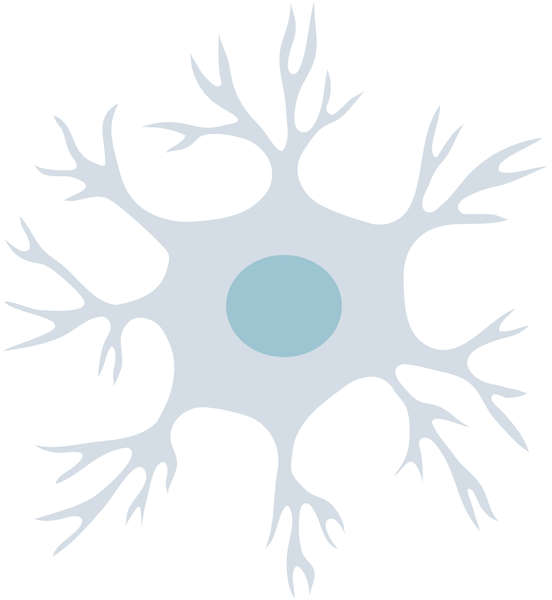

Parkinson's Disease Predictive Machine Learning Model

Luna Pérez Troncoso

Introduction

The **early detection of PD** is a **growing priority** within both clinical practice and research.

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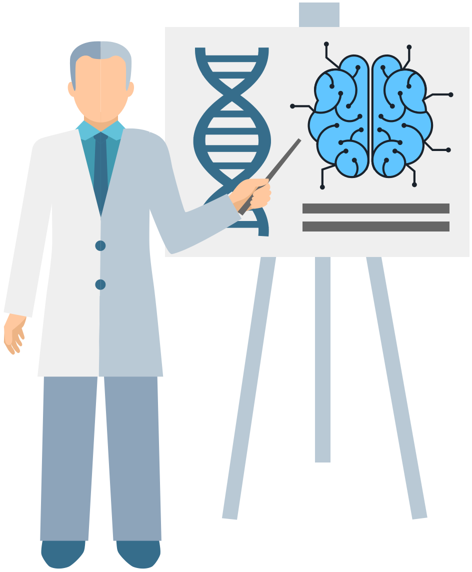
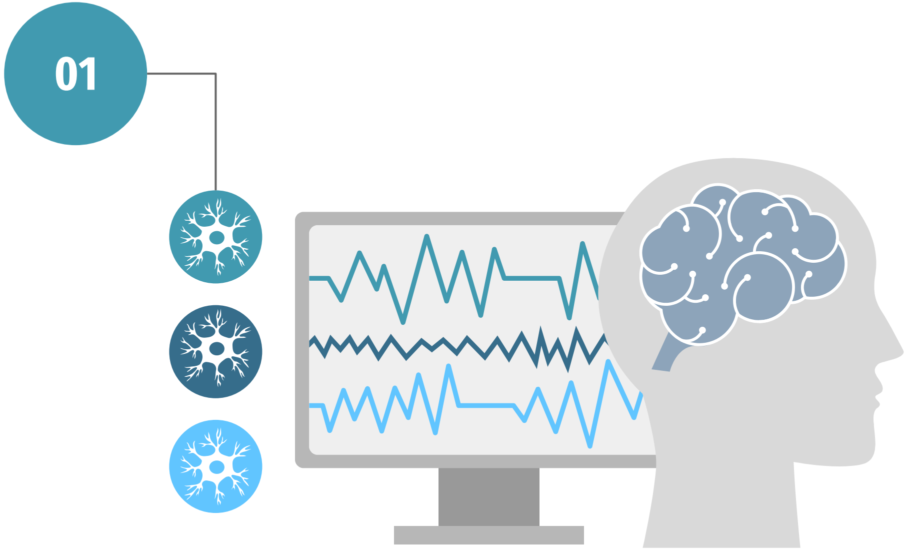
Many individuals remain undiagnosed until the disease has already progressed, limiting the effectiveness of available therapeutic interventions. Consequently, **timely diagnosis** can significantly **influence patient outcomes and long-term quality of life**.

Early identification could allow for **timelier monitoring, lifestyle adjustments, and targeted therapeutic strategies** that may slow **disease progression or improve quality of life**.

Why develop a predictive model?

A reliable predictive system has the potential to **support clinicians in recognizing subtle signs that might otherwise go unnoticed**.





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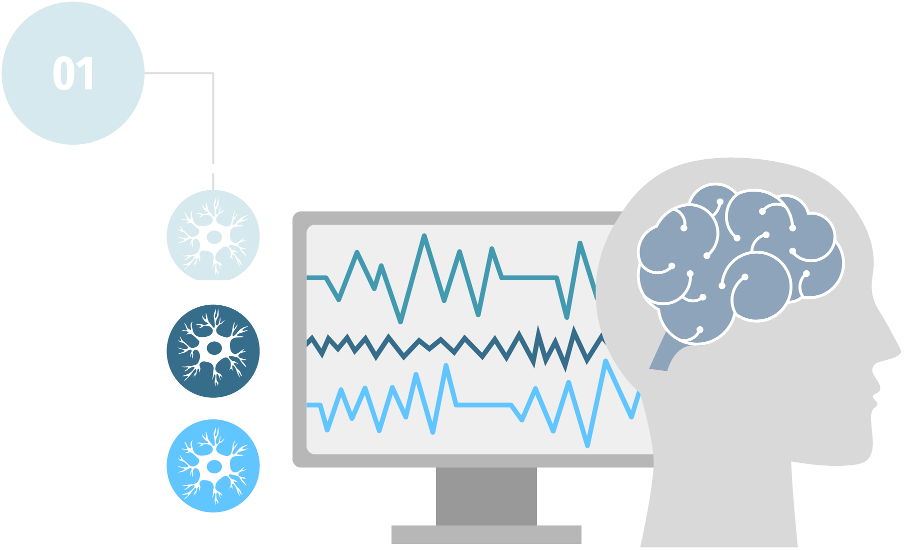

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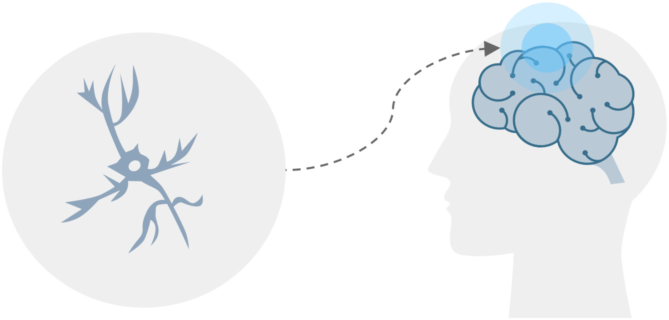
Predictive modeling can help researchers **gain deeper insight into the complex interactions that contribute to the onset of neurodegenerative disorders**



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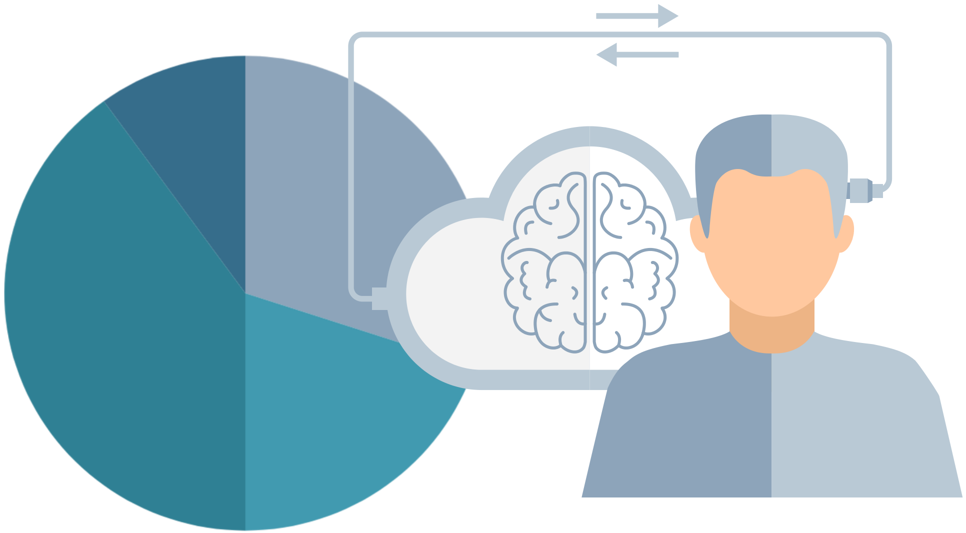
Beyond clinical impact, creating a predictive model encourages the integration of modern **data-driven approaches** into neurological healthcare, which stands out as a promising path to **more personalized and proactive patient care**.

Objective

Integrating diverse variables (demographic, lifestyle, clinical, cognitive, and symptom-related variables) into a unified predictive framework, the project seeks to **evaluate multiple machine learning algorithms and determine their capability to accurately identify patients at risk.**



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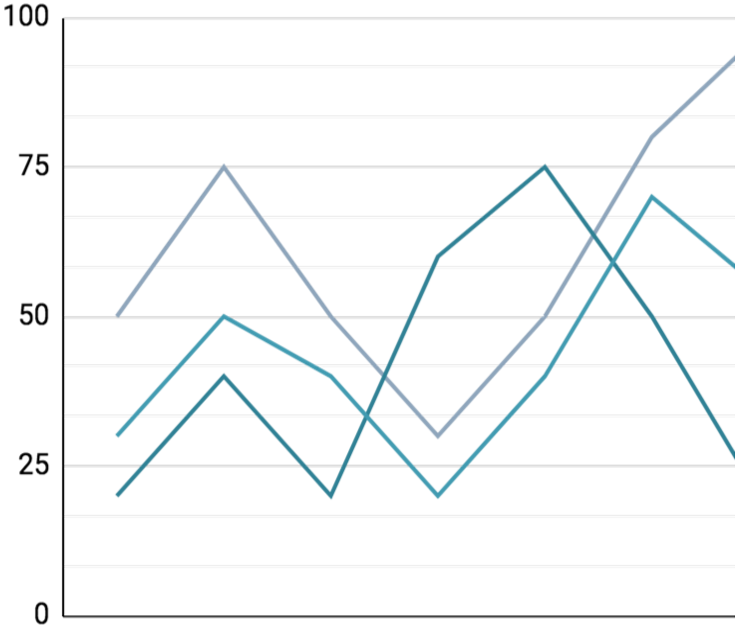

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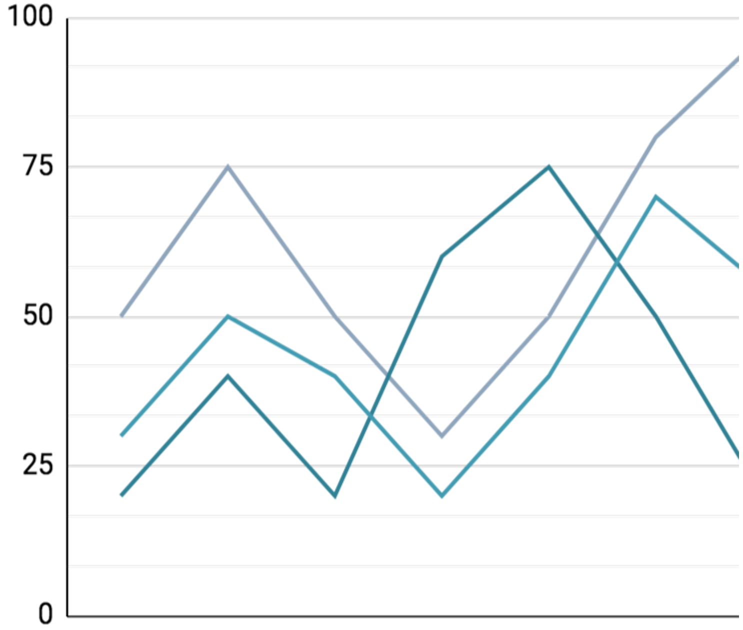

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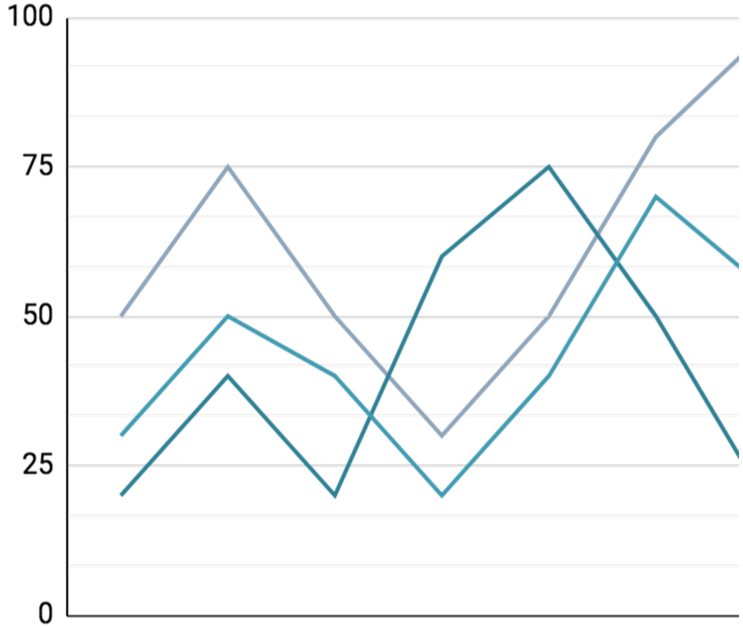

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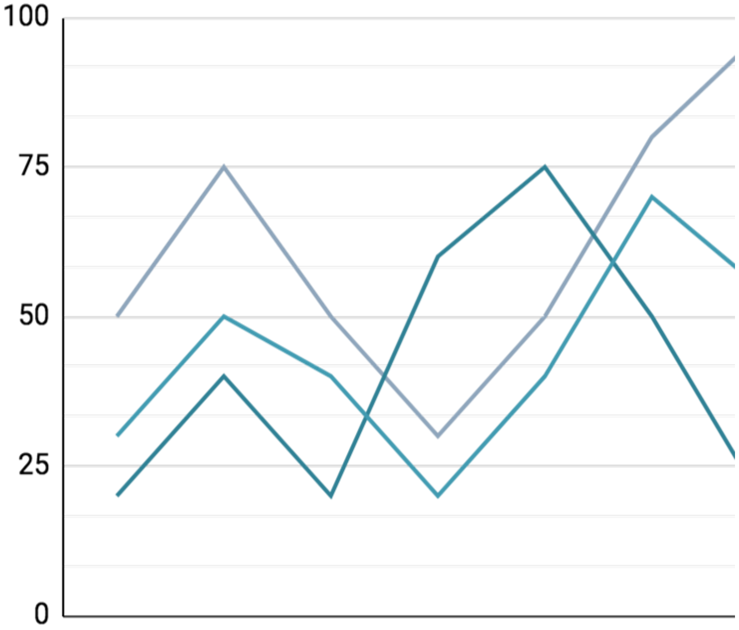

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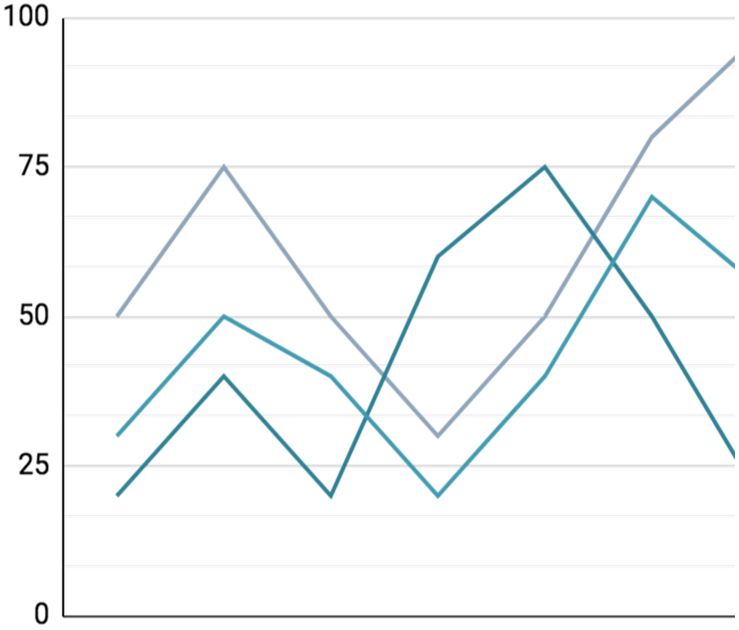

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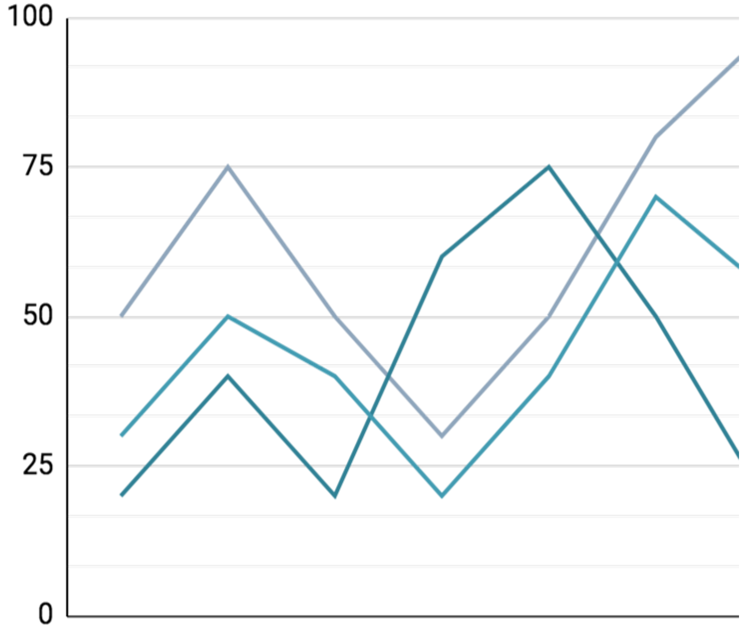

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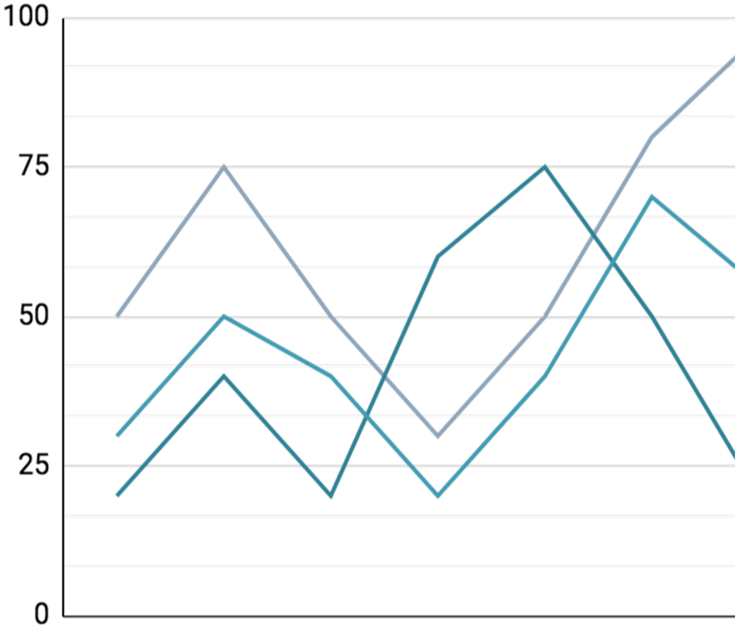

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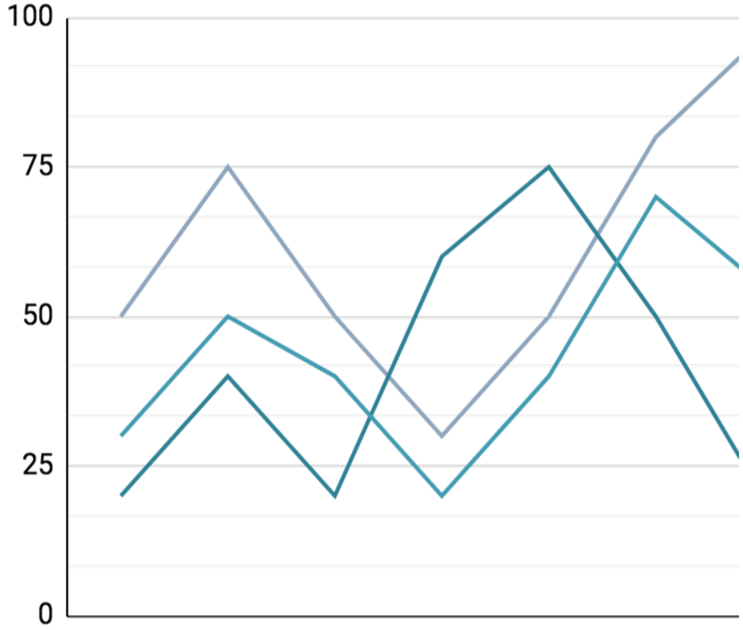

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- **Cognitive and Functional Assessments** (UPDRS, MoCA…).
- **Symptom indicators** (Tremor, Constipation, Rigidity).

Methodology

01

Standarization/Scaling

StandarScaler
MinMaxScaler or None

Methodology

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02

Imbalance Correction

SMOTENC or None

Methodology

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SelectKBest, RFECV,
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Classification Models

LogisticRegression, QuadraticDiscriminantAnalysis,
LinearSVC, SVC, KNeighborsClassifier,
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RandomForestClassifier, ExtraTreesClassifier,
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GridSearchCV and
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Hiperparameter Fine-Tuning and Cross-Validation

GridSearchCV and
RandomizedSearchCV

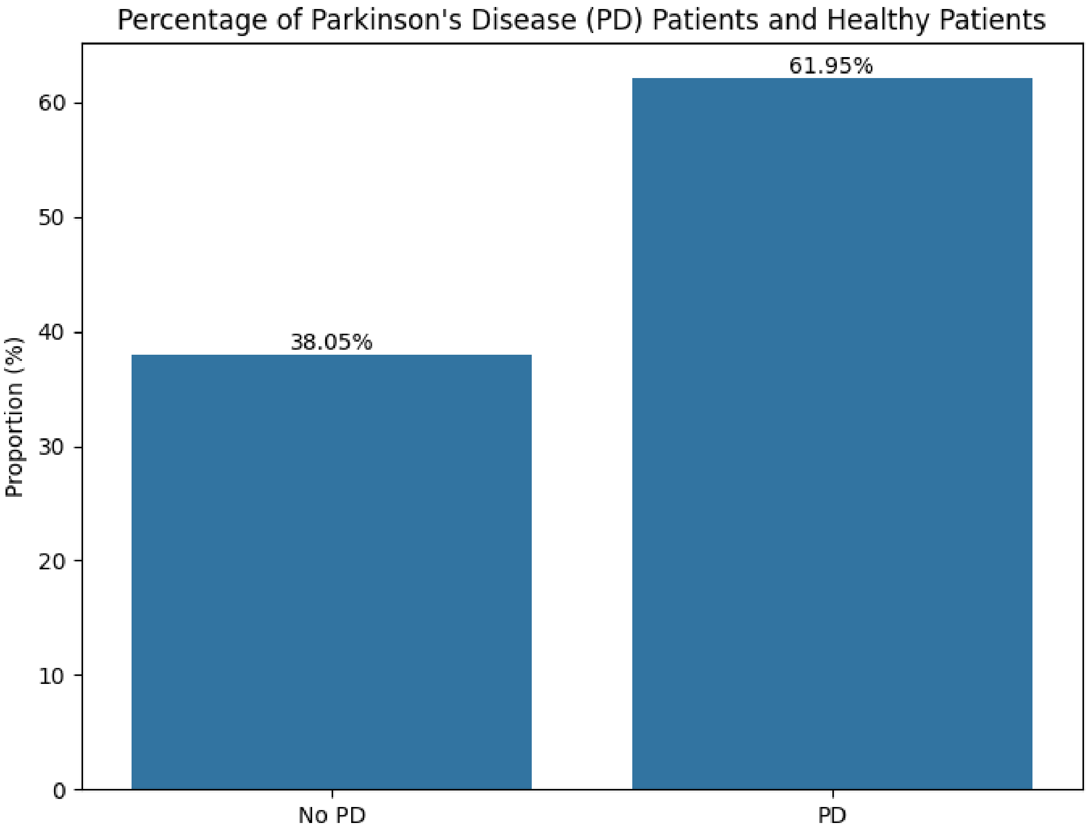
06

Model Testing and Saving

sklearn.metrics and
pickle

Exploratory Data Analysis

Exploratory Data Analysis



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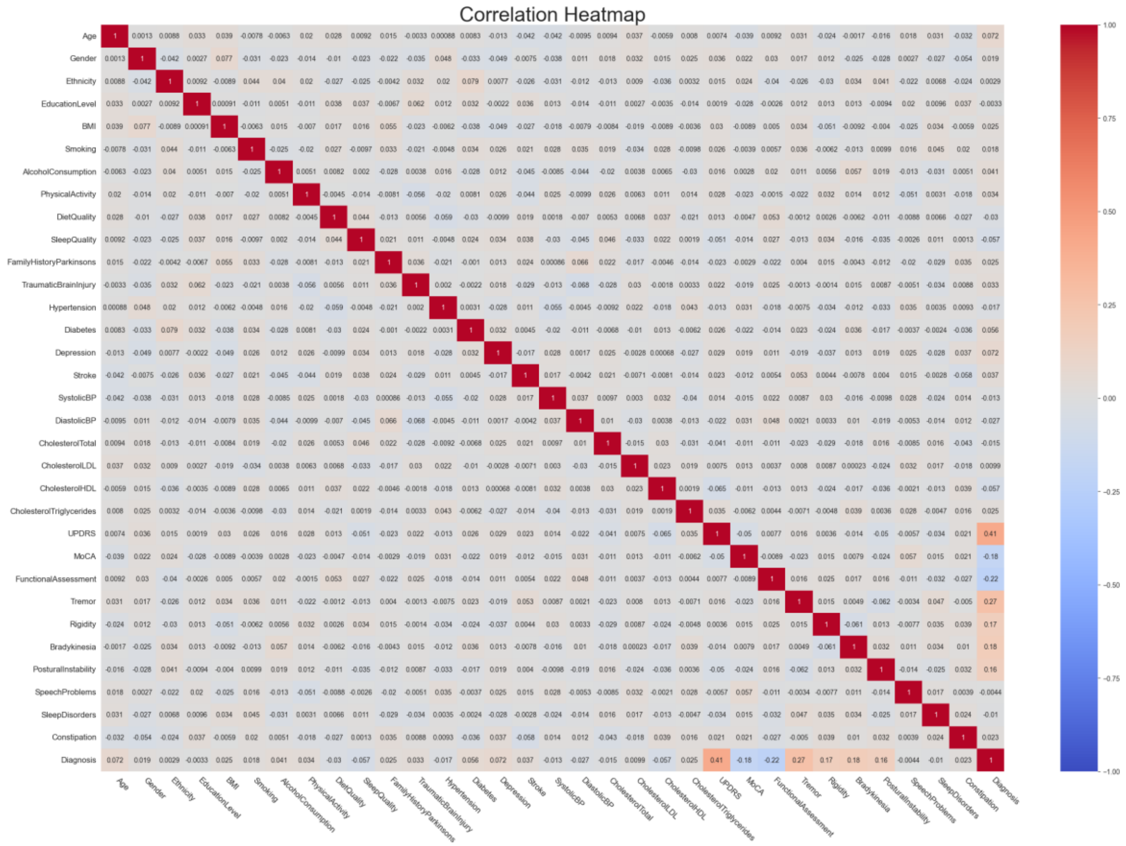

Exploratory Data Analysis

	Diagnosis
UPDRS	0.411858
Tremor	0.271641
Bradykinesia	0.183083
Rigidity	0.167933
PosturalInstability	0.159615
Depression	0.072315
Age	0.072114
Diabetes	0.056443
AlcoholConsumption	0.041170
Stroke	0.036873
PhysicalActivity	0.034081
TraumaticBrainInjury	0.033186
CholesterolTriglycerides	0.025269
FamilyHistoryParkinsons	0.024888
BMI	0.024799
Gender	0.019451
Smoking	0.017677
CholesterolLDL	0.009858
Ethnicity	0.002865
EducationLevel	-0.003334
SpeechProblems	-0.004429
SleepDisorders	-0.010265
SystolicBP	-0.013242
CholesterolTotal	-0.015405
Hypertension	-0.017471
DiastolicBP	-0.026635
DietQuality	-0.029933
SleepQuality	-0.057237
CholesterolHDL	-0.057320
MoCA	-0.179093
FunctionalAssessment	-0.217524

RESULTS: Final Models

In this project **two reliable predictive models with subtle differences** were developed

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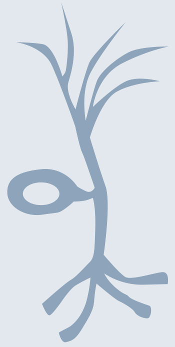


01

MODEL 1

Maximizes the accuracy score

RESULTS: Final Models

In this project **two reliable predictive models with subtle differences** were developed

01

MODEL 1

Maximizes the accuracy score

02

MODEL 2

Maximazes the sensitivity score

01

MODEL 1: Pipeline and Hyperparameters

01 MODEL 1: Pipeline and Hyperparameters

Random Forest Classifier

Pipeline

None

SelectKBest

Parameters

score_func	<function f_c...001DEA308A340>
k	7

RandomForestClassifier

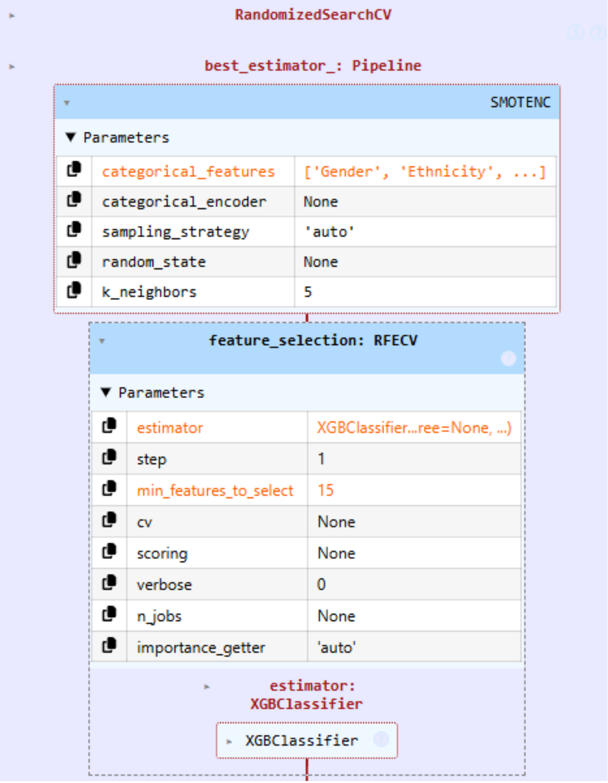
Parameters

n_estimators	100
criterion	'gini'
max_depth	None
min_samples_split	2
min_samples_leaf	1
min_weight_fraction_leaf	0.0
max_features	2
max_leaf_nodes	None
min_impurity_decrease	0.0
bootstrap	True
oob_score	False
n_jobs	None
random_state	1111
verbose	0
warm_start	False
class_weight	'balanced_subsample'
ccp_alpha	0.0
max_samples	None
monotonic_cst	None

01 MODEL 1: Pipeline and Hyperparameters

Random Forest Classifier

Extreme Gradient Boosting Classifier



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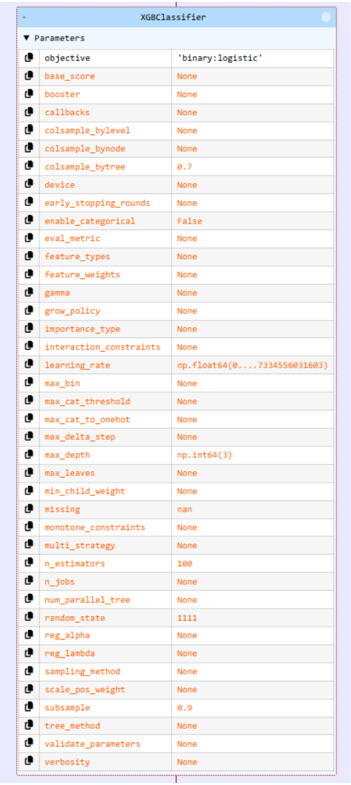

01

MODEL 1: Pipeline and Hyperparameters

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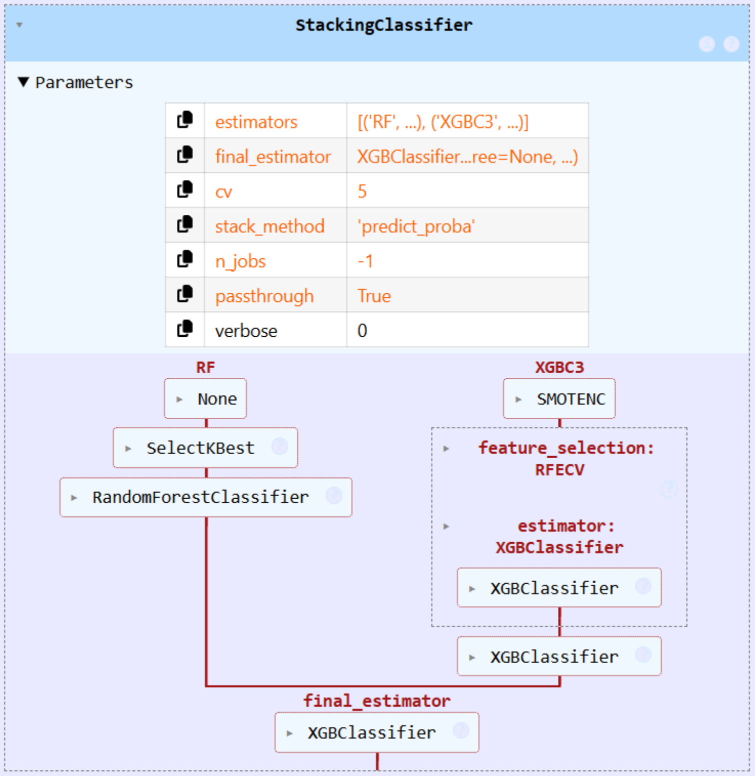
Stacking Model



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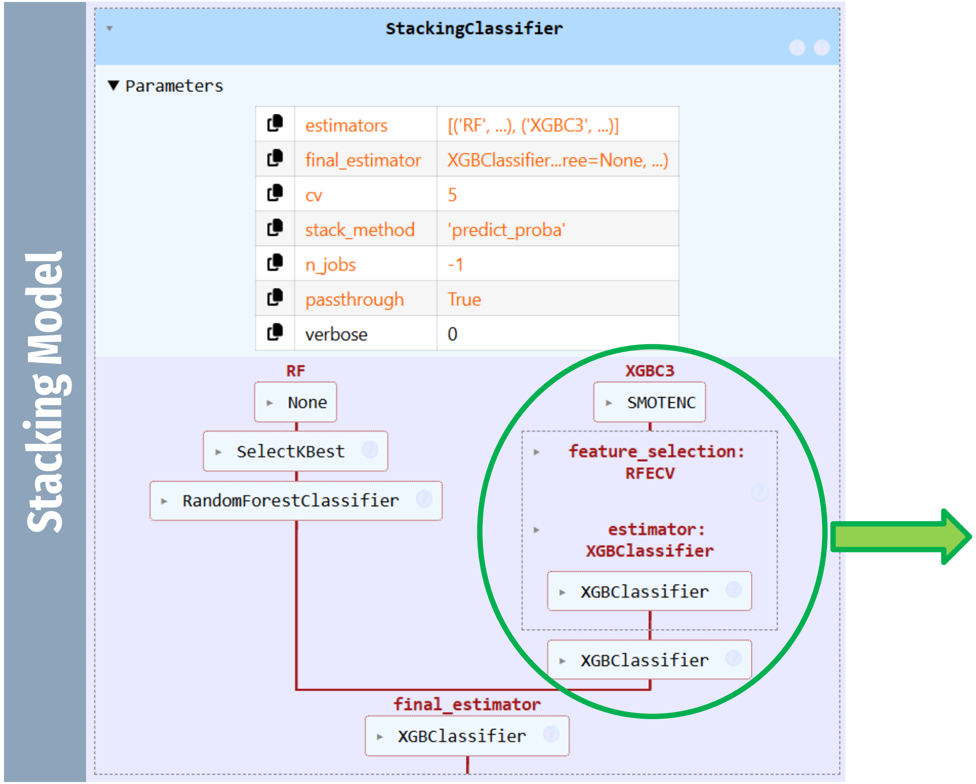

Greater Accuracy and Specificity Scores

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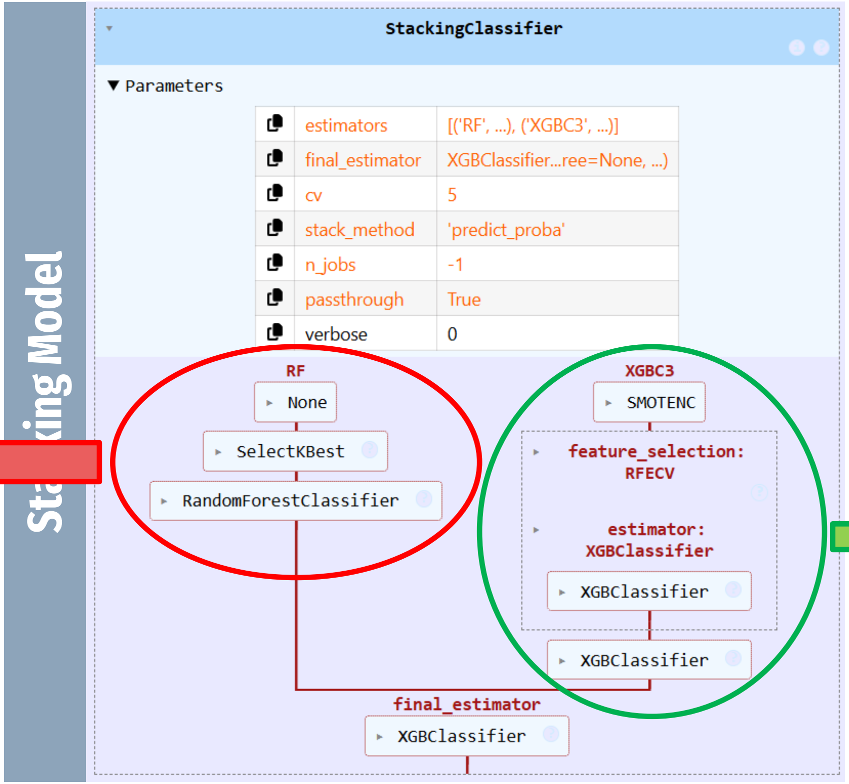

Greater Recall/Sensitivity Scores

Greater Accuracy and Specificity Scores

01 MODEL 1: Test Results

01

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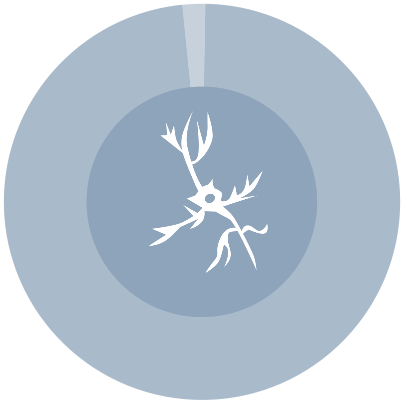

96.9% Accuracy

This model predicted correctly 408 of 421 patients' diagnosis

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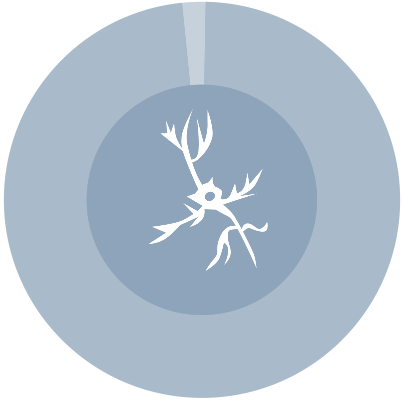

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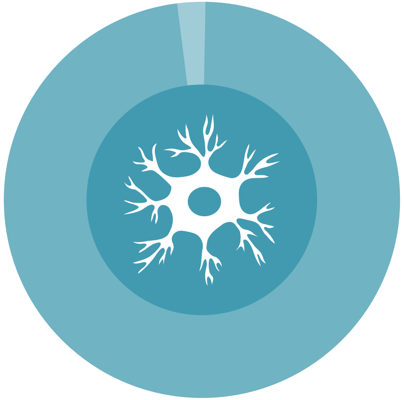

95.7% Specificity

155 of 162 of the heatlhy patients were diagnosed as healthy.

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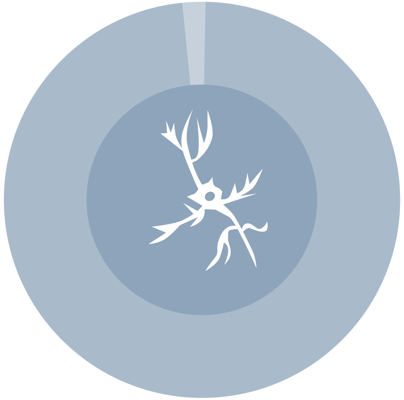

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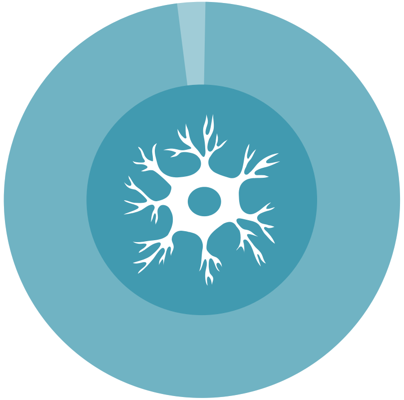

95.7% Specificity

155 of 162 of the heatlhy patients were diagnosed as healthy.

97.7% Sensitivity

253 of 259 Parkinson's Disease patients were detected

01 MODEL 1: Test Results

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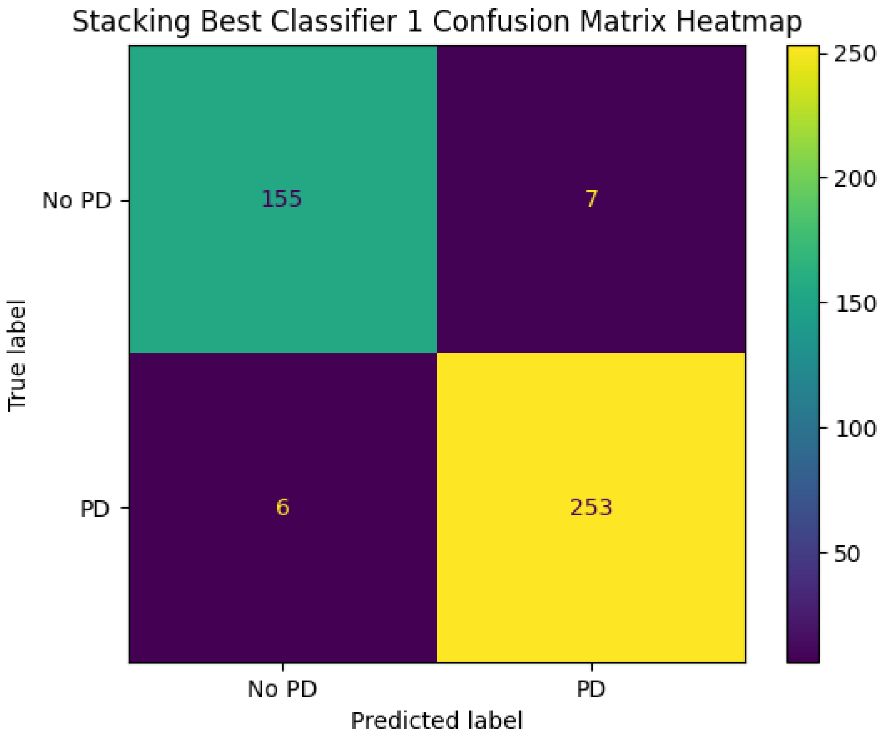

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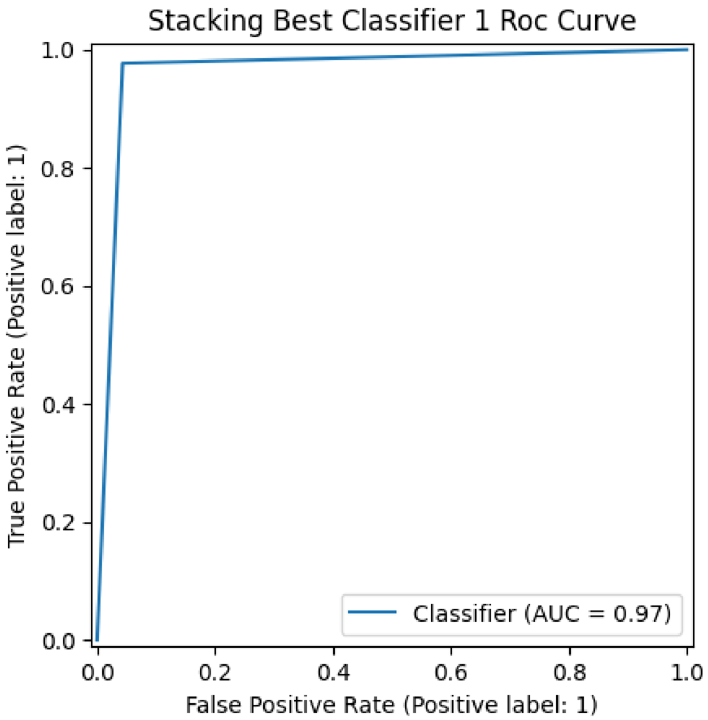

02

MODEL 2: Pipeline and Hyperparameters

02 MODEL 2: Pipeline and Hyperparameters

Random Forest Classifier

Pipeline

None

SelectKBest

Parameters

score_func	<function f_c...001DEA308A340>
k	7

RandomForestClassifier

Parameters

n_estimators	100
criterion	'gini'
max_depth	None
min_samples_split	2
min_samples_leaf	1
min_weight_fraction_leaf	0.0
max_features	2
max_leaf_nodes	None
min_impurity_decrease	0.0
bootstrap	True
oob_score	False
n_jobs	None
random_state	1111
verbose	0
warm_start	False
class_weight	'balanced_subsample'
ccp_alpha	0.0
max_samples	None
monotonic_cst	None

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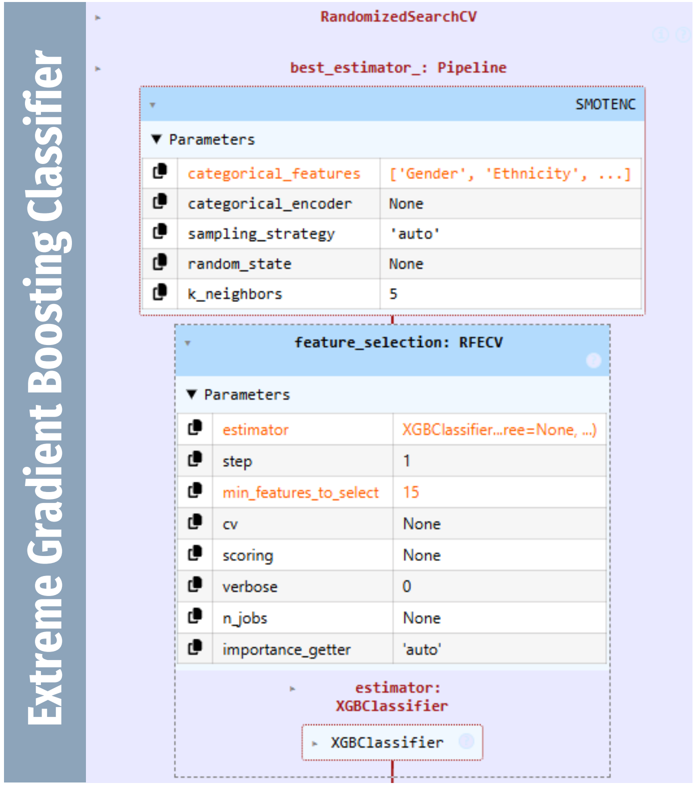

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max_samples	None
monotonic_cst	None

Extreme Gradient Boosting Classifier

RandomizedSearchCV

best_estimator_: Pipeline

SMOTENC

▼ Parameters

categorical_features	['Gender', 'Ethnicity', ...]
categorical_encoder	None
sampling_strategy	'auto'
random_state	None
k_neighbors	5

feature_selection: RFECV

▼ Parameters

estimator	XGBClassifier...ree=None, ...)
step	1
min_features_to_select	15
cv	None
scoring	None
verbose	0
n_jobs	None
importance_getter	'auto'

estimator: XGBClassifier

XGBClassifier

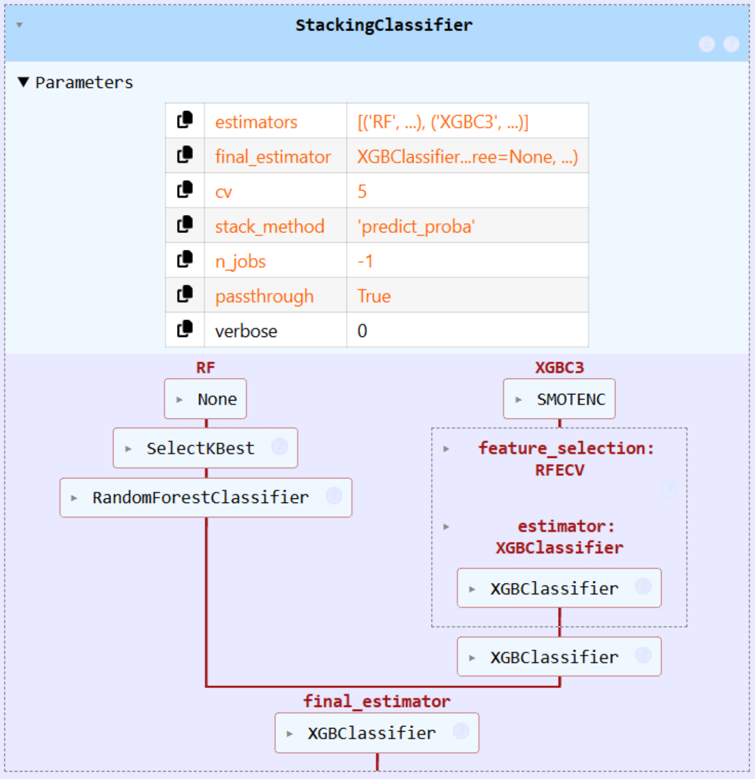
XGBClassifier

▼ Parameters

objective	'binary:logistic'
base_score	None
booster	None
callbacks	None
colsample_bylevel	None
colsample_bynode	None
colsample_bytree	0.7
device	None
early_stopping_rounds	None
enable_categorical	False
eval_metric	None
feature_types	None
feature_weights	None
gamma	None
grow_policy	None
importance_type	None
interaction_constraints	None
learning_rate	np.float64(0....7334556031603)
max_bin	None
max_cat_threshold	None
max_cat_to_onehot	None
max_delta_step	None
max_depth	np.int64(3)
max_leaves	None
min_child_weight	None
missing	nan
monotone_constraints	None
multi_strategy	None
n_estimators	100
n_jobs	None
num_parallel_tree	None
random_state	1111
reg_alpha	None
reg_lambda	None
sampling_method	None
scale_pos_weight	None
subsample	0.9
tree_method	None
validate_parameters	None
verbosity	None

02 MODEL 2: Pipeline and Hyperparameters

Stacking Model



02

MODEL 2: Test Results

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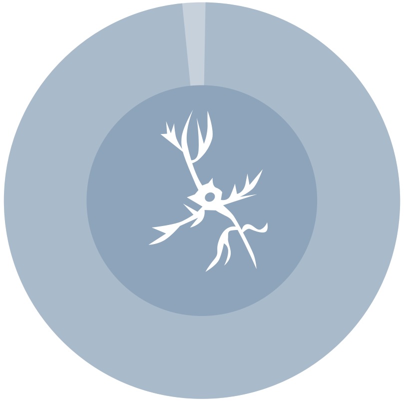

96.4% Accuracy

This model predicted correctly 406 of 421 patients' diagnosis

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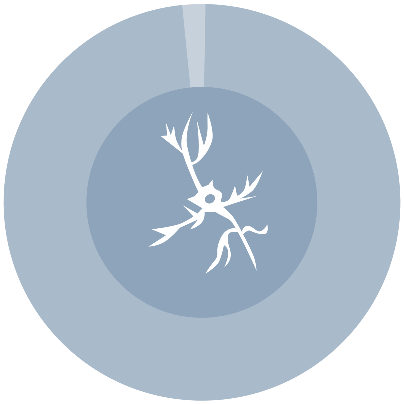

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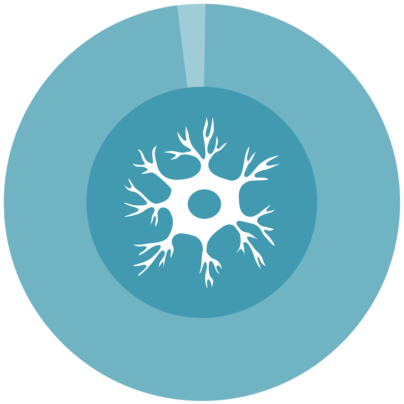

93.8% Specificity

152 of 162 of the heatlhy patients were diagnosed as healthy.

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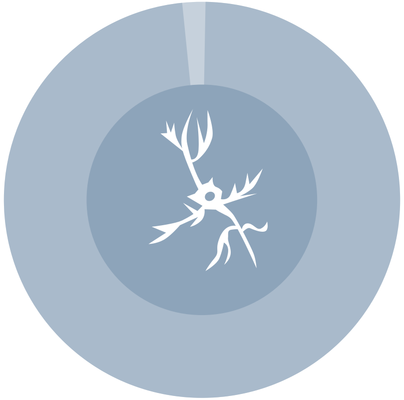

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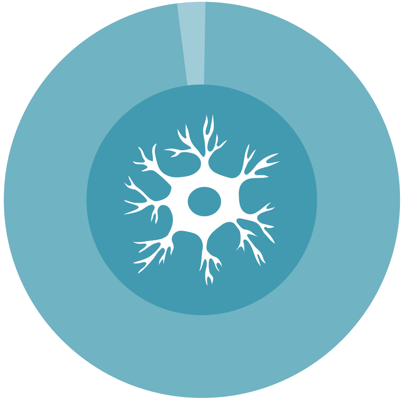

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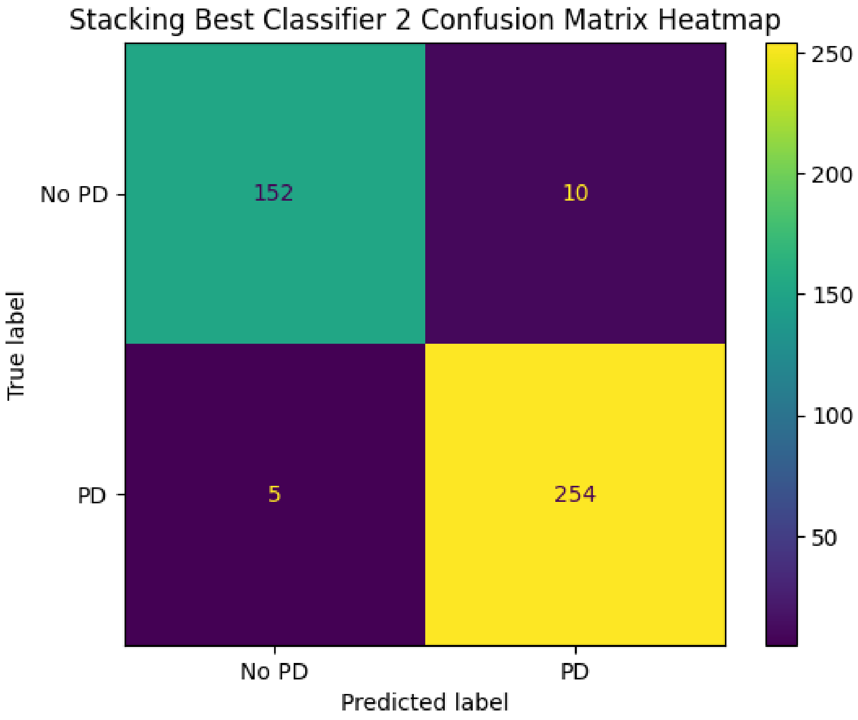
98.1% Sensitivity

254 of 259 Parkinson’s Disease patients were detected

02 MODEL 2: Test Results



02

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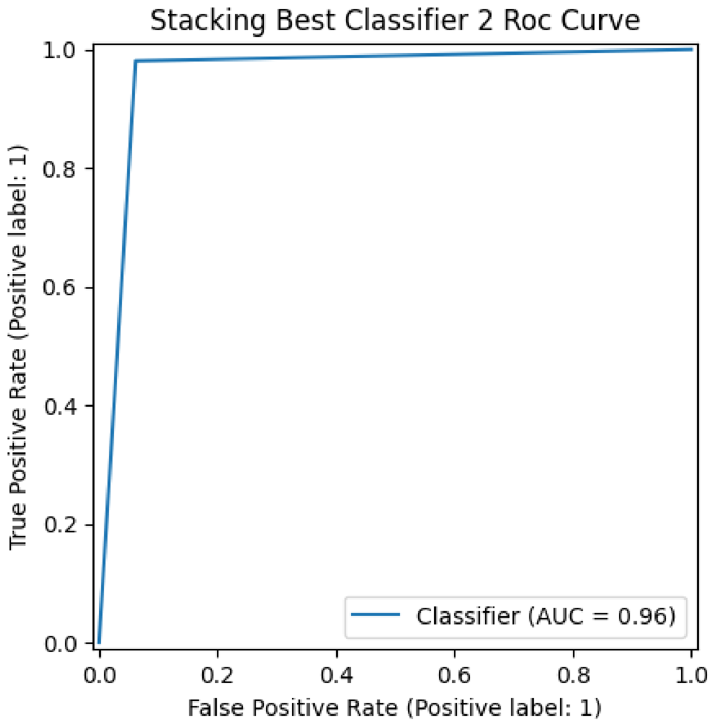

Conclusions

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These models can support clinicians in **recognizing subtle signs** that might otherwise go unnoticed, **gain deeper insight** into the **complex interactions that contribute to neurodegenerative disorders** and reach **more personalized and proactive patient care**.

Timely diagnosis will improve the **effectiveness of available therapeutic interventions**, **influencing patient outcomes and long-term quality of life**.

Strenghs and Limitations

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- Predictive models obtained impresive sensitivity scores (~98%).
- Components of the model are scalable and fast-performing, allowing fast prediction of huge datasets in seconds.
- Models has great flexibility. Consequently it can be adjusted and re-trained with new data with training times of less than one minute in train dataset of 2000 registers.

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Limitations

- Although the models obtained impresive sensitivity scores (~98%), specificity was compromised (93-96%), leading to some healthy patients incorrectly diagnosed as Parkinson’s Disease patients.
- The model has not been tested in datasets with missing values.

THANKS FOR YOUR ATTENTION

[Github Repository]

[Streamlit Webpage]