DETECTION OF PARKINSON’S DISEASE BASED ON THE INTEGERATION OF AUDIO FEATURES AND RFE ALGORITHM

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I, Divyansh Tyagi, 2k22/SPD/03. Am student of MTech. (Signal Processing and Digital Design), hereby declare that the project Dissertation titled "**Parkinson's Disease detection based on combination of Audio features and RFE Algorithm** " which is submitted by me to the Department of Electronics and Communication Engineering Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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ABSTRACT

In recent times, the scientific community has exhibited a notable upsurge in curiosity concerning the potential application of acoustic signals as biomarkers in the detection of Parkinson's disease. Approximately 90% of individuals diagnosed with Parkinson's disease demonstrate symptoms of vocal impairment in the early phases of the condition, according to research. In this article, a novel approach is presented for analyzing the effect of a dataset that includes both short-term and long-term features, MFCC (melt frequency cepstral coefficients), on the efficacy of a random forest model designed to detect Parkinson's disease. The research employs Recursive Feature Elimination (RFE) to produce an optimal subset of critical features, thereby enhancing the model's performance and mitigating overfitting that may occur during training. The results indicate that the integration of MFCC with long-term features led to a Random Forest Classifier accuracy of 89.94%.

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ACRONYMS

CNN :	Convolution Neural Network
LSTM :	Long Short-Term Memory
RNN :	Recurrent Neural Network

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO PARKINSON’S DISEASE

Parkinson's disease (PD) was initially labeled as "tremulous palsy" by Dr. James Parkinson in his seminal work "An Essay on the Shaking Palsy." This neurological disorder is characterized by a range of motor and non-motor symptoms, and its etiology remains incompletely understood. PD primarily affects the dopaminergic neurons in the substantia nigra region of the brain, leading to a decrease in dopamine levels and subsequent motor impairment. Despite ongoing research efforts, a cure for PD remains elusive, highlighting the complexity of this debilitating condition. James Parkinson published his famous work in the year 1817. This work is a landmark in the field of medicine and has since influenced numerous scholars and researchers in the study of Parkinson's disease. It is widely recognized as a chronic and progressive neurodegenerative disorder that manifests with a combination of both motor and non-motor symptoms. This disease has noteworthy clinical implications for patients, families, and caregivers due to its progressive debilitating effects on movement and muscle control. The motor symptoms associated with Parkinson's Disease (PD) have traditionally been linked to the degeneration of dopamine neurons in the striatum. However, the presence of non-motor symptoms suggests that neuronal loss may also occur in non-dopaminergic regions of the brain. This highlights the complexity of PD pathology and the need for further research to fully understand the disease process. The term parkinsonism refers to a collection of symptoms utilized for characterizing the motor manifestations associated with Parkinson's disease. These symptoms typically include resting tremor, bradykinesia, and muscle rigidity [1].

Parkinson's Disease (PD) is the primary etiological factor underlying parkinsonism, although there exist numerous secondary causes, which encompass conditions resembling PD and causes related to drug use. Research findings indicate that the pathophysiological alterations linked to PD may commence prior to the onset of motor impairments and may encompass non-motor symptoms like disturbances in sleep patterns, depressive symptoms, and cognitive impairments. Evidence at this preclinical stage has sparked interest in research devoted to preventative or preventive therapies.

Parkinson's Disease (PD) is commonly associated with the elderly population, however, there have been cases of individuals developing the disease in their 30s and 40s. Gender disparities in PD incidence are evident, with a ratio of 3 males to 2 females. The delayed onset of PD in females is believed to be linked to the neuroprotective properties of estrogen on the nigrostriatal dopaminergic system. Overall, these factors highlight the complex interplay of age and gender in the development of Parkinson's Disease [2].

The variability in PD's progression demonstrates a pronounced impact on patients, their families, and society. This impact is substantial and wide-reaching, affecting multiple facets of healthcare and social systems. Advanced and end-stage disease can result in severe complications, such as pneumonia, that are frequently linked with fatalities. Current treatment strategies primarily revolve around the symptomatic management of symptoms. Researchers and healthcare providers are actively working towards improving therapeutic approaches for addressing the underlying causes of the condition. Research indicates that individuals diagnosed with Parkinson's disease (PD) may experience favorable outcomes when receiving care through a multidisciplinary team comprised of movement specialists, social workers, pharmacists, and various other healthcare professionals. Studies have demonstrated the potential advantages of incorporating a comprehensive approach to managing PD, which involves the coordination of diverse expertise to address the multifaceted needs of patients [3].

1.1.1 STAGES OF PARKINSO'S DISEASE

1. Preclinical Phase**:**

- During this stage, cellular changes are occurring, however, no noticeable symptoms are present.
- Dopamine-producing neurons undergo degeneration, resulting in a gradual reduction in dopamine levels. This process leads to the decline of dopamine production over time.
- Clinically, there are no observable signs of PD at this point.

2. Prodromal Phase**:**

- During the prodromal phase of Parkinson's disease, individuals may experience subtle symptoms that are not specific enough to warrant a definitive diagnosis of PD.
- These early signs might include:
    - Mild alterations in movement coordination may be observed in patients, who may experience challenges in performing fine motor tasks.
    - Non-motor symptoms: Constipation: Gastrointestinal dysfunction is common in prodromal PD, Sleep disturbances: Insomnia, restless legs, or vivid dreams may occur, Loss of smell (anosmia): Reduced ability to detect odours, Depression or anxiety: Emotional changes can precede motor symptoms.

3. Clinical Phase:

- This is the point at which traditional Parkinsonian symptoms begin to manifest.
- Common motor symptoms include:
    - Tremors: Typically starting in one hand and progressing to other limbs. Resting tremors are characteristic.
    - Rigidity: Stiffness in muscles, making movement less fluid**.**
    - Bradykinesia: Slowing down of voluntary movements, affecting tasks like buttoning a shirt or walking.

    - Hypomimia: Reduced facial expression (often referred to as “masked face”).
    - Micrographia: Smaller handwriting due to reduced fine motor control.

- Diagnosis is usually made during this stage based on clinical evaluation and patient history.

4**.** Motor Fluctuations:

- Motor fluctuations may arise approximately five to ten years following the initial diagnosis of the condition. These fluctuations refer to changes in motor symptoms experienced by individuals with the condition over time.
- These fluctuations involve variations in medication effectiveness (especially levodopa) and the emergence of dyskinesias (involuntary movements).
- Patients may experience “on” periods (when medication works well) and “off” periods (when symptoms worsen).

5. Postural Instability:

- Approximately a decade following diagnosis, postural instability begins to emerge as a prominent symptom.
- Patients often face challenges with maintaining balance, which can ultimately result in a heightened susceptibility to falls. This underscores the importance of implementing targeted interventions to mitigate the risk of falls and improve patient outcomes.
- Gait disturbances and freezing episodes may occur.
- Assistive devices (e.g., canes, walkers) become necessary.

Stages of Parkinson’s				
Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Tremor on one side of the body	Tremor, rigidity and other movement symptoms affect both sides of the body	Loss of balance and slowed movement	Movement is limited	Difficult or unable to stand
Mild clumsiness	Walking, bathing and changing clothes take a longer time to complete	Falls become more common	Patient requires assistive devices like walking canes	Requires a wheelchair

Slowed facial expressions and movement	Stiff trunk muscles	Daily activities of living are hindered. But patient is mostly still independent	Needs help with daily activities of living	Difficulty swallowing

Table 1 Parkinson's disease symptoms are gradual in nature.

1.1.2 Etiology and Risk Factors of Parkinson's Disease:

Parkinson's disease (PD) is a complex neurodegenerative condition, influenced by a variety of contributing factors. It is recognized by the gradual decline of neurons that produce dopamine within the substantia nigra area of the brain. The etiology of this condition involves a multifaceted interplay between genetic susceptibility and environmental factors [4].

1.Genetic Factors:

Genetic predisposition plays a significant role in Parkinson's disease, with both familial and sporadic forms of the condition highlighting the importance of genetic factors.

- Mutations in Specific Genes: Parkinson's disease has been linked to genetic mutations in several genes, such as SNCA (alpha-synuclein), LRRK2 (Leucine-Rich Repeat Kinase 2), PARK2 (parkin), PARK7 (DJ-1), and PINK1 (PTEN-induced kinase 1). These mutations have been found to interrupt a multitude of cellular processes, including protein folding, mitochondrial function, and autophagy, ultimately resulting in the onset of neurodegenerative disorders.
- Genetic Variants: Genome-wide association studies (GWAS) have been instrumental in the discovery of common genetic variants linked to the risk of Parkinson's disease. These studies have provided valuable insights into the genetic factors contributing to the development of this neurodegenerative disorder. The findings from GWAS have enhanced our understanding of the underlying genetic architecture of Parkinson's disease, paving the way for further research into the development of targeted therapies and interventions. The identified variants are implicated in a range of biological pathways, such as dopamine metabolism, synaptic transmission, and inflammation. Individual genetic variants have been shown to increase disease risk to a small extent; however, when these variants are considered together, their cumulative effects significantly contribute to overall disease susceptibility. This suggests that the combined impact of multiple genetic variants should be taken into account in assessing an individual's risk for developing a particular disease.

2. Environmental Factors:

Environmental exposures have been implicated in the increased risk of developing Parkinson's disease, especially in those individuals with specific genetic vulnerabilities.

- Pesticides, Herbicides, and Industrial Chemicals: Exposure to environmental toxins such as pesticides (e.g., rotenone, paraquat), herbicides, and industrial chemicals has been associated with an increased risk of Parkinson's disease. These substances can induce oxidative stress, mitochondrial dysfunction, and alpha-synuclein aggregation, leading to neuronal damage.

- Heavy Metals: Occupational exposure to heavy metals, including lead, manganese, and iron, constitutes a significant environmental risk factor for the development of Parkinson's disease. The presence of certain metals has been shown to interfere with cellular homeostasis, compromise mitochondrial function, and incite neuroinflammation, thus playing a significant role in the progression of neurodegenerative diseases.

- Dietary Factors: Emerging research suggests that dietary factors may modulate Parkinson's disease risk. Antioxidants, found in fruits and vegetables, may have neuroprotective effects, while certain pesticides and dairy products may increase the risk. Additionally, caffeine and tobacco use have been associated with a reduced risk of Parkinson's disease, possibly due to their neuroprotective properties.

- Other Environmental Exposures: Solvents, industrial chemicals, air pollution, and geographic variations have also been implicated in Parkinson's disease risk. These factors may interact with genetic predispositions, leading to alterations in cellular function, inflammation, and oxidative stress.

3. Quality of Life and Psychosocial Impact:

Parkinson's disease is known to have a significant impact on various aspects of patients' lives, including their quality of life, daily functioning, and psychosocial well-being. This neurological condition can present challenges that can greatly affect the overall well-being and functioning of individuals diagnosed with the disease. Addressing the various aspects outlined above is imperative for achieving comprehensive disease management. It is important to consider all facets of the disease in order to effectively address and combat its effects.

- Motor and Non-Motor Symptoms: Parkinson's Disease presents a variety of motor symptoms, including tremors, rigidity, bradykinesia, and postural instability. Additionally, non-motor symptoms such as cognitive impairment, mood disorders, and sleep disturbances are commonly observed in individuals diagnosed with this condition. The symptoms experienced by patients can have a substantial impact on their quality of life and ability to function independently.

- Psychosocial Support: Psychosocial support services, such as counseling, support groups, and caregiver education programs, play a critical role in addressing the emotional and social ramifications of Parkinson's disease on both patients and their families. These services are essential for providing necessary support to individuals affected by the disease and aiding in their overall well-being and quality of life. These services offer a conducive environment for individuals to share their experiences, exchange coping strategies, and receive practical advice on effectively managing the difficulties associated with living with Parkinson's disease.

4. Disease Progression and Management:

Parkinson's disease is characterized by a progressive course, with symptoms worsening over time. Management strategies aim to alleviate symptoms, improve quality of life, and slow disease progression.

- Pharmacological Medications: Dopamine substitution treatment, counting the utilize of levodopa and dopamine agonists, speaks to the foundation of pharmacological administration in people with Parkinson's malady. The utilize of these drugs is viable in relieving engine side effects, be that as it may, they may be connected to long-term complications such as engine variances and dyskinesias.

- Surgical Intercessions: Profound brain incitement (DBS) surgery develops as a reasonable helpful choice for people analyzed with progressed Parkinson's illness, characterized by both engine vacillations and medication-related complications. This strategy offers a focused-on approach to viably oversee the side effects related with the infection, giving patients with moved forward quality of life and indication administration. Profound Brain Incitement (DBS) could be a neurosurgical method that involves the implantation of terminals in focused on ranges of the brain to direct neuronal movement and give help from indications. This strategy has been appeared to be compelling in overseeing a assortment of neurological and psychiatric clutters.

- Non-Pharmacological Approaches: Physical treatment, word related treatment, and discourse treatment collectively serve as basic components within the comprehensive administration of Parkinson's infection side effects and upgrade of useful freedom. These helpful mediations are significant in tending to the engine and non-motor impedances related with the condition, eventually pointing to optimize the quality of life for people with Parkinson's illness. Work out programs that are customized to meet the special needs of each person have been appeared to be viable in protecting portability, upgrading adjust, and moving forward by and large quality of life. Such custom-made work out regimens have been found to be advantageous in keeping up physical work and advancing autonomy in day-by-day exercises. It is vital for healthcare experts to consider the particular capacities and restrictions of each individual when planning an work out program, in arrange to optimize the benefits and minimize the dangers of damage. By centering on person needs, work out intercessions can play a basic part in upgrading the well-being and quality of life for individuals of all ages.

1.2 CHALLENGES

The detection of Parkinson's disease (PD) using long-term acoustic features combined with Mel-frequency cepstral coefficients (MFCC) faces several challenges that must be addressed for successful implementation in clinical settings. First, variability in speech due to factors like age, gender, and individual speaking styles can affect the accuracy of PD detection, necessitating robust preprocessing techniques to normalize these variations. Additionally, the extraction of long-term acoustic features requires extensive computational resources and sophisticated algorithms to capture subtle changes over time, which can be challenging in real-time applications. Ensuring the quality and consistency of voice recordings is also crucial, as background noise and recording conditions can introduce artifacts that may skew the analysis. Moreover, the integration of MFCC with long-term features demands careful feature selection and dimensionality reduction to prevent model overfitting and ensure generalizability across diverse populations. Finally, obtaining large, annotated datasets representative of the wide spectrum of PD symptoms is essential for training reliable models but often poses significant logistical and ethical challenges.

1.3 SCOPE OF WORK

The scope of this proposal includes the advancement and assessment of an programmed Parkinson's infection (PD) location framework based on the combination of long-term acoustic highlights and Mel-frequency cepstral coefficients (MFCC). This investigate will include a few key components: Firstly, a comprehensive examination of existing strategies for voice-based PD discovery will be conducted, highlighting the points of interest and impediments of utilizing long-term acoustic highlights and MFCC. The proposal will at that point center on planning an compelling include extraction handle, coordination both long-term and MFCC highlights to capture the nuanced vocal impedances related with PD. Progressed machine learning models, counting profound learning designs such as Convolutional Neural Systems (CNNs) and Repetitive Neural Systems (RNNs), will be actualized to prepare these highlights and classify PD precisely. The consider will utilize freely accessible datasets, guaranteeing the models are prepared and approved on different and agent voice tests. Additionally, the inquire about will address commonsense challenges such as taking care of boisterous information, guaranteeing computational proficiency, and making strides show generalizability. By combining these approaches, the proposition points to contribute a vigorous, effective, and adaptable arrangement for early PD location, possibly helping in convenient conclusion and superior administration of the malady.

1.4 DISSERTATION ORGANIZATION

The content of the dissertation is organized into six chapters:

- Chapter I INTRODUCTION TO PARKINSON'S DISEASE
- Chapter II LITERATURE SURVEY
- Chapter III BACKGROUND TECHNIQUES
- Chapter IV PROPOSED ALGORITHM
- Chapter V EXPERIMENTAL RESULTS

Chapter I – Includes the introduction to Parkinson's disease system and overview about causes of this disease.

Chapter II – This chapter is literature survey, which gives an insight about the research papers published based on Parkinson's Disease detection.

Chapter III – This chapter gives an insight into the background techniques that are being used in the implementation of the proposed work.

Chapter IV – This chapter covers the proposed Algorithm RFE(Recursive Feature Elimination) working and comparison with other existing Algorithms.

Chapter V – This chapter includes the experimental results.

CHAPTER 2

LITERATURE SURVEY

2.1 VOCAL BIOMARKERS AND ADVANCED MACHINE LEARNING ALGORTIMS

Later ponders within the field of Parkinson's Infection (PD) discovery have set a developing accentuation on utilizing vocal biomarkers in conjunction with advanced machine learning calculations to viably pinpoint the introductory pointers of the malady. Vocal biomarkers, counting modifications in discourse rate, phonation, verbalization, and prosody, serve as pivotal pointers of Parkinson's Malady (PD). Particular acoustic characteristics such as jitter, sparkle, and Harmonics-to-Noise Proportion (HNR) play a striking part as critical markers in recognizing PD. Progressed machine learning calculations such as Back Vector Machines (SVMs), Convolutional Neural Systems (CNNs), and Irregular Timberlands are utilized to analyze vocal biomarkers. Ponders have appeared that Bolster Vector Machines (SVMs) have a prevalent execution in managing with high-dimensional discourse information. On the other hand, Convolutional Neural Systems (CNNs) are capable at capturing complex designs and varieties display in voice recordings. Irregular Timberlands are known for their vigorous execution and interpretability. They are able to proficiently handle loud information and put accentuation on the significance of highlights. This makes them a well known choice within the field of machine learning. Comparative assessments have appeared that profound learning models, particularly Convolutional Neural Networks (CNNs), tend to display more prominent precision within the discovery of Parkinson's Malady (PD). Be that as it may, it ought to be noted that accomplishing this level of exactness frequently requires the utilize of expansive datasets and critical computational assets. Coordination these calculations with comprehensive vocal evaluations presents a promising heading for improving the early location and persistent checking of Parkinson’s Infection. Besides, the utilize of such innovation in conjunction with conventional symptomatic strategies has the potential to revolutionize the field of Parkinson's Infection determination and management [5].

2.2 DYNAMIC FEATURES OF SPEECH

The detection of Parkinson’s Disease (PD) using dynamic features of speech has seen significant advancements through the application of deep learning methodologies. Recent studies have explored a variety of vocal biomarkers, such as alterations in speech rate, articulation precision, and phonatory quality, which are indicative of PD. These biomarkers are quantitatively analyzed using features like jitter, shimmer, and Harmonics-to-Noise Ratio (HNR). Deep learning models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have been particularly effective in capturing the complex temporal dynamics of speech. These models outperform traditional machine learning algorithms by leveraging their ability to process large datasets and learn intricate patterns. Comparative analyses indicate that CNNs excel in spatial feature extraction, while LSTMs are adept at handling temporal dependencies, making them highly suitable for sequential speech data. Integrating these models with advanced preprocessing techniques, such as spectral analysis and feature normalization, has further enhanced their diagnostic accuracy. Overall, the synergy between dynamic speech features and deep learning algorithms presents a robust framework for early and non-invasive PD detection [6].

2.3 **ARTICULATORY AND PHONATORY ASPECTS**

Later progressions within the field of identifying and assessing Parkinson's Malady (PD) utilizing voice and discourse investigation have demonstrated considerable potential, particularly within the zones of verbalization and phonation. Later thinks about have appeared that people analyzed with Parkinson's infection (PD) display special discourse impedances, counting uncertain consonant generation, diminished discourse rate, and modifications in prosody. These disabilities are commonly recognized through acoustic and kinematic examinations. Vowel formant investigation and electromagnetic articulography (EMA) have been utilized to show a decrease in exactness in tongue and lip developments. Within the domain of phonation, parameters related with voice quality such as jitter, sparkle, and Harmonics-to-Noise Proportion (HNR) serve to clarify the appearances of breathiness and roughness that are commonly watched in people with Parkinson's malady (PD). Moreover, strategies such as electroglottography (EGG) are utilized to identify the nearness of inconsistencies in vocal overlay vibration designs. These apparatuses and methods play a significant part within the appraisal and characterization of vocal brokenness in people influenced by PD. Machine learning models prepared on discourse highlights have illustrated outstanding victory in observing Parkinson's illness (PD) patients from solid people. This progression has opened up openings for the improvement of versatile and home-based evaluation devices that empower progressing observing. As research propels, the integration of discourse investigation procedures with other clinical evaluations and personalized treatment approaches has the potential to greatly move forward the early conclusion and administration of Parkinson’s Disease [7].

2.4 ANALYSIS OF SPEECH AND VOICE

Later headways within the computerized investigation of discourse and voice for Parkinson's Illness (PD) location have centered on both articulatory and phonatory disabilities, advertising promising roads for early determination and checking. Articulatory investigation highlights changes in vowel formants and decreased vowel space range (VSA), demonstrating decreased accuracy in tongue and lip developments, regularly surveyed through electromagnetic articulography (EMA). Worldly measures uncover bradykinesia and hypokinesia, reflected in slower and less reliable discourse. On the phonatory side, PD patients commonly show expanded jitter, shine, and decreased Harmonics-to-Noise Proportion (HNR), driving to raspy and breathy voice quality. Machine learning calculations, such as Back Vector Machines (SVMs) and Convolutional Neural Systems (CNNs), are utilized to examine these vocal biomarkers, illustrating tall precision in recognizing PD patients from sound controls. These headways in discourse and voice examination, coupled with computational methods, give non-invasive, cost-effective apparatuses for the early discovery and nonstop observing of Parkinson’s Disease [8,9].

CHAPTER 3

BACKGROUND TECHNIQUES

3.1 RANDOM FOREST

Random Forest is a robust and adaptable supervised machine learning algorithm that builds and merges numerous decision trees to form a "forest". It can address both classification and regression tasks in programming languages such as R and Python. Supervised machine learning involves the creation of an algorithm, also known as a model, using a designated training dataset. This dataset serves as the basis for the algorithm to learn patterns and make predictions. The model undergoes training with a diverse set of examples encompassing various inputs and outputs, facilitating its capacity to categorize any novel input data it encounters subsequently. The process involves the model assimilating information from a multitude of instances, which enables it to refine its classification abilities for future data evaluation. Algorithms play a significant role in forecasting future events and outcomes by efficiently processing available data and making informed predictions. The utilization of algorithms in predictive analysis has proven to be a valuable tool in various fields such as financial forecasting, weather prediction, and medical diagnosis. By carefully analyzing patterns and trends within data sets, algorithms can help identify potential future scenarios and provide valuable insights for decision-making processes. Furthermore, the accuracy and effectiveness of predictive algorithms rely heavily on the quality of input data, the complexity of the algorithm utilized, and the expertise of the individuals involved in implementing and interpreting the results. Through continuous refinement and improvement, algorithms continue to evolve and enhance their predictive capabilities, contributing to advancements in various industries and domains [10].

3.2 REGRESSION AND CLASSIFICATION IN MACHINE LEARNING

Utilizing calculations, machine learning classifies particular inputs, occasions, or perceptions. For occurrence, an e-mail spam channel separates between "spam" and "non-spam" substance based on each particular message. In any case, the mail outline is uncomplicated; encourage elaboration will be given on how the prescient capacity of such models can essentially affect trade technique and decision-making. As a result, classification and relapse are both administered machine learning errands that look for to anticipate the outcome's esteem or category. In classification investigation, the subordinate highlight could be a categorial quality. People are teaching by classification assignments on how to assign course names to occasions in a indicated issue space. As already specified, the e-mail spam channel serves as a unremarkable illustration of classification. In relapse examination, the subordinate trait comprises of numeric values. Regression is utilized when the yield variable may be a nonstop or real esteem, counting compensation, age, or weight. To supply clarity on the refinement, it is imperative to note that classification centers on foreseeing an identifier (such as "spam" or "not spam"), whereas relapse predicts a quantity [11].

3.3 DECISION TREE

The Random Forest model is a machine learning algorithm that amalgamates multiple decision trees to form a "forest." A decision tree is a different type of algorithm employed for data classification. A decision tree can be conceptualized as a flowchart illustrating a structured pathway leading to a specific decision or outcome. At its inception, the tree begins at a singular point before diverging into two or more branches, each representing distinct potential outcomes. This organizational structure allows for a systematic visualization of multiple potential scenarios and their corresponding resultants.

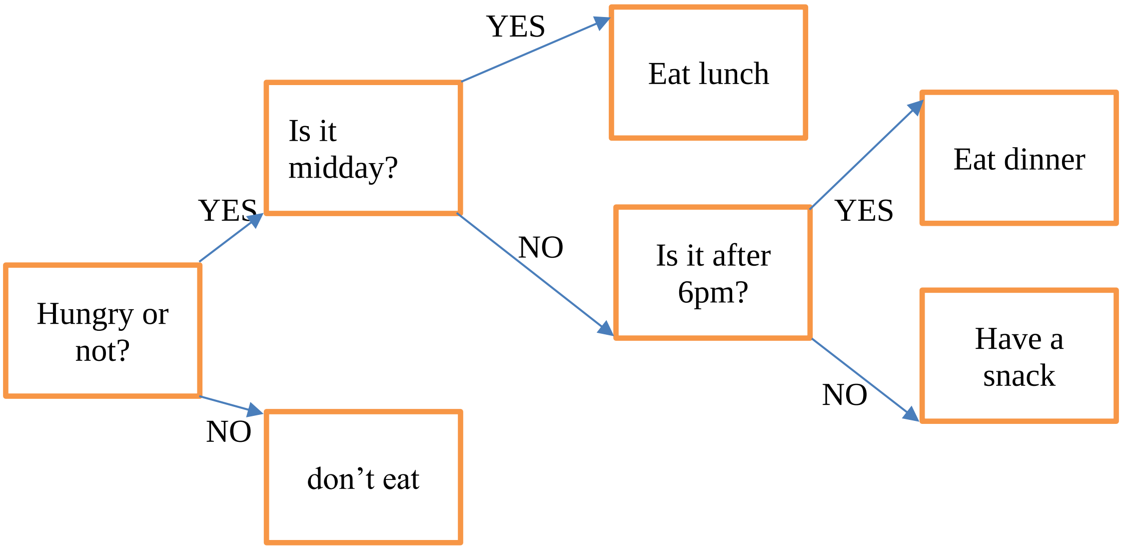

Figure 3.1 Decision Tree Example

Classification is considered a crucial component within the field of data science, and Random Forest stands out as a prominent algorithm that can be effectively utilized for carrying out classification tasks. Random Forest is an ensemble learning method that combines multiple decision trees to produce a single predictive model. The output of Random Forest is typically calculated by either taking the mode or mean of the predictions made by each individual tree in the ensemble. This approach offers improved accuracy and stability in the generated results through the utilization of numerous trees, as opposed to relying on a single decision tree.

3.4 RANDOM FOREST ALGORITHM

Irregular Woodland could be a machine learning calculation that utilizes an gathering procedure by developing numerous choice trees. These decision trees are at that point combined or consolidated to form a stronger and more exact forecast demonstrate. This strategy of combining numerous choice trees makes a difference in moving forward the in general expectation execution of the calculation. The Irregular Timberland show is based on the guideline that accumulating numerous uncorrelated models, too known as person choice trees, can abdicate predominant execution compared to each show working freely. When utilizing Irregular Forest for classification, each person tree gives a classification or "vote", with the ultimate classification being decided by the larger part of these "votes" inside the woodland. Alternately, for relapse errands, the Arbitrary Timberland calculation totals the yields of all trees to compute the normal yield. The core of the matter is the negligible or nonappearance of relationship between the individual models, specifically the choice trees comprising the overarching Arbitrary Timberland show. This need of relationship may be a principal angle that contributes to the adequacy and strength of the Irregular Woodland calculation. Person choice trees may result in mistakes; in any case, most of the bunch will be precise, eventually impacting the in general result in a positive direction [12,13].

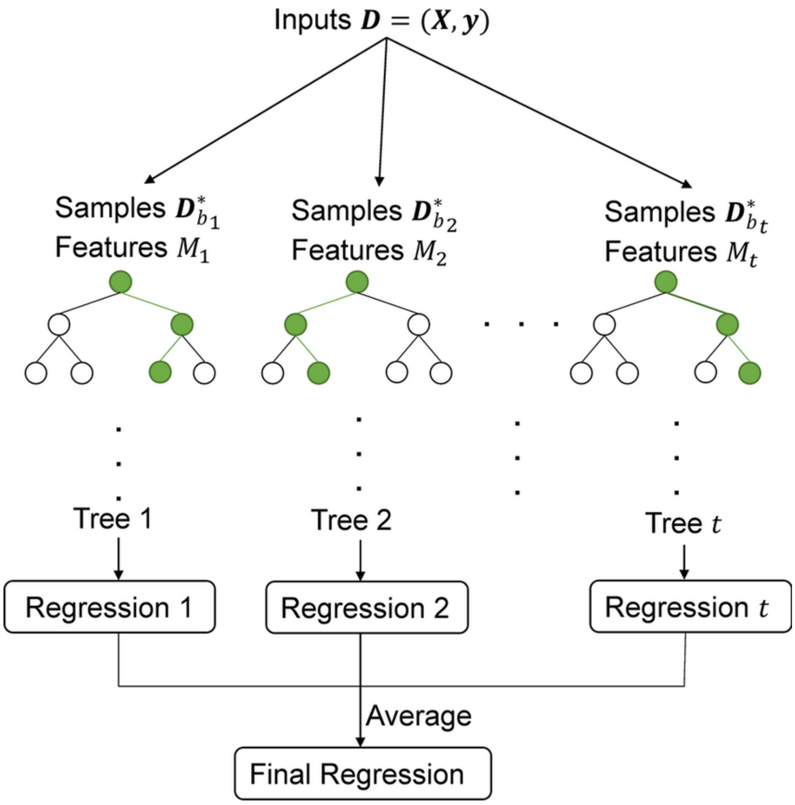

Figure 3.2 Random Forest Example

3.5 RANDOM FOREST TRAINING

Choice trees inside an outfit, such as those comprising a Irregular Woodland, are ordinarily prepared utilizing the "stowing" method. The strategy alluded to as "sacking" speaks to a particular sort of outfit machine learning calculation known as Bootstrap Accumulation. A gathering strategy amalgamates expectations determined from numerous machines learning calculations, in this manner improving the precision of expectations compared to those produced by a solitary demonstrate. Irregular Woodland in addition an outfit learning strategy. Bootstrap conducts arbitrary push examining and include examining from the dataset to produce test datasets for each show. Conglomeration solidifies these test datasets into rundown insights based on the perceptions and coordinating them. Bootstrap Conglomeration, commonly alluded to as sacking, serves as a viable strategy for decreasing the change related with tall fluctuation calculations, counting choice trees. By producing numerous forms of a indicator and utilizing these as a shape of collective decision-making, sacking upgrades the solidness and precision of prescient models. Fluctuation alludes to the mistake that emerges due to the model's affectability to minor varieties inside the dataset utilized for preparing. Tall change comes about in an calculation modeling extraneous information, or noise, present within the dataset instead of the required results, alluded to as the flag. This issue is alluded to as overfitting. An overfitted demonstrate shows ideal execution amid the preparing stage; be that as it may, it comes up short to successfully separate between commotion and flag amid genuine testings.

CHAPTER 4

PROPOSED FEATURE SELECTION ALGORITHM

4.1 WRAPPER METHODS

A wrapper method is a feature selection technique commonly employed in machine learning to identify a subset of features by assessing their importance within the model training phase. Wrapper methods differ from filter methods in their approach to feature selection. While filter methods use statistical measures to determine feature importance, wrapper methods involve training a model and evaluating feature performance based on the model's accuracy. This distinction highlights the importance of utilizing a predictive model in the feature selection process.

A typical wrapper method functions in the following manner. The method acts as a mediator between the calling code and the code that needs to be executed. It encapsulates the functionality of the underlying method, adding additional features or functionality as needed.

- Subset Generation: Wrapper methods are utilized in feature selection to generate various subsets of features. These subsets are created through a process that iterates through different combinations of features to evaluate their impact on the model's performance. The subsets can vary in size and composition.
- Model Training: Each subset of features is utilized for training a machine learning model. The evaluation of the model's performance involves the utilization of a selected performance metric, such as accuracy, precision, recall, or F1-score. This metric is used to assess the effectiveness and efficiency of the model in achieving its intended objectives.
- Feature Subset Evaluation: The model's performance is evaluated for each individual subset of features. This allows for a comprehensive understanding of how the model performs with varying combinations of features. The evaluation conducted in this study assesses the performance of the model in relation to the specified set of features.
- Feature Selection: The subset of features that results in the highest performance based on the selected metric is chosen. This selection process ensures that the features selected for the model have the greatest impact on the model's overall performance. This particular subset is regarded as the optimal collection of features.
- Final Model Training: Ultimately, after careful consideration and analysis, a specific subset of features is chosen for training the ultimate model. This model is subsequently utilized for generating predictions on data that has not been previously observed.

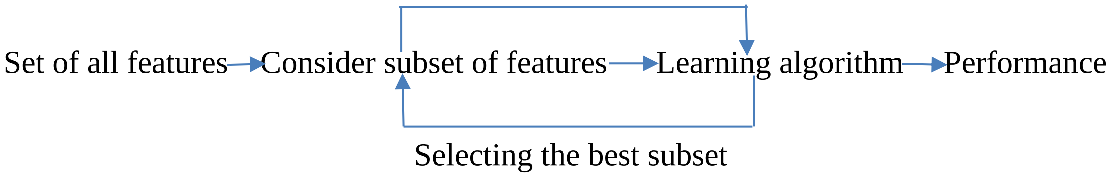

Figure 4.1 Wrapper Method briefly

4.2 TECHNIQUES UNDER WRAPPER METHOD

1. Forward Selection:

- Process: The process begins with an initial empty set of features and proceeds iteratively by adding one feature at a time. The feature selection is based on selecting the one that results in the greatest improvement in model performance. This approach allows for the optimization of the feature set in order to enhance the overall accuracy and effectiveness of the model.
- Algorithm: This algorithm is characterized by its greedy nature, where it consistently selects the most advantageous option at each individual stage.

2. Backward Elimination:

- Process: The iterative feature elimination process begins by considering all features in a model and progressively eliminating the least important features until no further improvement in model performance is detected.
- Algorithm: Similar to forward selection, greedy algorithm can also be used for its implementation.

3. Recursive Feature Elimination (RFE):

- Process: In the iterative process of feature selection, the algorithm recursively eliminates the least significant feature in each iteration until the desired number of features is achieved. This approach allows for a systematic reduction of the feature space while preserving the most relevant characteristics for analysis. By iteratively evaluating and prioritizing features, the algorithm can effectively identify the subset of features that best support the analytical objectives.
- Algorithm: This method frequently involves the utilization of machine learning algorithms that possess the capability to rank the importance of features. Common algorithms used for this purpose include support vector machines (SVM) and decision trees.

4. Exhaustive Feature Selection:

- Process: The process involves analyzing every potential combination of features and ultimately selecting the one that produces the highest performance metric. This method ensures that the chosen features will result in the most optimal outcome based on the specified criteria.
- Algorithm: The computational cost of this method can be high, particularly when dealing with datasets that contain a high dimensionality of features.

5. Genetic Algorithm:

- Process: Genetic algorithms are a computational technique inspired by natural selection, leveraging evolutionary principles to determine the optimal feature subset. This process involves maintaining a population of feature subsets and iteratively improving them through crossover and mutation operations. The algorithm seeks to mimic the process of evolution in nature, gradually refining and optimizing the selected features for a specific problem or task.
- Algorithm: Genetic algorithms are a computational approach that employs a population of potential solutions, known as feature subsets, which undergo evolution over successive generations in pursuit of an optimal solution.

Each of the aforementioned methodologies possesses distinct advantages and drawbacks. Despite their unique characteristics, they may vary in terms of effectiveness and efficiency. The selection of an appropriate wrapper method is contingent upon various factors including the size of the dataset, the intricacy of the model, and the computational resources at disposal. These considerations play a crucial role in determining the most suitable wrapper method for the given circumstances. Moreover, it is important to note that the effectiveness of wrapper methods can differ based on the machine learning algorithm utilized and the characteristics of the dataset. This variability underscores the need for careful consideration and evaluation when selecting and implementing wrapper methods in the context of machine learning applications. Hence, it is frequently advantageous to engage in experimentation with various wrapper techniques and assess their efficacy in order to ascertain the most suitable strategy for a particular issue.

4.3 PROPOSED RFE ALGORITHM

The proposed Recursive Feature Elimination (RFE) is a methodology utilized for feature selection to determine the most significant attributes within a given dataset. It operates by recursively eliminating certain features and evaluating their impact on the performance of a specified machine learning model. This iterative process helps to identify the key features that contribute most significantly to the predictive power of the model. RFE can be a valuable tool for enhancing the efficiency and accuracy of machine learning algorithms by reducing the dimensionality of the dataset and focusing on the most relevant features. The procedure entails constructing a model with the remaining features by iteratively eliminating the least significant components until the desired number of features is achieved. The selection process involves careful consideration of the significance of each feature in determining the final model. The Recursive Feature Elimination (RFE) technique is compatible with various supervised learning algorithms; however, it is most commonly employed alongside Support Vector Machines (SVM). SVM is the favored choice for utilizing RFE due to its effectiveness and robust performance in feature selection tasks.

ALGORITHM:

Ranking the importance of various features using the RFE machine learning algorithm is a crucial step in assessing their significance in predicting the target variable. This process involves evaluating the impact of each feature on the overall model performance and selecting the most relevant ones for accurate predictions. It helps in identifying the key drivers of the outcome and improving the interpretability of the model. Furthermore, it aids in simplifying the model by selecting only the most informative features, thereby reducing complexity, and enhancing computational efficiency.

- To enhance the overall quality and efficiency of the product, it is advised to remove the least significant feature. This will contribute to a more streamlined and focused design, ultimately leading to a better user experience.

- In the next step, it is essential to develop a model by utilizing the features that have not yet been incorporated into the analysis. This model will help further investigate the dynamics of the dataset and potentially better predict outcomes. Thus, it is imperative to carefully consider the selection and implementation of these remaining features to ensure the effectiveness of the model.

- To achieve the desired number of features, it is necessary to iterate through steps 1 to 3 repeatedly. This process should be continued until the specified feature quantity is attained.

PRACTICES FOR RFE

- Choose the Appropriate Number of Features:

One way to effectively balance model power and complexity is by selecting the appropriate number of features. This decision plays a crucial role in ensuring that the model is both powerful and manageable. It is essential to carefully evaluate the trade-offs involved in including too few or too many features, as this can significantly impact the model's predictive performance and interpretability. By striking the right balance, researchers and practitioners can enhance the overall effectiveness of their models and better understand the relationships between the features and the outcome of interest. Furthermore, a thoughtful selection of features can improve the model's generalizability and robustness, making it more applicable to a wider range of scenarios. Ultimately, the careful consideration of feature selection is key to constructing reliable and actionable models in various domains. Conducting experiments by varying the number of features and assessing the model's performance can provide valuable insights. It is essential to systematically analyze how different feature configurations impact the predictive capabilities of the model. Utilizing a range of feature sets allows for a comprehensive understanding of the model's strengths and weaknesses. For a thorough evaluation, it is recommended to try out various combinations of features and carefully examine the corresponding outcomes. By conducting systematic experiments with different feature sets, researchers can better comprehend the nuances of the model's behavior and optimize its performance.

- Sets the Number of Cross-Validation Folds:

Cross-validation, a method commonly utilized in machine learning, serves the reason of diminishing overfitting and improving the generalization capacity of a demonstrate. It includes part the dataset into different subsets, preparing the show on a subset, and testing it on a diverse subset. This prepare is rehashed numerous times to guarantee the show is vigorous and does not depend as well intensely on particular information designs. By utilizing cross-validation, analysts can get a more precise estimation of the model's execution and make more educated choices with respect to its generalizability and prescient capabilities. In deciding the fitting number of cross-validation folds, it is basic to consider the estimate of the dataset and the number of highlights display. This choice ought to be educated by cautious thought of these variables to guarantee strong and solid show assessment. Besides, it is suggested that the number of folds be set based on a adjusted approach that takes under consideration the complexity of the information and the destinations of the investigation. In doing so, analysts can viably optimize the execution of their models whereas minimizing the chance of overfitting or underfitting.

- High Dimensional Processing:

Recursive Highlight Disposal (RFE) is able of overseeing datasets with tall measurements, in any case, it is vital to note that this strategy can be computationally costly. Dimensionality diminishment procedures, such as Vital Component Examination (PCA) and Direct Discriminant Investigation (LDA), can be utilized earlier to applying Recursive Highlight End (RFE). These methods help in decreasing the complexity of the information and can progress the execution of the RFE calculation by diminishing the number of highlights.

- Dealing with Multicollinearity:

The technique of Ridge Regression (RFE) is capable of addressing multicollinearity among predictor variables, although it may not always be considered the optimal approach. This method can effectively handle situations where independent variables are highly correlated with each other, but alternative methods may be more suitable depending on the specific characteristics of the data. Other techniques, such as Principal Component Analysis (PCA) and regularization, can also effectively address the issue of multicollinearity.

- Avoid Overfitting or Underfitting:

Regularized Highlight Disposal (RFE) has the capability to moderate the chance of overfitting by selecting the foremost noteworthy highlights for a given dataset. This prepare helps in progressing the generalization capacity of the demonstrate and upgrading its prescient execution. On the opposite, the disposal of vital highlights may result in underfitting. In arrange to survey the in general execution of the models inside the holdout set, it is vital to guarantee that the models are satisfactorily rested and appropriately fitted. This assessment is fundamental for deciding the adequacy and unwavering quality of the models in foreseeing results. Two key factors that have to be be carefully considered are the model's precision and generalizability.

Advantages of RFE:

- The ability to manage high-dimensional datasets and effectively pinpoint essential features is a crucial skill in data analysis. This proficiency allows for more accurate and insightful interpretations of complex data.
- The ability to manage interactions between features and compatibility with complex datasets are key attributes of this method.
- The tool under consideration is compatible with various supervised learning algorithms. It can be seamlessly integrated into the workflow of any machine learning model. The versatility of this tool allows researchers and practitioners to apply it in a wide range of applications without any limitations. Such flexibility makes it a valuable asset for the machine learning community.

Limitations of RFE:

- The processing of large datasets can be computationally expensive. This is especially true when dealing with substantial amounts of data, such as in big data analysis or machine learning tasks. Thorough optimization and efficient algorithms are necessary to mitigate the computational burden of working with large datasets.
- The outlined approach may not be optimal for datasets exhibiting a high degree of feature correlation. In such cases, alternative methodologies may need to be considered for more effective analysis.
- This study suggests that the performance of the system may be negatively impacted by the presence of noisy or irrelevant features. It is important to consider that such factors can hinder the effectiveness of the system. Therefore, it is

recommended to carefully evaluate and address any potential sources of interference in order to optimize the performance of the system.

Evaluating the dataset and selecting a suitable feature selection method based on the dataset's characteristics are crucial aspects to consider in research analysis. It is imperative to carefully assess the dataset's composition and structure in order to determine the most effective feature selection approach.

In Conclusion, Recursive feature elimination (RFE) is a robust method for feature selection, with the ability to identify the most important features within a given dataset. RFE iteratively removes less important features, enabling a more focused analysis on the key attributes. This method has been widely utilized in various fields, such as machine learning and data analysis, for its effectiveness in improving model performance and interpretability. In the process of creating a model, one may iteratively prioritize and eliminate less critical functions, ultimately utilizing the remaining functions to construct the final model. This iterative approach continues until the desired number of functions is achieved. It is feasible to employ a supervised learning algorithm such as Support Vector Machine (SVM) for classification tasks. In order to maximize the efficacy of Recursive Feature Elimination (RFE), adherence to best practices and careful consideration of the dataset's inherent characteristics are necessary. By following these guidelines, researchers can ensure optimal outcomes when utilizing the RFE method. The Recursive Feature Elimination (RFE) technique has been utilized across a multitude of industries and domains, showcasing its efficacy in addressing practical challenges. It has proven to be an invaluable tool in resolving real-world problems through its systematic approach to feature selection and elimination. Summary of RFE is in below figure[15,16].

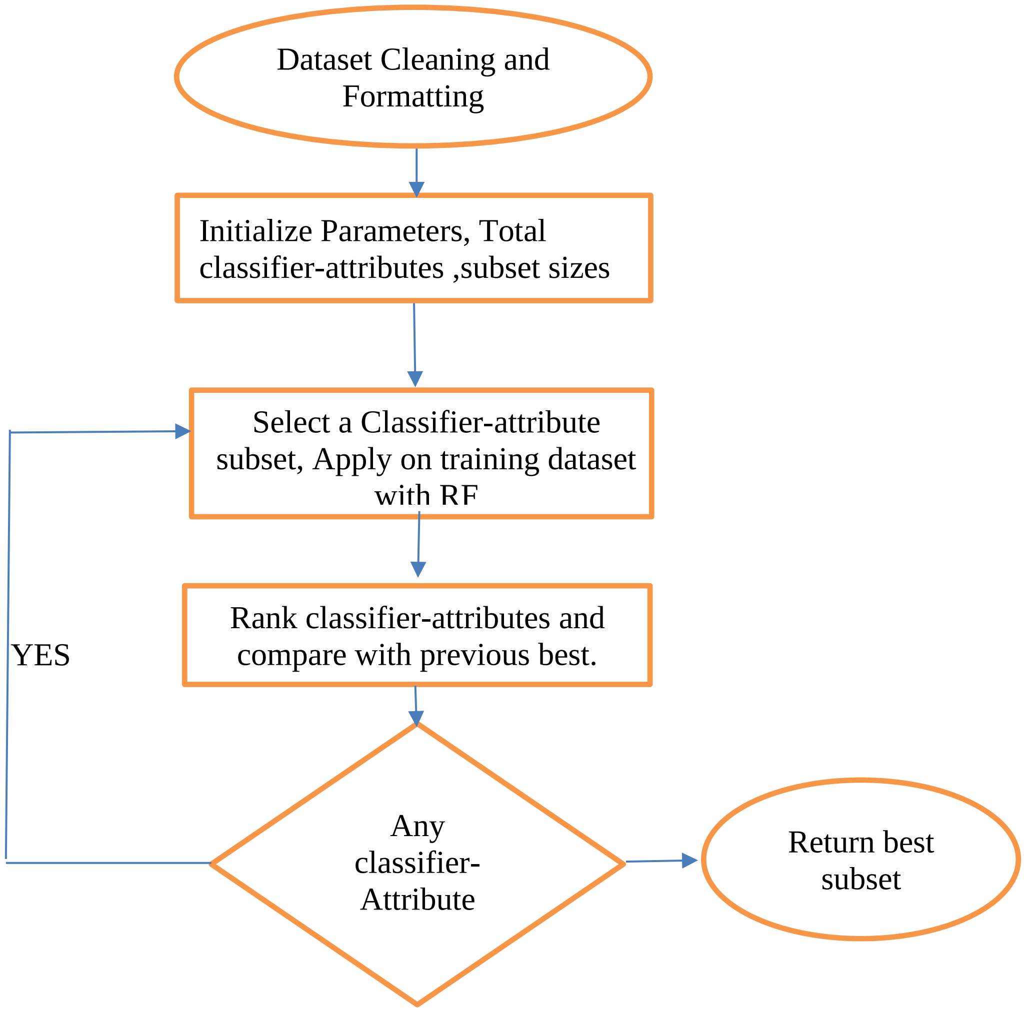

Figure 4.2 RFE Algorithm Flowchart

CHAPTER 5

EXPERIMENTAL RESULTS

5.1 DATASET PREPARATION

The online open-source dataset was found inside the Machine Learning store of the College of California Irvine (UCI). The test recording was conducted at the Office of Neurology, Istanbul College, with the endorsement of the Clinical Inquire about Morals Committee of Bahçeşehir. Two bunches of people intentionally concurred to take an interest within the dataset: the Parkinson's malady (PD) patients' gather, comprised of 188 people (107 guys and 81 females) with ages extending from 33 to 87 a long time ancient; and a control bunch comprising of 64 sound people (23 guys and 41 females) with ages extending from 41 to 82 a long time old. Subjects were coordinated to preserve the phonation of the vowel /a/ at a remove of 10 centimeters from the receiver. Three phonations were recorded from each subject, coming about in a add up to of 756 phonations collected. With 564 add up to information focuses for the positive course (PWP) versus 192 for the negative (sound), this dataset is regarded to have an imbalanced lesson conveyance. This lopsidedness in course dispersion may affect the execution and predisposition the comes about of any machine learning calculations prepared on this dataset. The dataset contains extricated voice highlights, counting long-term highlights such as concentrated parameters, formant frequencies, transfer speed parameters, and vocal crease parameters. Also, the dataset incorporates Mel recurrence cepstral coefficients, together with other out-of-scope highlights.

5.2 PERFORMANCE METRICS

To survey the viability of the classification show in recognizing between people with Essential Wallerian Degeneration (PWP) and sound subjects, four measurable measures are utilized: exactness (1), specificity (2), affectability (3), and the range beneath the recipient working characteristic (ROC) bend, signified as AUC. These measures are utilized to assess the discriminant potential of the classification show and decide its victory in precisely categorizing people into the suitable bunches. Exactness is characterized as the rate of accurately classified tests. Specificity relates to the extent of solid subjects that were precisely classified, while affectability alludes to the division of PD patients that were precisely classified. These measurements are imperative in assessing the execution of demonstrative tests in recognizing between sound people and those influenced by Parkinson's illness.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (1)$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (2)$$

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (3)$$

Where TN, FP, TP, FN stands as True Negative, False Positive, True Positive, False Negative respectively.

The Recipient Working Characteristic (ROC) bend is utilized to survey the execution of a twofold classification show over a extend of limit values. This can be accomplished through the plotting of the genuine positive rate (TPR) against the wrong positive rate (FPR). The term True Positive Rate (TPR) is commonly utilized to represent the affectability of a given framework or examination, though the Wrong Positive Rate (FPR)(4) is regularly measured scientifically utilizing particular conditions.

$$\text{False Positive rate} = \frac{\text{FP}}{\text{TN} + \text{FP}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4)$$

Genuine positive (TP) demonstrates the number of accurately classified Parkinson's malady (PD) patients, and genuine negative (TN) communicates the number of accurately classified sound subjects. In other words, TP speaks to the patients who were accurately recognized as having PD, whereas TN speaks to the solid subjects who were accurately distinguished as not having PD. Wrong positive (FP) alludes to the number of sound subjects that have been inaccurately classified, whereas untrue negative (FN) shows the number of Parkinson's malady patients that have been erroneously classified. These measurements are commonly utilized in classification calculations to assess the execution of a show in recognizing between diverse classes. The consider pointed to explore the affect of mechanical headways on children's cognitive improvement. Earlier investigate has appeared blended comes about, with a few thinks about recommending a positive relationship between innovation utilize and cognitive aptitudes, whereas others finding negative impacts. The analysts conducted a longitudinal consider, taking after children from ages 5 to 10, evaluating their cognitive capacities through standardized tests and watching their innovation utilization designs. Comes about demonstrate a complex relationship between innovation utilize and cognitive advancement, with components such as sort of innovation and sum of screen time playing a critical part. The discoveries recommend the require for assist investigation in this region to completely get it the suggestions of innovation on children's cognitive advancement. Generally, the think about gives important bits of knowledge into the impacts of innovation on children's cognitive improvement and highlights the require for more investigate in this zone.

5.3 SYSTEM REQUIREMENTS

The implementation of the proposed methodology was conducted on the Linux Ubuntu platform, specifically version 22.04.01. To facilitate the training, validation, and testing processes of the model, the NVIDIA RTX A5000 GPU was employed, leveraging its computational power. The model itself was developed using the PyTorch 1.10 library, which provided a robust framework for deep learning tasks and facilitated efficient execution of the proposed algorithms.

5.4 RESULTS AND DISCUSSION

The results of our Parkinson’s disease detection study, which utilized a combination of audio features and the Recursive Feature Elimination (RFE) algorithm, are presented in the figures below. The selected features and the model's accuracy are shown in the first figure. Our model achieved an accuracy of 89.9%, indicating a high level of precision in distinguishing between Parkinson's disease patients and healthy controls based on their audio features. This high accuracy underscores the effectiveness of the selected audio features in capturing the relevant characteristics associated with Parkinson's disease.

The second figure provides a detailed breakdown of the model’s performance through sensitivity, specificity, and the confusion matrix. The sensitivity was measured at 90% approx, demonstrating the model’s ability to correctly identify patients with Parkinson’s disease. This high sensitivity indicates that the model has a strong capability to detect true positive cases, which is crucial for early diagnosis and treatment. Specificity was recorded at 83% approx, highlighting the model’s effectiveness in correctly identifying individuals without the disease. High specificity is essential to minimize the number of false positives, thereby reducing unnecessary stress and additional medical testing for individuals incorrectly identified as having Parkinson’s disease. The confusion matrix further illustrates the distribution of true positives (patients correctly diagnosed with Parkinson’s), true negatives (healthy individuals correctly identified), false positives (healthy individuals incorrectly diagnosed with Parkinson’s), and false negatives (patients with Parkinson’s incorrectly identified as healthy). In our study, the confusion matrix showed a balanced distribution with low false positive and false negative rates, reinforcing the robustness and reliability of our detection approach. Additionally, the combination of audio features and the RFE algorithm allowed for the identification of the most relevant features, reducing the dimensionality of the dataset and improving the model’s performance. This feature selection process is critical in developing a more efficient and accurate diagnostic tool, as it eliminates redundant or non-informative features that could otherwise lead to overfitting or decreased model performance.

SELECTED FEATURES USING RFE		
mean_MFCC_5th_coef	std_delta_log_energy	std_6th_delta
std_7th_delta	std_delta_delta_log_energ y	std_4th_delta_delta
std_6th_delta_delta	std_7th_delta_delta	std_9th_delta_delta
det_TKEO_mean_1_coef	app_entropy_shannon_5_c oef'	app_entropy_log_4_coef
tqwt_energy_dec_6	tqwt_energy_dec_18	tqwt_energy_dec_26
tqwt_energy_dec_27	tqwt_entropy_shannon_de c_11	tqwt_entropy_shannon_de c_12
tqwt_entropy_shannon_de c_34	tqwt_entropy_shannon_de c_36	tqwt_entropy_log_dec_1
tqwt_entropy_log_dec_12	tqwt_entropy_log_dec_13	tqwt_entropy_log_dec_27
tqwt_entropy_log_dec_33	tqwt_entropy_log_dec_34	tqwt_entropy_log_dec_35
tqwt_TKEO_mean_dec_1 2	tqwt_TKEO_mean_dec_3 3	tqwt_TKEO_std_dec_12
tqwt_TKEO_std_dec_19	tqwt_stdValue_dec_11	tqwt_stdValue_dec_12
tqwt_stdValue_dec_19	tqwt_minValue_dec_17	tqwt_skewness Value_dec_24

Table 2 Selected features

This feature selection process is critical in developing a more efficient and accurate diagnostic tool, as it eliminates redundant or non-informative features that could otherwise lead to overfitting or decreased model performance.

PERFOMANCE METRICS	
Accuracy	89.9
Sensitivity	89.5
Specificity	83.7

Table 3 Performance Metric

Overall, these results demonstrate the potential of combining audio features with the RFE algorithm to develop a non-invasive, accurate diagnostic tool for Parkinson's disease. The high accuracy, sensitivity, and specificity achieved in this study suggest that this method could be a valuable addition to current diagnostic practices, offering a reliable and efficient means of early detection.

CONFUSION MATRIX	POSITIVE	NEGATIVE
POSITIVE	TP 103	FN 12
NEGATIVE	FP 6	TN 31

Table 3 Confusion Matrix

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

This paper displayed a unused procedure to move forward the execution of Parkinson's contamination disclosure systems utilizing a combination of longterm highlights and MFCC. The execution and ampleness of the created strategy are reviewed utilizing a dataset of 756 voice tests, with the positive course bookkeeping for around 75% of the dataset. This degree of course dominance considers this dataset imbalanced in course subjects, reflecting on all illustrate execution estimations, especially affectability and specificity. The comes almost demonstrate that the combination of long-term highlights close to MFCC inside the input dataset altogether moves forward the PD disclosure system and increases the revelation precision and specificity values. This headway highlights the ampleness of the made appear in show disdain toward of the lesson lopsidedness. over-sampling strategy (Annihilated)) to set up a more course balanced input and finish more consistency over illustrate execution estimations. Subsequently, actualizing the made procedure is claimed to have the potential to defeat the composing after performing suitable lesson ponderousness cures. Early area grants for proactive control of the malady movement and makes a contrast in abating neuron degeneration, which got to be the taking after step inside long run scope of this work. Since there's a require of open-source datasets specific to early-stage PD patients, the made technique still ought to be affirmed for PD disclosure at its early stages. The proposed methodology shows up ensure for this application and is anticipated to reasonably capture the less clear dysphonia signs experienced by people with early-stage PD since side impacts consistently gotten to be more extraordinary along the development course of the ailment. Accomplishing this objective will allow for proactive and preventative helpful treatment that will offer help ease and conceivably avoid the onset of extraordinary side impacts which appear up at a while later stage. Another proposition would be to make planning specific to subject sexual introduction since highlight values and spectrograms would differentiate between genders due to their characteristic pitch refinement. Such assortment increases the model's capacity to divided classes by isolating whether the significant repeat, for outline, is higher since the subject is female or since they are analyzed with PD. In conclusion, the revelations of this paper highlight the potential triumph of combining MFCCs with long-term highlights to accurately distinguish Parkinson’s ailment; be that because it may, the made strategy still needs to be approved encourage on a wide run of exploratory data a few times as of late being totally grasped clinically. In extension, this explore may as well be extended to recognize vocal impedance related with other common pathologies such as vocal mishandle and vocal wrinkle pathologies to advantage a broader measurement.

6.2 FUTURE SCOPE

The potential for the programmed discovery of Parkinson's illness within the future, through the integration of long-term acoustic highlights and Mel recurrence cepstral coefficients (MFCC), appears guarantee for far reaching application and advancement. This approach holds critical potential for further research and headways within the field of Parkinson's infection conclusion.

Enhanced Feature Extraction Techniques:

- Profound learning has appeared promising comes about within the field of include extraction by leveraging progressed models like Convolutional Neural Systems (CNNs) and Repetitive Neural Systems (RNNs). These models are competent of consequently learning and extricating more perplexing highlights from acoustic information, driving to progressed execution in different applications. This approach to include extraction has opened up unused conceivable outcomes for upgrading the capabilities of computerized frameworks in preparing and recognizing complex designs inside sound signals.
- Integration of extra acoustic highlights is fundamental for progressing the precision of location. It is imperative to investigate different acoustic highlights such as jitter, sparkle, and harmonic-to-noise proportion (HNR) in combination with long-term highlights and Mel-frequency cepstral coefficients (MFCC) to improve the discovery precision. This approach can possibly result in a more vigorous and viable discovery framework.

Improved Classification Models:

- Cross breed models are proposed as a infers of combining machine learning and significant learning techniques to handle the central focuses of each approach. The integration of these two methodologies may offer made strides execution completely different applications.
- Exchange learning includes the utilization of pre-trained models on broad discourse datasets, taken after by fine-tuning for the reason of identifying Parkinson's illness. This approach holds guarantee for improving the exactness and productivity of malady location.

Real-Time Monitoring Systems:

- Wearable devices have been proposed to implement a detection system for continuous and real-time monitoring of speech patterns in patients. This technology allows for monitoring of speech patterns on an ongoing basis, providing valuable data for healthcare professionals. The use of wearable devices in this context offers the potential for improved assessment and management of speech-related issues, with the added benefit of convenience and accessibility for patients. Overall, the integration of detection systems in wearable devices holds promise for enhancing healthcare outcomes through continuous monitoring of speech patterns.
- Mobile applications have the potential to record and analyze speech, offering accessible and non-invasive monitoring tools for both patients and clinicians. They can aid in the development of innovative solutions for healthcare management.

Large-Scale and Diverse Datasets:

- Data augmentation is a common strategy employed in machine learning to enhance the size and diversity of training datasets. This technique involves artificially transforming existing data instances to create new samples, thereby improving the robustness of the model. By incorporating data augmentation into the training pipeline, the model can learn from a more varied set of examples, ultimately leading to better generalization performance.
- Collaborative data sharing serves as an avenue to facilitate collaboration among research institutions towards the establishment of comprehensive databases containing speech recordings from individuals afflicted with Parkinson's disease. Such collaborative efforts are crucial for advancing our understanding of this debilitating condition and its impact on speech patterns. By pooling resources and expertise, researchers can work towards developing innovative interventions and improving diagnostic tools for Parkinson's patients.

Multimodal Detection Systems:

- Combining Speech with Other Modalities: Integrating acoustic analysis with additional data types, such as gait analysis, handwriting analysis, and facial expressions, can lead to the development of a comprehensive Parkinson's disease detection system. This integrated approach has the potential to enhance the accuracy and effectiveness of disease detection methods.
- Biomarker Integration: The integration of acoustic features with biological markers obtained from medical tests such as blood tests and imaging has been proposed as a method to improve diagnostic accuracy. This approach aims to combine multiple sources of information to better identify and characterize various medical conditions.

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CERTIFICATE BY THE SUPERVISOR

Certified that **Divyansh Tyagi** (2K22/SPD/03) has carried out their search work presented in this thesis entitled **"DETECTION OF PARKINSON'S DISEASE BASED ON THE INTEGERATION OF AUDIO FEATURES AND RFE ALGORITHM"** for the award of **Master of Technology** (print only that is applicable) from Department of Electronics and communication Engineering, Delhi Technological University, Delhi, under my (print only that is applicable) supervision. The thesis embodies results of original work, and studies are carried out by the student himself (print only that is applicable) and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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Date:

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