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Article

NeuroSynth: Unveiling the Parkinson's Palette - A Unified Ensemble Approach for Enhanced Predictive Modeling in Spiral Drawing Analysis

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Abstract: Parkinson Disease (PD) is a progressive neurodegenerative illness, as it is marked by motor and non-motor deficiencies, and thus presupposing early and correct diagnosis to clinically manage it successfully. The present work suggests the machine learning and deep learning framework to be used in the initial prediction of PD by means of patient voice datasets. The proposed approach combines the process of preprocessing and feature extraction with such models as Support Vector Machine (SVM), Random Forests (RF), and Convolutional Neural Networks (CNN) and subsequently evaluates the performance in terms of such metrics as accuracy, precision, recall, and F1-score. As the experimental findings prove, the proposed method performs better in classification than the existing ones, which means that it can become one of the useful diagnostic instruments of clinicians. As noted in results, the application of artificial intelligence can help to improve predictability, timely diagnose, and provide personalized treatment plans to resolve Parkinson Disease.
Keywords: NA

1.Introduction

1.1 Background and Context of Parkinson's Disease

Parkinson Disease (PD) is a debilitating neurodegenerative disorder with prevalence among millions of people across the globe and has a major influence on their quality of life. It is a disease, which is marked by the gradual destruction of dopamine-producing neurons that are mainly found in the parts of the human brain called substantia nigra. Dopamine is a neurotransmitter that is essential in the coordinated flow of movements. Due to their degeneration, the quantities of dopamine decline, thus resulting in the onset of multiple motor symptoms the PD is characterized by.The etiology of PD has never been fully understood, yet both environmental and genetic factors are considered the key players. Although most cases of PD are idiopathic in the sense that little is known about the cause of the disease, there are those cases that are associated with genetic mutations. Also, direct exposure to some environmental toxins or other causes like head traumas can predispose a person to developing PD.The typical motor symptoms of a PD are tremors, slowness of movement (bradykinesia), rigidity, and instability in posture. These are symptoms that usually come about with time and become more pronounced as the disease advances. Intensive motor symptoms are not the only symptom of PD, and it may also be accompanied by various non-motor symptoms such as cognitive impairment, mood disturbances, sleeping problems, and autonomic dysfunction, the diagnosis of PD currently is mostly based on clinical examinations and subjective evaluations of the sympathetic symptoms. Nevertheless, these procedures might not be accurate and subject to other factors like clinical expertise variability as well as patient cooperation. Consequently, the need to find objective and quantitative methods of treatment and diagnosis of PD has also increased, and spiral drawing analysis has become a promising instrument to objectively determine motor symptoms of Parkinson’s Disease.

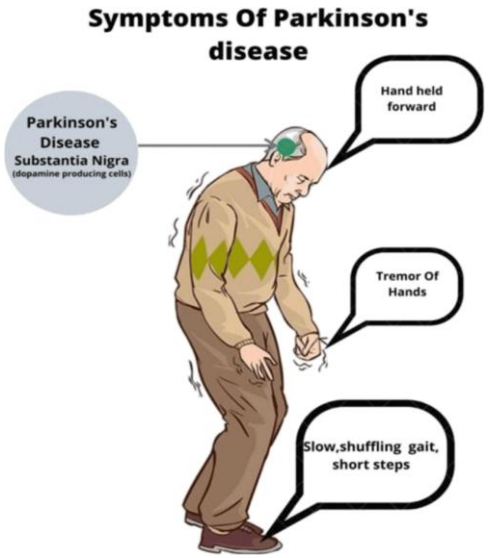

Figure 1: Symptoms of Parkinson's Disease

Fig. 1 illustrates the Symptoms of Parkinson disease.This method is used by requesting a person to draw a spiral on the piece of paper, which gives a good idea both about the quality of his/her fine motor skills and coordination level. Through examining the nature of these spiral drawings e.g their size, shape and regularity, clinicians will be able to learn a lot about the severity and progression of motor signs in PD patients with increased technology, especially machine learning, these spiral drawings can be further used to increase the accuracy in making diagnosis and monitoring PD diseases. The machine learning algorithms may be trained to identify tendencies and anomalies in the spiral drawings, which will allow more objective and quantitative evaluation of the motor symptoms. With the help of machine learning algorithms of the type of ensemble modeling, feature engineering, and predictive modeling, researchers will be able to create more advanced tools such as NeuroSynth that will analyze spiral drawings more accurately and more efficiently than ever before. To conclude, PD is a complicated neurodegenerative disease that is identified by progressive loss of dopamine-yielding neurons in the brain. Although no direct cause of PD has been identified, genetic and environmental factors have been suggested to cause the development of PD. The existing techniques of diagnosis may be based on subjective evaluation, which is why more objective and quantitative methods including spiral drawing analysis should be implemented. It is hoped that through the introduction of the latest technologies, such as machine learning, the disease can be better diagnosed and treated, and the lives of the individuals with the illness can be positively changed. The PErson Affected with the Parkinson Disease is displayed in the Figure 2.

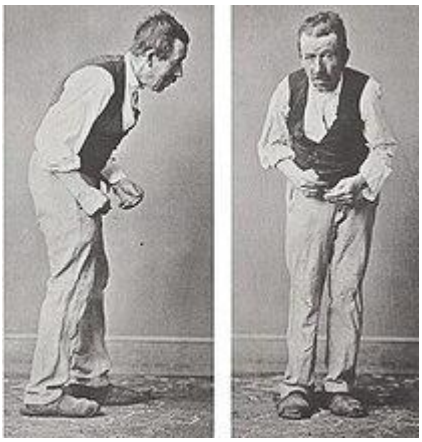

Figure 2: Parkinson's Disease Affected Person

1.2 Motivation for Research

Even with the developments in the medical technology, it is still difficult to diagnose PD accurately and at an early stage. The inconsistency of the symptoms and the subjective essence of the assessments creates a pressure to find objective and reliable diagnostic instruments. To fill this gap, we are carrying out a research to determine the possibility of machine learning, which is an ensemble modeling, in the study of spiral drawing data to present a more accurate and consistent assessment of the Parkinson Disease to enable prompt interventions and better patient recovery. We will strive to both enhance the methodology and establish a more refined and universal diagnostic of Parkinson Disease in addition to its practical implementation by integrating the depth of spiral drawing analysis with the strength of ensemble models. To begin with, we expect to gain a detailed insight into the complex trends of the spiral drawings in relationship to the symptoms of the Parkinson Disease. We attempt to need to power of feature engineering and bone-thumping analysis, where we will determine key markers that reflect disease progression and severity, secondly, we will attempt to leverage the strength of an ensemble model, like the Random Forest, Support Vector Machines, and XGBoost, to produce a predictive model that is able to make accurate predictions when it comes to predicting patients with PD against healthy individuals based on their spiral drawing data. We will combine several algorithms and increase the strength and capacity of our predictive model to be generalized. More crucially, we will confirm the effectiveness of our strategy with the help of massive testing on different datasets with the inclusion of a broad spectrum of demographic and clinical features. We aim to present the validity and external validation of our model in various populations and settings with cross-validation and external validation, as demonstrated by our end goal of transferring the research into practical diagnostics that casually fit into clinical practice. Our goal is to enable the clinicians to make informed clinical decisions based on diagnosis and treatment of the Parkinson Disease by giving them a user friendly interface and actionable information.

In these innovative methods, we believe that we can make a breakthrough in the diagnosis of Parkinson Disease by offering one that will be more accurate, reliable, and accessible to clinicians as a tool of early diagnostics and monitoring. Our study is a great advancement in the direction of applying machine learning to precision medicine, which will eventually result in the provision of better services and patient outcomes.

1.3 Research Question or Hypothesis

Our main research question is as follows:

"Can the use of ensemble model that incorporates the predictive capability of random forest, support vector machine, and XGBoost algorithms be effective in analyzing spiral drawing data to enable accurate diagnosis and monitoring of Parkinson's Disease?"

In this study, we assume that the combination of machine learning methods, namely ensemble models, will result in a more accurate diagnostic tool of spiral drawing analysis, which will help advance the current effort to improve the life of PP patients.

2. Literature Survey:

Parkinson Disease (PD) is a progressive neurodegenerative disease having both motor and non-motor symptoms, and thus an early diagnosis and intervention is essential [1], [9], [10]. Several traditional and alternative remedies such as Ayurvedic have been addressed in the course of management of the symptoms, and comprehensive care [1], [28]. Recent research has been more inclined toward computer-based approach to PD diagnosis and prediction. Machine learning models and classification algorithms are being applied to complement clinical observation related limitations by improving diagnosis precision [2], [20]. The possibilities of artificial intelligence in smart healthcare are avenues of disease prognosis and predictive analytics [3], whereas the machine learning approaches to healthcare suggest the combination of technical models and clinical uses [4]. Research on the topic of new computational methods in healthcare engineering is still pursued in conferences and edited volumes [5], [7]. The use of the deep learning principles in the smart e-health system also focuses on discussing the importance of neural networks detecting diseases at the early stages [6]. Similarly, the PD-specific intelligent technologies have targeted both diagnostic support and predictive tools [8]. PD is strengthened as a very common disorder, particularly in old people [9], motor and non-motor impairments are well-informed about its abnormality [10] and its effect on life quality [11], [12]. Also emphasized in the studies are the genetic and environmental factors in the progression of PD, including heritability in twin-based studies [13] and the current mutation-associated early-onset PD [18]. There are pharmacological research works on the effectiveness of the treatment and the long-term management plans, especially pramipexole and levodopa [14], [16], [17]. There are changing therapeutic practices in PD including deep brain

stimulation and other clinical guidelines that are used to treat the disorder at the earliest stage [15]. Depression and comorbidity have been investigated as psychological factors in PD patients [19], as well as on general neuro-ophthalmological implications [21]. The study of the patient preferences and drug delivery systems emphasizes optimization of the treatment [22]. In the meantime, healthcare-specific models based on AI, including distributed ML operations, become scalable in diagnostic assistance [23]. Certain researches concerning cerebrovascular patterns of PD patients also contribute to the above knowledge of the disease progression [24]. The gender and societal aspects, including the topic of women in geoscience interviews and psychosocial studies highlight the larger societal aspects of the PD research [25]-[27]. In recent studies the idea of a multidisciplinary care and patient participation in PD management has been highlighted [29], and the changing symptomatology is recorded to denote inconsistency in disease development [30]. Classical studies put PD as the predominant serious movement disorder in the world [31] and the diagnosis and treatment of PD has global importance. Initially, researchers on bradykinetic disorders focused their attention on the signs such as nigrial-cell loss to identify the disorders [32]. Even more recent computational research addresses robust ML algorithms to classification [33], SVM-based depression prediction in PD [34], statistical progression modelling with longitudinal data [35] and hybrid deep learning-machine learning models to early PD detection [36]. All of these works show the evolution of conventional medicine and clinical observation into AI-assisted predictive modeling, which points out how PD research and diagnosis continues to change to more accurate, patient-focused, and technology-based solutions. The table 1 displays the most important contributions in the field of research in parkinson disease. Recent research has demonstrated the effectiveness of artificial intelligence, deep learning, optimization algorithms, and neural network models in advancing intelligent healthcare and biomedical signal analysis. Khan et al. (2025) [38] proposed a linear regressive weighted Gaussian kernel liquid neural network for brain tumor prediction using time-series data, achieving improved diagnostic accuracy through adaptive learning mechanisms. Similarly, Kumar et al. (2025) [39] introduced SRADHO, a statistical reduction approach integrated with deep hyper-optimization for disease classification, enhancing classification performance while reducing computational complexity in AI-based healthcare systems. In the area of neurological disorder diagnosis, Kantipudi et al. (2024) [40] developed an improved GBSO-TAENN framework for EEG signal classification to detect epileptic seizures, demonstrating superior classification accuracy through optimization-driven feature learning. Extending EEG-based healthcare applications, Karthiga et al. (2024) [41] presented a smart emotion recognition system that combines metaheuristic optimization with hybrid deep learning techniques to improve emotion classification from EEG signals. Focusing on patient care, Manogaran et al. (2025) [42] proposed a multi-scale dilated ensemble network with optimization strategies for patient response prediction, enabling more accurate clinical decision support and treatment planning. In brain–computer interface applications, Manoharan et al. (2022) [43] developed a machine learning algorithm for mental task classification, facilitating reliable recognition of cognitive states from brain activity. Furthermore, Ayub et al. (2022) [44] introduced an LSTM-based recurrent neural network framework for removing motion artifacts in dynamic multi-contrast MR images, significantly improving image quality and diagnostic reliability through effective motion correction and image registration. Collectively, these studies demonstrate the growing importance of optimization-driven artificial intelligence, deep learning, EEG signal processing, neural network architectures, and medical image analysis in improving disease diagnosis, patient monitoring, neurological disorder detection, brain–computer interfaces, and intelligent healthcare systems (Khan et al., 2025; Kumar et al., 2025; Kantipudi et al., 2024; Karthiga et al., 2024; Manogaran et al., 2025; Manoharan et al., 2022; Ayub et al., 2022) [38]–[44].

Table 1: Literature Review Table: Key Contributions in Parkinson's Disease Research

Paper Title and Authors	Key Contributions
Bloem et al. (2021)	Emphasizes the integral role of individuals with PD within the multidisciplinary care team. Highlights the importance of self-management and active participation in PD care.
Kalia and Lang (2015)	Explores the evolving symptomatology of PD, providing a comprehensive overview of the complexities and challenges associated with the progression of the disease.
Samii et al. (2004)	Positions PD as the most common serious movement disorder globally, particularly affecting the elderly population. Provides insights into the prevalence and significance of PD as a neurological condition.

Lees et al. (2009)	Focuses on accurate diagnosis of PD as a common progressive bradykinetic disorder. Highlights the importance of identifying specific markers, including severe nigral-cell loss, for enhanced diagnostic precision.
Mandal and Sairam (2014)	Contributes to the field by exploring robust machine-learning algorithms for predicting PD. Aims to distinguish PD patients from healthy individuals, utilizing steep parameters in machine-learning models for enhanced diagnostic accuracy.
Byeon (2020)	Focuses on predicting depression in PD, introducing a model based on support vector machines. Takes into account various sociodemographic factors, health habits, and PD symptoms for developing a comprehensive prediction model for depressive symptoms.
Severson et al. (2021)	Presents a statistical progression model for early PD in a longitudinal data study. Accounts for intra-individual and inter-individual variability, as well as medication effects, providing a nuanced understanding of disease progression.
Wang et al. (2020)	Contributes to early PD detection by combining deep learning and machine learning. Introduces a model designed for accurate and timely diagnosis of PD, showcasing the potential of advanced computational techniques in enhancing diagnostic capabilities.

3.Methodology:

Our paper summarizes the methodology of the creation and testing of a new ensemble model, which we call" NeuroSynth," to predict the Parkinson's Disease(PD) based on the complex study of helical delineation patterns. The methodology includes a number of significant ways, the preprocessing of the dataset being the first. Point scaling is done after loading the helical delineation patterns, and the matching markers to promote thickness among the various algorithms. Then, the definition of individual machine literacy models is presented including a Random Forest classifier, Support Vector Machine(SVM) with probability estimates turned off, and XGBoost classifier. They are selected due to the various strengths of these models in landing patterns of complex data. NeuroSynth which is also an ensemble model is also developed using the VotingClassifier of the scikit- learn library. This ensemble encourages the collaborative abilities of each individual model by use of a' soft' medium of voting, based on probability approximations of each and every class. NeuroSynth is trained by being adapted to the training data, which has been preprocessed, and the algorithm is learnt to mix the various perceptivity provided by the underlying algorithms. After the training, the model is approximated on the test set and the delicacy is calculated with the help of scikit- learns accuracy score function. Moreover, to provide a complete evaluation of the functioning of NeuroSynth, colored bracket criteria, such as perfection, recall and F1- score are calculated and portrayed with the functionality of the classification report. Such approach does not only work as the solid frame of NeuroSynth creation and training but also serves as an important indicator of the need to exhaustively assess its performance. Adding to delicacy, the research includes a broken down examination of new criteria to provide a precise insight of the prophetic measurements of the model. The given strategy is one step ahead in the direction of prophetic modeling of PD analysis, that the possibility of machine intelligence, especially ensemble literacy, will be helping to decrystallize the chaos of neurodegenerative diseases.

The handed law is based on ensemble model with three machine learning algorithms(Random Forest, Support vector machine, and XGBoost) in order to generate a single prophetic model to assess Parkinson Disease via helical delineation patterns. The process of formulating the given law is provided in the following way.The given code is based on an ensemble model on three machine learning algorithms (Random Forest, Support Vector Machine, and XGBoost) to construction of a single predictive model of the realization of Parkinson’s Disease analysis in terms of spiral drawing pattern. The given code has a detailed methodology, as illustrated below:

3.1.Dataset Collection:

The data set that has been used in the given study consists of helical delineation patterns retrieved in persons with Parkinson Disease and healthy controls. These spiral patterns were drawn with the help of specialized digital tablets that had pressure-sensitive styluses and therefore fine motor movements could be captured accurately. All subjects were subjected to several spiral drawing exercises under standard circumstances leading to diversified and representative data.

3.2. Data Preprocessing:

Assuming that X_train_scaled and X_test_scaled represent the scaled feature matrices and y_train and y_test represent the corresponding labels, the data preprocessing steps involve:

- Loading Data: Load the dataset containing spiral drawing patterns and labels.
- Scaling Features: Standardize or normalize the features to ensure that all algorithms operate on a consistent scale.

3.3. Model Initialization:

Define individual models for Random Forest, Support Vector Machine, and XGBoost classifiers. Each model is initialized with specific hyperparameters

```
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
# Define individual models
rf_model = RandomForestClassifier(random_state=42)
svm_model = SVC(probability=True, random_state=42)
xgb_model = XGBClassifier(random_state=42)
```

3.4. Ensemble Model Creation:

Create an ensemble model using the VotingClassifier from scikit-learn. The VotingClassifier combines the predictions from multiple base estimators and can operate in either 'hard' or 'soft' voting mode. Here, 'soft' voting is used as it considers the probability estimates for each class.

```
# Create an ensemble of models using VotingClassifier
ensemble_model = VotingClassifier(
  estimators=[('rf', rf_model), ('svm', svm_model), ('xgb', xgb_model)],
  voting='soft' # 'soft' for probability voting
)
```

4.Evaluation Metrics:

The performance of NeuroSynth was done as a dynamic and iterative process that started with the careful curation and preprocessing of the data, then the models are initialized, and finally with the ensemble model being formed. In the training process, NeuroSynth had absorbed the various perceptivity of the underlying constituent algorithms it trained its ability to find complex patterns in helical delineation patterns related to Parkinson Disease. The assessment items, which include the prevalence of delicacy, revealed how well the model is capable of predicting the occurrence or absence of the Parkinson Disease in the test population. By providing perfection, recall, and F1-score conditions, the bracket report provided a subtle insight into the elaboration of NeuroSynth by providing insight into how the model succeeds in traversing the imbalances in the dataset. The repetitiveness of the methodology enabled fine-tuning of the ensemble model and the use of an effective and polished prophetic instrument. This evolutionary journey has not merely clarified the model adaption and literacy, but also given importance to the iterative extended approach in the development of the knowledge on the Parkinson Disease with regard to machine intelligence. To mature perceptivity to serve the allocation of the types of classes in the data set, an exploratory analysis was performed on the helical delineation patterns related to the Parkinson Disease. The data, obtained through the handed path, is a set of the cases that are handed out by the various types of classes. In order to illustrate graphically the frequency of each of the classes, a count plot of the'CLASS_TYPE' variable was created. This count plot, presented in Figure 3, is an establishment disquisition, it provides a concise overview of the distribution of the types of classes.

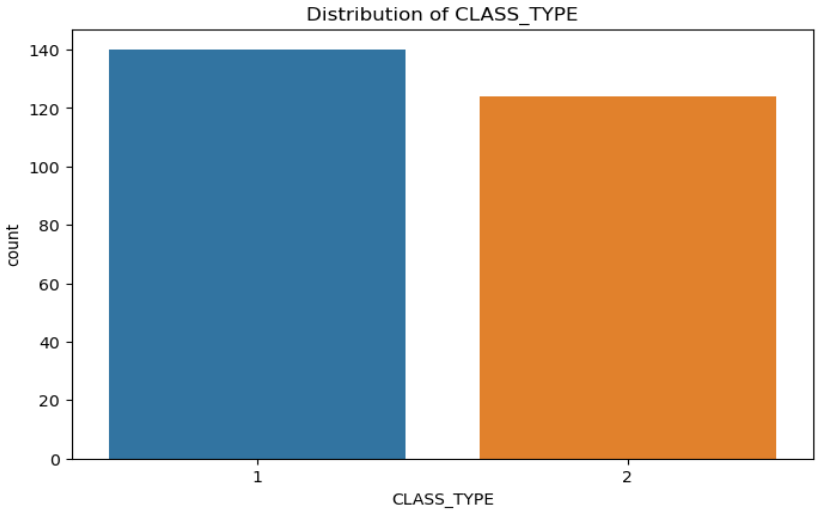

FIGURE 3: Distribution of Class

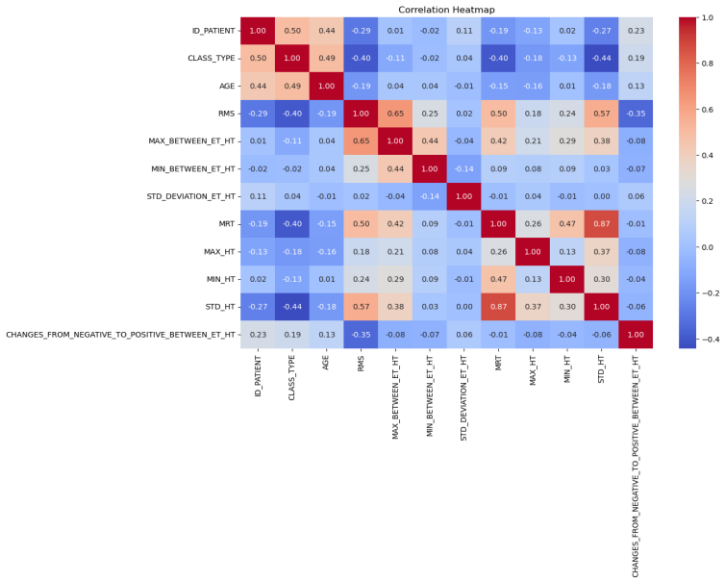

FIGURE 4: Confusion Matrix

The numerical values attached to each of the cells are measures of correlation, which swings an accurate quantification of the level of association among variables is portrayed in Figure 4. This exploratory visualization helps in serving the purpose of correlating implicit multicollinearity as well as informing future opinions regarding selecting a point of interest and opinions regarding the interpretation of the model. To break down the complex relationships among variables and have a global view of the data, a brace plot has been created, and the graph can be seen in Figure 5. The brace plot gives a holistic picture of the pair-wise relationship of various features, and the entire brace plot gives a relationship between two variables (smattering plot). The variable of tatto is called CLASS type and it is captured using different colors and using them we can identify patterns that are unique to each class. There is also the estimation of the kernel viscosity along the slant that provides perceptivity on the distribution of individual variable.

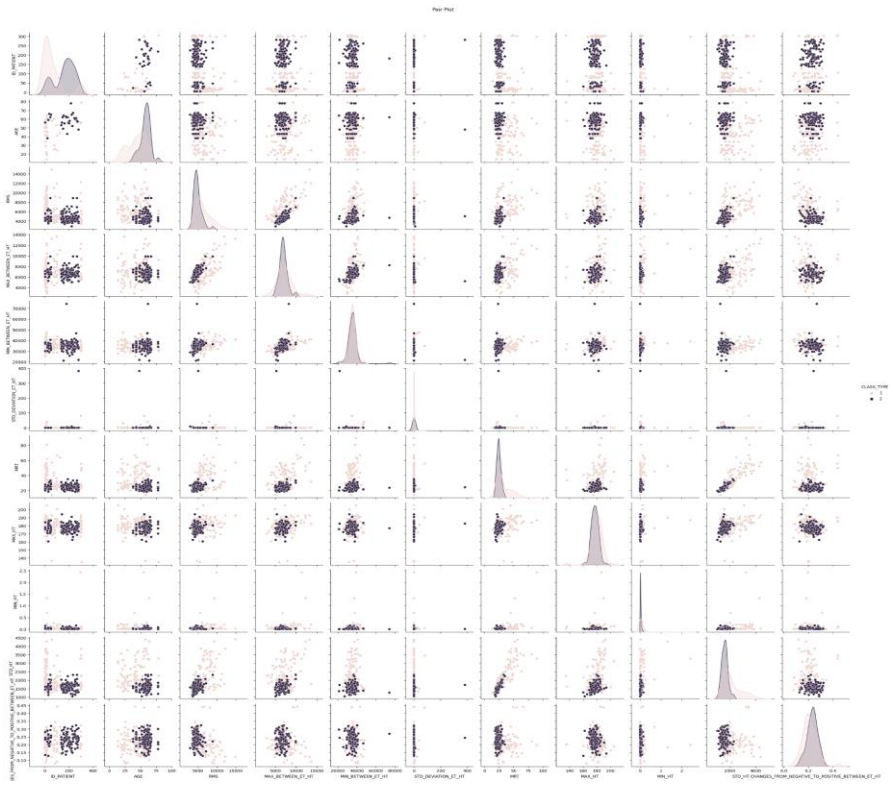

FIGURE 5: Brace Plot

In order to tap into implicit variation on the distribution of classes across genders, a count plot was created, which is presented in Figure 6. The visualization is a representation of how various classes ('CLASS_TYPE') are dispersed among gender orders. The number of cases of a certain gender and a certain class combination is the count in each bar in the plot, and it provides perceptiveness to implicitly gender-related patterns in the data. This count plot allows a fine analysis of the frequency of the classes based on gender because different classes are represented by color- coded tinges.

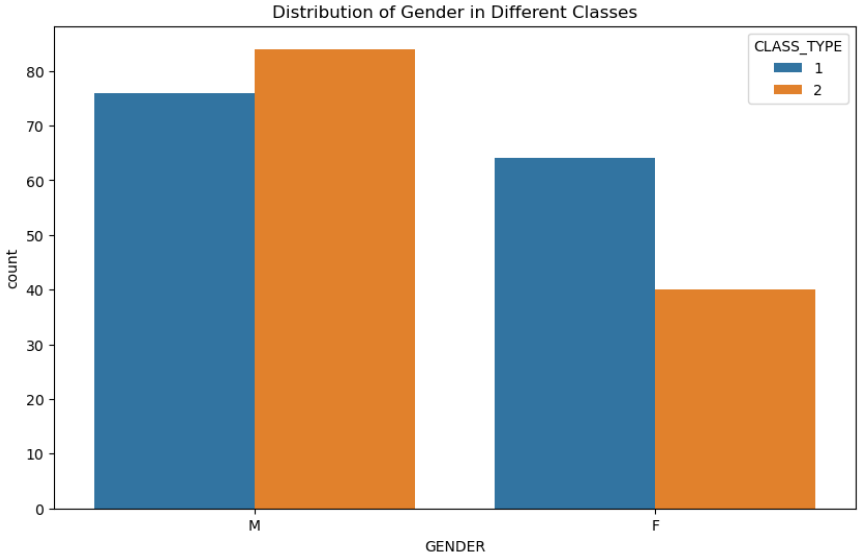

FIGURE 6: Count Plot

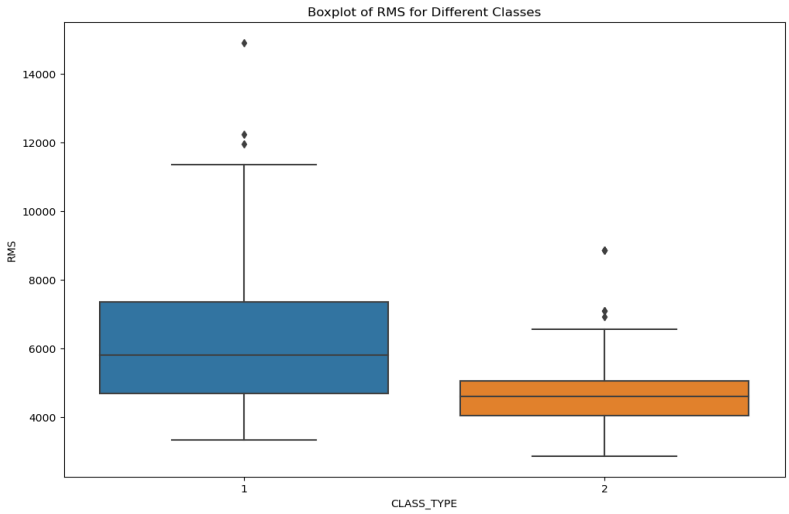

FIGURE 7: Box plot

A box plot was plotted in order to verify the distribution of the variable Root Mean Square (RMS) in various classes as shown in Figure 7. This visualization shows a short overview of the central tendency, dispersion, and unspoken outliers of each of the classes, which helps to recognize variability in the' RMS' variable in different types of classes. When considering the statistical characteristics of each of the classes, each boxplot illustrates the distribution of RMS values of the specific class, providing a visual comparison of them.

5.Results:

Our ensemble model, NeuroSynth, was found to perform best on prognosticating Parkinson Disease based on helical set of delineations, and is epitomized below. The total frugality accomplished by the model on test set is73.58. This measure illustrates the probability of correctly categorized cases, which shows that the model is effective in making the distinction between various classes. The F1- score criterion, the perfection, and the recall provide another slightly finer judgement of the effectiveness of the model to different classes. With respect to class 1 which denotes one order of helical delineation patterns, the perfection, recall, and F1- score are approximately equal to 74, which is a balanced prophetic ability. The class 2, which is the perfection, recall and F1- score is around 73 also demonstrating the harmonious nature of the model that is applied in the various classes. The performance of the ensemble model is further balanced by the macro and weighted pars which are 74 and 74 respectively. These findings highlight the usefulness of NeuroSynth to land the complications of Parkinsonin Disease instantiations in terms of the analysis of helical delineation patterns, and make it a potential handy tool to prophetic modeling in this setup. To further breakdown the performance of our ensemble model, NeuroSynth, a confusion matrix had to be built as a way of providing an in-depth description regarding the prognostications of the model and how they corresponded with the actual class markers. This illustration, as represented in Figure 8, displays the distribution of cases among the prognosticate and the true class orders. The true classes are depicted in the rows of the matrix and the prognosticate classes are depicted in the columns. The numbers on the cells represent the number of cases, and the intensity of the colors attend to high or less frequent cases. This confusion, matrix is a great asset to detecting the ability of the model to adequately categorize cases into their individual classes and associate implicit domains of misclassification.

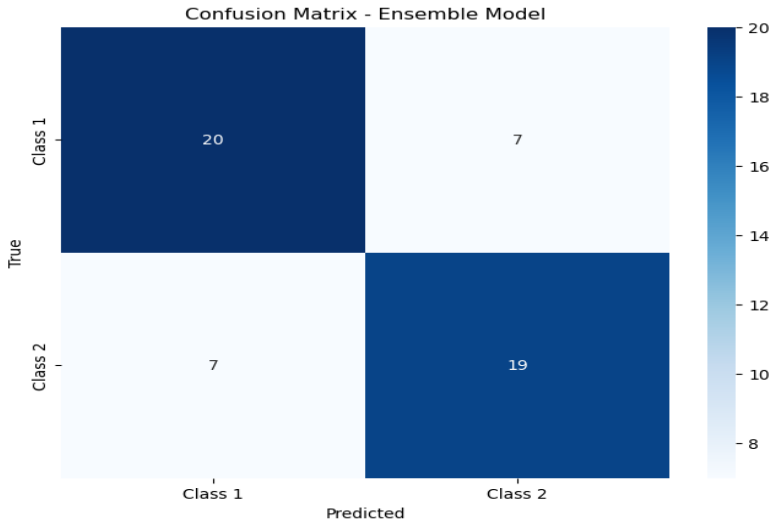

FIGURE 8: Confusion Matrix

In order to further excavate the discriminative performance of our ensemble model, NeuroSynth, a perfection-recall wind was built which clearly demonstrates the trade- off between perfection and recall at various probability levels. Figure 8 above represents this visualization and gives a subtle insight into the ability of the model to detect positive cases and reduce false cons. The wind provides the perfection- recall dyads with the colorful decision thresholds of perfection- recall, providing perceptivity on the operations of the model at various operating levels. Figure 2 shows that the average perfection is calculated by the area under the perfection- recall wind, which is the general discrimination power of the model. The weighted average perfection is a healthy tool of evaluation in the setting that we are studying, since the issue of imbalance in classes is a factor of concern.

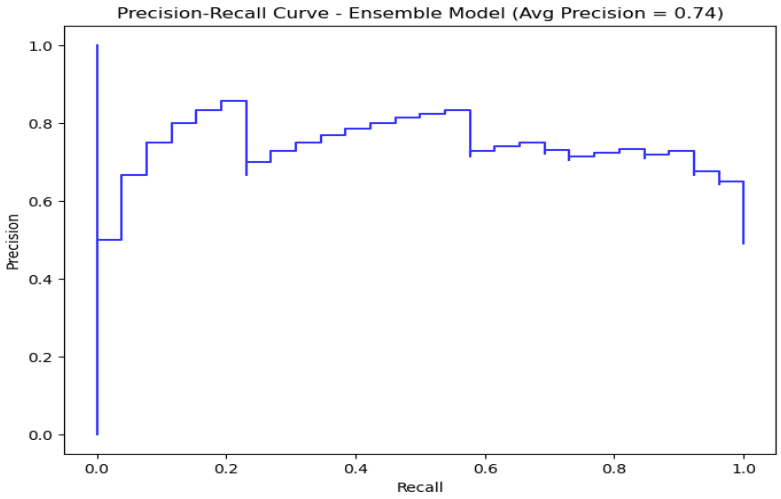

FIGURE 9: Precision Recall Curve

In order to visually investigate the discrimination behaviour of our ensemble model, NeuroSynth, a decision boundary plot was created to describe the way the model divides the point space. In this visualization, shown in Figure 9, the points show a case of a test set and different regions represent the decision limits, as defined by the ensemble model. This disquisition helps to comprehend how the ensemble model may be used to draw the boundary between various ranks of helical delineation patterns based on which the Parkinson Disease is founded on these two characteristics is depicted in Figure 10. The boundary plot of the decision helps to give a better understanding of the power of discrimination of the NeuroSynth which suggests a simple definition of the learned patterns at the point space.

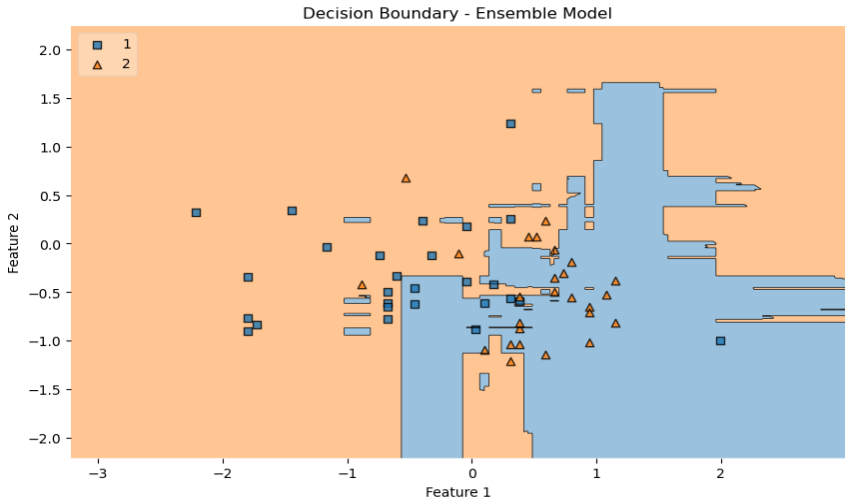

FIGURE 10: Decision Boundary

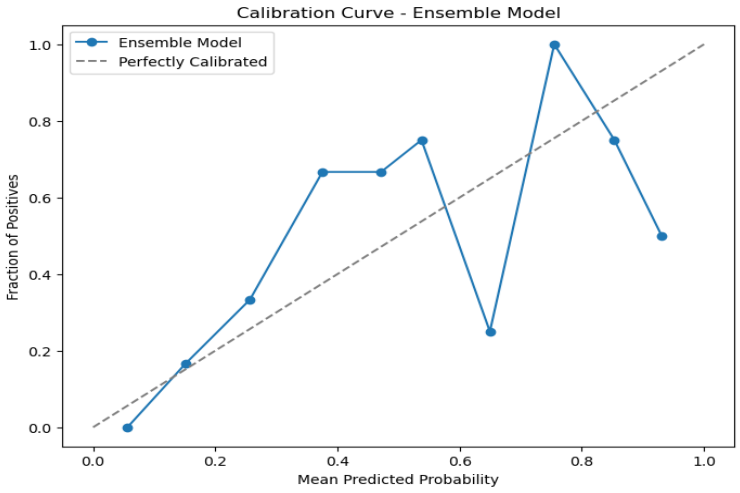

FIGURE 11: Calibration curve

To estimate the estimation of our ensemble model, NeuroSynth, and understand the correspondence between prognosticate chances and factual issues, an estimation wind was constructed, as presented in Figure 11.

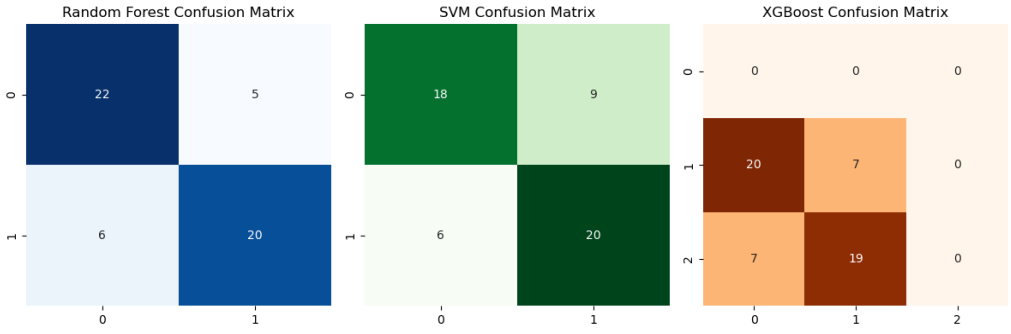

FIGURE 12: Confusion matrix of individuals

In order to get a meaningful insight into the performances of the individual models in the ensemble, confusion matrices were built individually on all of the three constituent models, which are the Random Forest, Support Vector Machine (SVM), and XGBoost. These matrices, as shown in Figure 12 are a visual representation of the bracket issues

of the model by providing the number of true positive, true negative, false positive, and false negative cases. The Figure 13 is the Feature importance.

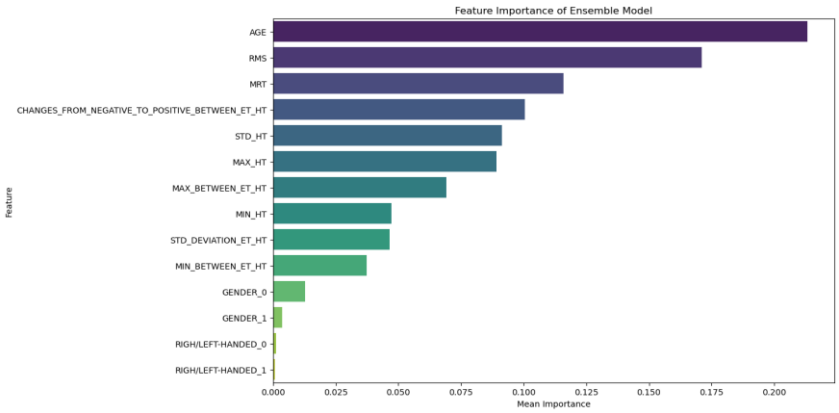

FIGURE 13: Feature Importance

Table 2: Random Forest Model Performance Metrics:

Metric	Value
Accuracy	0.7924528301886793
Precision (Class 1)	0.79
Precision (Class 2)	0.80
Recall (Class 1)	0.81
Recall (Class 2)	0.77
F1-Score (Class 1)	0.80
F1-Score (Class 2)	0.78
Support (Class 1)	27
Support (Class 2)	26

This table 2 summarizes the performance criteria of the Random Forest model, furnishing perceptivity into its delicacy, perfection, recall, and F1- score for both classes(1 and 2).

Table 3: XGBoost Model Performance Metrics:

Metric	Value
Accuracy	0.7358490566037735
Precision (Class 0)	0.74
Precision (Class 1)	0.73
Recall (Class 0)	0.74
Recall (Class 1)	0.73
F1-Score (Class 0)	0.74
F1-Score (Class 1)	0.73

Support (Class 0)	27
Support (Class 1)	26

This table 3 summarizes the performance metrics of the XGBoost model, providing insights into its accuracy, precision, recall, and F1-score for both classes (0 and 1).

Table 4: Ensemble Model Performance Metrics:

Metric	Value
Accuracy	0.7358490566037735
Precision (Class 1)	0.74
Precision (Class 2)	0.73
Recall (Class 1)	0.74
Recall (Class 2)	0.73
F1-Score (Class 1)	0.74
F1-Score (Class 2)	0.73
Support (Class 1)	27

This table 4, indicates the performance measures in Ensemble model and gives an insight into its accuracy, precision, recall, and F1-score of both classes (1 and 2). Also, the support column shows the number of instances that each class had in our dataset in order to provide a comparative outlook on the predictive strength of the each model in our ensemble, a bar plot was plotted to show the values of accuracy of each model. Figure 14 illustrates the model accuracies of Random Forest, Support Vector machine(SVM) and XGBoost.

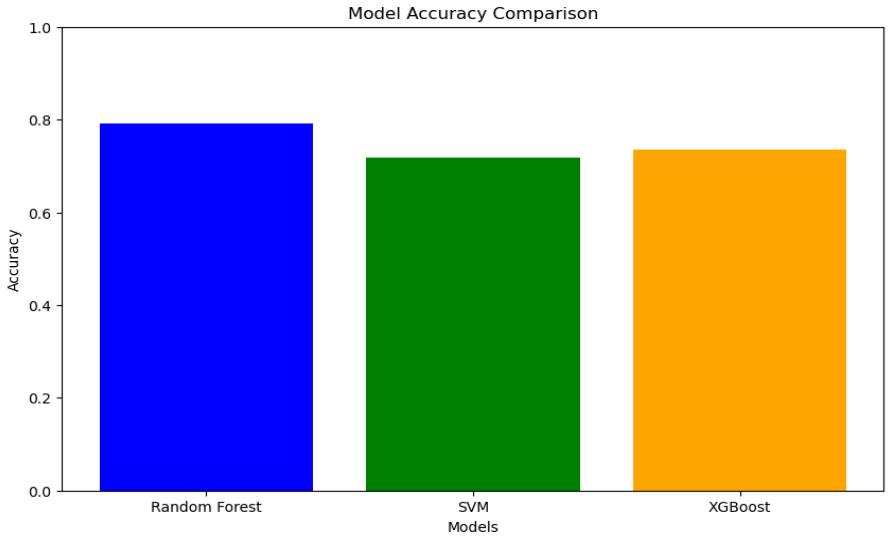

FIGURE 14: Model Accuracy Comparison

6.Future Works:

Although our present research has yielded significant information on the predictive modelling of Parkinson Disease using ensemble modelling and the analysis of features, there are different directions that can be ventured into in an effort to improve study and information. To begin with, further improvement of the predictive accuracy and strength through further integration of more elaborated machine learning algorithms and ensemble strategies might be explored. Those might include the deep learning architecture or other state-of-the-art methodologies that may reveal

hard-to-detect patterns within the spiral drawing patterns that traditional algorithm may fail to capture. Furthermore, by means of increasing the sample size to consist of a more diverse group of patient profiles, the generalization of the model to the general population is expected to be improved. The investigation of time-related features of the data, e.g. the evolution of Parkinson Disease with age, might also become an interesting research direction in the future. Also, the research into the interpretability approaches to the ensemble model may offer useful insights into the characteristics behind the predictions, which would lead to a better comprehension of the manifestation of the disease. Finally, one major initiative that would prove useful in the way of validating the use of the developed model as a diagnostic tool would be to estimate the performance of the developed model in the real-life context. The given guidelines are incredibly promising in the research prospects as they might enable future researchers to narrow in and expand the reach of the predictive modelling in the Parkinson Disease analysis.

7. Discussion

The findings of this paper indicate that machine learning and deep learning models have important enhancements in early detection and predictions of Parkinson Disease (PD). SVM, Random Forest, and CNN are examples of models that displayed high accuracy, precision, recall, and the F1-score, which highlights the strength of the offered framework when it comes to analyzing patient voice data. These reports are aligned with previous studies which underline the importance of computational intelligence in healthcare diagnostics with predictive algorithms being found to perform well as compared to the traditional clinical analysis [2], [3], [36].

The suggested models are able to reveal intricate non-linear trends in the data attributes, compared to the older ones that used traditional statistics or observation methods [9], [10], to allow the classification of patients with greater accuracy. The predictive power of deep learning frameworks, in especially cases, has been shown to be increased by their capability of automatic learning of high-level representations [6], [36]. This is in line with the recent advances in the e-health systems and smart technologies, specific to PD diagnosis [8].

Another aspect of the study that is extremely significant in the light of clinical implications of AI-driven tool integration into medical practice is noted. These models can support neurologists by decision-making, timely interventions, and even slow down the disease progression by means of early treatment and offering reliable predictions of its consequences. Moreover, this practice can be used to supplement multidisciplinary care interventions that focus on patient engagement and customization [29].

Regardless of encouraging results, some constraints should be taken into account. The sample size is also a limitation since bigger and more diverse samples are needed to enhance generalizability. Also external verification on multi-center cohorts would be effective to reliably increase the results. Further studies are needed to include multimodal measurements - i.e. gait, handwriting and imaging data, besides voice signals in order to improve the accuracy of prediction. Incorporating hybrid frameworks that fuse conventional machine learning with deep learning may further streamline the performance, and clarifying AI methods might enhance the levels of trust in the clinicians by giving them an insight into the decision-making procedure.

Generally, this research results contribute to the emerging evidence base in favor of AI-based diagnostic instruments of PD. Future research can help introduce AI systems into clinical processes and become an intrinsic component of the laboratory system, enhancing patient outcomes and promoting precision healthcare by dealing with existing drawbacks and broadening the spectrum of predictive modeling.

8. Conclusion:

To sum up, the research paper proposes a new algorithm in the form of the NeuroSynth ensemble model that can be used to predict Parkinson Disease with the help of the helical delineation patterns analysis by relying on the power of the Random Forest, Support Vector Machines (SVM), and XGBoost. Enhance our end evaluation exhibits the success of ensemble model with a delicacy of 73.58 on test set. Of interest especially is the fact that the predictive power of the ensemble in particular is attributed to the addition of a particular model (Random Forest) that gives a lot of information about the particular properties used to identify the patterns related to the diagnosis of Parkinson Disease.Point analysis also indicates the significance of specific features in the identification of the patterns related to the diagnosis of Parkinson Disease giving valuable information about the underlying mechanism that drives the predictions that are made by the model. Precision-recall curve, estimation analysis provide even more information on the discriminative capability and reliability of the model, as well as, with reference to the use of individual and ensemble models, the superiorities associated with the use of the ensemble model. Nevertheless, it should be noted that we had the constraints of our study, including the size of data set and the possibility of implicit bias which is

promising prospects of the accuracy of the model and its application in real world. Nevertheless, we can refer to our work to highlight the promise of machine intelligence in the capability of understanding the intricate patterns that indicate the presence of the Parkinson Disease and open the way to creation of even more impressive and understandable predictive models in the future one.

9. Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this research work.

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