Machine Learning CSE343

Mid Semester Presentation

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Motivation

- Importance of Early Diagnosis in Parkinson's Disease (PD):
  - By the time motor symptoms appear, over **60% of dopaminergic neurons** are damaged, limiting treatment effectiveness.
  - Early detection is crucial to slow disease progression and improve patient outcomes
- Personal Relevance:
  - Three team members are currently studying **Cognition of Motor Movements (PSY308)**, gaining insights into the challenges of PD diagnosis, deepening the motivation for improving diagnostic methodologies

Literature Review

- Study 1: Alshammri et al. (2023)
  - **Objective:** Used telemedicine and machine learning to detect early-stage PD using the MDVP voice dataset.
  - **Approach:** Trained four models—Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression.
  - **Results:** Random Forest achieved the highest accuracy (91.83%) and sensitivity (0.95), indicating its potential for PD detection. However, the study faced limitations due to the **small sample size (31 participants)** and the **exclusive use of voice data**, which may not capture all PD symptoms

Literature Review

- Study 2: Singh et al. (2016)
  - **Objective:** Investigated early PD detection using over 100 features extracted from brain MRI images.
  - **Approach:** Used SVM with Principal Component Analysis (PCA) for dimensionality reduction and Fisher Discriminant Ratio (FDR) for feature selection.
  - **Results:** Yielded very high classification accuracies but had high computational costs.

Literature Review

- Study 3: Prashanth et al. (2016)
  - **Objective:** Investigated early PD detection using multimodal features (REM sleep behavior, olfactory loss, cerebrospinal fluid markers) from the PPMI database.
  - **Approach:** Used Naïve Bayes, Support Vector Machine (SVM), Boosted Trees and Random Forests classifiers.
  - **Results:** Achieved a 96.40% accuracy for early PD diagnosis with 401 PD cases and 183 healthy controls. This study showed the effectiveness of combining non-motor features and imaging data for accurate diagnosis.

Dataset description

- **Source:** The dataset was sourced from the **Parkinson's Progression Markers Initiative (PPMI)**, an international effort to identify PD biomarkers.

- **Composition: 13,000+ records** from **3,096 participants**.
  1736 PD patients,
  1,018 prodromal cases,
  279 healthy controls,
  63 SWEDD cases (No Evidence of Dopaminergic Deficit).

Parkinson's Progression Markers Initiative

- **Key Attributes:**
  Combination of motor and non-motor features like sleep behavior disorder, olfactory loss, CSF proteins and cognitive-behavioral test results.

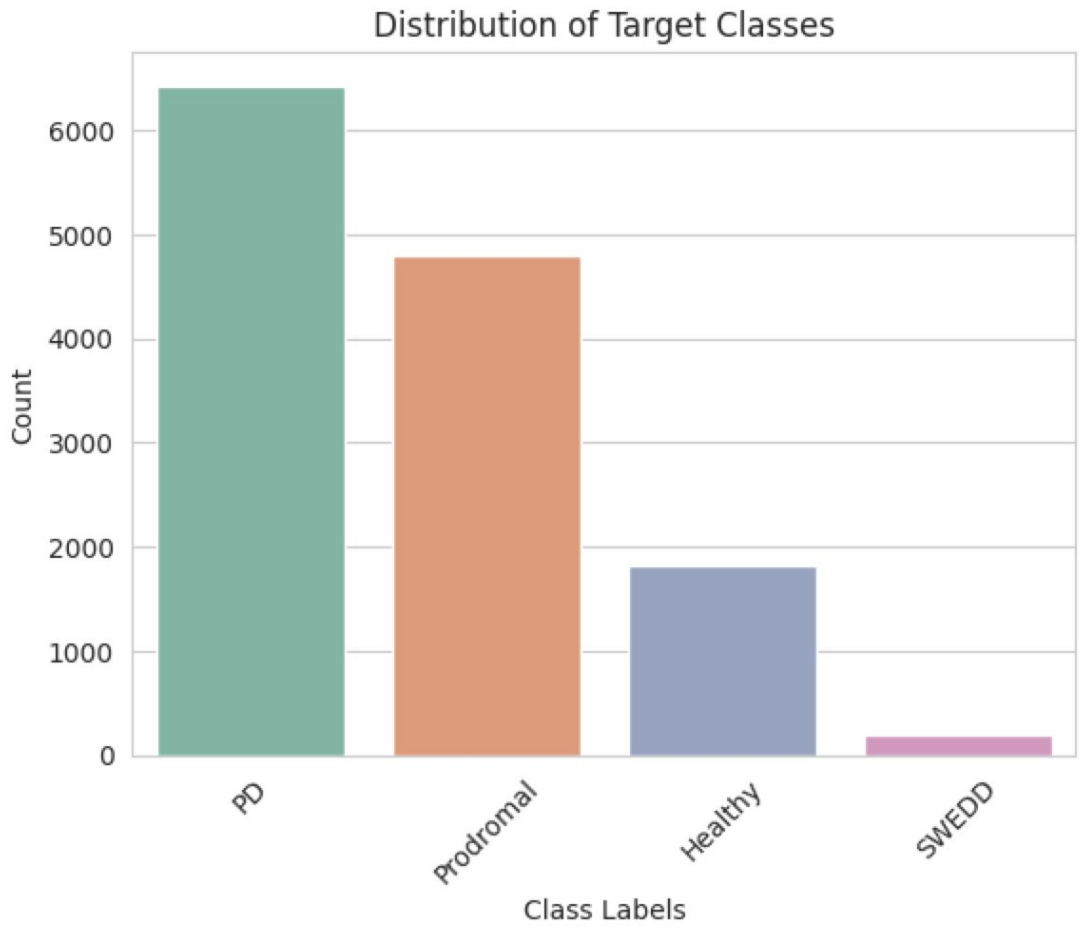
Key Features in Dataset

Category	Feature	Description
Clinical	**UPSIT**	University of Pennsylvania Smell Identification Test, Used to measure olfactory dysfunction
Clinical	**REM**	Measure of REM sleep disorder in patients, is a strong early non-motor symptom linked to PD
Biologics	**Abeta**	Protein in cerebrospinal fluid, related to cognitive decline & Alzheimer's
Biologics	**Tau**	Protein in cerebrospinal fluid, related to cognitive decline & Alzheimer's

Key Features in Dataset

Category	Feature	Description
Biologics	**Ptau**	Protein associated with cognitive decline and helps distinguish PD from other neurodegenerative diseases
Clinical	**MSEADLG**	Modified Schwab & England ADL Score, evaluates cognitive impairment impact on daily living activities
Demographics	**Age**	A major risk factor for PD, with its prevalence increasing in older populations
Demographics	**fampd**	Family history of PD, higher risk of developing the condition due to hereditary factors

Data Distribution



Before Preprocessing:

The dataset exhibited **class imbalance**, where certain classes (e.g., Parkinson's Disease and Prodromal cases) had significantly more samples compared to the Healthy Control group, making it harder for the model to learn effectively from the minority class.

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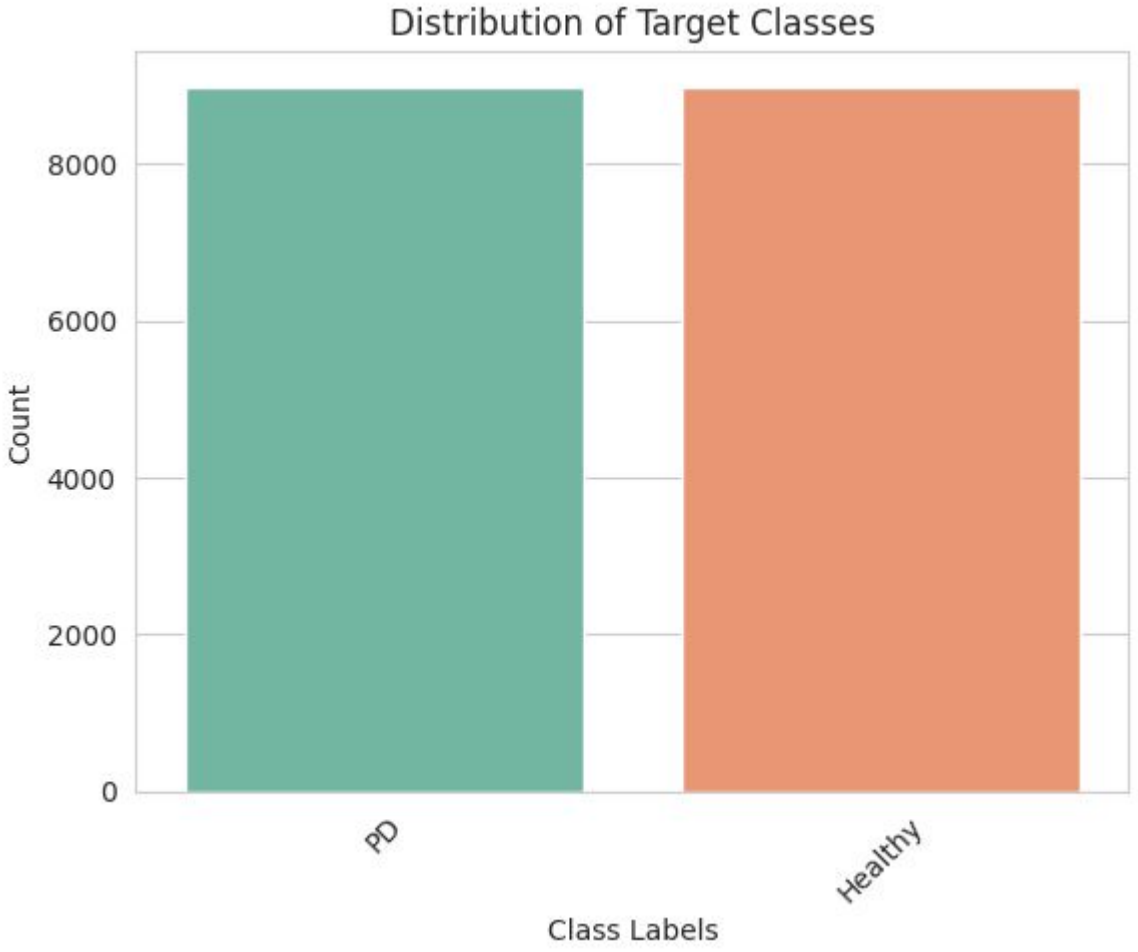

After Preprocessing:

Class imbalance was reduced using **SMOTE (Synthetic Minority Over-sampling Technique)**, resulting in a more even distribution of samples across classes, improving the model's ability to learn from underrepresented classes.

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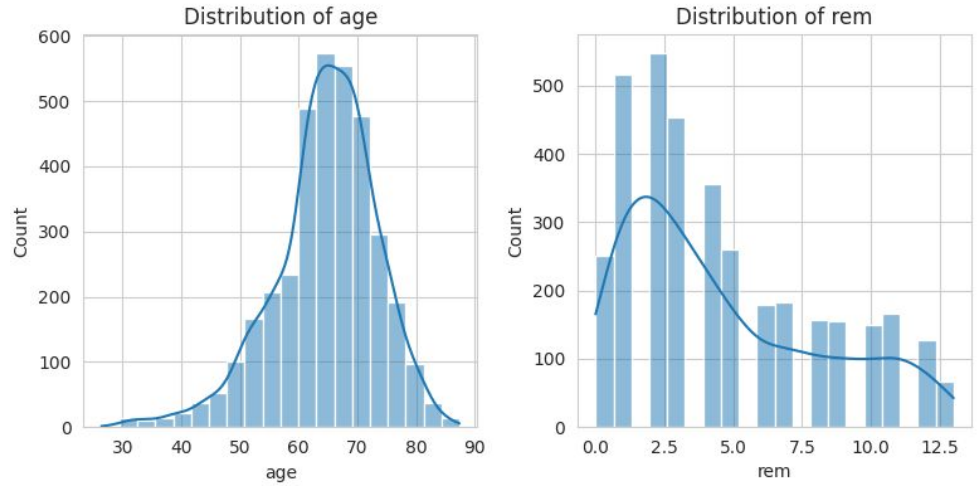

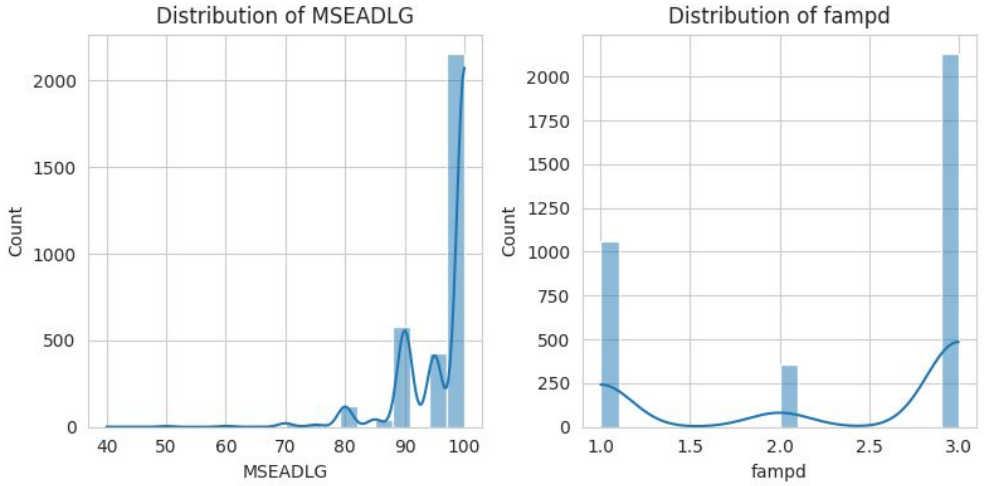

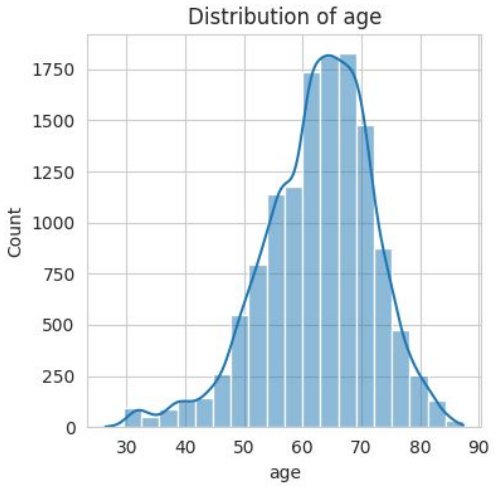

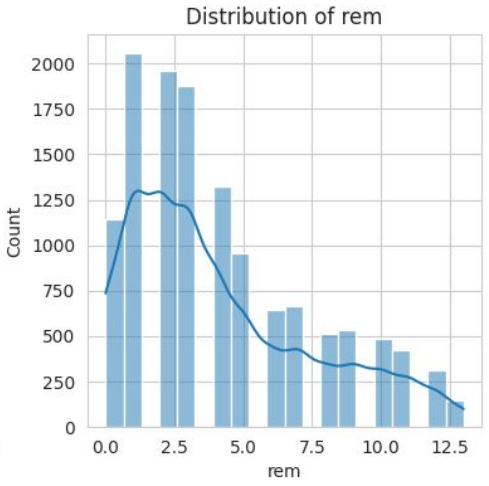

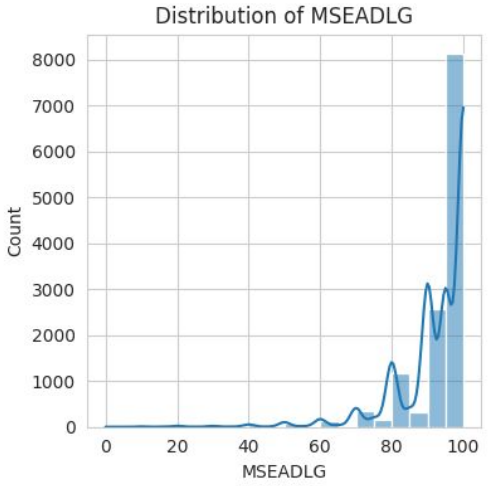

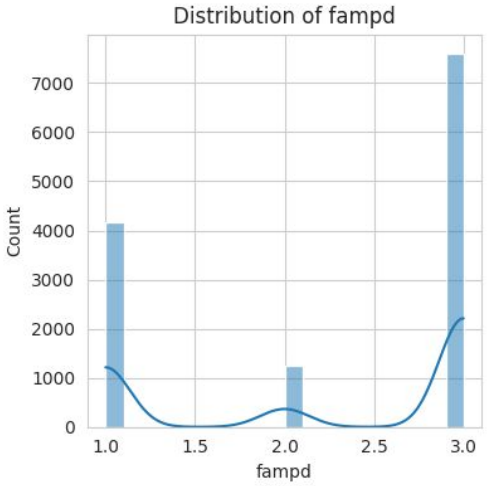

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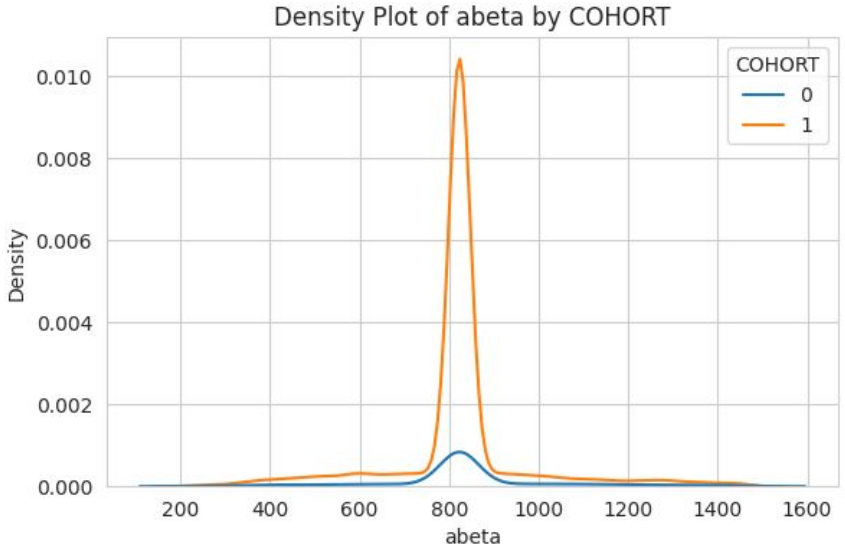

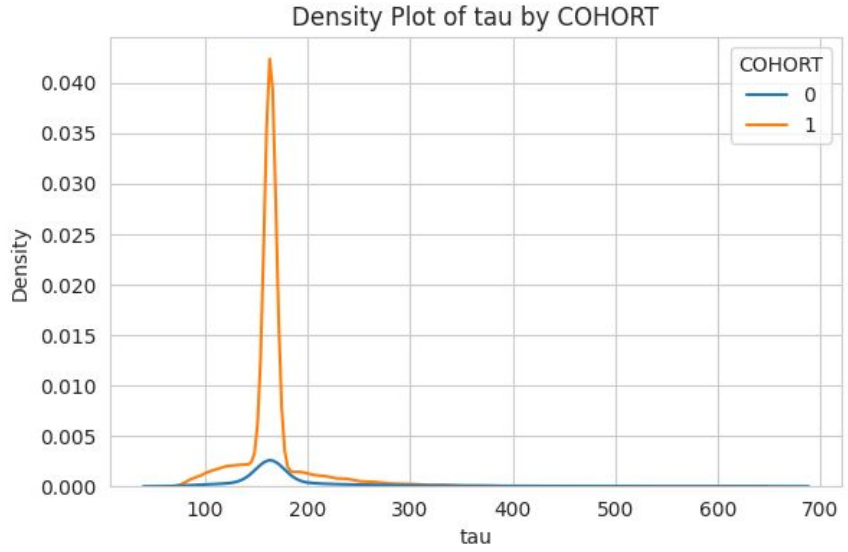

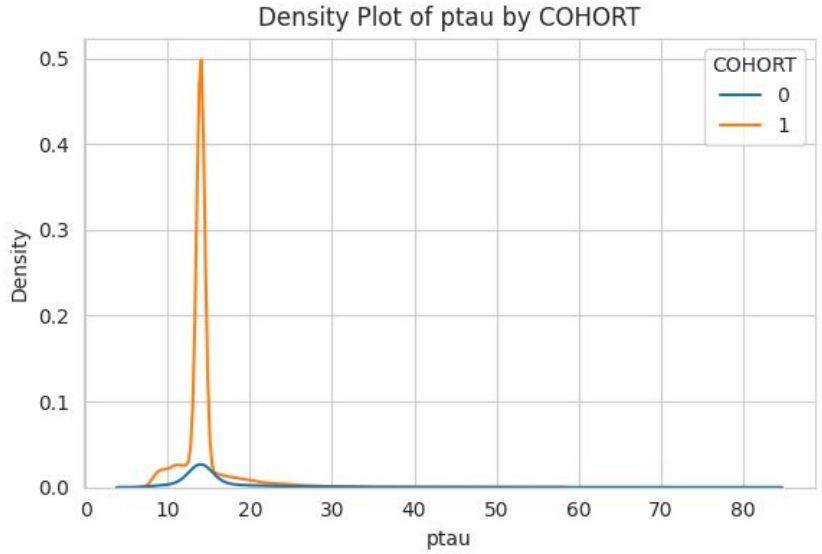

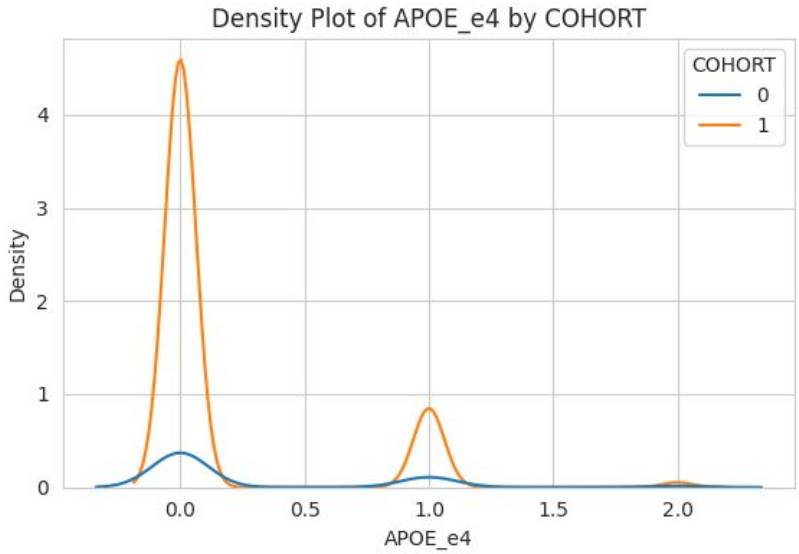

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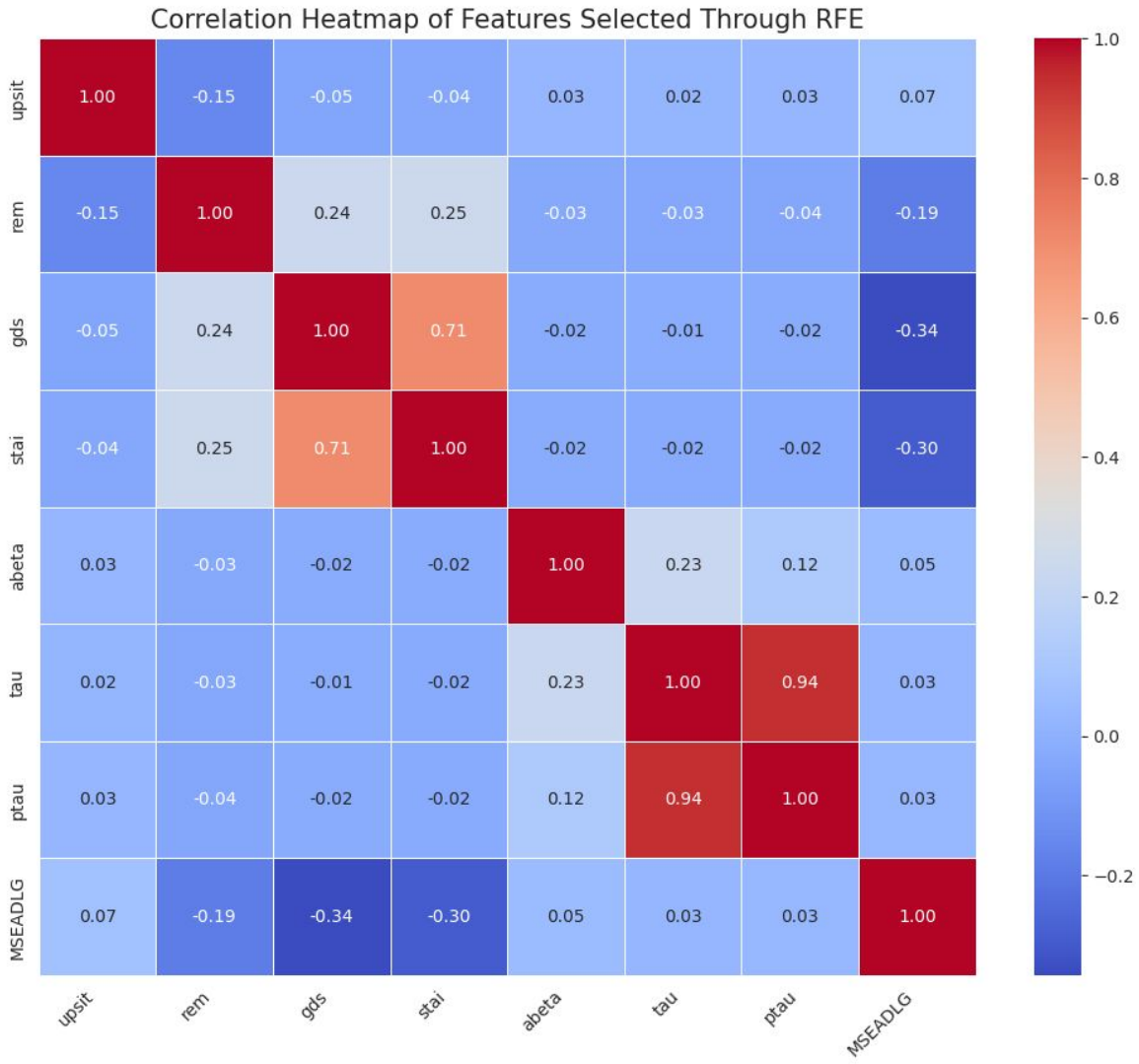

Positive Correlation: Strong positive correlation observed between MSEADLG and tau/ptau, indicating that as cognitive decline worsens (higher MSEADLG score), tau protein levels also increase.

Negative Correlation: Negative correlation found between MSEADLG and upsit/rem, suggesting that higher cognitive decline is associated with lower olfactory function (UPSIT) and REM sleep quality.

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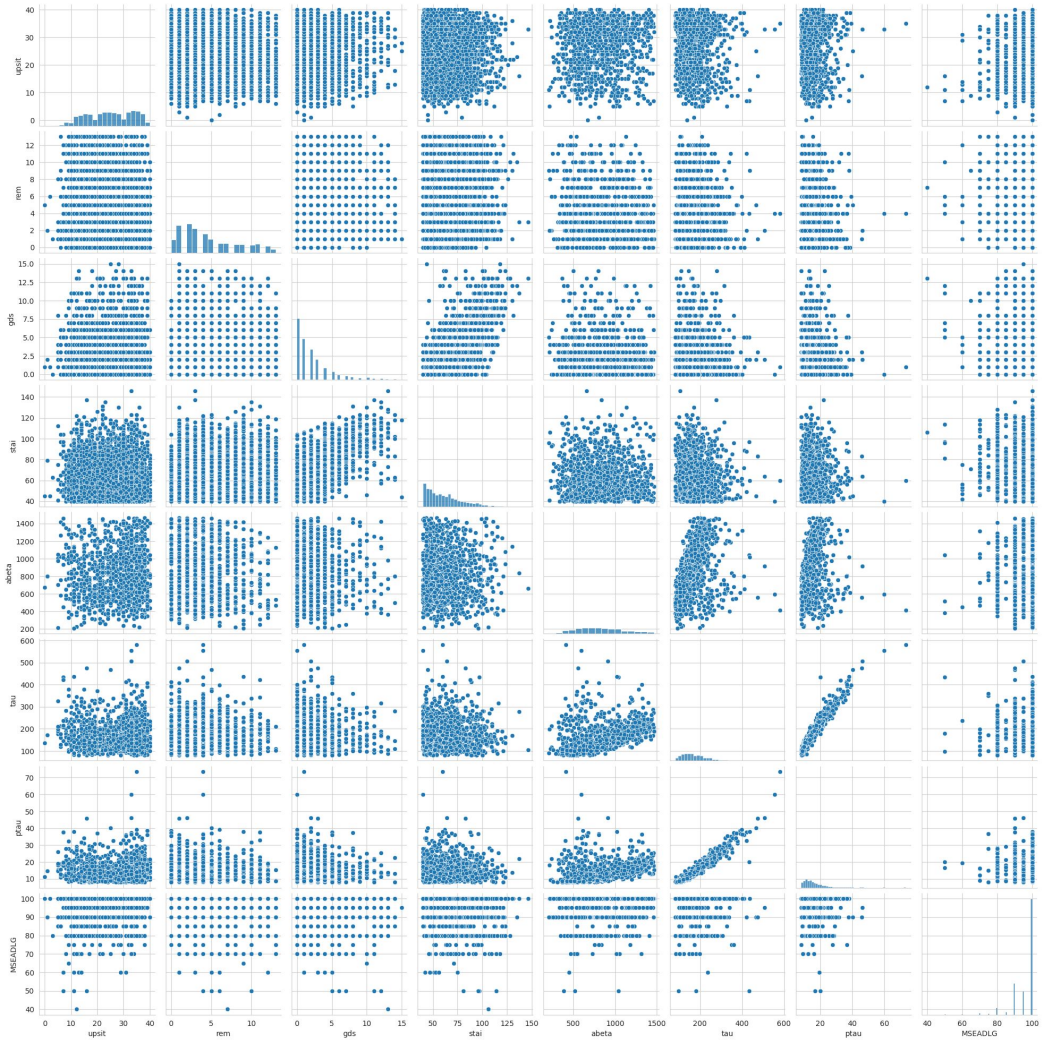

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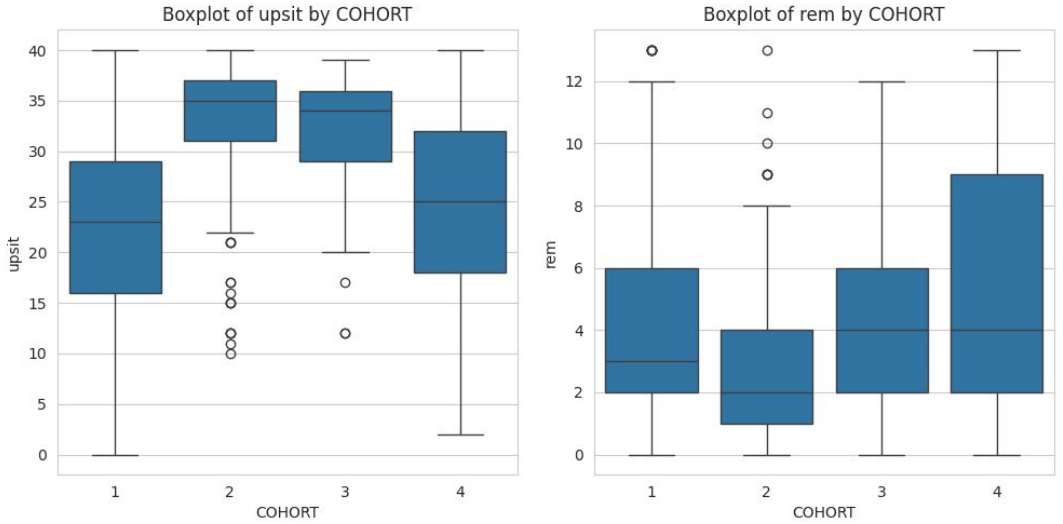

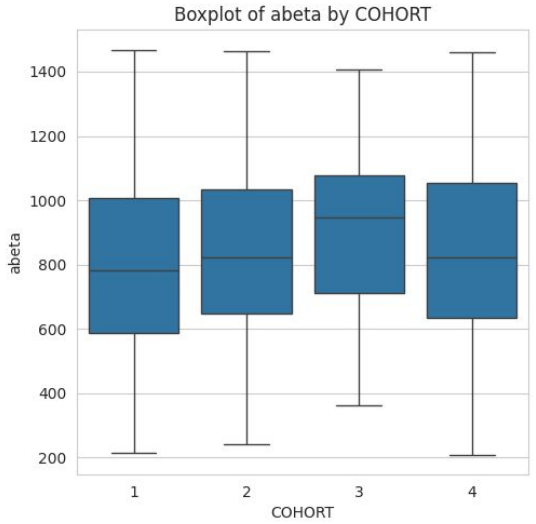

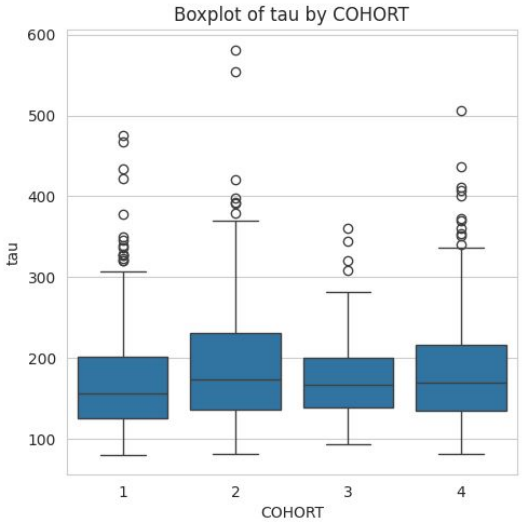

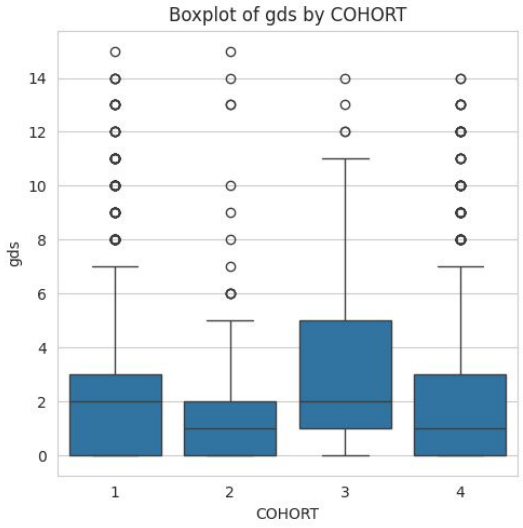

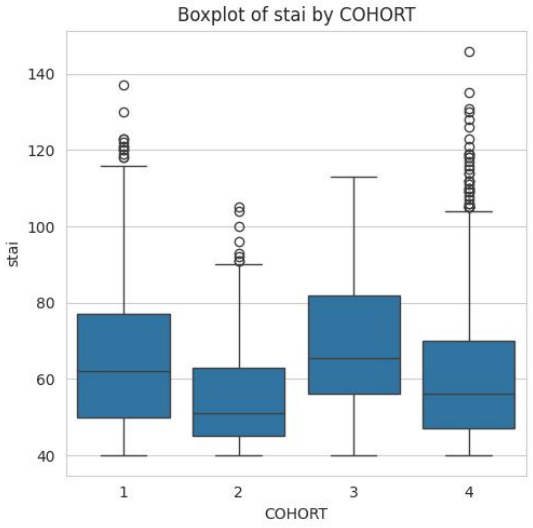

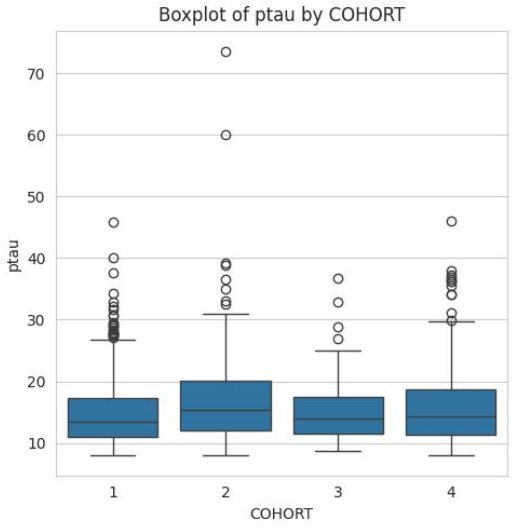

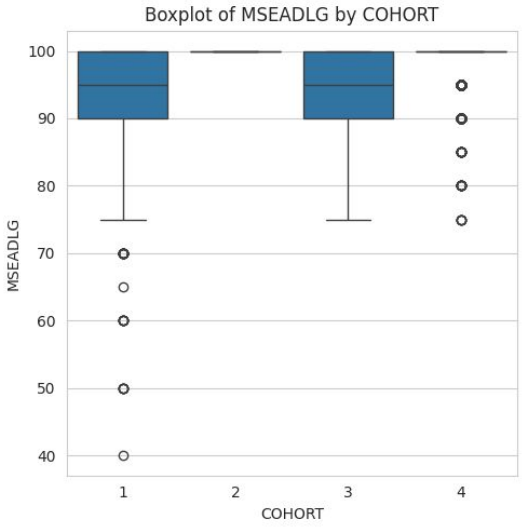

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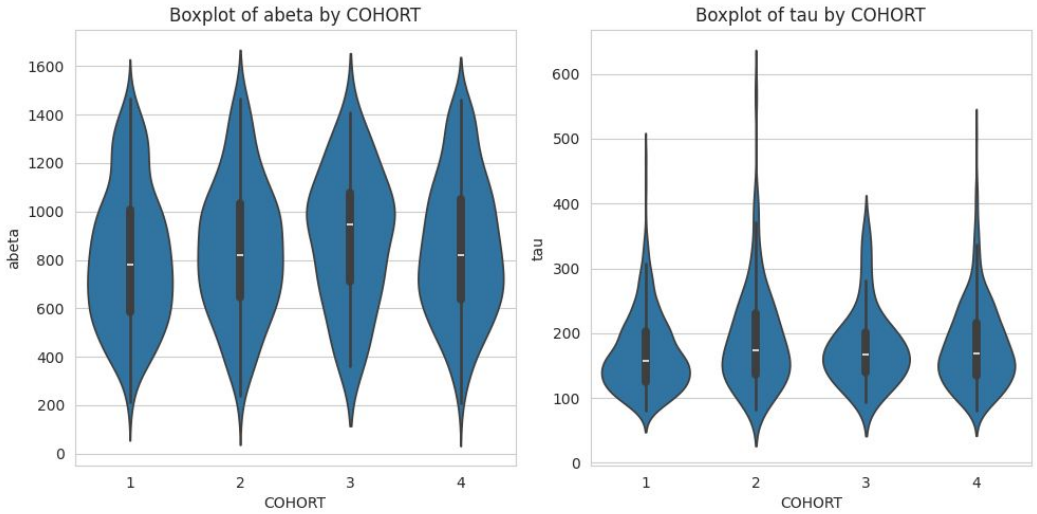

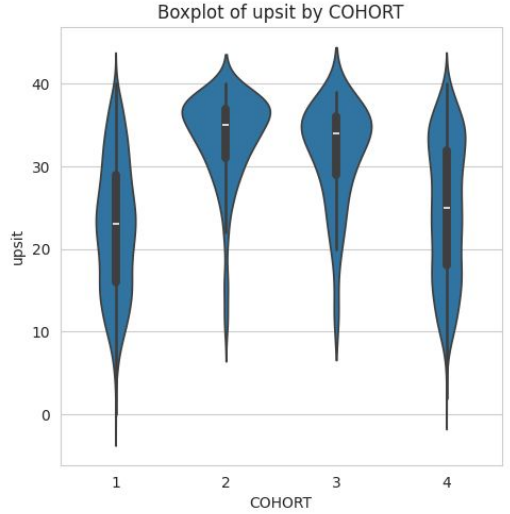

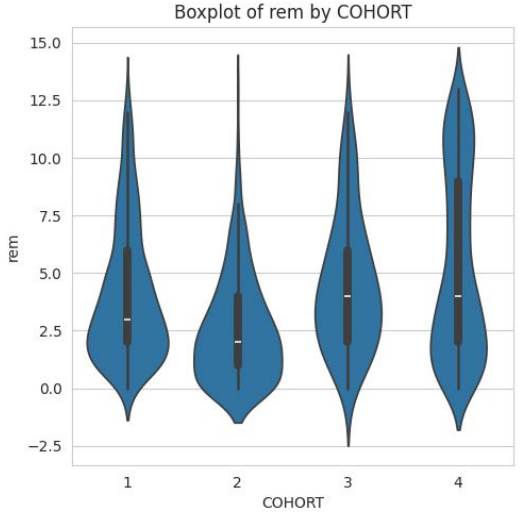

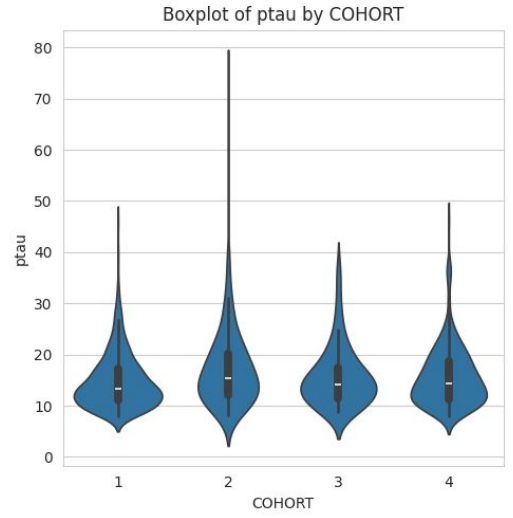

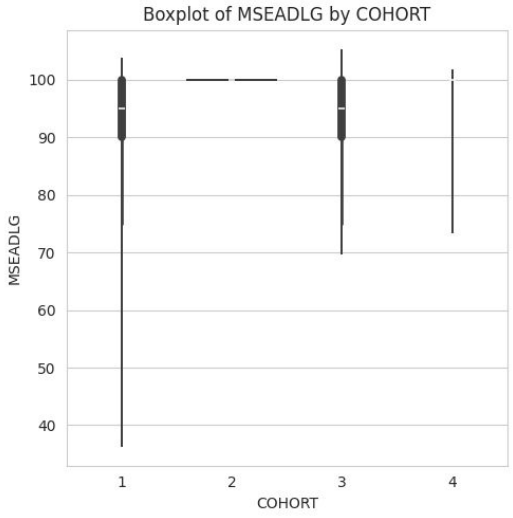

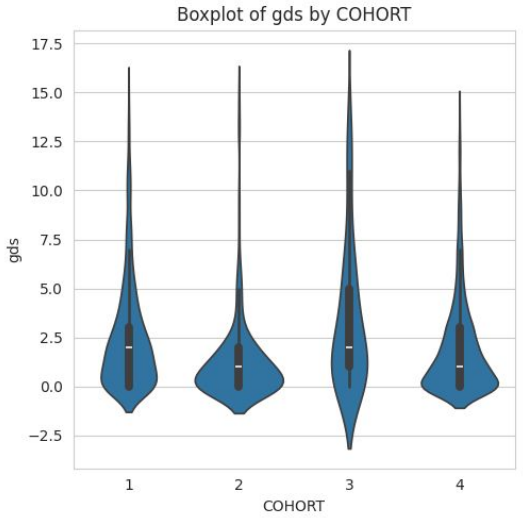

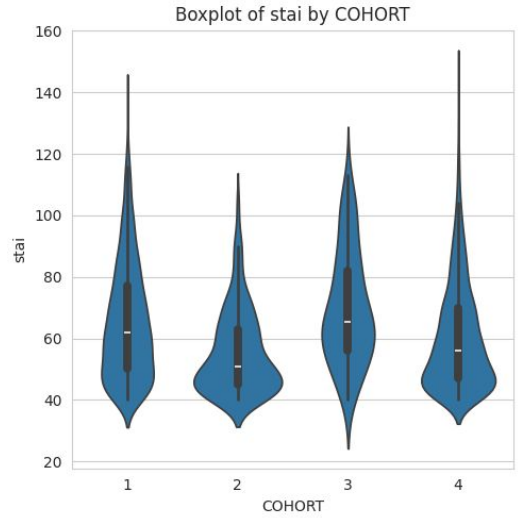

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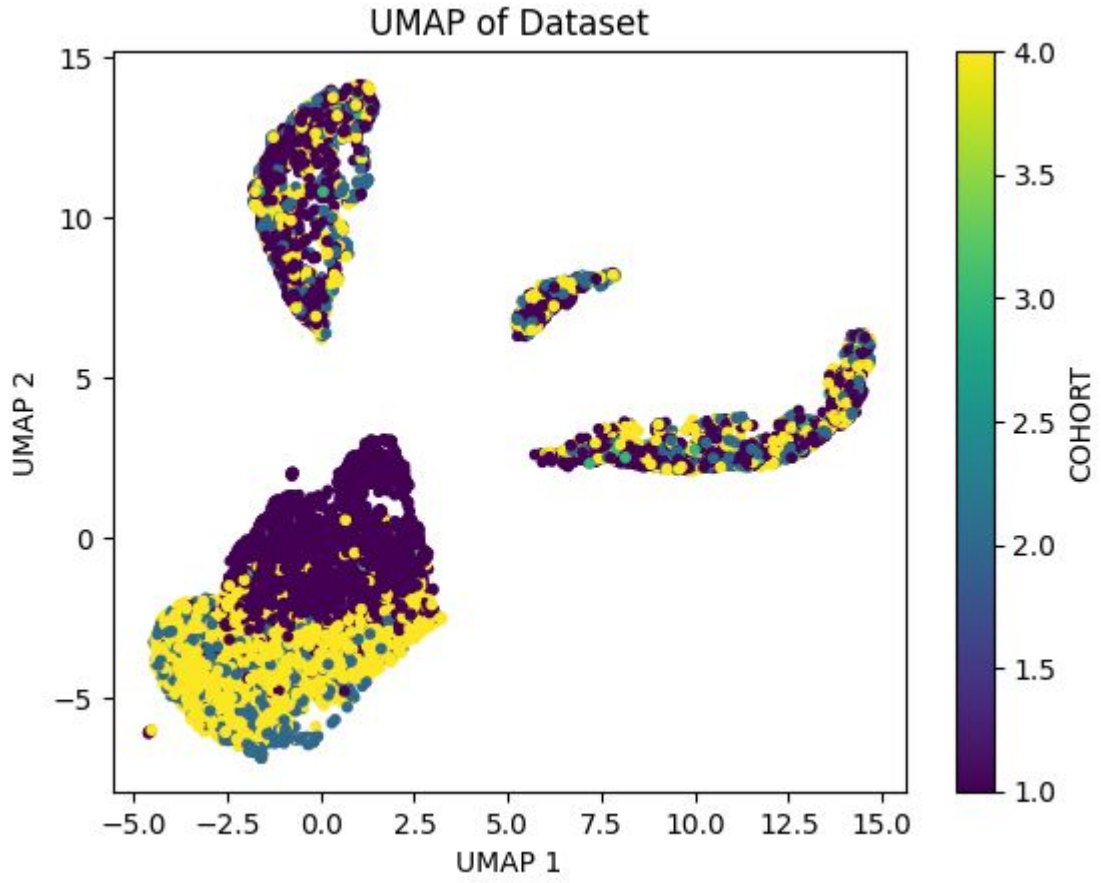


UMAP Components: Shows two reduced dimensions (UMAP 1 & 2).

Clusters: Distinct groups of data points are visible, indicating meaningful separation.

Color (Cohort): Color represents cohort values (1-4), with dark to light gradients.

Class Separation: Clear separation between different cohorts, especially in lower left and upper regions.

Pattern: UMAP reveals both local and global structures in the data.

Data Preprocessing

01

- Removed features with over **50% missing values.**
- **Imputed missing values** for numerical features using the mean and for categorical features using the mode.

Handling Missing Data

02

- Applied Recursive Feature Elimination (RFE) to **reduce features from 158 to 44**.
- Selected features include combination of motor, non-motor and genetic factors (e.g., REM, UPSIT, Tau, Abeta, MSEADLG).

Feature Selection

03

- **Initially a four-class problem** (PD, Prodromal, Healthy Controls, SWEDD).
- Simplified into a **binary classification t**ask by merging PD and Prodromal cases, and excluding SWEDD.

Target Variable

Data Preprocessing

04

- Observed imbalance between PD/Prodromal cases and Healthy Controls.
- Addressed using SMOTE (Synthetic Minority Over-sampling Technique) to balance the classes.

Class Imbalance

05

- Applied **standard scaling** to normalize the feature values for models like logistic regression, which are sensitive to data scale

Feature Scaling

Methodology & Models

Objective: Predict Parkinson's disease prediction using clinical and biomarker data, **focusing on non-motor symptoms.**

Data Collection: Conducted literature survey and looked through multiple datasets online using tools like Google Scholar.

Data Preprocessing: Handling missing data, feature selection, Standard scaling for features

- **Feature Selection**: Used Recursive Feature Elimination (RFE) to identify critical features like UPSIT, REM sleep disorder, Abeta, Tau, Ptau, MSEADLG, age, and family history (FAMPD).
- **Class Imbalance Handling**: Applied SMOTE to balance the dataset.
- **Data Split**: 80:20 split for training and testing.
- **Data Scaling**: Standard scaling applied for consistency in model performance.

Models Used: Evaluated Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machine.

Results & Analysis

Table 1. Performance metrics for different models

Metric	LR	NB	RF	SVM
Train Accuracy (%)	85.80	91.06	100.00	95.58
Test Accuracy (%)	82.10	85.97	96.59	90.23
Train Sensitivity (%)	81.76	84.59	100.00	92.26
Test Sensitivity (%)	81.17	84.42	98.71	90.78
Train Specificity (%)	89.85	97.53	100.00	98.90
Test Specificity (%)	87.88	95.59	83.47	86.78
Train AUC (%)	92.13	96.03	100.00	98.90
Test AUC (%)	91.71	94.38	99.09	95.96

Conclusion & Learnings

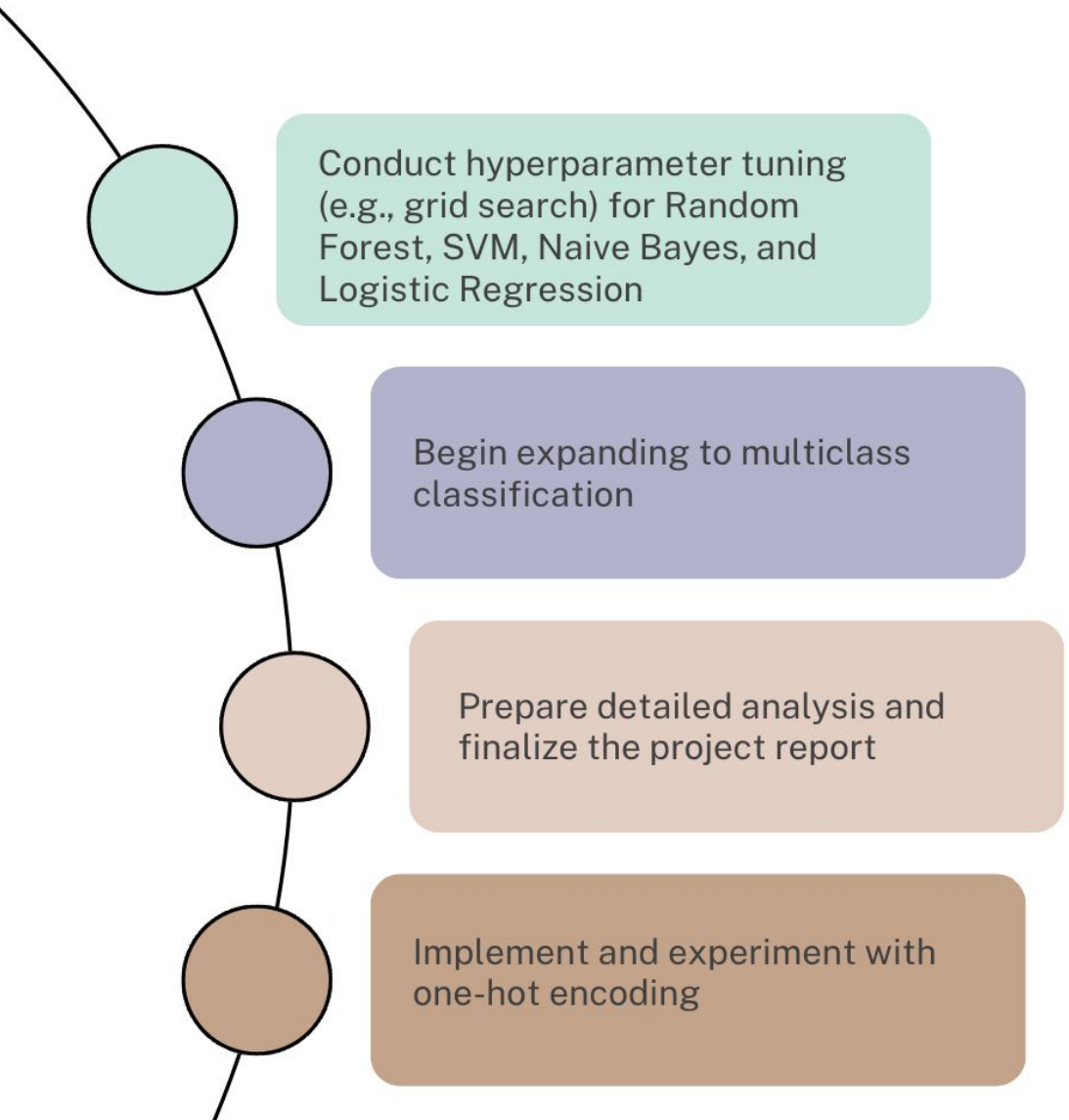
- Model Comparison:

  Random Forest stands out as the top-performing model, with high accuracy, sensitivity, and AUC scores. However, it showed signs of overfitting on the training data.

- Were able to use a combination of motor and non motor symptoms to predict PD

- Future Work:
  - Focus on **hyperparameter tuning** for better generalization.
  - Expand from **binary to multiclass classification** to include Prodromal and SWEDD cases.
  - Implement and improve feature engineering/selection techniques, including **one-hot encoding** for categorical variables.

Future Timeline & Contributions



- Vaibhav Singh: Data Collection, Feature Selection, Literature Survey
- Vansh Yadav: Feature Selection, Model Training, Data Collection
- Utkarsh Dhilliwal: Feature Selection, Model Training, Data Collection
- Shamik Sinha: Feature Selection, Literature Survey, Data Collection

Thank You!

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