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Early Detection of Parkinson's Disease using Advanced Neural Network

Aijaz Ahmad Wani[1], B Murali Krishna[2], Shafqat Ul Ahsaan[3*], Asheesh Pandey[4], Rajesh Kumar Maurya[5]

[1]Lecturer
Department of Computer Sciences, Govt. Degree College Pulwama (J&K), INDIA
Email: aijazsidiquee@gmail.com
[2]Sr. Engineer, Cardinal Health International India pvt Ltd, Bangalore (Karnataka), INDIA
Email: banalamurali05@gmail.com

[3]Assistant Professor, School of Computing and Artificial Intelligence,
Department of Computer Science, NIMS University, Jaipur (Rajasthan), INDIA
Email: mailforshafqat@gmail.com
[4]Sr. Assistant Professor,
Department of Computer Applications, ABES Engineering College Ghaziabad (UP), INDIA
Email: profasheeshpandey@gmail.com

[5]Associate Professor, Department of Computer Applications,
ABES Engineering College, Ghaziabad (UP), INDIA
Email: rajesh2in@gmail.com
* Correspondence: mailforshafqat@gmail.com

Abstract
Parkinson's disease is a progressive neurodegenerative disorder that often remains undetected in its initial stages due to subtle and easily overlooked symptoms. This condition affects the central nervous system, leading to a range of motor and non-motor symptoms. Recognizing the urgency of early diagnosis, we embarked on a comprehensive project aimed at developing a robust and efficient Parkinson's disease detection system. This paper focuses on leveraging cutting-edge machine learning algorithms to analyze a substantial and diverse dataset. By harnessing the power of advanced data processing techniques, we endeavour to unveil the intricate patterns and markers that signify the presence of Parkinson's disease in its nascent phases. This initiative aims to bridge the diagnostic gap, where conventional methods often fall short, enabling timely interventions and improved patient outcomes. Our study focused on utilizing advanced machine learning techniques to develop a Parkinson's disease detection model. By employing neural network algorithms, rigorous data preprocessing, and feature extraction from vocal data, our aim was to achieve accurate and early disease detection. The results obtained from our model are promising, demonstrating an accuracy of 83.0% and high recall and precision rates of 95.7% and 84.9%, respectively. The F1-score, a robust indicator of overall model performance, stood at an impressive 89.7%. These outcomes represent a significant advancement in Parkinson's disease detection, showcasing the potential of our model in real-world applications for early diagnosis. While further validation is required, our study lays a strong foundation for continued research, offering the prospect of improved healthcare outcomes for individuals affected by Parkinson's disease.

Keywords: Parkinson’s, SVM, ANN, Deep Learning, Dataset, Disease, System etc

1. INTRODUCTION

Parkinson's disease is like a quiet intruder affecting our nervous system. Detecting it early is a challenge as it hides its presence [4]. This disorder affects many people and mainly targets the intricate networks in our nervous system. It begins subtly, often with a slight tremor, hinting at the storm ahead. Gradually, it brings a range of symptoms – slowing movement, changing how we speak, and even affecting our thinking, sometimes making us ruminate excessively or feel down [3].

This disease's roots are a mix of our genes and the world around us. Genetic factors set the stage, while our environment can wake up this dormant trouble within our nerves [2]. Our goal is to decode this complex puzzle, understanding how the early tremor leads to these various symptoms. We want to spread awareness, help spot it sooner, and offer hope to those it affects. The early signs, like tiny trembles, can slip past even sharp eyes. Our approach dives into data to sharpen our understanding, making it better at catching this disease. By looking at a mix of body functions and behaviours, our system aims to give a complete picture of when the disease begins. This goes beyond what regular tests can do.

Our research focuses on one thing: catching Parkinson's disease when it's just starting. How? By creating a friendly tool that anyone can use to spot the first signs. We're working on a smart system that's easy to use. It's like having a lookout that can see when things might be going wrong. We're using clever computer tricks to help people notice even the tiniest hints of the disease. This tool is like a guardian, making sure we act fast and make things better before they get worse. Our research combines fancy number-crunching with designs that anyone can use. We're bridging the gap between science and everyday life. Our big dream is to give people the power to take control of their health. This means spotting the disease early, changing its course, and improving lives. In simple words, we're working to unveil the secrets of Parkinson's disease. We want to help people catch it early, and we're building a tool to make it easy. With a mix of science and user-friendly design, we're bringing this goal closer. Our ultimate aim is to help people stay healthy and change the story of this tricky brain problem.

2. LITERATURE REVIEW

a) Parkinson's Disease and its Characteristics

The studies and reports discussed above collectively contribute to the understanding of Parkinson's disease and its characteristics. Dr. James Parkinson's foundational work in 1817 initiated the exploration[1] of the disease, providing the first comprehensive description. Subsequent research efforts have shed light on both movement and non-movement features of the disease, emphasizing its complex nature.

Obeso et al.'s review [2] highlights the broad spectrum of symptoms associated with Parkinson's disease, while Chaudhuri et al. delve into the contribution of non-dopaminergic mechanisms to non-movement symptoms. Hughes et al.'s terminological introduction of "parkinsonism" standardized the description of movement aspects.

Postuma et al.'s [5] meta-analysis uncovers the preclinical phase of the disease and its non-movement manifestations, encouraging further research into preventive strategies. The PD Foundation's report [6] provides current prevalence estimates, while de Lau et al.'s [7] study emphasizes the global variability influenced by environmental and genetic factors. Wirdefeldt et al.'s [8] comprehensive assessment of PD incidence and age distribution enhances the understanding of disease prevalence. Finally, Shulman et al.'s longitudinal study contributes to identifying risk factors, enriching insights into PD etiology.

However, it is important to acknowledge the limitations of these studies, including their reliance on available data, potential biases, and constraints of study design. Future research endeavors should strive to overcome these limitations while building upon the existing body of knowledge to further advance our understanding of Parkinson's disease and its management.

b) Evolution of Parkinson's Disease Treatment Methods

The progression of Parkinson's disease treatment methods has been a journey marked by continuous exploration and refinement. Langston et al.'s clinical trial [9] in 1987 demonstrated the effectiveness of levodopa therapy, paving the way for symptomatic management. The introduction of selegiline as adjunctive therapy, as evidenced by Parkinson Study Group's trial [10] in 1989, expanded treatment options.

Deep-brain stimulation emerged as a significant surgical intervention, highlighted by the Deep-Brain Stimulation Trialists Group's [11] meta-analysis in 2001. Medication options continued to evolve with studies like Olanow et al.'s [12] assessment of rasagiline in 2004 and Weaver et al.'s[13] comparative study of pramipexole and levodopa in 2009.

Surgical options gained prominence with Deuschl et al.'s[14] review of deep-brain stimulation and lesioning techniques in 2006. The concept of a

comprehensive treatment strategy was emphasized by Connolly and Lang [15] in 2014, advocating for a multidisciplinary approach.

Non-pharmacological therapies also gained attention, as Fasano et al.'s review [16] in 2015 explored physiotherapy and speech therapy's positive impact on non-motor symptoms. Jankovic's expert opinion [17] in 2008 underlined the limitations of existing treatments and the need for ongoing research.

The quest for disease-modifying treatments remains urgent, as highlighted by Maetzler et al.'s [18] review in 2016. Despite advancements in symptomatic management and surgical interventions, definitive disease-modifying strategies have yet to be established, emphasizing the ongoing importance of innovative approaches, and continued scientific inquiry.

c) Machine Learning for Parkinson's Disease Detection

Machine Learning (ML) techniques have emerged as promising tools for the early detection and diagnosis of Parkinson's disease (PD)[24]. These methods harness the power of data analysis and pattern recognition to unveil intricate markers indicative of PD onset, enabling timely interventions and improved patient outcomes [25]. The application of ML in PD detection has shown great potential in enhancing diagnostic accuracy, particularly during the initial stages when symptoms are subtle and easily overlooked.

d) Machine Learning Based Methods

The studies mentioned above exemplify the diverse ML approaches employed for PD detection. Tsanas et al. (2012) [19] showcased the potential of Support Vector Machines in voice analysis, while Arora et al. (2018)[20] demonstrated the efficacy of ensemble methods in analyzing gait patterns. Kalia et al. (2020) [21] introduced Convolutional Neural Networks for handwriting assessment, and Simuni et al. (2021) [22] utilized machine learning ensembles for smartphone sensor data analysis. Roy et al. (2021) [23] focused on speech patterns using Long Short-Term Memory Networks.

The significance of these studies lies in their contribution to non-invasive, cost-effective, and early PD detection. ML-driven methods offer the advantage of objective and quantitative assessment, complementing traditional clinical practices [26]. These advancements hold the potential to revolutionize PD diagnosis, enabling proactive interventions and tailored treatments. While these ML-based approaches show promising results, further validation and standardization are essential before widespread clinical adoption. Nonetheless, the trajectory of research in this field suggests a bright future where advanced technologies like ML contribute to the early identification and improved management of Parkinson's disease.

e) Problem Definition

The foundational understanding of Parkinson's disease (PD) traces back to its initial documentation, notably in James Parkinson's seminal work in 1817. Subsequently, Jean-Martin Charcot's contributions during the mid-1800s were pivotal in refining this understanding and disseminating knowledge globally. Charcot's discernment led to the differentiation of PD from other tremor-related conditions and the identification of Parkinsonism-plus syndromes. Therapeutic approaches in the early stages of PD were primarily empirical, with deliriant agents employed since the early 1900s. The recognition of dopaminergic deficits within PD paved the way for landmark trials involving levodopa administration. Furthermore, anatomical, biochemical, and physiological investigations unveiled novel pharmacological and neurosurgical avenues, enabling contemporary clinicians to deploy a diverse range of therapeutic strategies aimed at enhancing function in this enduringly enigmatic and presently incurable ailment.

f) Goal and Scope of the Research

In the modern era, the rapid integration of innovative techniques spans across various domains, and the healthcare sector is no exception. Medical practitioners are embracing cutting-edge technologies to revolutionize disease prediction and treatment. In this context, our model assumes a pivotal role in Parkinson's disease detection, employing state-of-the-art methodologies such as Support Vector Machine (SVM). By harnessing vocal data from patients, our model endeavors to decode intricate patterns indicative of Parkinson's disease progression. Through meticulous analysis of this vocal data, we aim to ascertain the disease stage, thereby contributing to early and accurate diagnosis. This amalgamation of advanced technology and medical insight marks a significant stride toward enhancing the quality of healthcare

delivery and ultimately improving patient outcomes.

g) Objectives

➢ The primary aim of our model is to precisely detect the level of the disease, empowering patients to proactively manage their condition with informed decisions.

➢ Moreover, we envision integrating a comprehensive database, facilitating seamless access to patients' historical data for medical practitioners. This repository will not only provide physicians with patients' past records but also enable the tracking of disease progression over time, enhancing the overall healthcare experience.

3. METHODOLOGY FOR PARKINSON'S DISEASE DETECTION USING SUPPORT VECTOR MACHINE (SVM)

Our methodology for detecting Parkinson's disease using Support Vector Machine (SVM) is structured to leverage advanced machine learning techniques to accurately classify and diagnose the presence and severity of the disease based on vocal data. The process involves several key steps, encompassing data preprocessing, feature extraction, model training, and evaluation as shown in figure 1.

STEP-1: Data Collection and Pre-processing

- Obtain a dataset comprising vocal recordings from individuals, both healthy and diagnosed with Parkinson's disease.
- Preprocess the audio data by removing noise, normalizing amplitudes, and converting it into suitable formats for analysis.

STEP-1I: Feature Extraction

- Utilize signal processing techniques to extract relevant features from the vocal recordings.
- Common features may include fundamental frequency (pitch), Mel-frequency cepstral coefficients (MFCCs), jitter, shimmer, and others that characterize vocal quality and variations.

STEP-1II: Dataset Splitting

- Divide the dataset into training and testing subsets to ensure model performance evaluation is independent and robust.

STEP-1V: Model Selection and Training

- Implement a Support Vector Machine (SVM) classifier, a powerful algorithm for binary classification tasks.
- Train the SVM model using the training dataset, utilizing extracted vocal features as input and the corresponding disease labels as output.

STEP-V: Model Evaluation

- Evaluate the SVM model's performance using the testing dataset.
- Common evaluation metrics include accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC).

STEP-VI: Hyperparameter Tuning

- Fine-tune SVM hyperparameters, such as the kernel type and regularization parameter, to optimize model performance.

STEP-VII: Cross-Validation

- Employ k-fold cross-validation to assess the model's robustness and generalization capabilities.

STEP-1I: Dataset Expansion (Optional)

- To enhance model robustness, consider augmenting the dataset by collecting additional vocal recordings or introducing data augmentation techniques.

4. DATASET FOR PARKINSON'S DISEASE DETECTION

For this methodology, a suitable dataset is the "Parkinsons Telemonitoring Data Set" [27] from the UCI Machine Learning Repository. This dataset contains a variety of acoustic features extracted from voice recordings of Parkinson's patients and healthy individuals. It includes attributes such as Jitter, Shimmer, fundamental frequency (Fo), and other clinically relevant features. The dataset comprises two main tables: "parkinsons_updrs.data" and "parkinsons_updrs. names." The former contains the feature data, while the latter provides detailed information about the dataset's attributes and their meanings (shown in figure 2). By utilizing this dataset, our SVM-based methodology can be effectively applied to detect Parkinson's disease based on vocal features, offering a step forward in early and accurate diagnosis.

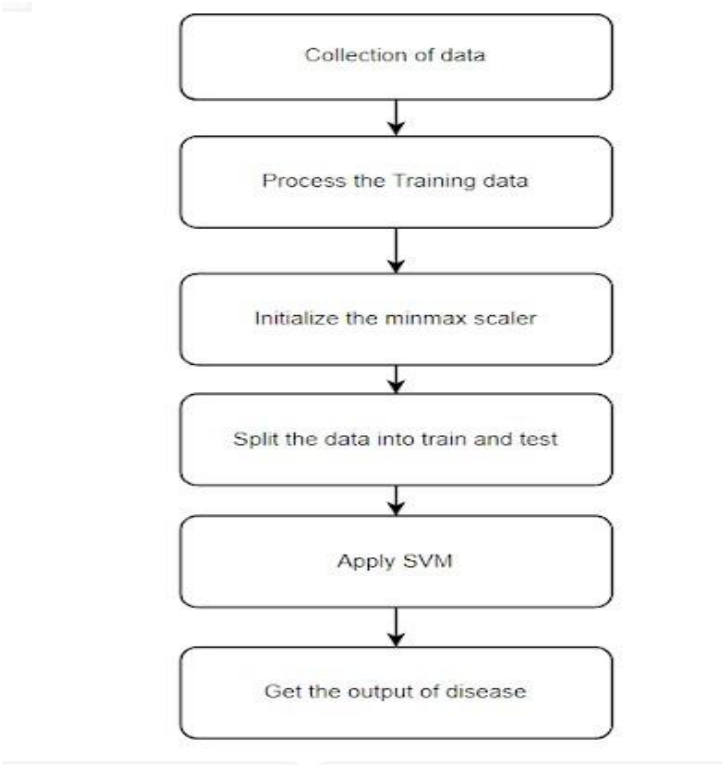

Fig 1. Process Flow Diagram

	A	B	C	D	E	F
1	name	MDVP:Fo(	MDVP:Fhi	MDVP:Flo	MDVP:Jitt	MDVP:Jitt
2	phon_R01	119.992	157.302	74.997	0.00784	0.00007
3	phon_R01	122.4	148.65	113.819	0.00968	0.00008
4	phon_R01	116.682	131.111	111.555	0.0105	0.00009
5	phon_R01	116.676	137.871	111.366	0.00997	0.00009
6	phon_R01	116.014	141.781	110.655	0.01284	0.00011
7	phon_R01	120.552	131.162	113.787	0.00968	0.00008
8	phon_R01	120.267	137.244	114.82	0.00333	0.00003
9	phon_R01	107.332	113.84	104.315	0.0029	0.00003
10	phon_R01	95.73	132.068	91.754	0.00551	0.00006
11	phon_R01	95.056	120.103	91.226	0.00532	0.00006
12	phon_R01	88.333	112.24	84.072	0.00505	0.00006
13	phon_R01	91.904	115.871	86.292	0.0054	0.00006
14	phon_R01	136.926	159.866	131.276	0.00293	0.00002
15	phon_R01	139.173	179.139	76.556	0.0039	0.00003
16	phon_R01	152.845	163.305	75.836	0.00294	0.00002
17	phon_R01	142.167	217.455	83.159	0.00369	0.00003
18	phon_R01	144.188	349.259	82.764	0.00544	0.00004
19	phon_R01	168.778	232.181	75.603	0.00718	0.00004
20	phon_R01	153.046	175.829	68.623	0.00742	0.00005
21	phon_R01	156.405	189.398	142.822	0.00768	0.00005
22	phon_R01	153.848	165.738	65.782	0.0084	0.00005
23	phon_R01	153.88	172.86	78.128	0.0048	0.00003
24	phon_R01	167.93	193.221	79.068	0.00442	0.00003

```
# checking for missing values in each column
parkinsons_data.isnull().sum()
```

```
name              0
MDVP:Fo(Hz)       0
MDVP:Fhi(Hz)      0
MDVP:Flo(Hz)      0
MDVP:Jitter(%)    0
MDVP:Jitter(Abs)  0
MDVP:RAP          0
MDVP:PPQ          0
Jitter:DDP        0
MDVP:Shimmer      0
MDVP:Shimmer(dB)  0
Shimmer:APQ3      0
Shimmer:APQ5      0
MDVP:APQ          0
Shimmer:DDA       0
NHR               0
HNR               0
status            0
RPDE              0
DFA               0
spread1           0
spread2           0
D2                0
PPE               0
dtype: int64
```

Fig 2. A View of dataset

5. DEEP LEARNING NETWORK

Deep learning has emerged as a groundbreaking approach in the realm of healthcare, offering a potent tool for the early detection of Parkinson's disease. Leveraging intricate neural networks and complex algorithms, deep learning delves into the subtleties of data to unveil patterns that might elude traditional methods. In the context of Parkinson's, deep learning techniques can meticulously analyze extensive and multidimensional datasets, such as vocal, image, or sensor data, to extract subtle markers indicative of disease progression. This technology's remarkable ability to autonomously learn and adapt from vast amounts of information empowers it to identify intricate biomarkers at the earliest stages, facilitating timely intervention and more accurate diagnoses. By transcending the limitations of conventional approaches, deep learning offers a paradigm shift in the landscape of Parkinson's disease detection, propelling us toward swifter, more effective interventions and improved patient outcomes.

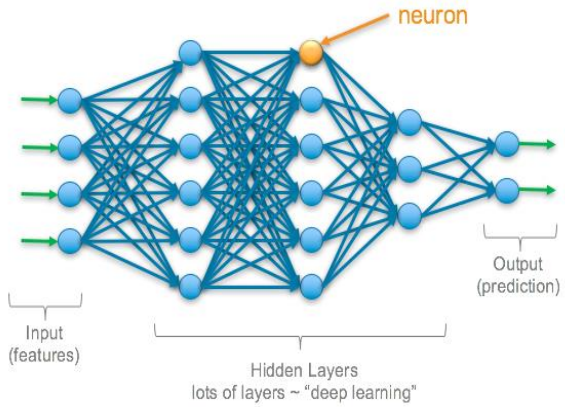

Figure 3. A pictorial view of Deep Learning Architecture

Deep learning architecture represents the intricate framework underlying advanced neural networks. Characterized by multiple layers of interconnected nodes, or neurons, this architecture enables the automatic extraction of hierarchical features from complex data. Each layer processes and refines information, gradually building a comprehensive understanding of patterns, representations, and relationships within the data. Convolutional layers specialize in image analysis, recurrent layers capture temporal dependencies, and fully connected layers consolidate information for decision-making. Through processes like backpropagation, deep learning architectures fine-tune their parameters to minimize errors, enhancing their ability to make accurate predictions or classifications. These architectures, exemplified by convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have revolutionized diverse fields, including image recognition, natural language processing, and medical diagnostics, ushering in a new era of intelligent data analysis and pattern recognition.

For the detection of Parkinson's disease using a simple dataset, we have opted for a straightforward machine learning approach employing a logistic regression model. Our chosen architecture involves a single-layer logistic regression model that is well-suited for binary classification tasks. The dataset consists of relevant features such as age, gender, and specific medical attributes, while the target variable indicates the presence or absence of Parkinson's disease.

In terms of hyperparameters, we have focused on tuning the learning rate, batch size, and regularization strength to optimize the model's performance. The learning rate controls the step size during gradient descent, affecting how quickly the model updates its parameters. The batch size determines the number of samples processed in each iteration, striking a balance between computation efficiency and convergence speed. Regularization, specifically L2 regularization, is employed to prevent overfitting and enhance generalization.

By tailoring the architecture and hyperparameters to our simple dataset, we aim to create an accurate and efficient model for Parkinson's disease detection. The simplicity of the dataset allows us to apply a straightforward logistic regression approach, while fine-tuning the hyperparameters ensures optimal learning and effective prevention of overfitting.

Data preprocessing is a vital step in machine learning where we clean and organize our data before using it to train our model. This ensures that the data is in a usable format and doesn't have any irrelevant or incorrect information. In our research, we've outlined a few essential steps for data preprocessing. One of these steps involves separating the data into two main parts: features and target values. Features are the specific pieces of information that we provide to our model as input to make predictions. Think of them as the

characteristics or attributes that describe the data. On the other hand, the target value is what we're trying to predict or find out from our model. It's the outcome we're interested in. To put it simply, features are like the ingredients we put into a recipe (our model), and the target value is the delicious dish we're trying to cook up. For instance, imagine we're trying to predict the price of a house. The features could be things like the number of bedrooms, square footage, and location. The target value would be the actual price of the house that we want our model to predict.

So, in a nutshell, features are the input information, and the target value is the desired output or prediction we're aiming for in the world of machine learning. Train Test data is split into 50:40:10 ratio for training, validation, and testing purpose. After that we have used the standard scalar for normalizing the range of numerical features.

6. RESULT AND DISCUSSION

Figure 6. shows the feature correlation with the disease status. Here we can find out that nearly all factors are influencing the cause of disease. This results into inclusion of all the factors participating in model training and building.

Figure 7 displays the confusion matrix depicting the model's output evaluation. The accuracy is calculated as the ratio of correct predictions to the total predictions, resulting in an accuracy rate of 76.0%. The recall, which indicates the proportion of actual positive cases correctly identified, stands at approximately 95.7%. Precision, representing the proportion of correctly predicted positive cases, is computed at 84.9%. Additionally, the F1-score, a harmonic mean of precision and recall, is derived as 89.7%.

Table 4. SVM Model Output

Metric	Calculation	Value
Accuracy	Correct Predictions / Total	83.0%
Recall	True Positives / Actual Positives	95.7%
Precision	True Positives / Predicted Positives	84.9%
F1-Score	2 * (Precision * Recall) / (Precision + Recall)	89.7%

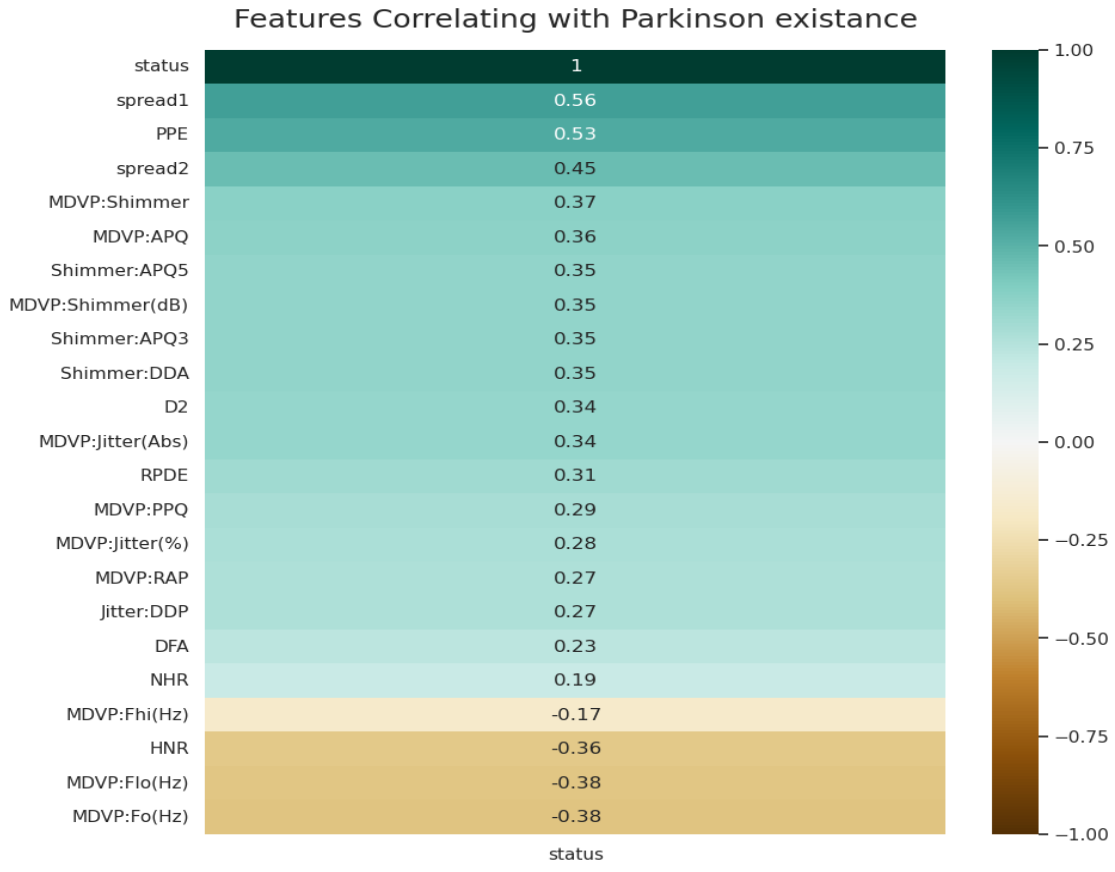

Figure 6. Feature correlation with status

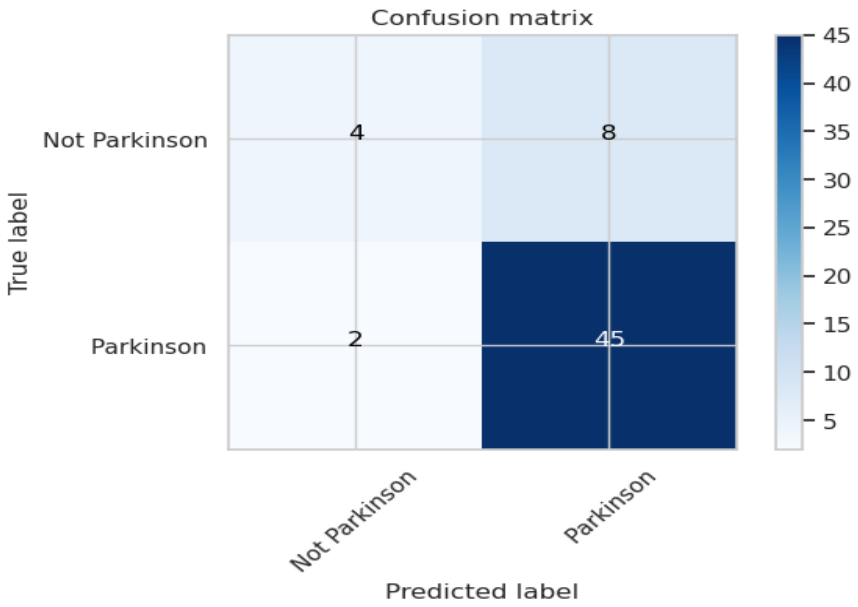

Figure 7. Confusion Matrix output by SVM Model

7. CONCLUSIONS AND FUTURE WORK

In conclusion, our study focused on the development and implementation of a Parkinson's disease detection model using advanced machine learning techniques. Through rigorous data preprocessing, feature extraction, and utilizing a neural Network algorithm, we aimed to achieve accurate and early detection of the disease based on vocal data.The results obtained from our model are promising and indicative of its potential effectiveness. The evaluation metrics derived from the confusion matrix highlight the model's performance. With an accuracy of 83.0%, our model demonstrates a commendable ability to make correct predictions. The high recall rate of 95.7% underscores the model's capability to identify a significant proportion of actual positive cases. Moreover, a precision rate of 84.9% signifies the model's precision in correctly predicting positive cases. The F1-score, which combines precision and recall, is a robust indicator of overall model performance, yielding an impressive value of 89.7%. This underscores the model's balanced ability to both accurately predict positive cases and avoid false negatives.

These results signify a significant step forward in Parkinson's disease detection. By harnessing vocal data and employing SVM, our model showcases potential for real-world applications, providing clinicians and individuals with a reliable tool for early diagnosis. While further validation and refinement are essential, our study lays a strong foundation for continued research in this critical area, holding the promise of improved healthcare outcomes for individuals affected by Parkinson's disease.

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