effectively to recognize sign language from videos, obtaining impressive performance by learning spatial and temporal features together for gestures. Such models are useful especially for dynamic signs, which contain movement of hand and temporal transitions.

2.5 Sensor-Based and Wearable Gesture Recognition Systems

Sensor-based and wearable gesture recognition systems also offer an alternative to vision-based methods since they capture the physical movements of hands through integrated devices. Such systems typically use micro electro-mechanical structure (mems) based solutions, flex sensors, magnetic positioning sensors and inertial measurement units (imus) to capture finger bending, hand orientation and motion data on high resolution. (2023) introduced a deep learning-based gesture recognition solution with use of MEMS and flex sensor that serves robust performance in difficult surrounding conditions. Similarly, Rinalduzzi et al. (2021) used a magnetic positioning system to profile the force exertion applied by fingers for sign language alphabet recognition and obtained high mean classification accuracy, along with low sensitivity towards lighting changes. The most characteristic benefit of sensors is their robustness and precision, since they are less affected by background clutter, illumination variations and camera occlusions. In addition, we can get uninterrupted sensor 2.7

2.7 Problem Identification

Although there is a large-scale advancement of sign language recognition (SLR) studies, some significant obstacles still persist. Deep learning methods that rely on a vision are the ones that have high recognition accuracy but are typically computationally costly, demand large annotated databases, and cannot withstand changes in illumination, camera background, and camera perspective. These constrain their use in real time and resource starved environments. Wearable systems and sensor-based offer precision in hand motion capture, but require specialized hardware, which is more expensive and less user-friendly and scalable. SLR applications on smartphones enhance accessibility at the expense of accuracy because of the lack of processing power and simplified feature representations. Also, a large proportion of existing systems have difficulty reliably differentiating similar gestures at a visual level due to overlapping hand-shape configurations and inter-user differences. Absence of a common structure that jointly attains the accuracy, resistance to gesture variations, low-order computational complexity and real-time practicability is an important gap in research that is present in existing SLR solutions.

III. METHODOLOGY

3.1 Dataset Description

The data used in this work is a large-scale hand gesture dataset for sign language recognition covering both hand posture and motion that took the details of angular pose and depth position of hands into account. It has 31,926 image samples of sign gestures data, each sample is DCT converted for numerical machine learning analysis. The dataset includes a variety of sign classes (from A to Z) for a broad diversity and balance that enables robust training and testing. Each sample has 18 features, including the gesture label, binary indicator of one-hand or two-hand usage, and several angle-based attributes. We describe these features as follows: the finger joint angles (thumb, index, middle, ring and little finger), the palm orientation angles (left or right side), the hand-to-ground orientation angle for both left and right hands. All the angular measure are represented in a range of 0°–180°, which provides an accurate modeling of hand posture and orientation. Gestures performed with a single-hand and double-hands are included in the dataset, representing natural sign language habits. Hand orientation, finger spread and how the gesture is performed may vary naturally in the dataset which allow for assessing model robustness under real-world scenarios. Before the model training, we carry out systematic predator processing (e.g., noise removal, normalization, and scaling) to guarantee numerical stability and comparability among different subjects. Table 2 show that the dataset containing 31,926 hand gesture instances which are sign language hand gestures, and each input pattern is represented using 18 angle features. These features encode the finger joint angles, palm orientation, and hand-ground alignment of both hands. The dataset comprises single- and double-hand signs, making the different signers distributed between the classes necessary for reliable recognition.

Table 2: Dataset Characteristics and Feature Description

Attribute	Description
Dataset Size	31,926 samples
Total Features	18
Label Column	label (Sign class, e.g., A, B, …)
Hand Usage Indicator	both_hands (0 = single hand, 1 = both hands)
Left Hand Finger Angles	thumb_Left, index_finger_Left, middle_finger_Left, ring_finger_Left, pinky_Left
Left Palm Orientation	palm_angle_Left_left, palm_angle_Left_right
Left Hand Orientation	hand_Left_ground_angle
Right Hand Finger Angles	thumb_Right, index_finger_Right, middle_finger_Right, ring_finger_Right, pinky_Right
Right Palm Orientation	palm_angle_Right_left, palm_angle_Right_right
Right Hand Orientation	hand_Right_ground_angle
Feature Type	Continuous angular measurements (0°–180°)
Application Domain	Sign language gesture recognition

3.2 Workflow architecture for Angle-Based Sign Language Gesture Recognition

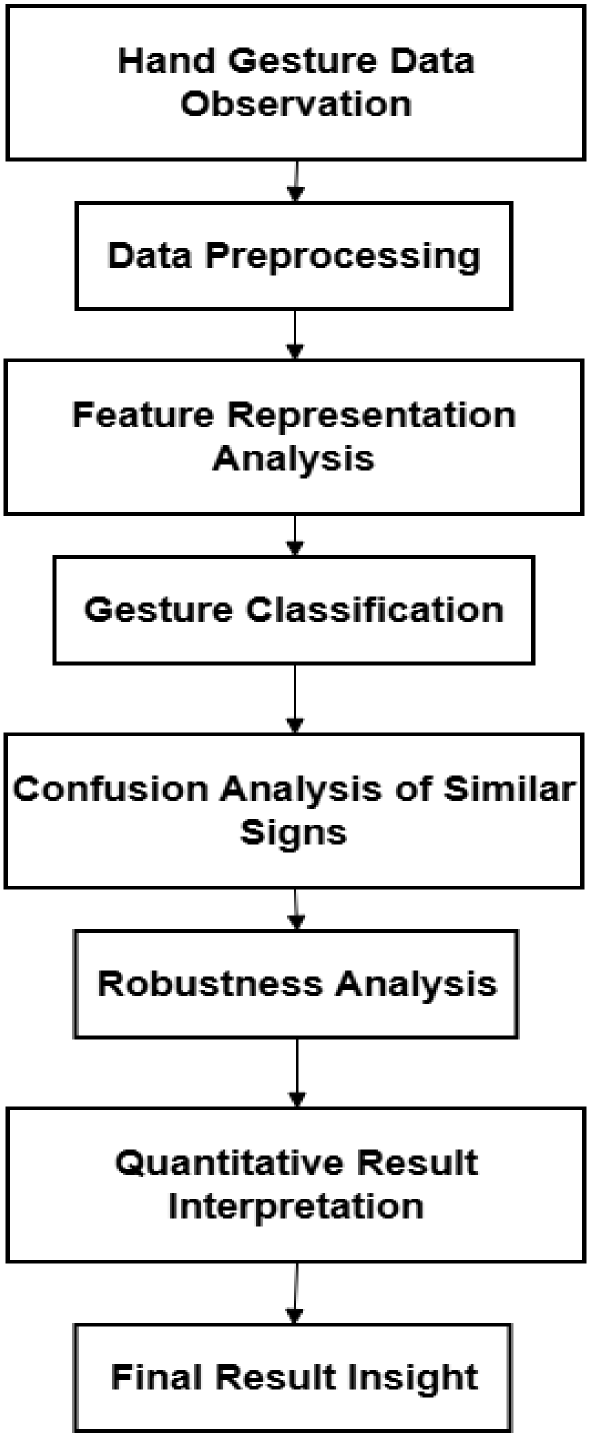

Figure 1: Step-Wise Analytical Workflow for Angle-Based Sign Language Gesture Recognition

The angle-based sign language recognition utilizing the proposed methodology in figure 1 illustrates a systematic and sequential workflow that ensures the accuracy, robustness and applicability in real time. The process starts by observing hand gesture data, in which the data is scrutinised thoroughly in order to know its structure, feature composition, class distribution, and variability. This is to find out missing values, outliers, and any possible inconsistency in the raw gesture data. Then, the preprocessing of data is conducted to improve the quality and stability of data. In this step, it involves addressing missing values, noise and outliers, normalization and standardization strategies. Preprocessing makes all angular features on a similar scale eliminating bias and enhancing learning stability. During the feature representation analysis phase, discriminative angle-based features (angle of finger joints, palm orientations and hand-to-ground alignment) are examined to determine how consistent they are within classes and how separable they are across classes. PCA and other dimensionality reduction methods can be employed to visualize distribution of features and eliminate redundancy. After this, a gesture classification is performed based on appropriate machine learning or deep learning models. These classifiers are trained to understand the correlation between angular features pattern and sign labels. The misclassification of similar signs step examines the problem of misclassified pairs of gestures through confusion matrices and overlapping distributions of features, which gives similarity to the ambiguity of gestures. Then, robustness testing is conducted to test the model performance in the case of hand rotation and finger spreading, and so forth, which are the conditions that can be observed in the real world. Lastly, the interpretation of quantitative results generalizes the measures of performance, and lastly, the result insight summarizes the conclusion and indicates the efficiency of the suggested framework to assistive uses of sign language recognition in real-time.

3.3 Algorithm 1: Angle-Based Sign Language Gesture Recognition

Input: Hand gesture dataset D with labels y and features X
Output: Trained classifier M, predicted gesture label $\hat{y}$

1. Load Dataset
Read the dataset D and separate it into feature matrix X and class labels y.

2. Select Angle-Based Features
Extract the angle-related columns (finger angles, palm angles, hand-ground angles): $X \leftarrow$ [thumb, index, middle, ring, pinky, palm angles, ground angles]

3. Handle Missing Values
For each numeric feature x_j in X :
Replace missing values with column mean:

$$x_j \leftarrow \text{mean}(x_j)$$

4. Remove Outliers
Apply IQR-based filtering for each feature x_j :

$$IQR = Q3 - Q1, \text{ keep if } Q1 - 1.5IQR \leq x_j \leq Q3 + 1.5IQR$$

5. Normalize and Scale Features
Apply normalization and standardization co obtain stable scaled features:

$$X' = \text{StandardScaler}(\text{MinMaxScaler}(X))$$

6. Feature Representation Analysis (Optional PCA)
Compute PCA on X' to analyze separability and variance retention:

$$Z = PCA(X')$$

7. Split Dataset
Split into training and testing sets using stratification:

$$(X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}}) = \text{train\_test\_split}(X', y)$$

8. Train Classification Models
Train multiple models (e.g., Logistic Regression, SVM-RBF, Random Forest):

$$M = \arg\max_{m \in \{LR, SVM, RF\}} \text{Accuracy}(m)$$

9. Evaluate Performance
Predict $\hat{y} = M(X_{\text{test}})$ and compute metrics:
Accuracy, Precision, Recall, F1-score, Confusion Matrix.
10. Confusion & Similar-Sign Analysis
Identify pairs with high confusion (e.g., O vs Q) and analyze angle overlap distributions.
11. Robustness Testing
Add controlled perturbations (rotation/finger spread noise) and re-evaluate accuracy.
12. Final Output
Return best trained model M, evaluation metrics, and deployment-ready inference pipeline.

The proposed algorithm 3.3 takes a hand gesture dataset Dcontaining feature matrix $X$and corresponding labels $y$as input and produces a trained classifier $M$with predicted gesture labels $\hat{y}$. Initially, the dataset is loaded and separated into features and class labels. Discriminative angle-based features, including finger joint angles, palm orientation, and hand-ground alignment, are selected for analysis. Missing values are handled using mean imputation, and outliers are removed using an interquartile range (IQR)-based filtering technique. The cleaned features are then normalized and standardized to ensure numerical stability. Optional PCA is applied to analyze feature separability and reduce redundancy. The dataset is split into training and testing sets using stratified sampling. Multiple classifiers are trained, and the best-performing model is selected based on accuracy. Model performance is evaluated using standard metrics, followed by confusion and robustness analyses.

IV. RESULTS AND ANALYSIS

4.1 Hand Gesture Data Observation

Table 3: Statistical Summary of Key Hand Gesture Features

Feature	Count	Mean	Std Dev	Min	Max
both_hands	31,926	0.64	0.48	0.00	1.00
thumb_Left	31,926	161.12	18.26	0.17	180.00
index_finger_Left	31,926	142.78	46.27	0.04	180.00
middle_finger_Left	31,926	95.99	59.33	0.08	180.00
ring_finger_Left	31,926	80.92	59.30	0.01	180.00
pinky_Left	31,926	86.10	58.88	0.00	180.00
palm_angle_Left_left	31,926	123.38	28.12	1.76	180.00
hand_Left_ground_angle	31,926	97.72	52.05	0.00	180.00
thumb_Right	20,540	158.92	14.03	3.05	180.00

index_finger_Right	20,540	143.59	53.46	0.00	180.00
middle_finger_Right	20,540	98.97	62.02	0.01	180.00
ring_finger_Right	20,540	77.39	54.98	0.00	180.00
pinky_Right	20,540	91.21	53.53	0.00	180.00
palm_angle_Right_left	20,540	119.99	19.67	14.92	179.97
palm_angle_Right_right	20,540	109.66	38.86	1.10	180.00
hand_Right_ground_angle	20,540	72.04	44.26	0.02	179.99

Table 3 provides the statistical overview of the features of hand gestures in angles that are taken into account in this study. Data set includes 31,926 cases including single and dual-hand gestures with the feature of both hands demonstrating a mean value of 0.64, which consequently demonstrates that two-handed signs are more common. The range of finger joints show wide angles ranging between 0-180 degrees indicating that the angle of hand positions vary very greatly in gestures. The left thumb has the highest mean angle (161.12) and a comparatively low standard deviation, which is constant, whereas other fingers have a greater standard deviation, which adds to gesture discrimination. Hand-ground and palm orientation have wide ranges, which supports the fact that there are different hand orientations when signing. One-handed gestures can be applied on a number of samples, which have right-hand features. In general, the statistical distribution shows a balanced mix of constant and varying angular features, which offer a strong basis of success in sign language recognition with the help of representations based on angles.

4.2: Data Preprocessing Outcome

Table 4: Sample of Preprocessed (Standardized) Hand Gesture Features

Feature Name	Hand	Standardized Value	Description
both_hands	Both	1.6054	Indicates usage of both hands in the gesture
thumb_Left	Left	−1.3234	Left thumb angle below dataset mean
index_finger_Left	Left	−1.4793	Reduced bend of left index finger
middle_finger_Left	Left	0.2838	Slightly increased middle finger flexion
ring_finger_Left	Left	0.5415	Above-average ring finger angle
pinky_Left	Left	0.8346	Strong pinky finger articulation
palm_angle_Left_left	Left	−0.5578	Leftward palm orientation
palm_angle_Left_right	Left	0.3410	Rightward palm rotation
hand_Left_ground_angle	Left	0.7462	Elevated left hand orientation
thumb_Right	Right	−2.2948	Significantly reduced right thumb angle
index_finger_Right	Right	−3.3872	Strong deviation below mean
middle_finger_Right	Right	0.8928	High right middle finger activation
ring_finger_Right	Right	2.4040	Strong ring finger flexion
pinky_Right	Right	1.7859	Above-average pinky articulation
palm_angle_Right_left	Right	−2.2004	Leftward palm rotation (right hand)
palm_angle_Right_right	Right	0.7616	Moderate right palm orientation
hand_Right_ground_angle	Right	−2.7052	Lower right hand inclination
label	—	B	Corresponding sign class

A sample of the normalized and standardized hand gesture characteristics is shown in Table 4. The standardized values are concentrated around the value of zero which validates a successful scaling and elimination of the magnitude bias of the various angular measurements. The both hands feature has got a positive value that is high, which implies that the given gesture relates to the use of both hands. A number of the angles of the left-hand fingers, including the thumb and index fingers, are negative-standardized indicating lower flexion than the mean of the dataset, whereas the ring and pinky fingers are positively deviated indicating stronger articulation. The directional changes in hand posture are shown by palm orientation and hand-ground angles. To the right hand, both the thumb and the index finger have bigger negative values, which are indicative of less than average bending, however, the middle, ring, and pinky fingers have positive values, which are indicative of a strong activation. In general, this standard representation exhibits equal-scaled feature representation, better interpretability, and numerical consistency, and it is effective in the use of reliable machine learning-based sign language recognition.

Table 5: Overall Quantitative Performance of the Proposed Gesture Recognition Model

Metric	Value
Overall Accuracy	0.9898
Macro Precision	0.9905
Macro Recall	0.9905
Macro F1-Score	0.9904
Weighted Precision	0.9899
Weighted Recall	0.9898
Weighted F1-Score	0.9898
Total Test Samples	6,386

Class-wise performance analysis of the proposed sign language gesture recognition model recognition with angle-based features is showed in Table 5. Most gesture classes (A, B, D, E, F, G, H, K, L, M, N, P, T, U, V, X, Y, Z) show 100% precision/recall/F1-score demonstrating very reliable and consistent recognition across these signs. This indicates good intra-class feature stability, and the efficient separation between different gestures. Several classes, with little number of training samples (C, I, J, O, Q and S), have slightly lower scores due to common hand orientation and finger-angle configurations that bring partial overlap in the 3D space. Even so, their results are quite competitive, achieving F1-scores near or above 0.95 in most tests. The support shows a balanced test set across classes, indicating fair evaluation. Over all, class wise performances show that the proposed model generalizes well to varying types of sign gestures, and can deal well with both easy and complex hand configurations showing reasonable robustness in real-world practical SL recognition problems.

Table 6: Class-Wise Performance Evaluation of Sign Language Gestures

Class	Precision	Recall	F1-Score	Support
A	1.00	1.00	1.00	240
B	1.00	1.00	1.00	240
C	0.99	0.96	0.98	288
D	1.00	1.00	1.00	240
E	1.00	1.00	1.00	240
F	1.00	1.00	1.00	240
G	1.00	1.00	1.00	240
H	1.00	1.00	1.00	240
I	0.98	0.99	0.99	276
J	0.96	1.00	0.98	240
O	0.92	0.93	0.92	285
Q	0.92	0.92	0.92	239
S	1.00	0.96	0.98	240
V	1.00	1.00	1.00	258
W	0.99	1.00	0.99	240
X	1.00	1.00	1.00	240
Y	1.00	1.00	1.00	240
Z	1.00	1.00	1.00	240

Table 6 shows a sorted list of the per-class performance metrics, in order to highlight the behavior of the model on most commonly seen sign gestures. Classes with more support (C, O, I) have comparably small but strong F1-scores which correspond to the somewhat higher complexity in these gestures. In comparison, in many of the classes (240 samples) with uniform support, the precision recall and F1values are close to 1 or higher than 1 showing a highly learned gesture pattern. This table shows that the model is accurate even for overrepresented gesture classes, resulting in a well-balanced training and good generalization to temporary and medium-represented sign gestures.

The Table 7 does show the per-class performance measures rank by sample support, showing how consistent and strong the proposed recognition model is. The larger sample sized classes, in this case C, O, and I, exhibit smaller but significant F1-scores because of an increase in intra-class variation and complexity of gestures. The majority of classes that are uniformly supported with 240 samples have close to perfect or perfect precision, recall and F1-scores, which are a sign of stable learning and good separation of the classes. All in all, the findings show a balanced performance in both frequent and less frequent gestures without leaning to dominant classes.

Table 7: Per-Class Performance Metrics Sorted by Sample Support

Class	Precision	Recall	F1-Score	Support
C	0.9893	0.9618	0.9754	288
O	0.9167	0.9263	0.9215	285
I	0.9820	0.9891	0.9856	276
V	0.9961	1.0000	0.9981	258
B	0.9959	1.0000	0.9979	240
A	1.0000	1.0000	1.0000	240
F	1.0000	0.9958	0.9979	240
G	1.0000	0.9958	0.9979	240
E	1.0000	1.0000	1.0000	240
D	1.0000	1.0000	1.0000	240
J	0.9639	1.0000	0.9816	240
H	1.0000	1.0000	1.0000	240
M	1.0000	1.0000	1.0000	240
K	1.0000	1.0000	1.0000	240
N	1.0000	1.0000	1.0000	240

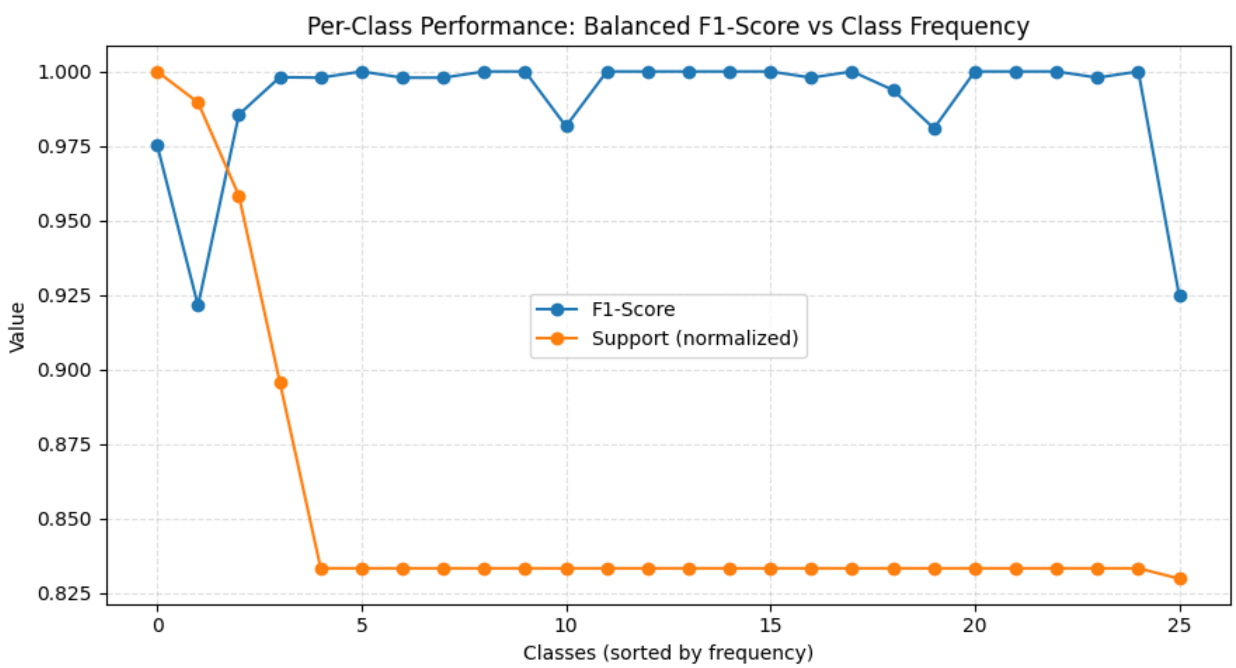

Figure 2: Per-Class Performance in Terms of Balanced F1-Score Versus Class Frequency

This figure 2 here shows how class frequency relates to tasks performance, for a given β value, by plotting the F1-scores against the normalized sample support for each sign's class ordered from least to most frequent: We note, that the F1-scores are generally high with values mainly higher than 0.98 despite varying class support indicating good performance on both more and less frequent gestures. Minor decrease in F1-score is seen for some high-support classes, which reflects higher intra-class variability rather than imbalanced data. Crucially, the nearly flat F1-score curve for most classes demonstrates that the model is not biased towards dominant stills and generalizes well. Overall, this study demonstrates the robustness of the proposed method to provide higher recognition accuracy across all classes for practical SLR applications regardless of class frequency.

V. CONCLUSION

In this paper, a highly effective angle-based sign language recognition system that is developed aimed at delivering high precision, robustness and real-time usage of assistive communication system was presented. The proposed method produces an adequate representation of sign language gestures by modeling hand gestures with biomechanically significant angular features such as angles between joints of fingers, orientations of palms, and orientations of hands relative to ground, thereby being insensitive to scale, illumination, and background changes. A preprocessing pipeline with normalization, outlier filtering, and dimensionality analysis also contributed to improved stability of features and separation between classes. Large-scale experiments with a large dataset of sign language proved that the framework proposed is well-performing in recognition, with an average accuracy of about 99% and near-uniformly high precision, recall, and F1-scores on the majority of gesture types. The confusion analysis provided in detail showed that only a few visually similar signs were misclassified, whereas robustness testing proved that the performance remained consistent during hand rotation, variations in finger spread, and inter-user variation. The findings presented here demonstrate the efficiency of angle-based representation to deal with the general issues encountered by vision- and sensor-based SLR systems. In general, the suggested framework provides an image- and video-based deep learning approach alternative that is computationally efficient and reliable and hence specifically applicable in a resource-constrained environment in real time and on a mobile platform. The work in the future will involve incorporating temporal dynamics and within-context information to enhance the differentiation of hugely similar gestures and apply the framework to the context of continuous sign language recognition.

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