4. Conclusion

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Abstract

This paper investigates the performance of multiple machine learning models for detecting

Parkinson's Disease using voice features, including both classical and information-theoretic features

(e.g., RPDE and DFA). A total of 8 models were compared: Logistic Regression, SVM, KNN,

Random Forest, Gradient Boosting, Decision Tree, Naive Bayes, and QDA. Metrics such as

accuracy, ROC AUC, confusion matrices, feature importances, runtime benchmarks, and t-SNE

visualizations were analyzed.

1. Introduction

Parkinson's Disease (PD) is a neurodegenerative disorder characterized by motor and non-motor

symptoms. Voice impairment is an early biomarker for PD, making it a non-invasive and

cost-effective diagnostic tool. In this study, we utilize the well-known voice dataset from the UCI

repository and evaluate the discriminative power of different feature sets and classifiers.

2. Methods

We use a set of voice features including fundamental frequency, jitter, shimmer, noise-to-harmonic

ratio (NHR), nonlinear dynamic complexity (DFA), and signal entropy (RPDE). Models were

evaluated using stratified cross-validation. GridSearchCV was used for hyperparameter tuning

where applicable. Visual diagnostics included ROC curves, confusion matrix breakdowns, t-SNE

clustering, and runtime comparisons.

3. Results

KNN, Gradient Boosting, and Logistic Regression achieved the highest accuracies (~95%) using the

full feature set. Random Forest and Gradient Boosting were most accurate with RPDE+DFA only.

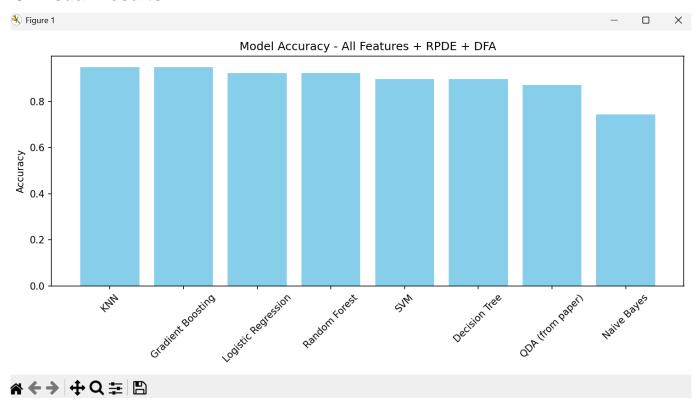
Naive Bayes performed weakest. Runtime varied substantially, with KNN being the slowest. Feature

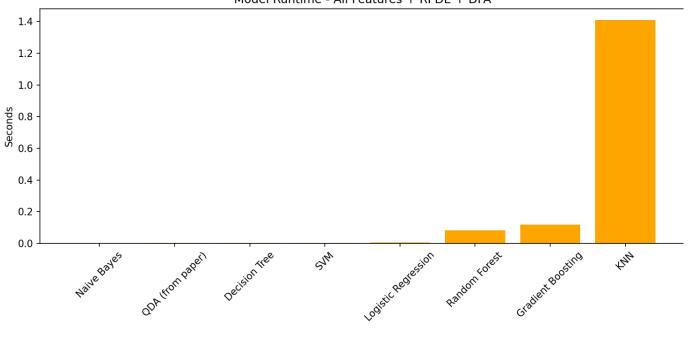
importance analysis revealed RPDE and PPE as top predictors. t-SNE clustering further confirmed class separability for the best model (KNN).

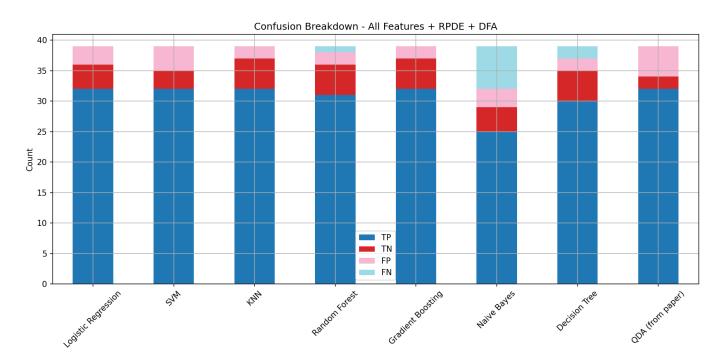
## 4. Conclusion

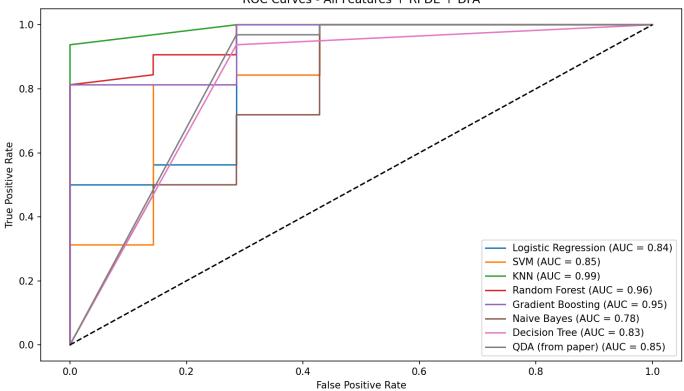
Results show that modern ensemble methods and KNN are highly effective for PD voice detection when all features are included. However, even just RPDE and DFA maintain strong performance. Future work includes deploying this in mobile apps using TensorFlow Lite, and expanding the dataset to include more diverse patient recordings.

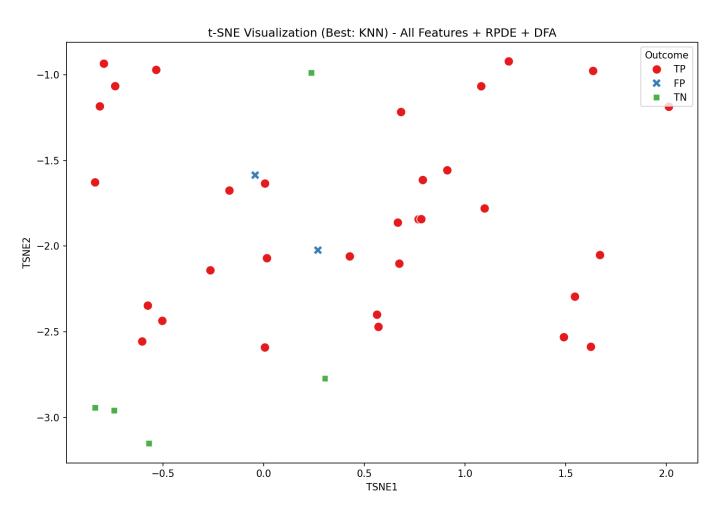
## 5. Visual Results



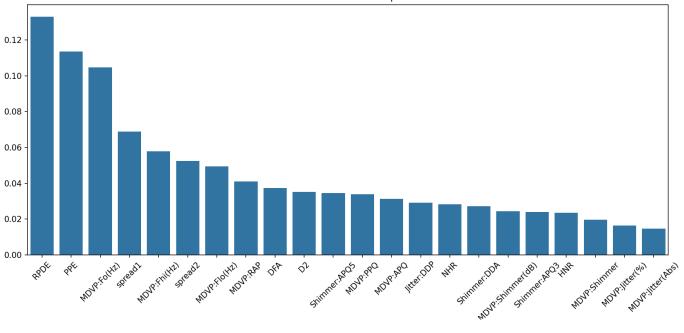


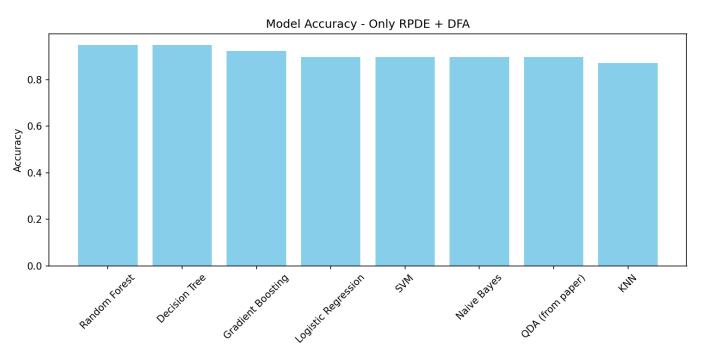


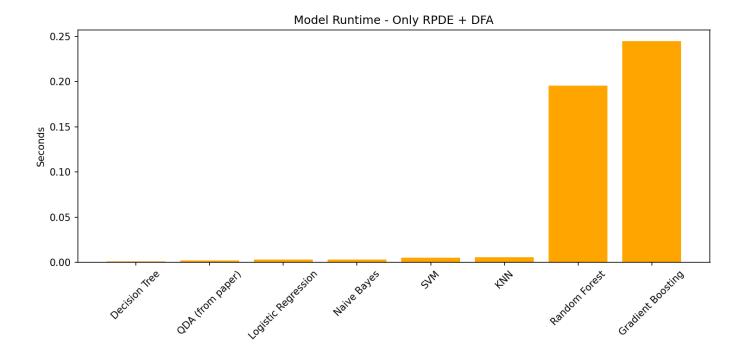


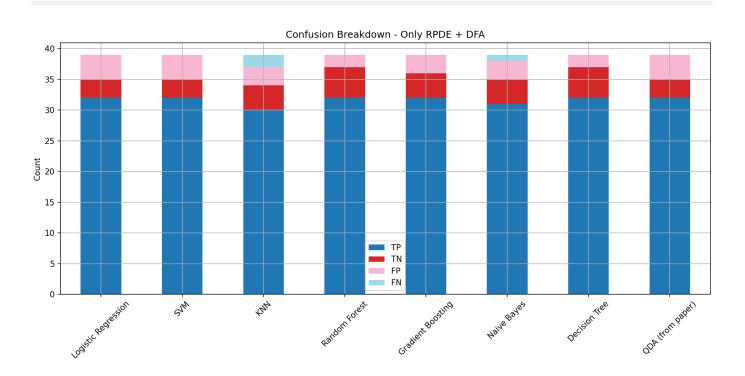


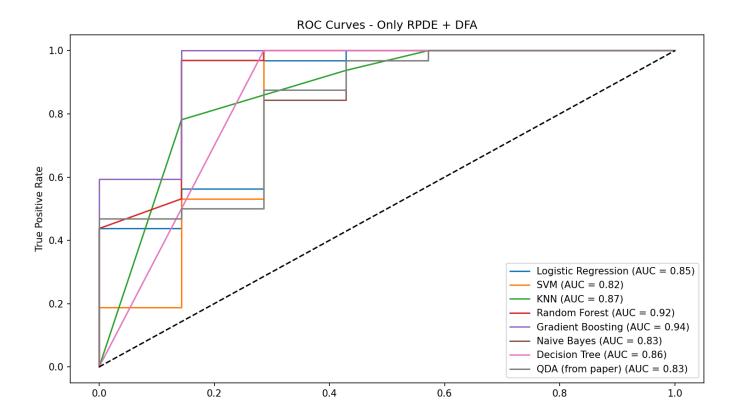












False Positive Rate