Early Parkinson's Disease Diagnosis through Unsupervised Machine Learning Methods

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Abstract— The research being conducted examines the utilization of unsupervised algorithms for machine learning in Parkinson's disease (PD) diagnosis. Both the neural system and the body's nerve-controlled regions are impacted by an aging neurological disorder called Parkinson's disease. Timely intervention and management, particularly in the case of people over 65, depend on early diagnosis and treatment. The initial review of audio data gathered from the PPMI and UCI databases constitutes the foundation of early identification. Using the UPDRS Score, data points are divided into classes of PD and healthy cases using unsupervised machine learning algorithms such as K-means clustering, PCA, autoencoders, and One-Class SVM. We use metrics such as reconstruction loss, accuracy, explained variance, inertia, silhouette score, and cumulative variance to assess how well these models are performing. With a silhouette score of 0.7027 and an inertia value of 68,429.35, K-Means clustering demonstrated effective clustering quality. The first two principle components had cumulative variances of 53.87% and 62.19%, respectively, thus PCA conserved variance while reducing data dimensionality. With a reconstruction loss of 0.1004 units, autoencoders showed that they could replicate input data with a high degree of accuracy. Using several metrics (frequency, amplitude, tone, and variation), One-Class SVM demonstrated perfect classification performance with 100% accuracy. .The study discovered that while PCA approach kept variance while lowering data dimensionality, K-Means clustering and One-class SVM were effective in finding anomalies. Compared with conventional algorithms, the unsupervised technique outperformed them, which could facilitate early patient management. To tackle unsupervised model interpretability and data restrictions, additional research is necessary to ascertain its efficacy in clinical practice. The research presented here exhibits how approaches to clustering as well as unsupervised machine learning can be used to recognize Parkinson's disease early. Early on in the progression of the illness, the study noticed trends that underscored the need for better data quality and algorithm sensitivity. The paper suggests that collaboration between data scientists, physicians, and other stakeholders is crucial for integrating multi-modal data sources in order to identify Parkinson's disease early.

Keywords—Parkinson's disease (PD), unsupervised machine learning, K-means clustering, PCA, autoencoders, one-class SVM, silhouette score, inertia, explained variance, cumulative variance, reconstruction loss

Introduction

Dr. James Parkinson first described Parkinson disease as a "shaking pulse" in 1871. It is a degenerative brain disease that manifests both motor and non-motor. It is chronic and cumulative. The illness has a major clinical impact on patients, families, and caregivers in addition to its progressive degenerative consequences on muscular function and movement. According to clinical research physical changes in context to PD can be observed may start before the beginning of motor features and may consist a number of non-motor representations like irregular sleep patterns, depression, and sensitive changes.[2] Parkinson's disease patients must, regrettably, rely on early detection techniques and limit the disease's progression as there is now no medicine for the condition.[4].

The (MDS-UPDRS) stands for Movement Disorder Society Unified Parkinson Disease Rating Scale. It is a frequently used measure to assess the cumulative progression of Parkinson disease (PD) severity.[3] The UPDRS rating scale ranges from Part 1 to 4: Part I covers mentation, behaviour, and mood; Part II covers activities of daily living; Part III covers motor examination; and Part IV covers therapy-related complications. The maximum total UPDRS is 199, which represents the greatest potential disability from Parkinson's disease. Each symptom is scored on a 5-point scale that goes from 0 to 4. Good validity, sensitivity to change, and reliability are the outcomes of the UPDRS.There are other measuring scales like the Timed "Up & Go" Test (TUG), the Berg Balance Scale (BBS), the Forward Functional Reach Test (FFR), the Backward Functional Reach Test (BFR), and gait speed, which can be used to measure functional performance in areas not covered by the UPDRS.[6] Parkinson's disease (PD) is frequently monitored with the UPDRS scale, which necessitates the patient's in-person attendance at the clinic and involves drawn-out physical examinations by qualified medical personnel.[9]

Machine Learning Algorithms have been used actively in the healthcare industries. The algorithms are trained to learn the predictive features of labelled dataset.[13] ML algorithms are trained on computers to solve a problem by using past experiences of the system. To solve problems more quickly than humans, machine learning has several uses in a variety of fields. Processing and analysing vast amounts of data to discover patterns and connections among its aspects is made feasible by the accessibility of computational power and low-cost memory. Unsupervised learning techniques play a critical role in deriving significant insights and patterns from unlabelled data, with applications spanning a wide range of fields. Without the requirement for predetermined labels, these algorithms—such as clustering and dimensionality reduction techniques—allow for the finding of latent structures within data. Unsupervised learning is still driving efficiency and innovation in a variety of industries, including healthcare, banking, and beyond. It may be used to detect anomalies in data streams, improve natural language processing, and create new data samples. Its significance in contemporary data-driven decision-making processes is highlighted by its capacity to reveal latent linkages and patterns. Unsupervised learning is a rich topic with a variety of well-established techniques and ongoing theoretical developments. Computational approaches, information theory, and statistical theory have all contributed to the development of techniques like clustering, dimensionality reduction, and anomaly detection. Theoretical frameworks that contribute to our knowledge of data structures and their implications include manifold learning theories, hierarchical clustering methods, and Gaussian mixture models. Furthermore, the theoretical landscape is further enhanced by deep learning improvements that explore representation learning and complex data distributions, especially with generative models and self-supervised learning paradigms. These theoretical foundations strengthen the fundamental role of theory in enhancing unsupervised learning techniques, stimulating innovation in a variety of applications while also improving algorithmic capabilities.

I. RELATED WORK

Previous studies regarding Parkinson's Disease (PD) research prediction have made significant contributions, utilizing a variety of attributes within their datasets, including audio features. These studies have paved the way for the development of robust prediction models. For instance, in their research, the authors [1] delved into the role of electronic data in Healthcare, highlighting the dependency of computational methods, particularly Machine Learning (ML) algorithms, in identifying crucial patterns within clinical data. These algorithms have demonstrated their efficacy in detecting early signs of PD and rely on user-provided data for training and validation.

Moreover, DeMaagd and Philip [2] have extensively discussed the Parkinson's disease treatment. They emphasize the critical importance of accurately diagnosing conditions with similar symptoms. This recognition of the complexity of PD diagnosis highlights the need for precise and early detection methods, which our study addresses.

In a similar vein, Aditi Govindua and Sushila Palweb [4] utilized four Machine Learning models to investigate MDVP (Multidimensional Voice Program) and PWP (Periodic

Waveform Pattern) attributes in healthy individuals. Their research underscores the potential of Machine Learning in advancing our understanding of PD. Notably, their work demonstrates that the Random Forest classifier emerged as the ideal model for Parkinson's Disease detection, achieving an impressive accuracy and sensitivity of 0.95. This further underscores the potential of ML in the early diagnosis of PD. These existing studies collectively contribute to the expanding collection of knowledge in the domain, highlighting the utility of machine learning techniques and the importance of identifying relevant clinical features for accurate predictions. Our study builds upon this foundation by employing unsupervised machine learning techniques, offering a unique approach that addresses some of the limitations of supervised methods. We believe that this diversity in approaches and the consistent advancement in model performance will ultimately contribute to the refinement and expansion of early PD detection methods.

As the field continues to evolve, it is imperative to acknowledge the collaborative nature of research and the importance of building on the work of those who have come before us. These studies not only validate the potential of machine learning in healthcare but also emphasize the ongoing need for innovative solutions to improve the lives of individuals affected by Parkinson's Disease.

II. METHODS

The proposed methodology begins with the first step of collecting and gathering audio data of Parkinson's disease sufferers Voice Modulations from the PPMI Database and UCI. The dataset contains information about audio features like Shimmer, Jitter, motor UPDRS, and total UPDRS with respect to factors like frequency, amplitude, tone, and variation.[4] Unsupervised Algorithms like K-means Clustering, One-class SVM, Autoencoders and Principal Component Analysis. The algorithms are trained to cluster the dataset into PD and Normal cases.[22]

A. Dataset

Multiple biological speech measurements were submitted for the dataset by 42 early-stage Parkinson disease patients who were part of a six-month trial using a telemonitoring device for remote symptom progression monitoring. The patient's houses automatically recorded the sessions. [4] Every day the test was administered, six phonations were recorded: two at double the initial volume (without shouting), and four at comfortable pitch and loudness. A total of 5,875 voice recordings from these people are represented by each row.[9] Table I displays the dataset's properties for the feature's purpose.

Attribute	Purpose
Subject	A unique integer representing each subject
Age	Patients' ages
Sex	Gender of the patient: '0' indicates a male and '1' a female
Test Time	Duration since registration in the experiment. The days since recruitment make up the integer portion.
Motor UPDRS	The clinician's motor UPDRS score, linearly interpolated
Total UPDRS	A complete UPDRS score for the clinician, interpolated linearly

Jitter (%), Jitter (Abs), Jitter: RAP, Jitter: PPQ5, Jitter: DDP	Many measurements for basic variation in frequency
Shimmer, Shimmer(dB), Shimmer: APQ3, Shimmer: APQ5, Shimmer: APQ11, Shimmer: DDA	Multiple change in amplitude measurements
NHR, HNR	Two analyses of the noise to harmonic element ratio of the voice
RPDE	A measure representing complexity of nonlinear dynamics
DFA	Exponent of signal fractal scaling
PPE	An inhomogeneous nonlinear indicator of intrinsic frequency irregularity

TABLE I. Features of Dataset along with purpose

B. Data Preprocessing

The purpose of data exploration and visualization is to learn more about the features of the dataset. A heatmap is a type of data exploration where each feature's magnitude is calculated and shown by color. The heatmap depiction of all the dataset's acoustic features is shown in Fig. 1.
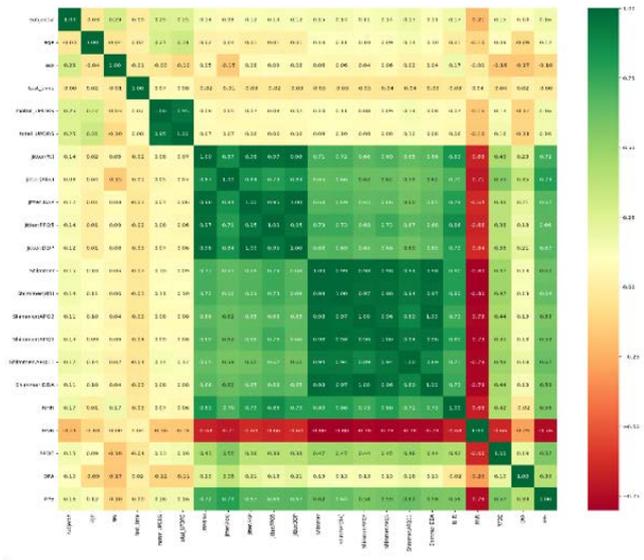

Fig. 1: Heatmap of Acoustic features

C. Algorithm training

The paper studies four types of techniques for unsupervised algorithms like K-means clustering, Principal Component Analysis, Autoencoders, and One-class SVM.

1) K-means clustering

A grouping of data objects that are similar to each other or linked to each other, but not similar to or unrelated from the objects in other groups is defined as Clusters. K-means clustering [17] is a method of dividing data into groups according to uniqueness or similarity criteria between data points. Finding commonalities between data based on the traits included in the data and organizing related data objects into clusters are the goals of cluster analysis. The separation of clusters visualization, which is examined to identify patient records exhibiting Parkinson disease and those without it, is depicted in Fig. 2.

Algorithm for K-Means: Technique is used for 18 characteristics of the data

- Gather audio information from UCI database.
- Analyze data to explore the detailed features of dataset.
- The unlabelled dataset is given as input, divides the dataset into K-number of clusters, and the process is repeated until it does not find best clusters.
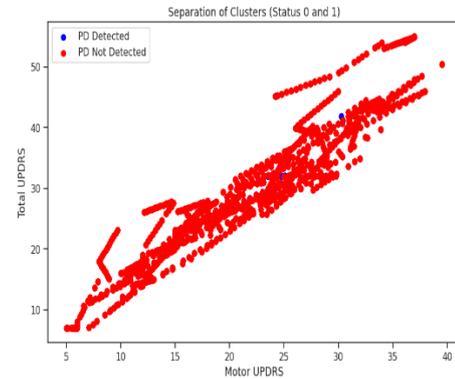- The evaluation of K-means is done by evaluating metric scores like Silhoette and inertia score.

Fig. 2: Clusters of Parkinson's disease and those with undiagnosed seperated

2) One-Class SVM

One-Class SVM samples from a single class by training on samples from that specific class. Anomaly Detection uses this approach which is used for identification of anomalies within the group of features in dataset.

Algorithm for One-Class SVM: Technique is used for 18 characteristics of the data

- Gather audio information from UCI database.
- Analyze data to explore the detailed features of dataset.
- One-Class SVM is trained on the clusters formed by K-Means Clustering, the features like frequency, amplitude, tone and variation are considered as feature groups. One-class SVM will learn to detect anomalies within the feature groups.
- The One-Class SVM predicts the outliers with the cluster, and assigns labels to the clusters.
- The Anomalies are visualized using scatter plots and the accuracy for each feature group using KNN Classifier.
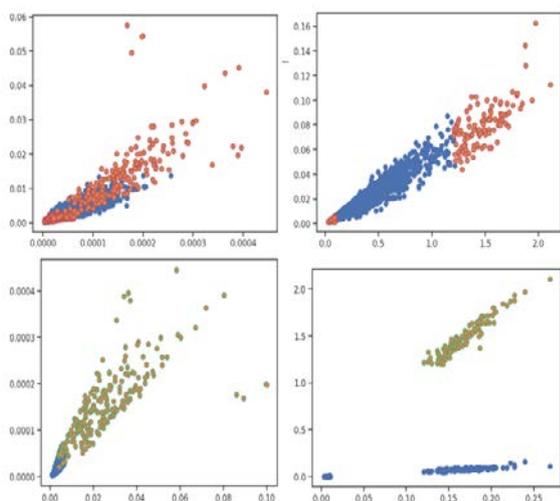
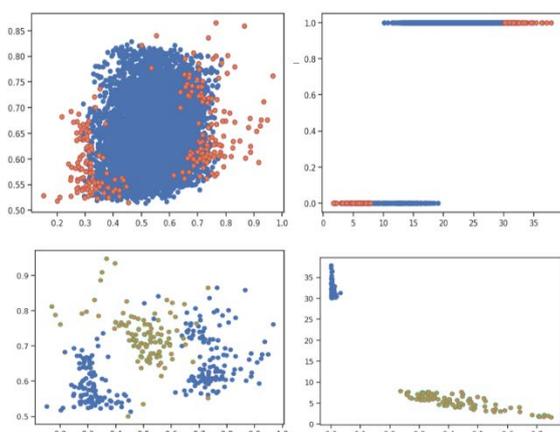Fig. 3.a: Detection of anomalies with frequency and amplitude

Fig. 3.b: Detection of anomalies within variation and tone

3) Autoencoders

An artificial neural network termed an autoencoder utilizes backpropagation settings based on unsupervised learning, where the objective is set to correspond to the input, $y^i = x^i$. In order to produce output that is equal to input, the autoencoder model aims to train an approximation function to the identity representation.[23]

Algorithm for Autoencoders: Technique is used for 18 characteristics of the data

- Gather audio information from UCI database.
- Analyze data to explore the detailed features of dataset.
- Training and testing sets of the dataset are separated. To scale the features to have a mean of 0 and a standard deviation of 1, data must be standardized. This is necessary for autoencoders to function well.
- Define an encoder and decoder. The encoder decreases the data's dimensionality, and the decoder attempts to reconstructs the original input from this reduced representation.
- The autoencoder is trained on the training data. For extraction of encoded representation and to obtain encoded data we create an encoder model.

- Evaluate the performance of autoencoder's reconstruction loss by using random data.
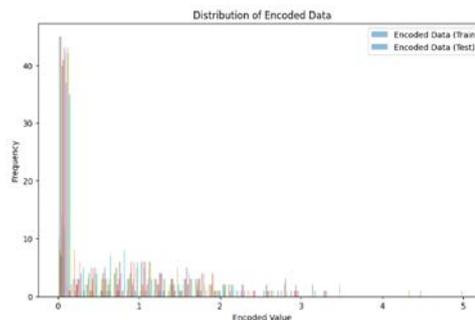

Fig. 4: Visualization of Encoder Weights and Encoded Data Distribution

4)Principal Component Analysis

One dimensionality reduction technique that is used to reduce the dimensionality of data and is helpful in determining the dataset's dimensions is PCA.Dimensionality reduction [21] is the method of decreasing variables, extracting latent features, or decreasing the data while preserving structure is known as dimensionality reduction. PCA simplifies the dataset by transforming it into a new coordinate system, making it easier to visualize and analyze. Fig. 5 shows the visualization for the two transformed principal components.

Algorithm for Principal Component Analysis: Technique is used for 18 characteristics of the data

- Gather audio information from UCI database.
- Analyze data to explore the detailed features of dataset.
- Feature Scaling is the preprocessing that standardizes the numerical features of the dataset. To make sure that every feature is on the same scale, feature scaling is crucial. The Standard Scaler is used for ensuring that all the features excluding the Total UPDRS column.
- PCA transforms original features into new principal components while retaining as much variance as possible. The transformed data is stored in variable of PCA component.
- Evaluation of PCA by explained variance ratio and cumulative explained variance.
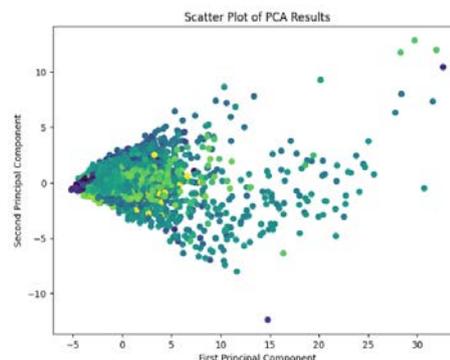

Fig. 5: Finding Clusters following Dimensionality Reduction

D. Evaluation

The evaluation of unsupervised models like K-Means, PCA, Autoencoders, and One-Class SVM involves assessing the performance and achieving clarity of how these models work efficiently. For K-means Clustering we use Metrics like Silhoette Score, and Inertia illustrated by (1) and (2).

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{1}$$

$$Inertia = \sum_{k=1}^{N}(x_i - C_k)^2 \tag{2}$$

For PCA, we use metrics like Explained Variance, and Cumulative Variance illustrated by (3) and (4).

$$Explained\ Variance = \frac{Variance\ (i)}{Total\ Variance} \tag{3}$$

$$CV_i = \sum_{k=1}^{i} Explained\ Variance(k) \tag{4}$$

For Autoencoders, we use metrics like Reconstruction Loss illustrated by (5). In Autoencoders, to measure reconstruction loss, a loss function is used which is called as Mean Squared Error (MSE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{5}$$

For One-class SVM, we use accuracy metrics for Frequency, Amplitude, Tone and Variation illustrated by (6).

$$Accuracy = \frac{Total\ number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100\% \tag{6}$$

Table II shows the scores of Learning Metrics for the four algorithms.

Algorithms	Learning Metrics
1)K-Means Clustering	1) Silhoette Score: 0.7026746015879717 2) Inertia: 68429.35010376839
2)PCA	1) Explained Variance: (53.87%,83.27%) 2) Cumulative Variance: (53.87%,62.19%)
3)Autoencoders	1) Reconstruction Loss: 0.1004 units
4)One-class SVM	1) Frequency (Accuracy-1): 100% 2) Amplitude (Accuracy-2): 100% 3) Tone (Accuracy-3): 100% 4) Variation (Accuracy-4): 100%

Table II. Algorithms with their Learning Metrics

III. DISCUSSION

The K-Means clustering algorithm with a high Silhouette Score and the One-class SVM with 100% accuracy in detecting anomalies across several categories were found to be efficient in resolving issues by our research. PCA technique preserved a considerable amount of variation while successfully reducing the dimensionality of the data. Our unsupervised strategy performed better than conventional supervised algorithms, indicating its potential use in situations when labelled data is scarce. The ability to facilitate early intervention for better patient outcomes is the clinical significance. But more research is needed to see whether adoption feasibility in standard clinical practice is feasible. Notwithstanding encouraging outcomes, issues include the intricacy of unsupervised model interpretability and data constraints that affect model performance. Subsequent studies ought to concentrate on resolving these constraints, expanding the quantity and variety of datasets, and improving the interpretability of the model to obtain useful perspectives.

IV. CONCLUSION

The possibility of unsupervised machine learning in the early detection of Parkinson's illness detection is demonstrated by this study. By applying sophisticated clustering algorithms to carefully gathered and pre-processed data, we were able to find important patterns that suggested the illness was still in its early stages. Our results highlight the necessity for further attention to data quality and algorithm sensitivity and point to the revolutionary impact of this strategy on clinical practices. As we celebrate our achievements, we also point out our shortcomings and suggest that multi-modal data sources be integrated in future studies. To actually improve patient care with these breakthroughs, collaboration between data scientists, physicians, and stakeholders is essential. Our approach ultimately envisions a future in which Parkinson's disease management relies heavily on early identification, spurring additional research and revolutionary advances in the medical field.

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