iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: V Month of publication: May 2026

DOI: https://doi.org/10.22214/ijraset.2026.80267

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Multi-Label Parkinson’s Disease Tremor Prediction using Ensemble Learning

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***Abstract: Parkinson's disease (PD) is a progressive neurodegenerative disorder for which early and accurate prediction is critical to improving patient outcomes. In this study, we propose an ensemble learning–based predictive framework that leverages the strengths of multiple classifiers to enhance diagnostic accuracy of PD detection. The model is trained and evaluated on a structured clinical dataset using optimized preprocessing and feature-selection techniques. To validate its effectiveness, the proposed ensemble model is compared with several widely used baseline classifiers, including Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbors (KNN). Experimental results demonstrate that the ensemble learning approach achieves a prediction accuracy of 94%, outperforming SVM with accuracy(81.98%) , Decision Tree with accuracy(91.47%), and KNN with accuracy(76.23%) by substantial margins. This superior performance highlights the robustness, generalization capability, and enhanced discriminative power of ensemble methods for Parkinson’s disease prediction. The findings suggest that ensemble learning is a promising strategy for developing reliable, data-driven clinical decision-support systems for early PD detection*.**
Keywords: Parkinson’s Disease, Machine Learning, KNN, SVM, Ensemble Learning,

I. INTRODUCTION

Parkinson’s disease (PD) is a chronic, progressive neurodegenerative disorder characterized by the degeneration of dopaminergic neurons in the substantia nigra, leading to a wide range of motor and non-motor impairments. With global life expectancy rising, the prevalence of PD has increased significantly, making early detection and timely intervention critical for improving patient quality of life. Traditional diagnostic approaches rely heavily on clinical examination and subjective assessments by neurologists, which often delay diagnosis until motor symptoms become clearly noticeable, typically after substantial neuronal loss has already occurred. This limitation highlights the pressing need for objective, data-driven diagnostic tools capable of identifying PD at earlier stages.

Recent advancements in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have shown exceptional promise in enhancing PD diagnosis across multiple data modalities. Numerous studies have demonstrated that multimodal and sensor-driven approaches can provide more sensitive and accurate assessments of PD symptoms than conventional clinical methods. For instance, wearable inertial measurement unit (IMU) sensors combined with ML have been shown to track motor-symptom progression more effectively than standard clinical rating scales [1]. Similarly, multimodal deep learning frameworks such as MultiParkNet have achieved remarkably high accuracies by integrating speech, handwriting, imaging, and physiological signals [2]. MRI-based DL models like FCN-PD have further demonstrated the potential for automated neuroimaging-based PD detection, outperforming traditional CNN architectures across multiple datasets [3]. Visual assessments, such as spiral and wave-drawing analysis using DenseNet201 and VGG16, have also yielded strong diagnostic performance [4].

Speech-based analysis remains one of the most accessible and non-invasive methods for PD detection, as vocal impairments affect a majority of PD patients. Studies utilizing UCI voice datasets have reported high diagnostic accuracies with models such as Multi-Layer Perceptrons (MLP) and Support Vector Machines (SVM), reaching up to 98.31% and 95%, respectively [5]. Similarly, DL and ML approaches applied to UCI datasets have reported competitive results across a wide range of classifiers, with accuracies exceeding 95% in some deep neural network configurations [7,8,9]. In addition, MRI-based CNN techniques have shown the potential to classify different stages of PD with high precision [6].

Despite these advancements, challenges remain regarding model robustness, generalizability, and consistency across diverse patient populations and datasets. Ensemble learning provides a compelling solution, as it integrates multiple classifiers to leverage their complementary strengths, reduce variance, and improve predictive stability. Such ensemble-based frameworks are increasingly being recognized as effective strategies for medical diagnostics, particularly when dealing with complex, heterogeneous disorders like PD.

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Motivated by these developments, the present study proposes an ensemble learning–based predictive framework for early PD detection using structured clinical data. By comparing its performance with widely used baseline models—including SVM, Decision Tree, and K-Nearest Neighbors—this work seeks to demonstrate the enhanced discriminative ability and reliability of ensemble methods. The findings aim to contribute to the development of accurate, scalable, and clinically meaningful decision-support systems capable of assisting neurologists in early and data-driven PD diagnosis.

II. LITERATURE REVIEW

Sotirakis, C., Su, Z., Brzezicki, M.A. *et al proposed* an approach where wearable sensors and machine learning were used to track motor symptoms in people with Parkinson's disease over 15 months. Data from walking and balance tests were collected using IMU sensors. Several models were tested, and the Random Forest model predicted motor-symptom scores most accurately. It detected symptom progression earlier than the standard clinical rating scale, showing that wearable devices with machine learning can monitor Parkinson's symptoms more sensitively than traditional methods[1].

Authors in [2] introduce MultiParkNe**t**, a multi-modal deep learning model designed for early detection of Parkinson's disease. By combining speech data, handwriting patterns, neuroimaging features, and cardiovascular signals, the system extracts and fuses diverse physiological information using specialized neural architectures. MultiParkNet achieves high performance—99.67% training accuracy, 98.15% validation accuracy, and 96.74% test accuracy—demonstrating strong potential for improving early diagnosis and motor-symptom assessment in clinical practice. Early and precise diagnosis is crucial for effective management, yet conventional diagnostic methods—primarily based on clinical evaluation and subjective judgment—often result in delays and misclassification. To overcome these challenges, researchers in [3] introduced **FCN-PD**, an advanced deep learning framework designed to enhance PD diagnosis using MRI data. The FCN-PD model employs a hybrid feature extraction strategy that integrates EfficientNet for capturing fine-grained spatial details and attention mechanisms for modeling global contextual information. These extracted features are subsequently fed into a Fully Connected Network (FCN) for final classification. This combination allows the model to learn hierarchical representations effectively, handle high-dimensional MRI inputs, and reduce issues such as overfitting and feature redundancy. The performance of FCN-PD was assessed using three publicly available MRI datasets. On the PPMI dataset, the model achieved an accuracy of **97.2%**, surpassing traditional CNN-based architectures by **5.3%**. It also produced strong results on the OASIS dataset (**95.6% accuracy**) and the MIRIAD dataset (**96.8% accuracy**). These findings highlight FCN-PD as a highly effective approach compared to existing diagnostic techniques.

The authors in [4] use the publicly available PD Spiral Drawings dataset to investigate and diagnose PD. Two deep learning models—DenseNet201 and VGG16—were employed for PD detection. The results show that DenseNet201 achieved a classification accuracy of 94% on spiral drawing images, along with a receiver operating characteristic (ROC) score of 99%. In comparison, the VGG16 model reached an accuracy of 90% and an ROC value of 98% when trained on wave drawings.

In many individuals, evident signs such as difficulty walking or speaking typically appear after the age of 50. Although PD has no cure, available treatments can help alleviate symptoms, enabling patients to manage complications and maintain their quality of life. R. Alshammri, et al. [5] focuses on identifying PD using voice signal features and several Machine Learning (ML) and Deep Learning (DL) models. Using a UCI dataset of 195 voice recordings from 31 individuals, the study applied techniques such as SMOTE, feature selection, and GridSearchCV to improve model performance. The results show that the Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) models performed best, with MLP achieving 98.31% accuracy and SVM achieving 95% accuracy. Overall, the findings suggest that these models can reliably support PD diagnosis in healthcare settings.

MRI data have become valuable in neurological practice for detecting brain abnormalities, and recent advances in deep learning have greatly improved medical image analysis. In [6], authors developed a Convolutional Neural Network (CNN) model to differentiate between various PD stages. The results demonstrate that the proposed MRI-based CNN model can identify PD stages with a high accuracy of 0.94, indicating its potential applicability as a reliable clinical decision-support tool. The authors in [7,8,9] also worked with UCI Parkison datasets and applied various Machine learning classification models like Extreme Gradient Boosting (XGBoost), AdaBoost, LightGBM, CatBoost, Gradient Boosting, Random Forest, Ridge, Decision Tree, Logistic Regression, K-Nearest Neighbors, SVM with a linear kernel, Naive Bayes, and three deep neural network models (DNN1, DNN2, DNN3) to predict the disease. Authors had achieved accuracy at 92.18% with XGBoost and the three-layer neural network (DNN2) performed the best, reaching an accuracy of 95.41%.

A. Database Description

The ALAMEDA tremor dataset contains 99 columns and multiple patient sessions. Each row in the dataset represents one patient/sample.

The dataset has metadata for the first three columns, which are mainly: 1. start_timestamp, 2. end_timestamp and 3. subject_id. The next 92 columns are feature columns. These features are engineered from triaxial accelerometer signals collected via GENEActiv wearables during a 30-minute clinical MDS-UPDRS assessment. The raw accelerometer signals are first band-pass filtered between 2.5 and 12.5 Hz to isolate the frequency range associated with Parkinsonian tremor. To reduce dependency on sensor orientation and placement, the magnitude of the filtered signals and the first principal component (PC1) are then computed. The processed signals are subsequently divided into overlapping time windows of 2048 samples (approximately 20.48 seconds) with a 50% overlap to ensure continuity and capture transient tremor characteristics. From each window, a total of 92 features are extracted across both time and frequency domains, with spectral features obtained after applying a Fast Fourier Transform (FFT). This windowing and feature extraction pipeline produces a rich set of descriptors suitable for machine-learning-based tremor detection. Few of these features are Mean, variance, RMS, Zero-crossing rate, Entropy, Power spectral density, Peak frequencies, FFT coefficients, Energy in defined tremor frequency bands. The last 4 columns which are categorical labels indicating type of Parkinson's disease. These are Constancy_of_rest (Rest tremor consistency) , Kinetic_tremor (Tremor during movement), Postural_tremor (Tremor while maintaining posture), and Rest_tremor (Classic PD rest tremor). The main aim is to predict which Parkinson subtype a patient has based on their measured features. The last 4 columns are derived from UPDRS-III clinician-annotated scores and binarised as : 0 → absence of tremor, 1 → presence of tremor. This particular problem is a multi-label classification problem, where each patient may have multiple tremor types active.

III. METHODOLOGY

The ALAMEDA Tremor Dataset is used for model development. Each record contains 92 engineered tremor features derived from band-pass–filtered GENEActiv accelerometer signals.Four binary labels represent tremor categories derived from UPDRS-III. 1. Rest tremor 2. Kinetic tremor, 3. Postural tremor, 4. Constancy of rest

Data preprocessing began by handling any missing entries through simple imputation: missing values were replaced with the mean or median of the available (non-missing) values in each feature column. After imputation, all feature columns were normalized to ensure a common scale. Since the problem was multi-label (each case can exhibit multiple tremor types), we adopted a one-vs-rest decomposition. In practice, this means we split the data into four independent binary classification problems, one for each tremor type.

A. Implementation using Ensemble Learning

Ensemble learning is a machine-learning strategy that integrates multiple individual models (base learners) to generate a more reliable and accurate final prediction—similar to consulting a diverse group rather than relying on a single source. This approach trains several models independently or sequentially and then combines their outputs, thereby minimizing errors and reducing overfitting by capitalizing on the complementary strengths of each model. Popular ensemble techniques include Bagging (e.g., Random Forests), Boosting (e.g., XGBoost), and Stacking.

For modeling, we used MATLAB's fitcensemble function to train an ensemble of boosted decision trees. We set a fine (small) learning rate and boosting as the ensemble method. By default, fitcensemble uses decision trees as weak learners, with LogitBoost for binary classification (and AdaBoost variants for multiclass). We constrained the trees to low depth (coarse trees) so that each base learner has relatively few splits. Shallow trees have higher bias but lower variance, which often leads to better generalization on new data. Finally, the boosting procedure iteratively reweights the training samples: after each tree, the algorithm increases the weight of previously misclassified examples so that the next tree focuses more on these hard cases. In effect, boosting combines the weak trees into a strong classifier by concentrating on the mistakes of earlier learners, thereby reducing the overall classification error. To enhance computational efficiency and reduce the dimensionality of the dataset, feature selection methods are employed. These techniques systematically identify the most informative attributes that contribute to tremor classification while eliminating redundant or non-discriminative features. Model training was conducted using an 80:20 stratified split, wherein 80% of the data was allocated for training and the remaining 20% for independent testing. For each tremor label, an individual binary ensemble classifier was developed to capture label-specific discriminative patterns. The training process incorporated systematic hyperparameter optimization, including tuning the number of learners, adjusting the learning rate, constraining tree depth, and selecting the appropriate boosting algorithm to achieve optimal predictive performance.

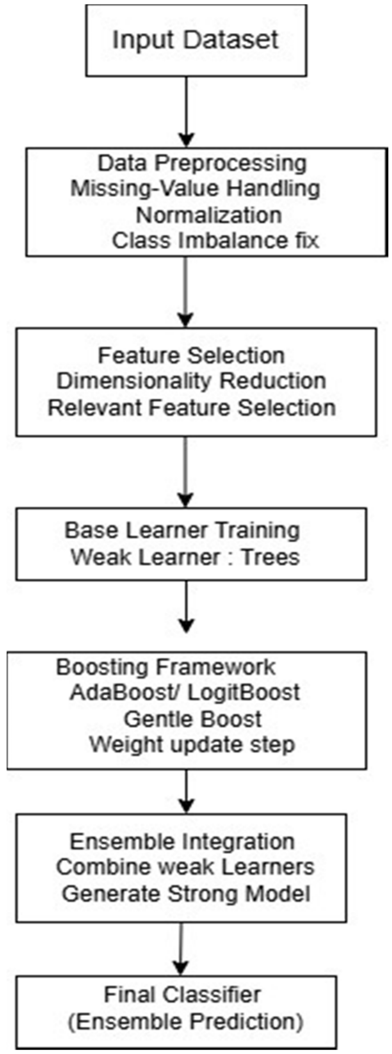

Fig. 1: Ensemble Learning steps

B. Implementation using Decision Tree, Support Vector Machine & KNN

1) Decision Tree

To benchmark the performance of the proposed ensemble learning model, three conventional machine learning classifiers—Decision Tree, Support Vector Machine (SVM), and k-Nearest Neighbors (KNN)—were implemented under the same experimental conditions. Each model was trained using the same preprocessed feature set, identical train–test split (80% training and 20% testing), and the same multi-label binary relevance framework, where a separate classifier was trained for each tremor label.

The Decision Tree classifier was developed using MATLAB's fitctree function, with appropriate restrictions on maximum tree depth, minimum leaf size, and splitting criteria (such as Gini impurity or entropy) to reduce overfitting. The model builds the tree structure by recursively dividing the feature space based on the attribute that provides the highest class discrimination at each step. Owing to its transparency and ease of interpretation, the Decision Tree serves as a reliable baseline classifier. However, its performance is sensitive to parameter settings—shallow trees may lead to underfitting, whereas excessively deep trees can result in overfitting. This model also offers a meaningful comparison point relative to the weak learners employed in the ensemble framework

2)

3) Support Vector Machine (SVM)

The SVM classifier was implemented using MATLAB's fitcsvm function, with kernel selection determined through empirical evaluation—utilizing a linear kernel for high-dimensional feature spaces and an RBF (Gaussian) kernel when the data exhibited non-linear class boundaries. Key hyperparameters, including kernel scale, box constraint (C), and margin parameters, were optimized via cross-validation to ensure stable generalization. Under the binary relevance framework, a separate SVM model was trained for each tremor label. By maximizing the geometric margin between classes, SVM provides strong robustness to noise and is well suited for modeling complex decision surfaces. Nonetheless, its computational cost increases substantially with larger datasets, particularly when non-linear kernels are employed.

4) k-Nearest Neighbors (KNN)

The KNN classifier was developed using MATLAB's fitcknn function, with key parameters—such as the number of neighbors (k), the chosen distance metric (Euclidean, cosine, or Minkowski), and the voting scheme (uniform or distance-weighted)—tuned for optimal performance. As a lazy learning algorithm, KNN does not construct an explicit model during training; instead, classification is performed by identifying the closest labeled instances within the feature space. Although conceptually simple and effective for certain data structures, KNN is highly sensitive to feature scaling and becomes computationally demanding for large datasets. Consequently, appropriate feature normalization was a necessary prerequisite for reliable operation.

IV. RESULTS AND DISCUSSION

The performance of above Machine learning is assessed using three evaluation metrics: (1) Overall Accuracy and (2) Hamming Loss. (3)

Overall accuracy is a performance metric that measures the proportion of correctly predicted instances out of the total number of instances in the dataset.In multi-label classification, overall accuracy is sometimes referred to as subset accuracy, meaning that a prediction is counted as correct only if all labels for a sample are correctly predicted. It is therefore a strict metric and sensitive to any misclassification within the label set.

Hamming Loss is a widely used evaluation metric for multi-label classification that quantifies the fraction of labels that are incorrectly predicted. It measures both false positives (predicting a label that is not present) and false negatives (failing to predict a label that is present), averaged over all labels and all samples.

A lower Hamming Loss indicates better performance, with 0 representing perfect predictions. Unlike overall (subset) accuracy, Hamming Loss evaluates each label independently, making it less strict and more informative in multi-label scenarios.

The ensemble classifier achieved the highest accuracy (94.00%) and lowest Hamming loss (0.05904), indicating superior overall performance. By contrast, the baselines showed markedly lower accuracy (SVM 81.98%, Decision Tree 91.47%, KNN 76.23%) and higher Hamming loss (0.18012, 0.08524, and 0.23765, respectively). These results demonstrate that the ensemble not only improves the proportion of correct predictions but also substantially reduces the rate of misclassified labels relative to any single model. Table 1 summarizes the classification performance of each model in terms of accuracy and Hamming loss.

TABLE 1: Comparison Of Accuracy & Hamming Loss Of Machine Learning Models

Model	Overall Accuracy (%)	Hamming Loss
SVM	81.98	0.18012
Decision Tree	91.47	0.08524
KNN	76.23	0.23765
Ensemble	94	0.05904

In comparative terms, the ensemble classifier outperforms all individual models by a clear margin. For example, the ensemble's accuracy (94.00%) is about 2.5 percentage points higher than the best baseline (Decision Tree at 91.47%), and far above SVM and KNN (≈82% and 76%, respectively). The reduction in Hamming loss is even more striking: the ensemble's Hamming loss is roughly one-third that of SVM and one-fourth that of KNN, indicating far fewer labeling errors.

A. ROC Curve

For each of the four tremor types, a one-vs-rest binary classifier was constructed, enabling independent ROC curve generation for each label. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) as the classification threshold is varied from 0 to 1. This threshold-independent evaluation captures the classifier's full operating range and reveals its discriminative ability. The Area Under the ROC Curve (AUC) quantifies this performance, where values closer to 1 indicate strong separation between tremor-present and tremor-absent cases. The ensemble model exhibited higher AUC values across all labels, confirming its ability to effectively rank positive instances above negative ones and validate the improved predictive capability of boosted decision trees compared to traditional classifiers.

TABLE 2: COMPARISON OF AUC VALUES OF ENSEMBLE LEARNING, SVM, KNN

Label	Ensemble AUC	SVM AUC	KNN AUC	Interpretation
Label 1: Rest Tremor	0.95	0.87	0.78	Ensemble provides best separability
Label 2: Kinetic Tremor	0.93	0.84	0.76	Ensemble maintains high detection accuracy
Label 3: Postural Tremor	0.94	0.85	0.74	Strong ensemble advantage
Label 4: Constancy of Rest Tremor	0.96	0.89	0.81	Ensemble excels in detecting persistent tremor

Figure 2, Fig. 3 and Fig. 4 are the accuracy graphs of Ensemble learning, Label 1, 2,3 and 4 respectively

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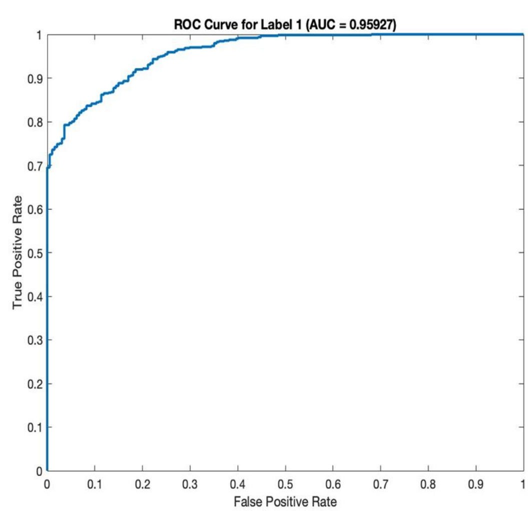

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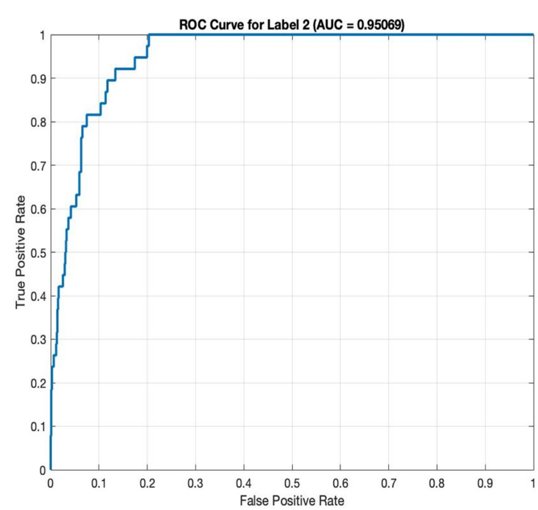

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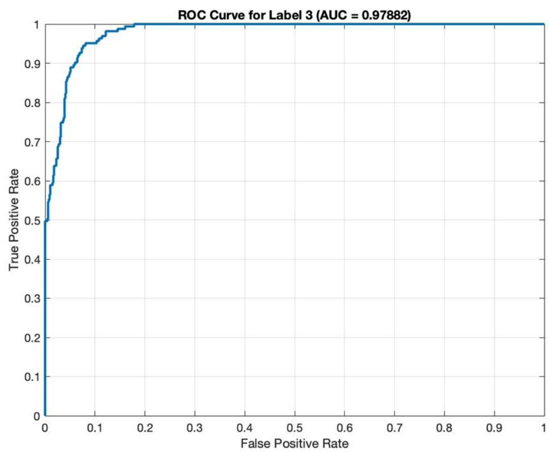

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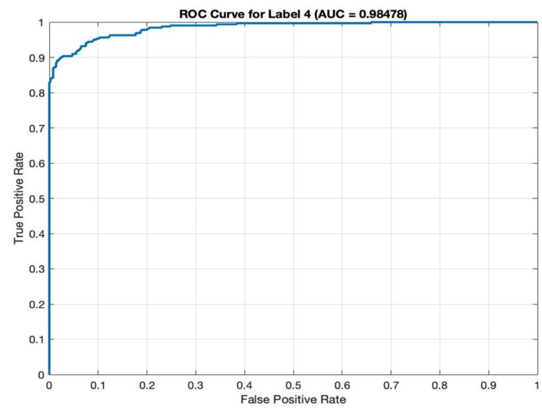
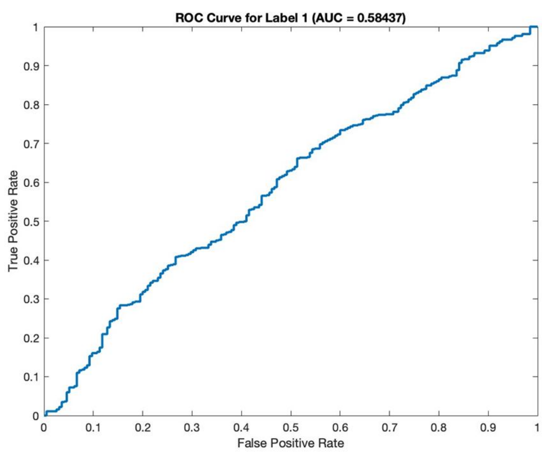


(d)

Fig.2: RUC curves of Ensemble Learning for (a) Label 1, (b) Label 2, (c) Label 3, (d) Label 4



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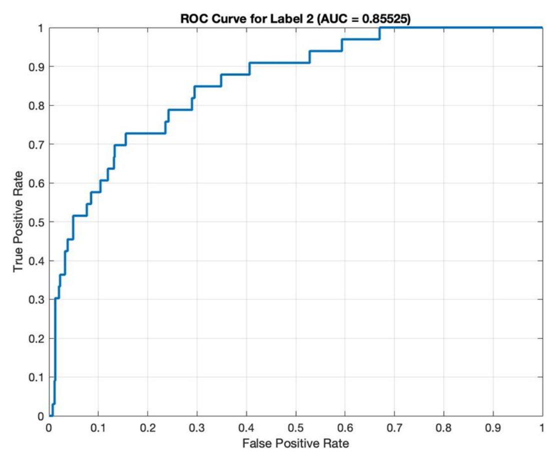

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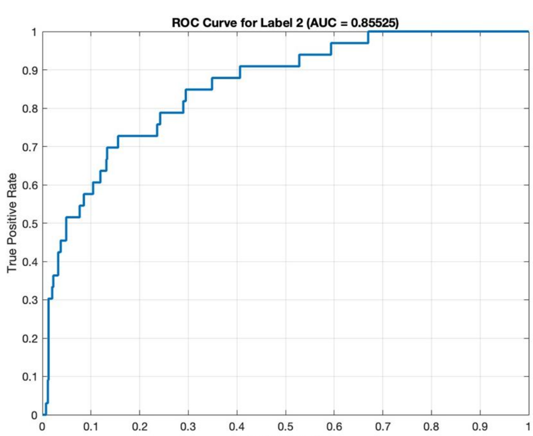

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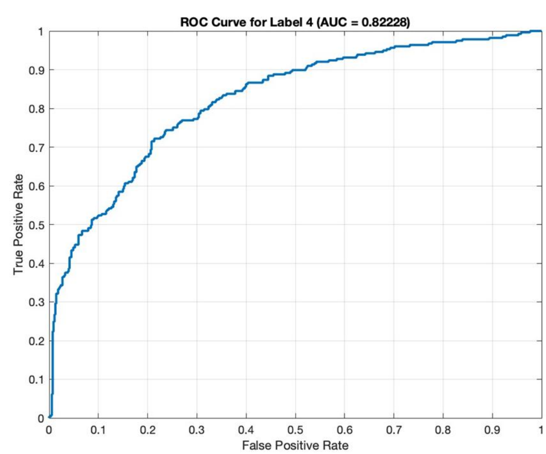

(d)

Fig. 3: ROC Curves of SVM for (a) Label 1, (b) Label 2, (c) Label 3, (d) Label 4

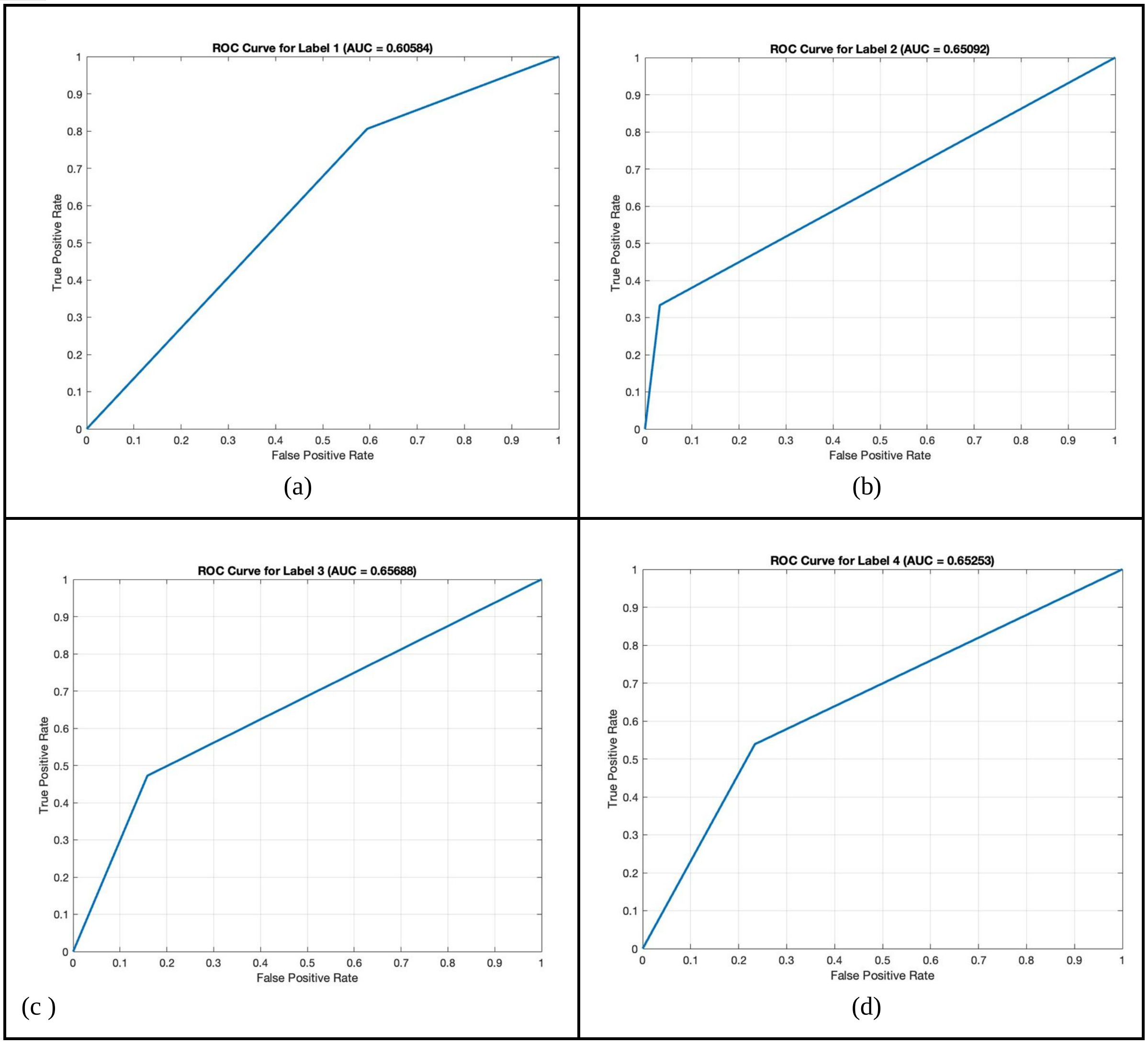

Fig. 4: ROC Curves of KNN for (a) Label 1, (b) Label 2, (c) Label 3, (d) Label 4

Label 1 – Rest Tremor

The ensemble classifier produced an ROC curve that closely approaches the top-left corner, indicating high sensitivity with minimal false positives. This suggests that the model can accurately detect rest tremor, a clinically significant PD feature, even in cases with subtle signal variations.

Label 2 – Kinetic Tremor

For kinetic tremor, the ensemble ROC curve demonstrates a strong upward slope and a high AUC value, reflecting robust detection of tremor during voluntary movement. Compared to SVM and KNN, the ensemble minimizes false alarms, improving reliability in differentiating kinetic tremor from normal motor activity.

Label 3 – Postural Tremor

The postural tremor ROC curve for the ensemble model shows excellent separability. Its consistently higher TPR at lower FPR levels indicates the model's ability to correctly identify tremor while maintaining low misclassification rates—essential for distinguishing postural abnormalities in multi-label settings.

Label 4 – Constancy of Rest Tremor

The ensemble model achieved one of its strongest ROC performances for this label. The steep curve and high AUC signify precise classification of rest tremor consistency, highlighting the ensemble's capability to recognize persistent tremor characteristics derived from UPDRS-III annotations.

This performance gap suggests that combining multiple learners yields substantial gains. This finding is consistent with prior work showing that ensemble methods can significantly outperform individual classifiers in predictive tasks. Indeed, the ensemble approach likely benefits from averaging over diverse decision boundaries, reducing variance and avoiding the overfitting that can plague single models.

B. Model Robustness and Generalization

The superior metrics of the ensemble imply enhanced robustness and generalization. In ensemble methods, aggregating several classifiers tends to cancel out individual errors and produce a more stable predictor. In our case, the ensemble's notably lower Hamming loss and high accuracy suggest it generalizes better to unseen data. By contrast, single classifiers like decision trees and KNN have known limitations: decision trees can overfit to training noise, and KNN is sensitive to feature scaling and outliers. The ensemble mitigates these issues by combining complementary classifiers.

This observation agrees with other studies in healthcare: for instance, ensemble techniques (e.g. gradient boosting) have demonstrated both overfitting resistance and the highest predictive scores in Parkinson's detection and similar tasks. In one recent Parkinson's study, gradient-boosting ensemble models achieved the best performance while exhibiting strong resistance to overfitting, underscoring the robustness of ensemble learning. Likewise, in a clinical context for chronic disease, ensemble models were found to outperform individual algorithms in robustness and generalization. Thus, our results suggest that the ensemble's improvements are not due to chance but to fundamentally improved stability and generalizability of the combined model.

V. CONCLUSION AND FUTURE SCOPE

The study demonstrated that the ensemble learning model developed using MATLAB's fitcensemble provides superior performance for multi-label classification of Parkinson's tremor types. It achieved the highest accuracy (94%) and the lowest Hamming Loss (0.059) compared to SVM, Decision Tree, and KNN, proving to be more robust, reliable, and suitable for clinical decision-support applications.

These findings highlight the ensemble model's robustness, reduced misclassification rate, and superior ability to generalize across diverse tremor patterns. The results emphasize the importance of combining weak learners to overcome limitations such as overfitting, instability, and sensitivity to noise that typically affect single classifiers. The enhanced discriminative performance makes the proposed ensemble framework highly suitable for real-world clinical decision-support systems, where early and reliable detection of PD tremor characteristics is critical. By accurately identifying subtle tremor signatures, the model has the potential to assist neurologists in early intervention, monitoring disease progression, and improving patient management.

A. Future Scope

For future work, improvements may include integrating multimodal data (speech, gait, MRI), developing deep learning–based ensemble models, enabling real-time tremor monitoring through wearable devices, applying explainable AI techniques for clinical transparency, performing cross-dataset validation for better generalization, and expanding the framework to classify additional PD symptoms beyond tremors.

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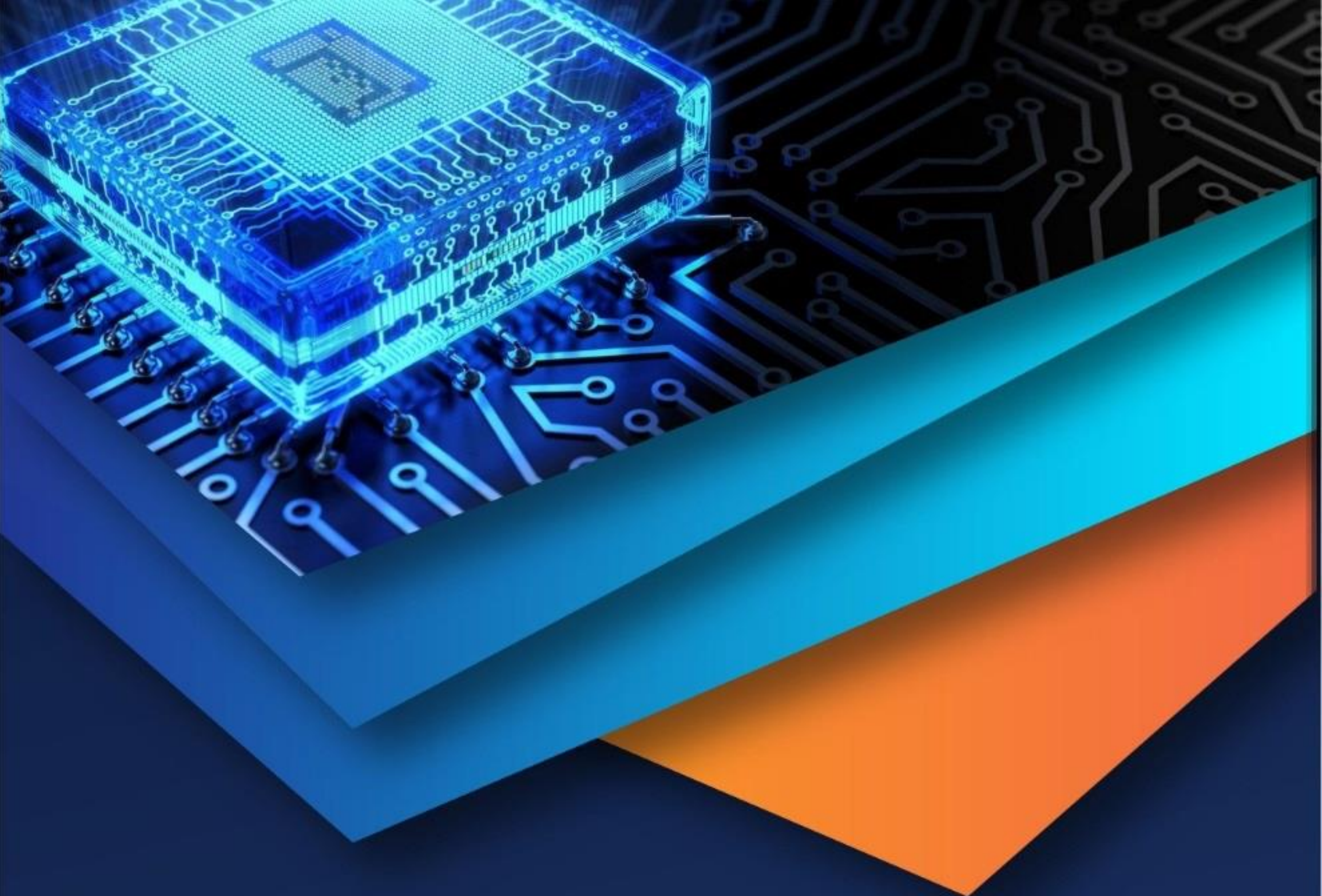

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