Auslan Recognition through Machine Learning

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Abstract

Sign language is the medium of communication for the hearing impaired people. It uses gestures instead of sound to convey meaning. It combines hand-shapes, orientation and movement of the hands, arms or body, facial expressions and lip-patterns for conveying messages. Our dataset comprises 95 signs, each with 1600 samples, collected over nine weeks from a native Auslan signer using sophisticated equipment. Methodology involves feature engineering, normalization, handling missing data, and exploring various models like Decision Trees, Random Forests, SVM, CNN, or RNN. Decision Trees and Random Forests showed better performance compared to Neural Networks across all classes.

Research Question

Building a machine learning model to recognize Australian Sign Language (Auslan) signs.

Related Work

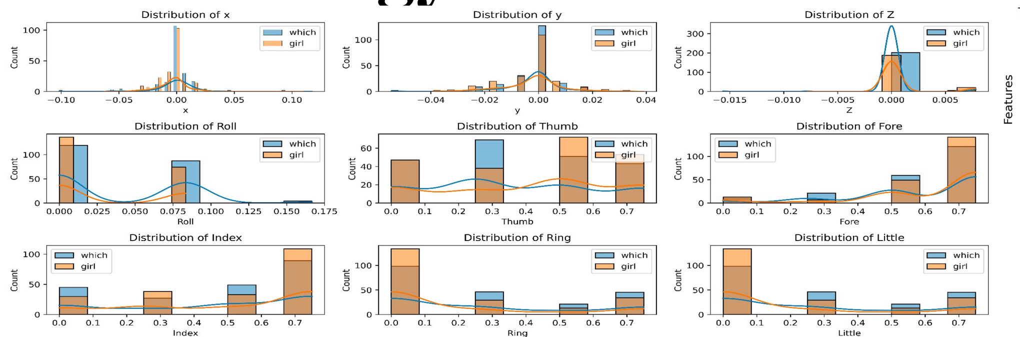
The initial studies concentrate on computer vision techniques, utilizing methods like edge detection, wavelet transforms, and machine learning (e.g., K-Nearest Neighbors) to identify sign language gestures. Despite showing promise, these methods have limitations such as sensitivity to noise, the impact of wavelet selection, and dataset biases. Consequently, further research is needed to enhance these techniques. Meanwhile, a separate set of studies investigates novel technologies such as PowerGloves and RF sensing for sign language recognition. PowerGloves, equipped with sensors, offer precise hand movement tracking, while RF sensing captures gestures without cameras or physical contact. These studies showcase ongoing efforts to explore diverse technological avenues for improving sign language recognition, each addressing unique limitations of its approach.

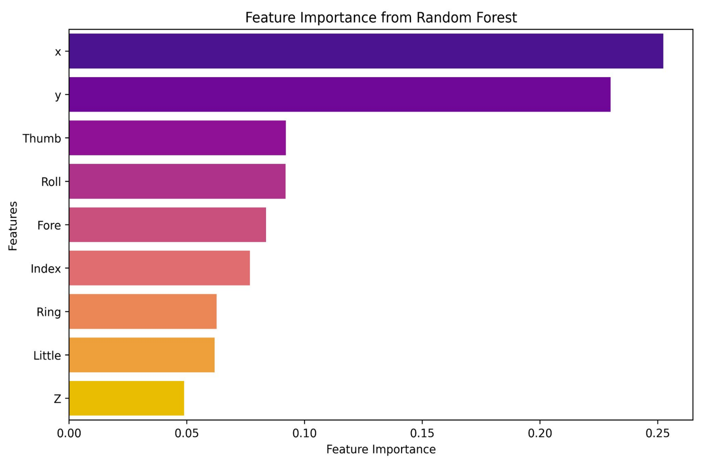
Dataset

The data was captured over nine weeks from a native Auslan signer using sophisticated equipment, including Fifth Dimension Technologies (5DT) gloves and Ascension Flock-of-Birds magnetic position trackers. The data set contains 95 different signs. Each Sign has 1600 samples.

	x	y	Z	Roll	pitch	Yaw	Thumb	Fore	Index	Ring	Little	Key code	Gs1	Gs2	Receiver values	Sign
0	-0.015625	-0.007812	0.0	0.000000	-1.0	-1.0	0.75	0.75	0.00	0.50	0.50	0x0	0x1	0x0	0x3F	which
1	-0.023438	-0.015625	0.0	0.000000	-1.0	-1.0	0.75	0.75	0.00	0.50	0.50	0x0	0x1	0x0	0x3F	which
2	-0.039062	-0.015625	0.0	0.083333	-1.0	-1.0	0.50	0.75	0.00	0.50	0.50	0x0	0x1	0x0	0x3F	which
3	0.031250	0.007812	0.0	0.000000	-1.0	-1.0	0.75	0.75	0.25	0.75	0.75	0x0	0x1	0x0	0x3F	girl
4	0.031250	0.007812	0.0	0.000000	-1.0	-1.0	0.75	0.75	0.25	0.75	0.75	0xFF	0x1	0x0	0x3F	girl

Methodology and EDA

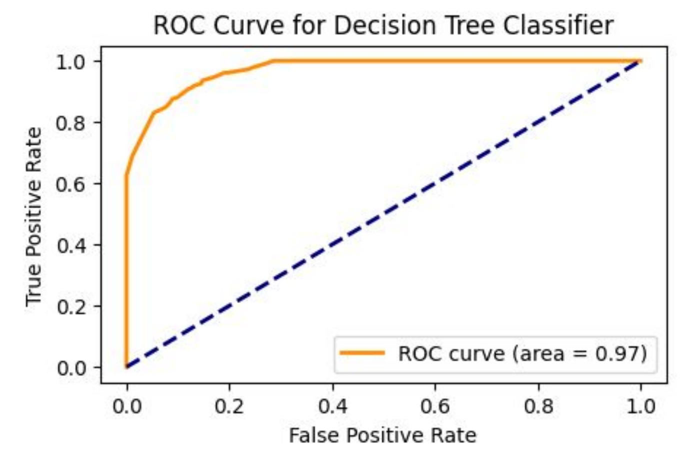


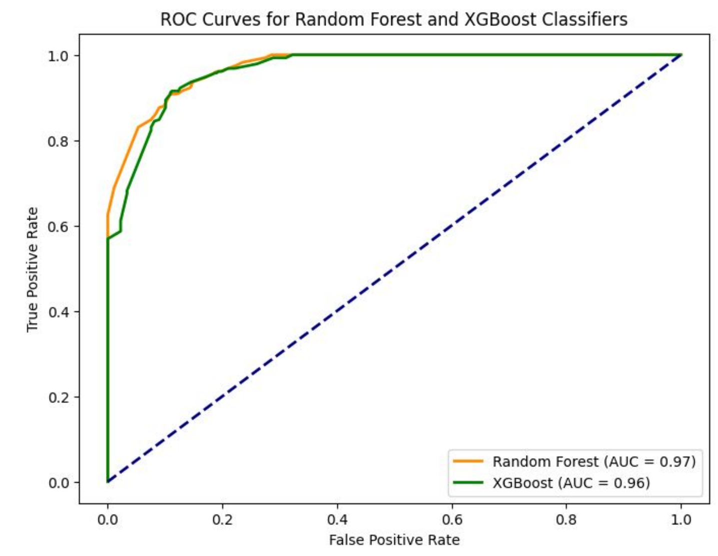


Methodology involves feature engineering to identify key features, normalization for consistent scales, and handling missing data. Feature selection combines statistical methods and dimensionality reduction using correlation analysis and PCA. Model selection includes experimenting with Decision Trees, Random Forests, SVM, CNN, or RNN, with hyperparameter tuning and exploration of ensemble techniques. Training and validation are performed, and models are fine-tuned based on evaluation metrics. Error analysis identifies patterns in misclassifications, and class imbalance is addressed using oversampling, undersampling, or specialized algorithms. LIME is used for interpretability.

Results

- Initially the the model were train with **TWO** CLASSES, then **THREE** classes and so on.
- For both Binary classification xgboost performs better than Decision Trees (DT) and Random Forest (RF), with accuracies 90.00%, 89.22% and 89.22% respectively.
- For Three-Class classification DT and RF perform similar and better than xgboost (85.42%, 85.42% and 85.10%).



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Decision Tree Accuracy: 89.22%
Classification Report for Decision Trees:
              precision    recall  f1-score   support

           0       0.92      0.88      0.90       357
           1       0.86      0.91      0.88       283

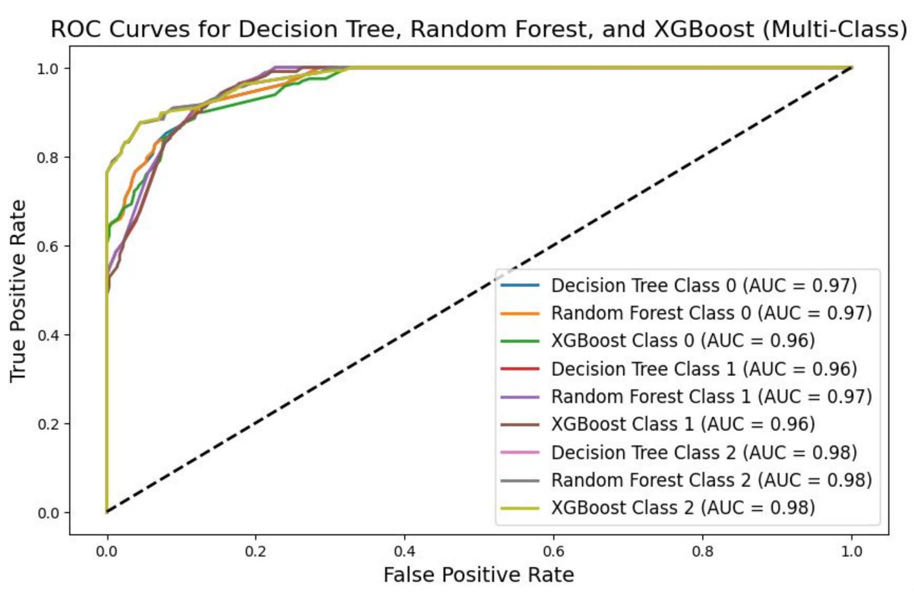
    accuracy                           0.89       640
   macro avg       0.89      0.89      0.89       640
weighted avg       0.89      0.89      0.89       640
Random Forest Accuracy (with PCA): 89.22%
Classification Report for Random Forest:
              precision    recall  f1-score   support

           0       0.92      0.88      0.90       357
           1       0.86      0.91      0.88       283

    accuracy                           0.89       640
   macro avg       0.89      0.89      0.89       640
weighted avg       0.89      0.89      0.89       640
XGBoost Accuracy: 90.00%
Classification Report for XGBoost:
              precision    recall  f1-score   support

           0       0.93      0.89      0.91       357
           1       0.87      0.91      0.89       283

    accuracy                           0.90       640
   macro avg       0.90      0.90      0.90       640
weighted avg       0.90      0.90      0.90       640
```

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Decision Tree Accuracy: 85.42%
Random Forest Accuracy: 85.42%
XGBoost Accuracy: 85.10%

Classification Report for Decision Tree:
              precision    recall  f1-score   support

           0       0.86      0.84      0.85       358
           1       0.81      0.89      0.84       328
           2       0.91      0.83      0.87       274

    accuracy                           0.85       960
   macro avg       0.86      0.85      0.86       960
weighted avg       0.86      0.85      0.85       960


Classification Report for Random Forest:
              precision    recall  f1-score   support

           0       0.88      0.83      0.85       358
           1       0.80      0.90      0.85       328
           2       0.91      0.83      0.87       274

    accuracy                           0.85       960
   macro avg       0.86      0.85      0.86       960
weighted avg       0.86      0.85      0.85       960


Classification Report for XGBoost:
              precision    recall  f1-score   support

           0       0.86      0.84      0.85       358
           1       0.81      0.88      0.84       328
           2       0.90      0.83      0.87       274

    accuracy                           0.85       960
   macro avg       0.86      0.85      0.85       960
weighted avg       0.85      0.85      0.85       960
```
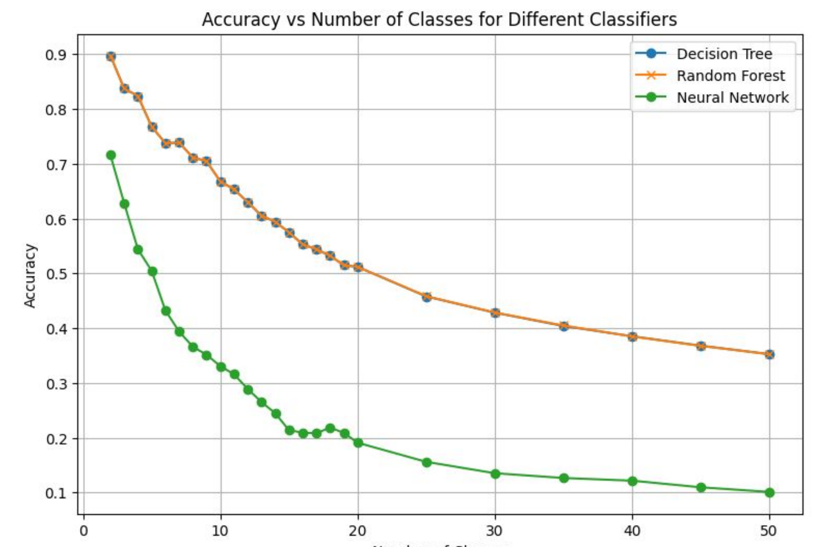

- When all classes are trained the Decision Tree and Random Forest perform better than Neural Network



Conclusion & Future Work

This study contributes to advancing the development of Auslan sign recognition using machine learning techniques. Through rigorous experimentation and analysis, it was observed that Decision Trees and Random Forests outperformed Neural Networks in recognizing Auslan signs when trained across all classes. However, the study acknowledges the complexity inherent in sign language recognition, with challenges such as noise sensitivity, dataset biases, and the impact of feature selection. Future research should focus on refining models to mitigate these challenges and exploring hybrid approaches that combine the strengths of different machine learning techniques.

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