Design and Evaluation of a Static Filipino Sign Language Alphabet Recognition System Using Support Vector Machine

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ABSTRACT

Filipino Sign Language (FSL) is the recognized form of communication for the deaf and hard-of-hearing individuals under Republic Act No. 11106. Despite this, Filipino Sign Language remains underrepresented in technological research and development. This study aims to develop and evaluate an AI-based system for recognizing static FSL alphabet hand gestures. The study follows a quantitative and experimental research design. The study implements hyperparameter optimization of the regularization parameter of the Support Vector Machine (SVM) utilizing Histogram of Oriented Gradients (HOG) feature extraction. The regularization parameter controls the trade-off between the margin and minimizing classification errors.

The system is trained and evaluated using a public dataset available in Kaggle consisting of 11,700 preaugmented hand gesture images representing the 26 letters of FSL alphabet. The preprocessing techniques used are grayscale conversion, otsu's thresholding technique, and morphological operations to enhance the hand segmentation, afterwards HOG features are extracted and used as an input to the SVM classifier. Two data split configurations (50:50 and 80:20) employed to assess the model generalization and robustness. To compare the performance of the SVM model, a Convolutional Neural Network (CNN) is implemented as a baseline for performance comparison.

Results show that the SVM model achieved a maximum accuracy of 98.55% using a 80-20 training validation split outperforming its performance under a 50:50 configuration, which yields 91.86% accuracy. The baseline CNN model achieves a comparable accuracy of 97.99%, indicating that non-neural network techniques can perform as effectively as deep learning models for static gesture tasks. Moreover, confusion matrix analysis reveals that misclassifications primarily occur among visually similar gestures.

Overall, SVM classifications for static FSL recognition are highly effective under 80:20 test validation split and C = 0.5 reaching an accuracy of 98.55%. The study demonstrates the potential of computationally efficient models for use in accessible learning tools, while at the same time providing a baseline for further work in dynamic and multimodal sign language recognition systems.

Keywords: Filipino Sign Language (FSL), Static Hand Gesture Recognition, Support Vector Machine (SVM), Computer Vision, Image Classification

INTRODUCTION

Filipino Sign Language (FSL) is the primary mode of communication for the deaf and hard-of-hearing community in the Philippines. It is legally recognized under the Republic Act No. 11106, also known as the Filipino Sign Language Act of 2018, which states that FSL is a national sign language and the primary language of instruction for Deaf learners (Republic of the Philippines, 2018). According to Philippine Statistics Authority (2022), 1.78 million Filipinos are reported to have hearing difficulty even with hearing aids. This shows the importance of accessible education and learning tools for people with hearing difficulties.

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Despite being recognized by law, the majority of FSL instruction is still provided in private specialized schools, institutions, and workshops using conventional teaching methods that mainly rely on live instructions, video lessons, and textbooks. In rural areas, the language is still underutilized, and this population is further marginalized by the lack of educational and technological resources (Garcia et al., 2025). A study made by Culla et al. (2025) highlights how and why the Filipino deaf communities demand inclusive education brought by the lack of teaching personnel, and the learning materials.

Moreover, a study by Balanquit (2023) denotes that FSL is among the understudied deaf community in Southeast Asia at national, community, and home varieties. This implies research on FSL is still limited where there is a gap in linguistic, social and cultural understanding of the deaf's community language practices.

Additionally, a study by Tabingo and Lovitos (2025), recognizes FSL as a complex linguistic deeply embedded in Filipino culture and values challenging the fallacies that FSL is derived from American Sign Language. Despite that, this study shows that fingerspelling is a core function of FSL and is still being heavily used despite the advanced and complex non-manual signs, such as facial expression and spatial grammar, to represent proper nouns, loan words, and technical terms.

In response to this gap, the researchers propose the development of a baseline Filipino Sign Language recognition model using classical computer vision and machine learning techniques. The proposed system utilizes still hand images from publicly available FSL datasets and focuses on recognizing static hand gestures corresponding to the FSL alphabet. The focus of this research on static alphabet recognition is deliberately limited as a first step toward more sophisticated FSL translation systems. The research on static gestures is intended to create a framework for testing feature extraction and classification performance before moving on to more complex dynamic and multimodal aspects.

Research Objectives

- To apply classical computer vision techniques to extract meaningful features from FSL hand images.
- To determine the accuracy of the proposed system in recognizing Filipino Sign Language alphabet hand gestures using machine learning classification.
- To know the limitations of a static image-based FSL recognition system.

METHODS

THEORETICAL FRAMEWORK

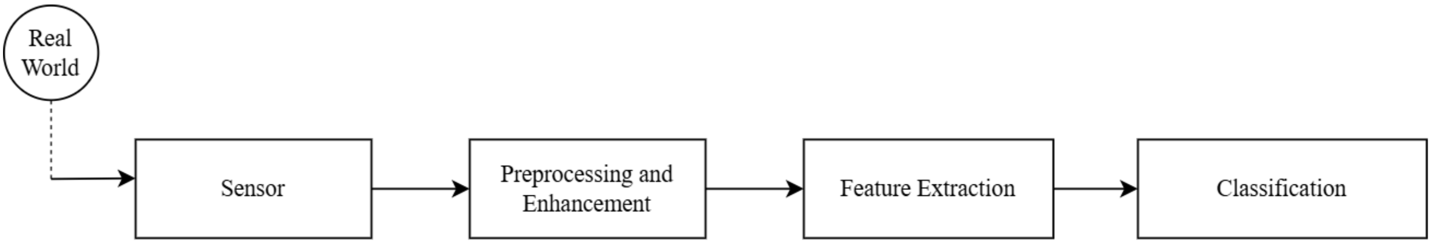

Figure 2.1 Pattern Recognition System

In the theoretical framework of this study, Figure 2.1 illustrates the technical setup for the proposed FSL translator, which follows a standard pattern recognition system. The system begins with a camera, followed by a preprocessing and enhancement phase to deal with the conversion to grayscale, otsu thresholding, morphological processing, and hand mask to normalize visual information. Feature extraction follows, utilizing Histogram of Oriented Gradients (HOG) to identify key features of the visual scene, including hand shapes features extracted from static images. The features are then fed into a classification phase, in which a Support Vector Machine (SVM) classification will be utilized to translate visual features into their textual equivalents in Filipino or English.

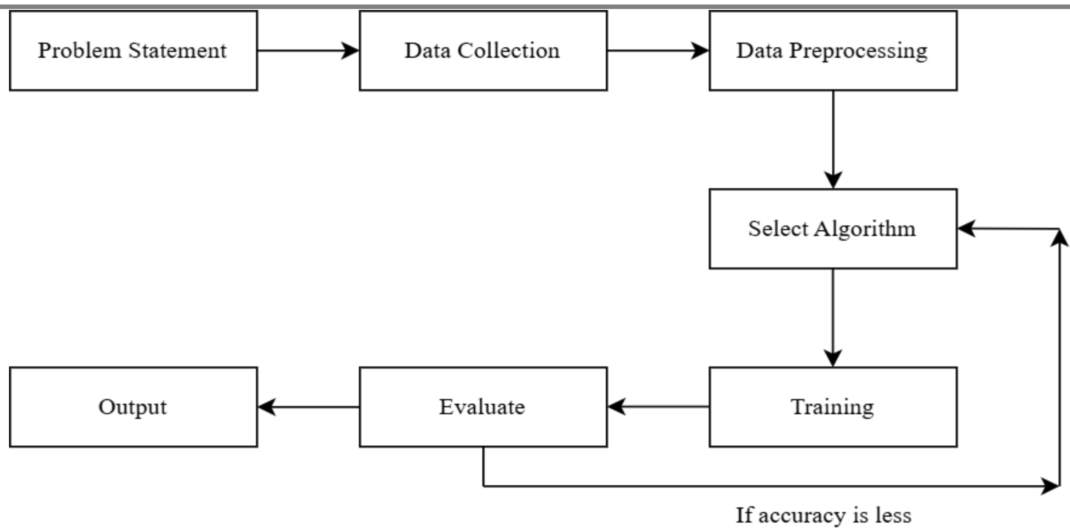

Figure 2.2 Machine Learning Theory

Figure 2.2 shows the development of the AI-detected FSL translator, the process begins with a problem statement followed by data collection from a public dataset. The next step is data preprocessing such as grayscale conversion, otsu thresholding, morphological operations, and hand masking are applied. The following stage is classification algorithms, specifically Support Vector Machine (SVM) and Convolutional Neural Network (CNN). Followed by training and evaluation of the model. Lastly, the final output to show the results.

CONCEPTUAL FRAMEWORK

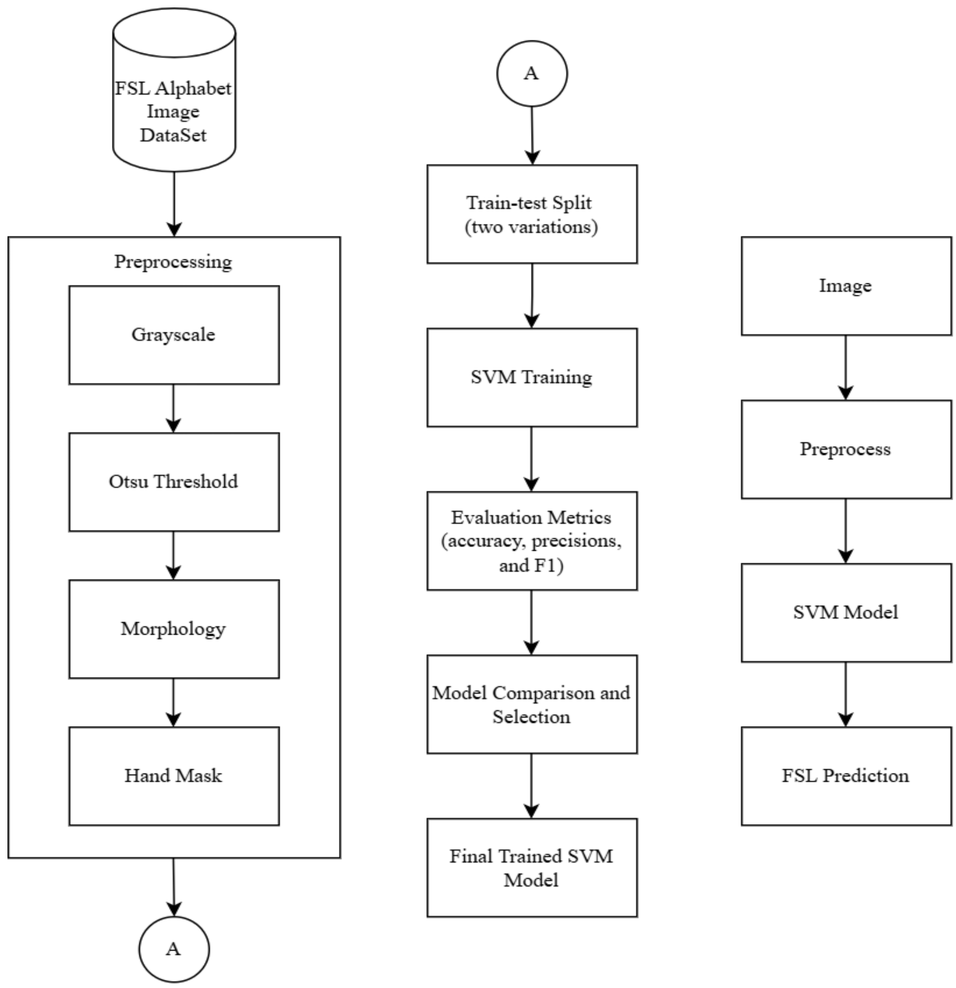

Figure 2.3 Conceptual Framework

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Figure 2.3 shows the conceptual framework illustrates the overall process of creating the recognition system for Filipino Sign Language (FSL), which was employed in this study. As the main source of data for training the model, it starts with the FSL alphabet image dataset. To improve image quality and isolate pertinent hand features, the images go through preprocessing procedures like hand masking, Otsu thresholding, morphological operations, and grayscale conversion. A Support Vector Machine (SVM) model is trained and assessed using performance metrics like accuracy, precision, recall, and F1-score after the processed data has been split into training and testing sets. The final trained SVM model is used for image classification then producing FSL predictions, following model comparison and selection.

Methods and Techniques of the Study

The methodology used in this study is quantitative experimental research design to develop and evaluate a machine learning–based system for recognizing Filipino Sign Language (FSL) alphabet hand gestures.

Population and Sample of the Study

This study used the dataset of FSL hand gesture images that are openly accessible on Kaggle containing 11,700 pre-augmented images of Filipino Sign Language hand gestures (A-Z) in 26 different classes. This study excludes the letters Ñ and the digraph NG due to the lack of dataset images.

Research Instrument

The study used different digital tools and software frameworks specifically developed for computer vision and statistical analysis. Jupyter Notebook was used as the main computational platform, allowing easy documentation. It also provided an iterative environment for the development of classification algorithms. Python 3.11 was the main programming language, and provided tools for data manipulation.

OpenCV was used as the main tool for pre-processing the data for image processing. The study used Scikit-learn as the principal tool for executing SVM and extracting HOG features. Additionally, TensorFlow and Keras were used as deep learning frameworks for developing the baseline CNN for comparing models. Matplotlib and Seaborn were used for developing the final visualizations of the data.

Data Gathering Procedure

In this study, the data gathered was obtained from the Kaggle repository named "FSL Dataset". It is composed of 11,700 images representing the Filipino Sign Language (FSL) alphabet. The following process was splitting the dataset into two to observe model sensitivity. The first split was an 80:20 split which contains 9,630 for training and 2,340 for validation. The second split was a 50:50 split that contained 5,850 for training and 5,850 for validation.

Dataset Preprocessing

The procedure for dataset preprocessing was to convert raw FSL images to a format fitted for machine learning. The images were converted into a 128 x 128 pixels resolution to make the images standardized and optimized for classical and deep learning models. The following preprocessing steps include grayscale conversion, otsu thresholding, morphological operations, and hand masking are applied to images as shown in Figure 3.1

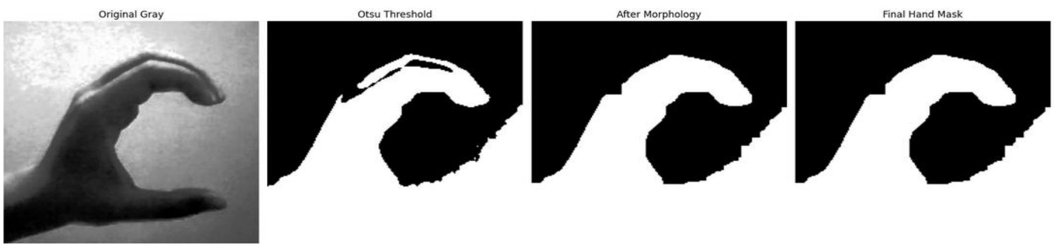

Figure 3.1 FSL hand sign letter C preprocessing

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Statistical Treatment

The trained models were carefully evaluated to measure the efficacy of the FSL recognition system. The confusion matrix was utilized to assess the performance of the SVM and CNN models and for identifying inter-class misclassifications. The quantitative performance was measured through four key statistical metrics: Accuracy, Recall, and F1-Score.

Ethical Considerations

The study utilized publicly available datasets that do not contain personally identifiable information. No human subjects were directly involved in the data collection process.

RESULTS AND DISCUSSION

SVM Performance Using 50:50 Train-Validation Split

Table 4.1 SVM summary results with **50:50** Train-Validation split using **C = 0.01, 0.1, 0.5, 1, 2, 4**

C	Accuracy	F1 Score	Recall	Precision
0.01	83.23%	83.28%	83.23%	83.57%
0.1	**91.86%**	**91.88%**	**91.86%**	**92.02%**
0.5	81.99%	81.96%	81.98%	82.31%
1	75.70%	75.63%	75.69%	75.97%
2	71.36%	71.31%	71.35%	71.66%
4	70.02%	69.99%	70.02%	70.30%

The results show that the model performance is highly sensitive to the value of the regularization parameter *C* when training data is limited. The highest accuracy was observed at 91.86% at C = 0.1. Increasing C beyond this point led to a steady decline in performance, indicating overfitting. Due to few training samples, a higher penalty C forces the SVM to create a decision boundary that is too complex and brittle capturing the noise in the small training set rather than the actual character shapes.

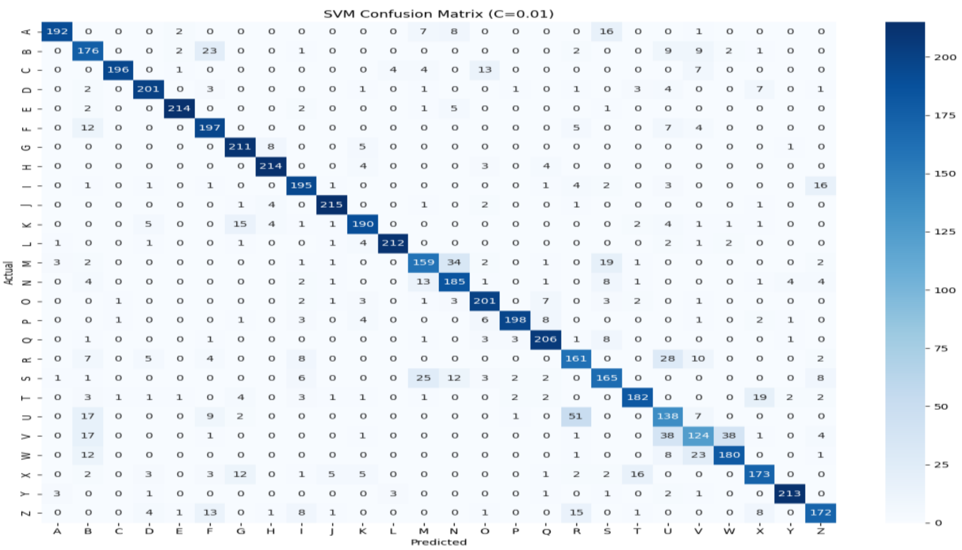

Figure 4.1 SVM Confusion Matrix with 50:50 Train-Validation split at C = 0.01

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The top performing classes overall are L (95.90%), Y (95.30%), with E being the top performer at 95.96%, with the highest precision being C at 98.49%, and the highest recall is J with 95.56%. The model encounters significant difficulty with letters sharing overlapping features such as U and V. V has a very low recall with 55.11%, implying that more than half of the actual V gestures are being misclassified as other letters, and U with 56.79% precision indicating that many other letters are being misclassified as U. The letters R, B, and S also displayed a lower-than average performance, at 68.51%, 72.73%, and 73.33% respectively.

There is also a display of high accuracy for poorly performing letters like U (96.72%). In the 26-class problem, the model gets additional points for knowing when the letter is not U. The F1-Score at 58.97% is the more appropriate metric.

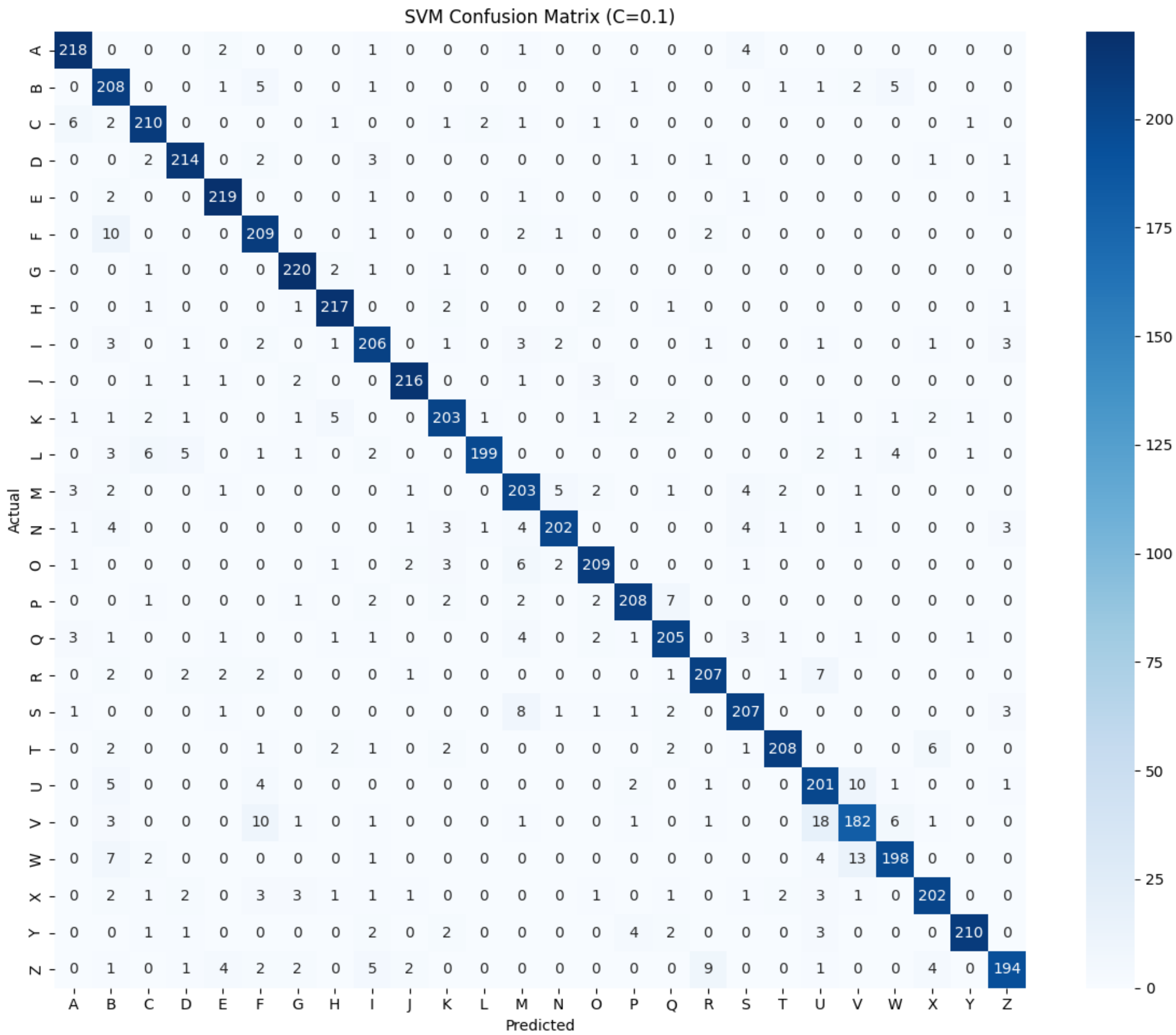

Figure 4.2 SVM Confusion Matrix with 50:50 Train-Validation split at C = 0.1

The model at C=0.1 represents a more baseline. The top performing classes continued to be E (94.80%), L (94.10%), and H (93.90%), with C remaining to maintain the high precision, and J showing a strong recall. However, the model still faces significant bottlenecks in the U-V-R cluster. While there is a slight improvement from the C=0.01 baseline, V remains the most problematic class with a low recall of 58.40%, suggesting that a substantial portion of "V" gestures are still being "absorbed" by structurally similar neighbors. Similarly, U shows a precision of 61.15%, while it improved from the previous model, it is still not sharp enough to prevent other letters from being misclassified as U.

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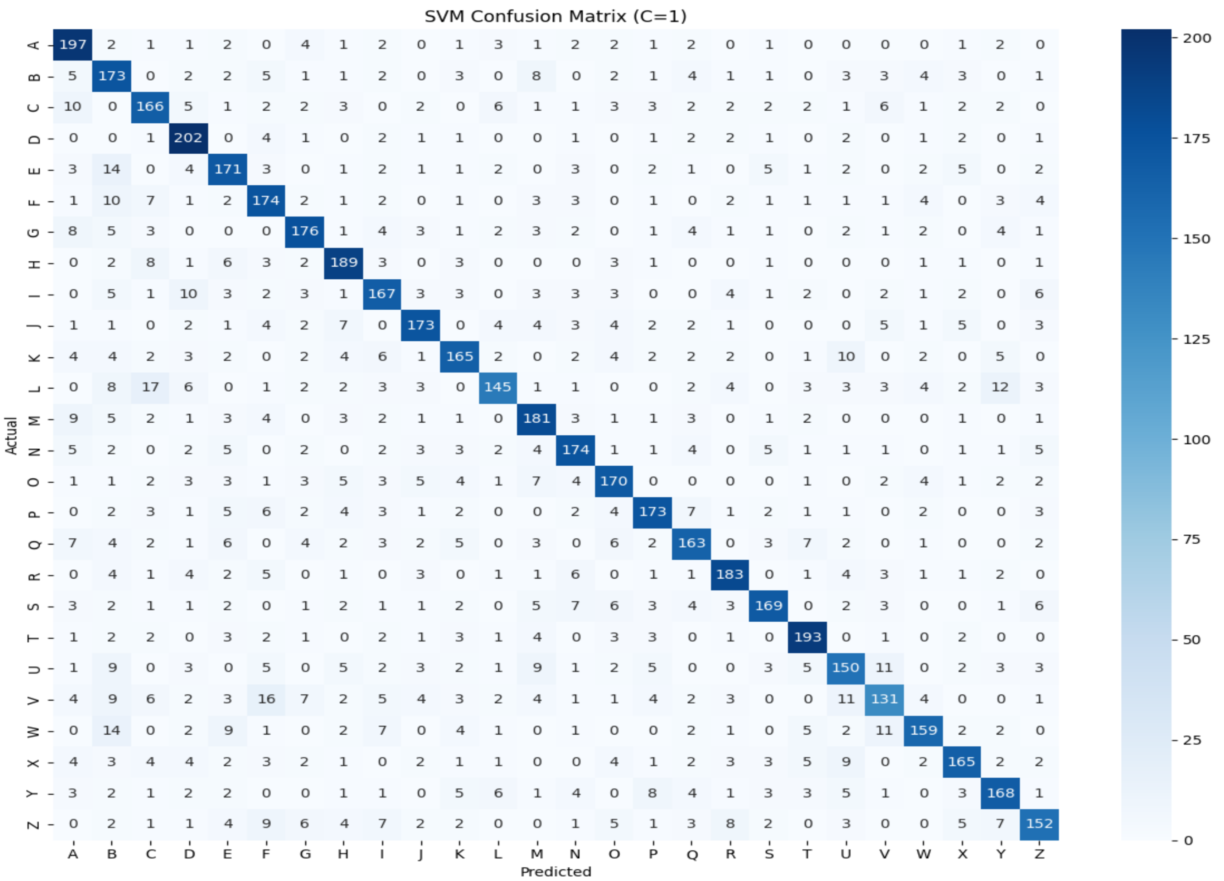

Figure 4.3 SVM Confusion Matrix with 50:50 Train-Validation split at C = 2

The model at regularization parameter, C, at 2 displayed a lower performance in comparison compared to the previous models. There are new top performing letters which are R (78.10%), T (78.43%), and A (77.3%).

The letter U and V remain the most challenging by having a low precision and recall respectively. V remains the weakest link with a low recall of 54.22%, indicating that the model still misses nearly half of the actual V signs. U also shows a relatively low precision of 65.40%, showing that it still acts as a "catch-all" for other similar gestures. While R, S, and T have improved significantly compared to the C=0.01 model (now reaching the 74%–78% range), the overall average has dipped, implying that the model is struggling to maintain the high performance of the "easy" letters while trying to fix the "hard" ones.

SVM Performance Using 80:20 Train-Validation Split

Table 4.2 SVM summary results with **80:20** Train-Validation split **using C = 0.01, 0.1, 0.5, 1, 2, 4**

C	Accuracy	F1 Score	Recall	Precision
0.01	92.86%	92.86%	92.86%	92.96%
0.1	98.16%	98.17%	98.16%	98.21%
0.5	**98.55%**	**98.55%**	**98.55%**	**98.59%**
1	98.55%	98.55%	98.55%	98.59%
2	98.55%	98.55%	98.55%	98.59%
4	98.55%	98.55%	98.55%	98.59%

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With a larger training set, the SVM demonstrates increased robustness to higher values of C. Evidently, there is a sharp performance leap between C=0.01 and C=0.1, with the accuracy rising from 92.86 % to 98.16%. However, performance stabilizes at approximately 98.55% accuracy for C ≥ 0.5. This indicates that at C = 0.5 the model has already found the optimal margin possible for the training data, as increasing C further does not change the orientation of the hyperplane as there is likely no remaining data that can be correctly reclassified with stricter margin.

The model stability at C ≥ 0.5 means the model is not overfitting as a very high C can lead to drop in generalization and instead focus on the memorization of the dataset.

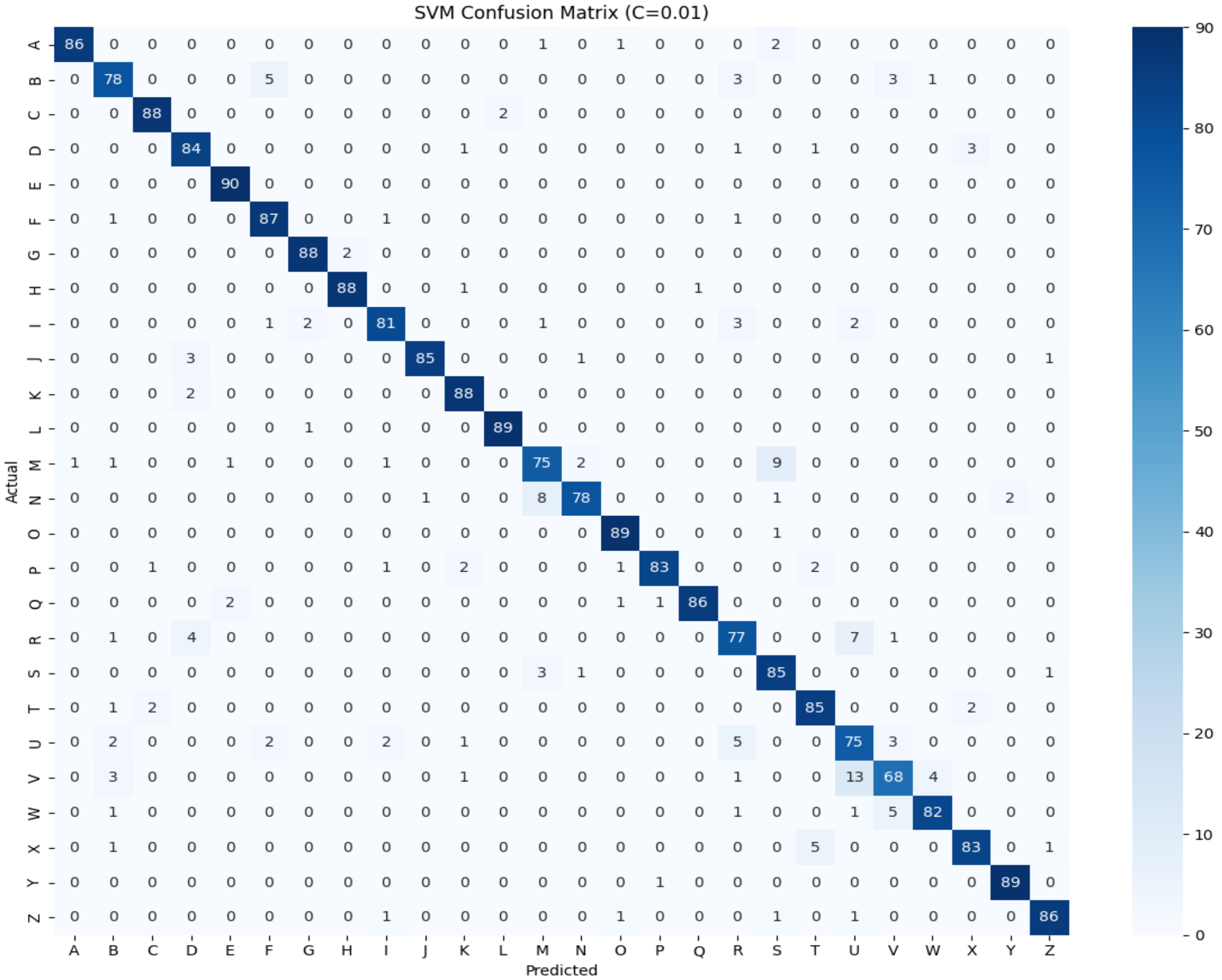

Figure 4.4 SVM Confusion Matrix with 80:20 Train-Validation split at C = 0.01

The top-performing classes are E (98.36%), L (98.34%), and Y (98.34%), with E achieving a perfect 100% recall, meaning the model never failed to identify an "E" gesture in the test set. The highest precision is shared by A, J, and Q at 98.85%, indicating that when the model predicts these letters, it is almost certainly correct. This leap in performance suggests that the increased volume of training data allowed the SVM to define much more accurate decision boundaries, even with the "soft" margin of C=0.01.

Despite the overall success, the model still encounters its most significant (though much improved) difficulty with the U and V gestures. V has the lowest recall at 75.56%, implying that nearly a quarter of actual "V" gestures are still being misclassified. U remains the overall weakest class with an F1-Score of 79.37% and a precision of 75.76%, indicating that it still serves as a destination for misclassified samples from other similar letters. The letters R (84.62%), M (84.27%), and B (87.15%) also sit below the average.

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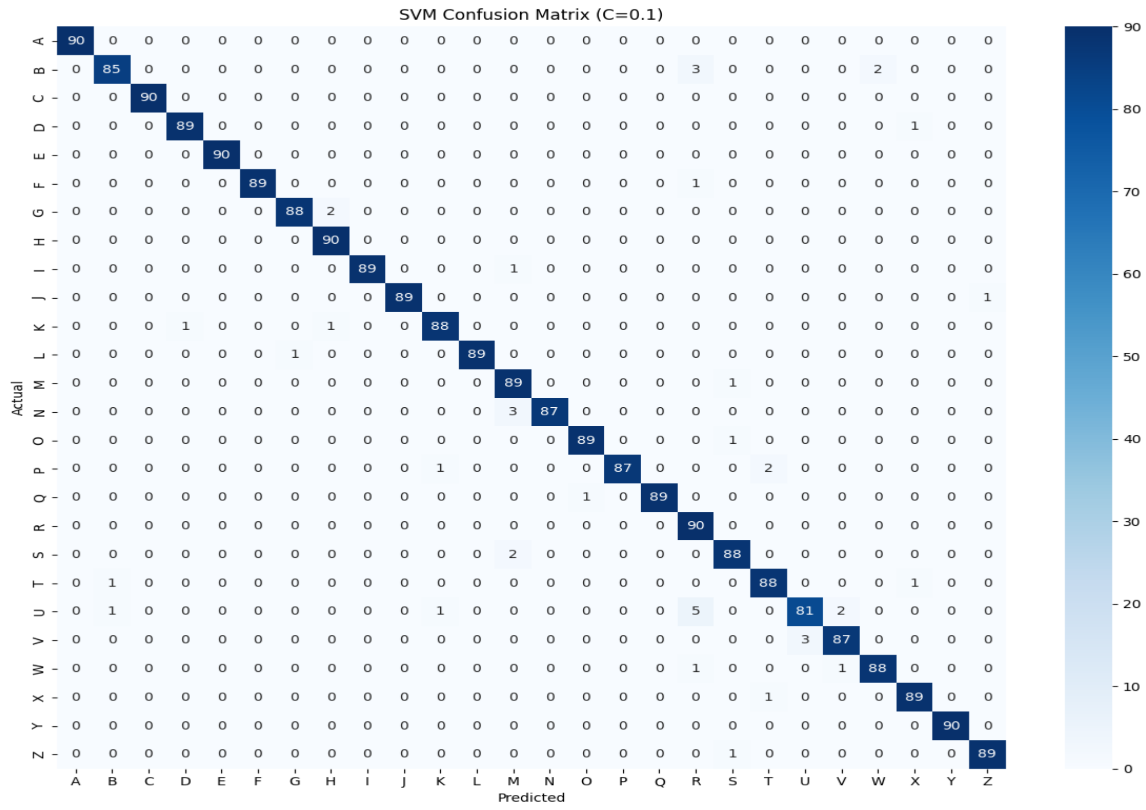

Figure 4.5 SVM Confusion Matrix with 80:20 Train-Validation split at C = 0.1

The model achieves perfect classification for classes A, C, E, and Y, all of which reached 100% across every metric. This implies that the decision boundaries for these gestures are now so well defined thus there is zero overlap with other classes in the test set. Letters H and R, achieved 100% recall, meaning the model successfully identified every instance of the letter H and R. Even in this high-performing state, the U and V cluster shows the only remaining signs of friction. Despite remaining to be the lowest; U had 90% recall while R had 90% precision. Showing an increase in classification among these difficult letters. While the model identified all the letters R in the dataset, it also pulled other letters into the letter R category.

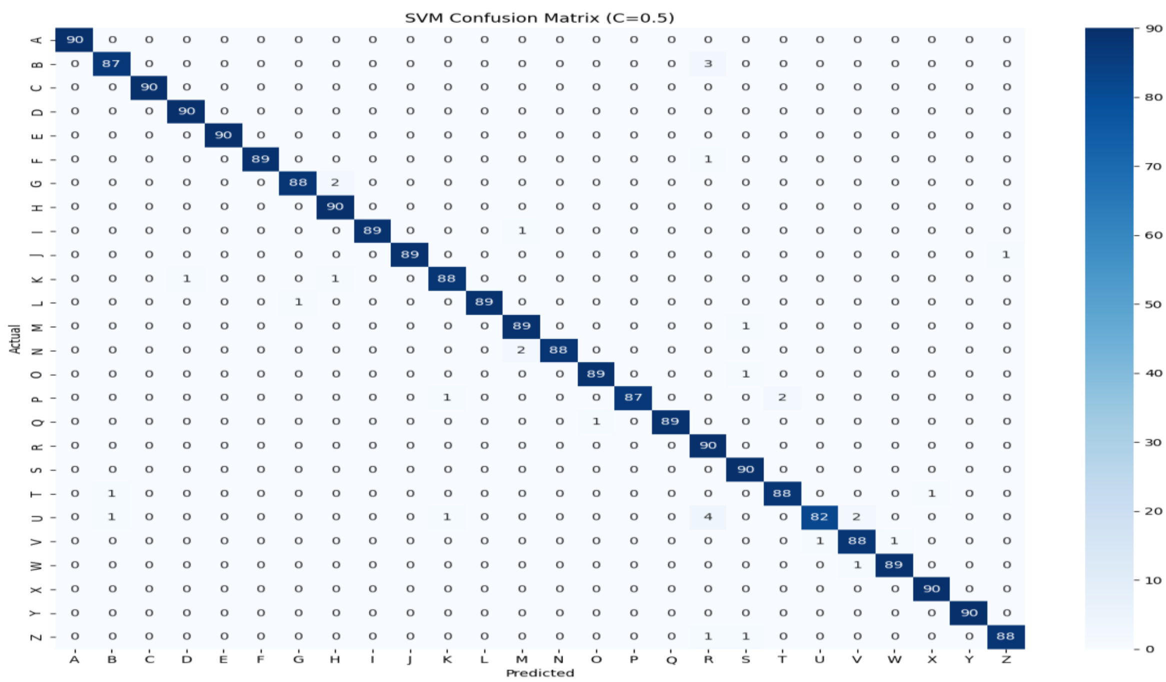

Figure 4.6 SVM Confusion Matrix with 80:20 Train-Validation split at C ≥ 0.5

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The model was able to perfectly identify the classes A, C, E and Y achieving a 100% F1-Score, while the classes D, H, R, S and X achieved 100% recall. Furthermore, the precision for the letters A, C, E, F, I, J, L, N, P, Q, and Y reached 100%. This level of performance suggests that the feature space is now perfectly partitioned. The difficult classes such as U and V received a significantly improved precision of 98.80% and F1-Score of 97.24% respectively. Class R, showed a slight precision dip at 90.91% meaning it still becomes the sink for the classes such as V and B.

Thus, the model with 80:20 train-evaluation split and C=0.5 represents the peak of the system's classification performance, achieving an overall accuracy of 98.55%. Increasing the regularization parameter beyond this point presents similar model performance.

CNN Performance for Comparative Analysis

To explore the performance of the SVM with regularization parameters at C=0.5 and 80:20 train-validation set. A deep learning approach using CNN was implemented as a baseline to compare the performance against the chosen SVM model. The architecture consisted of three convolutional layers for feature extraction and two dense layers for classification, trained on the 80:20 split to provide a direct comparison to the peak SVM model.

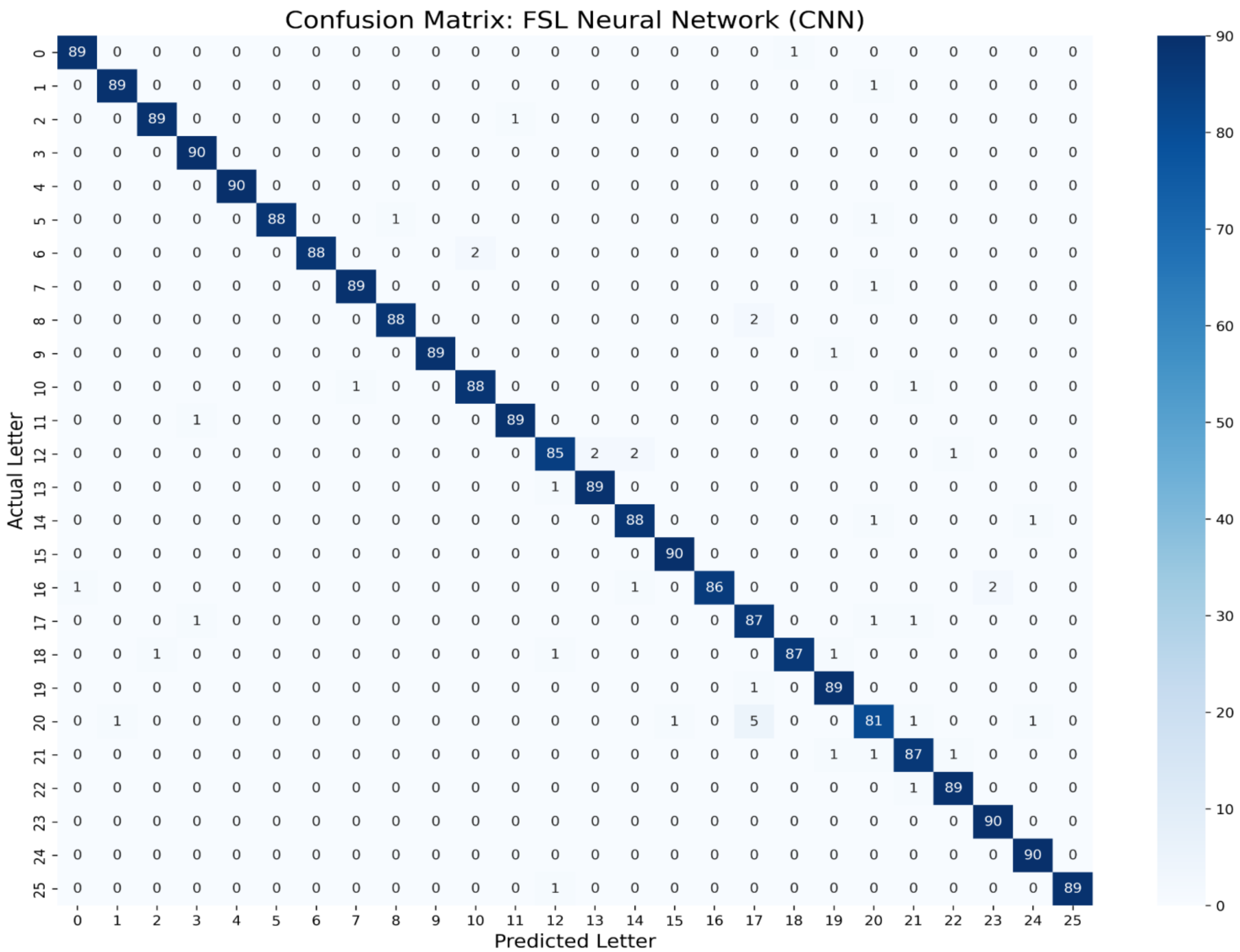

Figure 4.7 CNN Confusion Matrix with 80:20 Train-Validation Split

The CNN model achieved an overall accuracy of 97.99% with 100.00% F1-Score for class E and above 98% performance for the majority of the alphabet which includes A, C, and Y. Unlike the SVM model, the CNN deep learning model showed a significant strength in identifying the U-V-R cluster. V achieved a high F1-Score of

96.13%, while R reached 94.05%, while U remained the most challenging gesture gaining an F1-Score of 91.53%, it was more balanced compared to the previous reiterations of SVM.

Table 4.3 Comparison of Peak SVM and CNN Performance

Model	Accuracy	F1 Score	Recall	Precision
SVM (C = 0.5)	98.55	98.55	98.55	98.55
CNN	97.99	98.17	98.16	98.21

Table 4.3 shows that the SVM model outperformed the baseline CNN model accuracy by 0.56%. This represents that the handcrafted feature representation used with SVM effectively captured the distinct characteristics of the static hand gestures.

SUMMARY OF FINDINGS

After the evaluation of the results of the experiment, the researchers came up with following findings:

- Classical computer vision techniques can successfully extract meaningful features from FSL hand images by using shaped-based feature descriptors that capture the structural characteristics of hand gestures. This study used HOG descriptors to extract edge and gradient orientation features.
- The optimized Support Vector Machine (SVM) model (C = 0.5, 80:20 split) achieved a peak accuracy of 98.55%, demonstrating that classical machine learning can reliably classify static FSL alphabet gestures with high precision and recall.
- The system is limited to static alphabet gestures and does not include dynamic signs, non-manual features (e.g., facial expressions), real-world environmental variability, or full linguistic complexity of FSL.

CONCLUSION

Based on the results and findings of this study, the Histogram of Oriented Gradients (HOG) descriptor proved its effectiveness in extracting meaningful structural features from static Filipino Sign Language (FSL) hand images. The high classification performance of the proposed system using the extracted features demonstrates that classical computer vision approaches are successful in representing discriminative features of the FSL alphabet. It demonstrates that handcrafted feature extraction approaches are efficient in FSL gesture recognition.

The findings of this study also shows that the optimized Support Vector Machine (SVM) model, with C=0.5 and an 80:20 ratio of training and validation data, is efficient in achieving an accuracy of 98.55%. Moreover, it is evident that precision, recall, and F1-score values of the proposed system are equally high. It shows that the proposed system is competent in recognizing static FSL alphabet gestures with high reliability under specific conditions of the dataset and verifies that classical machine learning approaches are capable in achieving near perfect recognition accuracy for static FSL alphabet classification.

However, the proposed system remains limited to recognizing static FSL alphabet gestures and does not include dynamic motion, facial expressions, or other non-manual linguistic components essential to full sign language communication. The system's performance may vary in real-world conditions due to lighting variations, background noise, hand occlusion, and different camera quality, because the model was assessed using controlled datasets. These factors may reduce the system's robustness and generalizability in practical applications.

The proposed model based on the support vector machine (SVM) technique promises computational efficiency when compared with the deep learning-based models, especially because of the handcrafted feature aspect. This would be a major advantage when it comes to deploying the model in a constrained environment. However, it should be noted that the real-time aspect would require optimization of the preprocessing stage.

Despite its limitations, the proposed system can be useful for developing tools to teach the FSL alphabet, especially for beginners. In addition, it can be a basic building block for a sophisticated sign language translation system that uses dynamic gestures and/or multimodal input.

RECOMMENDATIONS

Based on the results and identified limitations, the following recommendations are proposed:

1. Future research can consider the application of dynamic and sequential approaches for video recognition of FSL.
2. Features such as posture, facial expressions, and head movements should be incorporated to better the linguistic structure of FSL.
3. The dataset should be expanded to include more diverse participants, with varied environments. Additionally, future datasets should include the letter Ñ and the digraph NG to better represent the FSL alphabet.
4. Future systems should expand beyond alphabet recognition to include commonly used vocabulary and sentence-level interpretation.
5. The optimized SVM model may be integrated into a mobile or web-based interactive learning application to support accessible, self-paced FSL education.

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