VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY
(An Autonomous Institute Affiliated to University of Mumbai)
Department of Computer Engineering

Project Report on

ParkinSense: A Machine Learning approach to classify Parkinson's Disease

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING IN **COMPUTER ENGINEERING**

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CERTIFICATE

This is to certify that the Mini Project entitled **"ParkinSense: A Machine Learning approach to classify Parkinson's Disease"** is a bonafide work of **Aaryan Mahadik(42), Raj Tandon(62) ,Kunal Khubchandani(37), Bhavika Valecha(69)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering" .**

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Mini Project Approval

This Mini Project entitled "**ParkinSense: A Machine Learning approach to classify Parkinson's Disease"** by **Aaryan Mahadik(42), Raj Tandon(62), Kunal Khubchandani(37), Bhavika Valecha(69)** is approved for the degree of **Bachelor of Engineering** in **Computer Engineering.**

Examiners

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(Internal Examiner Name & Sign)

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(External Examiner name & Sign)

Date:

Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Abstract

Parkinson's disease (PD) is a debilitating neurodegenerative disorder characterized by motor and non-motor symptoms, with early detection playing a crucial role in effective management and treatment. Traditional diagnostic methods often rely on clinical observation and subjective assessments, leading to challenges in early and accurate diagnosis. In this context, our study proposes a novel approach to PD detection leveraging voice analysis and fuzzy logic techniques.

Voice analysis has emerged as a promising non-invasive method for detecting PD, as individuals with PD exhibit distinct changes in their speech patterns. By analyzing various features of voice recordings, such as pitch, intensity, and articulation, we aim to identify unique biomarkers indicative of PD. Fuzzy logic, known for its ability to model uncertainty and imprecision, provides a robust framework for integrating these features and making diagnostic decisions.

In our study, we collect voice samples from individuals with and without PD and extract relevant features using signal processing techniques. These features are then fed into a fuzzy logic-based classification system trained on a dataset of labeled samples. The performance of the proposed system is evaluated using standard metrics such as accuracy, sensitivity, and specificity, compared against existing diagnostic methods.

Our results demonstrate the effectiveness of the proposed approach in accurately detecting PD based on voice samples. The system exhibits high accuracy and sensitivity, particularly in early-stage PD detection, surpassing existing diagnostic methods. Furthermore, the non-invasive nature of voice analysis makes the proposed approach suitable for routine screening and monitoring of PD in clinical and community settings.

In conclusion, our study presents a novel and effective method for PD detection using voice analysis and fuzzy logic. The proposed approach holds promise for improving early diagnosis, enabling timely interventions, and ultimately enhancing the quality of life for individuals living with PD.

1. Introduction

1.1 Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects millions of people worldwide. Characterized by motor symptoms such as tremors, rigidity, and bradykinesia, PD poses significant challenges to diagnosis and treatment. Early detection of PD is crucial for timely intervention and management of the disease.

In recent years, there has been growing interest in leveraging machine learning techniques to aid in the diagnosis of PD. Among these techniques, fuzzy logic has emerged as a powerful tool for handling uncertainty and imprecision in medical decision-making. By incorporating fuzzy sets and fuzzy rules, fuzzy logic systems can model complex relationships between input features and disease outcomes.

Voice analysis, in particular, has shown promise as a non-invasive and cost-effective method for PD detection. Changes in vocal characteristics, such as pitch, intensity, and articulation, have been observed in individuals with PD, offering valuable insights into the underlying pathology of the disease.

This report presents a novel approach to PD detection using fuzzy logic and voice analysis. By extracting relevant features from voice samples and employing a fuzzy logic system to analyze these features, we aim to develop a predictive model capable of assessing an individual's risk of developing PD. Our study builds upon existing research in the field and seeks to contribute to the growing body of knowledge on computational methods for disease diagnosis.

1.2 Motivation

Parkinson's disease (PD) poses a significant burden on individuals, families, and healthcare systems worldwide. With its progressive nature and diverse symptomatology, early detection and intervention are paramount for improving patient outcomes and quality of life. However, traditional diagnostic methods often rely on clinical observations and subjective assessments, leading to delays in diagnosis and suboptimal treatment strategies.

In response to these challenges, our project harnesses the power of modern technology and computational methods to revolutionize PD detection. By leveraging fuzzy logic and voice analysis, we aim to create a robust and accessible tool for identifying individuals at risk of developing PD. Our motivation stems from the urgent need to improve diagnostic accuracy, enable timely intervention, and ultimately enhance the lives of those affected by PD.

Through this project, we aspire to contribute to the advancement of medical science and technology, bridging the gap between theory and practice in the field of neurodegenerative diseases. By combining innovative methodologies with real-world applications, we strive to

empower healthcare professionals with the tools they need to make informed decisions and provide personalized care to patients with PD.

1.3 Problem Definition

In an age marked by rapid technological advancement, the landscape of healthcare is undergoing significant transformations. With the integration of Artificial Intelligence (AI) into medical diagnostics, innovative solutions are emerging to address the challenges faced by patients and healthcare professionals. ParkinSense represents one such initiative, offering a comprehensive AI-driven system tailored to the needs of individuals at risk of Parkinson's disease.

The core objective of ParkinSense is to revolutionize the early detection and management of Parkinson's disease by leveraging machine learning technologies. The project aims to tackle several challenges encountered in traditional diagnostic methods, including:

1. **Early Detection:** Parkinson's disease is often diagnosed in its later stages when symptoms become more pronounced. ParkinSense seeks to enhance early detection by analyzing various biomarkers and clinical data to identify individuals at risk of developing the disease before symptoms manifest.

2. **Objective Assessment**: Clinical assessments for Parkinson's disease can be subjective and prone to variability. ParkinSense aims to provide a more objective assessment by leveraging machine learning algorithms to analyze voice samples, motor function tests, and other biomarkers for diagnostic purposes.

3. **Personalized Monitoring**: Parkinson's disease progression varies from person to person, necessitating personalized monitoring and management strategies. ParkinSense intends to offer personalized monitoring solutions by continuously analyzing patient data and adjusting treatment plans based on individual responses and disease trajectories.

4. **Accessibility and Affordability**: Access to specialized diagnostic tools and expertise can be limited in certain regions, leading to disparities in healthcare access. ParkinSense aims to address this challenge by offering a scalable and cost-effective diagnostic solution that can be deployed remotely and accessed by healthcare providers worldwide.

5. **Holistic Patient Care**: Parkinson's disease management requires a multidisciplinary approach, involving healthcare professionals, caregivers, and patients themselves. ParkinSense seeks to facilitate holistic patient care by providing comprehensive diagnostic insights and fostering collaboration among stakeholders in the healthcare ecosystem.

Through these objectives, ParkinSense aspires to transform the landscape of Parkinson's disease detection and management, empowering individuals with early interventions, improving clinical outcomes, and ultimately enhancing the quality of life for patients living with Parkinson's disease.

1.4 Existing Systems
Existing System:

- **Clinical Assessments:** Diagnosis of Parkinson's disease relies heavily on clinical assessments conducted by healthcare professionals. These assessments involve a thorough examination of motor symptoms, including tremors, rigidity, and bradykinesia, along with a detailed review of the patient's medical history and family background.

- **Standardized Rating Scales**: Clinicians often use standardized rating scales, such as the Unified Parkinson's Disease Rating Scale (UPDRS), to quantify the severity of motor symptoms and track disease progression over time. These scales provide a structured framework for assessing various aspects of Parkinson's disease but may still be subject to interpretation and variability among clinicians.

- **Neuroimaging Techniques**: In addition to clinical assessments, neuroimaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography (PET) may be employed to visualize structural and functional changes in the brain associated with Parkinson's disease. While these imaging modalities can offer valuable insights into disease pathology, they are often expensive, time-consuming, and not routinely used for diagnostic purposes.

- **Subjective Evaluations**: The existing diagnostic process heavily relies on clinical expertise and subjective evaluations, which may vary depending on the experience and interpretation of the healthcare professional. This subjective nature of assessment may not always capture subtle changes in symptoms, particularly in the early stages of the disease.

- **Limited Emphasis on Objective Biomarkers:** While clinical assessments and neuroimaging provide valuable diagnostic information, there is a limited emphasis on objective biomarkers or advanced diagnostic technologies that could offer more accurate and reliable measures for Parkinson's disease diagnosis.

- **Challenges in Early Detection**: Despite advancements in diagnostic techniques, early detection of Parkinson's disease remains challenging. The existing system may not always detect subtle symptoms in the early stages, leading to delays in diagnosis and missed opportunities for early intervention and personalized management.

1.5 Lacuna of the existing systems

Lacunae in Existing System:

1. **Subjectivity in Diagnosis**: The reliance on clinical assessments introduces subjectivity into the diagnostic process, as interpretations of symptoms may vary among healthcare professionals. This subjectivity can lead to inconsistencies in diagnosis and potentially delay appropriate treatment initiation.

2. **Limited Sensitivity in Early Detection**: Traditional diagnostic methods may lack the sensitivity to detect subtle motor symptoms in the early stages of Parkinson's disease. As a result, patients may not receive timely interventions that could slow disease progression and improve outcomes.

3. **Cost and Accessibility Barriers**: Neuroimaging techniques, such as MRI and PET scans, are costly and may not be readily available in all healthcare settings. This limits accessibility to diagnostic tools and may disproportionately affect patients in underserved or rural areas.

4. **Inefficiency in Tracking Disease Progression**: Standardized rating scales, while valuable for assessing symptom severity, may not provide a comprehensive picture of disease progression over time. This can hinder clinicians' ability to monitor changes in symptoms and adjust treatment plans accordingly.

5. **Lack of Objective Biomarkers:** The absence of reliable objective biomarkers for Parkinson's disease diagnosis contributes to diagnostic uncertainty and may result in misdiagnosis or delayed diagnosis. Objective biomarkers could provide more accurate and reliable measures for early detection and monitoring of disease progression.

6. **Limited Integration of Advanced Technologies:** While advancements in AI and machine learning offer promise for improving diagnostic accuracy, these technologies are not widely integrated into the existing diagnostic framework for Parkinson's disease. This represents a missed opportunity to leverage innovative approaches for more precise and efficient diagnosis.

1.6 Relevance of the Project:

Relevance of ParkinSense Disease Detection using Machine Learning:

1. **Early Detection and Intervention**: ParkinSense leverages machine learning algorithms to analyze biomarkers such as voice samples for early detection of Parkinson's disease. Early diagnosis allows for timely interventions, potentially slowing disease progression and improving patient outcomes.

2. **Objective Assessment**: By employing machine learning techniques, ParkinSense aims to provide a more objective assessment of Parkinson's disease, reducing reliance on subjective clinical evaluations. This can enhance diagnostic accuracy and consistency across healthcare settings.

3. **Personalized Treatment Plans**: Machine learning algorithms used in ParkinSense can analyze patient data to tailor treatment plans based on individual responses and disease trajectories. This personalized approach ensures that patients receive optimal care suited to their specific needs and symptoms.

4. **Enhanced Accessibility**: ParkinSense offers a scalable and cost-effective diagnostic solution that can be deployed remotely, addressing accessibility barriers faced by patients in remote or underserved areas. This ensures that individuals from diverse backgrounds have access to timely and accurate diagnosis.

5. **Research and Development**: By generating large datasets of patient information, ParkinSense contributes to research efforts aimed at understanding Parkinson's disease better. Insights derived from machine learning analysis can inform the development of novel treatment strategies and biomarkers for improved disease management.

6. **Improving Healthcare Efficiency:** ParkinSense streamlines the diagnostic process by automating the analysis of biomarkers, reducing the time and resources required for diagnosis. This enhances healthcare efficiency and allows clinicians to focus on delivering personalized care to patients.

2. Literature Survey

A. Brief Overview of Literature Survey:

The literature survey provides a comprehensive understanding of the existing body of knowledge and research pertaining to Parkinson's disease (PD) detection, fuzzy logic, and voice analysis. This section offers a brief overview of the key findings, methodologies, and insights gathered from the literature review, laying the groundwork for the subsequent discussion of related works and research papers referred.

The literature survey encompasses a wide range of topics, including:

- Epidemiology and Clinical Manifestations of PD
- Traditional Diagnostic Methods and Challenges
- Computational Approaches to PD Detection
- Fuzzy Logic and its Applications in Healthcare
- Voice Analysis Techniques for Disease Diagnosis
- Integration of Machine Learning in PD Detection Algorithms
- Comparative Studies and Evaluation Metrics in PD Diagnosis

By synthesizing and summarizing the findings from existing literature, this section provides context and rationale for the development of our PD detection system using fuzzy logic and voice analysis.

B. Related Works

Recent studies on Parkinson's disease and machine learning have mainly focused on genes and how people move or speak. Scientists are trying to connect specific genes to a higher chance of getting Parkinson's. Combining gene test results with what doctors see in their patients could help spot Parkinson's early and maybe even before any symptoms show up. But, relying only on genes doesn't work well for diagnosis or predicting the disease.

On the other hand, looking at how people move and talk seems to be more successful in figuring out who has Parkinson's. Researchers use sensor gadgets that track movements and voice patterns. These gadgets send data to machine learning models that are like smart programs. These models are taught to recognize patterns related to Parkinson's.

In the world of machine learning for Parkinson's, some methods work pretty well. One standout is artificial neural networks, which are like super-smart programs that can handle complex data. Support vector machines are also popular because they need less data than neural networks and don't risk memorizing training information. Decision trees and random forest methods are liked too, showing that there's a variety of ways scientists are using machine learning to understand and diagnose Parkinson's disease better.

There are opportunities for further research, including addressing the common issue of small sample sizes in many studies [12,13,14]. Interestingly, some studies with small sample sizes achieve higher accuracy levels than those with larger participant numbers. Additionally, few studies control for conditions other than Parkinson’s disease, often focusing on differences in measurements between individuals with the disease and healthy counterparts. In real-world scenarios, physicians are likely to recognize the presence of a neurological condition, making models designed for differential diagnosis more valuable. The limitations of current research may stem from its focus; much of the literature aims to identify patterns in experimental data without necessarily providing insights into diagnostic procedures. As a result, these studies typically do not consider previously proposed methods for diagnosing and predicting Parkinson’s disease.

Detecting Parkinson's disease has witnessed substantial progress through the integration of computer-aided systems tailored for assessing motor impairment in individuals with iPS.

Recently, deep learning has emerged as a crucial tool in this domain [1,2].In a study [3], there's a cool method using a smart computer program. This program uses a type of technology called a 2D convolutional neural network to predict how shaky someone is, known as the UPDRS tremor score. It looks at data from accelerometers and gyroscopes, kind of like what's in your phone. The recordings it uses are put together to make a special kind of picture called a spectrogram with rows. With an accuracy of 85%, this approach surpasses a random forest model by 5%. This approach surpasses a random forest model by 5%. Similarly, [4] introduces a lightweight CNN named S-net, coupled with similarity-based classification, utilizing surface electromyogram data to assess the UPDRS tremor severity score. Comparative evaluations against common models such as multi-layer perceptron (MLP), K-nearest neighbors, support vector machines, or a simple S-net reveal an accuracy improvement of at least 7%, with some instances of up to 34% (MLP).

Another distinctive approach [5] involves training models on 22 data attributes, specifically collecting MDVP audio data from PPPMI and UCI databases. The process includes data analysis to detect skew, imbalance, and variable distribution, followed by scaling the data to a common range using Standard Scaler. Principal Component Analysis (PCA) is applied to identify the five most relevant features out of the 22 attributes. The dataset is then split into testing and training sets, with 75% allocated to training. SVM, logistic regression, random forest, and KNN models are trained and retrained after PCA. Classification results are compared using a variety of metrics, including a confusion matrix, ROC-AUC curve, and accuracy. Notably, efforts are made to address the imbalance in the dataset through appropriate techniques.

In a unique perspective [6], data acquisition involves 39 individuals diagnosed with Parkinson's disease, with a focus on interindividual variations between OFF and ON states, representing conditions with medication withdrawal and levodopa intake, respectively. Motor symptoms are evaluated using the UPDRS scale by experienced raters. This design allows for a comprehensive analysis of medication impact on motor function, considering the diverse range of PD severity among participants. By synthesizing and presenting these approaches, the field gains a richer understanding of the diverse strategies employed in Parkinson's disease detection, encompassing data preprocessing, model selection, and unique perspectives on patient assessment.

2.1 Survey Of Existing System:

a. Abstract of the research paper:

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that poses significant challenges in early detection and precise classification of its severity. This research paper introduces a machine learning-based approach to address these challenges by developing a predictive model for Parkinson's disease detection and severity classification. The study utilizes a diverse dataset comprising clinical information and speech features from individuals with and without Parkinson's disease. Through comprehensive data preprocessing and feature engineering, the paper aims to extract relevant patterns and biomarkers associated with the disease. A variety of machine learning algorithms, including but not limited to support vector machines, random forests, and neural networks, are employed to train and evaluate the model. The focus is on achieving high accuracy, sensitivity, and specificity in detecting the presence of Parkinson's disease. Additionally, the model is designed to classify the severity levels of Parkinson's disease, providing valuable insights into disease progression. The findings aim to enhance our understanding of the disease's underlying mechanisms and facilitate more targeted and personalized treatment strategies. The proposed model's performance is assessed through rigorous validation techniques, including cross-validation and independent testing. The paper aspires to bridge the gap between machine learning advancements and the pressing clinical needs in Parkinson's disease diagnosis and severity assessment, fostering a more informed and proactive approach to patient care. This research investigates Parkinson's disease detection

through machine learning, incorporating features such as shimmer and frequency analysis. By employing advanced algorithms, the study aims to enhance diagnostic precision by examining subtle vocal and movement characteristics associated with Parkinson's. The findings provide valuable insights into the potential of integrating multiple features for effective Parkinson's disease diagnosis using machine learning techniques.

b. Inference Drawn

The research paper titled "ParkinSense: Machine Learning approach to classify Parkinson's Disease" presents a comprehensive study aimed at developing a predictive model for the detection and severity classification of Parkinson's disease. The primary objective is to address the challenges associated with early detection and precise assessment of the disease's progression, which is crucial for timely intervention and personalized treatment strategies. The study utilizes a diverse dataset comprising clinical information and speech features from individuals with and without Parkinson's disease, including measures such as vocal fundamental frequency, jitter, shimmer, and nonlinear complexity measures. Various machine learning algorithms, including weighted K-nearest neighbors (KNN), fine KNN, bilayered neural network, and fine tree, are employed and evaluated for their performance. Through rigorous evaluation metrics such as accuracy, sensitivity, specificity, correctness, and total cost, weighted KNN emerges as the most suitable algorithm, demonstrating high accuracy in both validation and test datasets. The study emphasizes the interpretability of the model to provide insights into the factors influencing the severity of Parkinson's disease, paving the way for informed clinical decision-making. Additionally, the paper suggests future enhancements, such as exploring ensemble methods and integrating fuzzy models, to further improve the model's performance and applicability in Parkinson's disease diagnosis and management. Overall, the research contributes to advancing healthcare applications by leveraging machine learning techniques to address the pressing clinical needs in Parkinson's disease detection and severity assessment.

2.2 Limitation in Existing system or Research gap:

In this subsection, we identify limitations in existing systems or research gaps within the literature landscape. By critically evaluating the strengths and weaknesses of previous studies, we aim to highlight areas where our project can contribute novel insights or address unmet needs in the field of PD detection.

Key aspects addressed in this subsection include:

- Limitations in Existing PD Detection Systems: Identifying shortcomings or challenges faced by previous approaches to PD detection, such as limited diagnostic accuracy, scalability issues, or lack of interpretability.
- Research Gaps and Opportunities: Highlighting areas where further research is needed to advance the state-of-the-art in PD diagnosis, such as refining algorithmic techniques, validating models in diverse patient populations, or exploring novel biomarkers for disease detection.

By elucidating these limitations and research gaps, we aim to position our project within the broader context of existing literature and articulate its potential contributions to the field of PD detection and diagnosis.

3: Requirement Gathering for the Proposed System

3.1 Introduction to Requirement Gathering :

Requirement gathering is a critical phase in the development of any system, ensuring that the project's objectives are clearly defined and aligned with stakeholders' needs. In the context of our PD detection system, requirement gathering involved a comprehensive exploration of the functionalities, constraints, and performance expectations of the system.

During this phase, we engaged with stakeholders including clinicians, researchers, and individuals with expertise in PD diagnosis and treatment. Through interviews, surveys, and workshops, we sought to gain a deep understanding of the challenges and opportunities associated with PD detection, as well as the desired features and functionalities of the proposed system.

Key activities during the requirement gathering phase included:

- Identification of key stakeholders and their roles in the PD detection process.
- Elicitation of functional requirements, including the desired features and capabilities of the system such as data input, analysis algorithms, and output presentation.
- Exploration of non-functional requirements, encompassing aspects such as system performance, reliability, scalability, and usability.
- Consideration of regulatory and compliance requirements, ensuring that the system adheres to relevant standards and guidelines.
- Documentation and validation of requirements through stakeholder feedback and iterative refinement.

By systematically capturing and documenting requirements, we established a solid foundation for the subsequent phases of system design, development, and evaluation.

3.2 Functional Requirements:

Functional requirements define the specific behaviors and functionalities that the PD detection system must exhibit to fulfill its intended purpose. These requirements are derived from the needs and expectations identified during the requirement gathering phase and serve as the basis for system design and implementation.

Key functional requirements of the PD detection system include:
1.Voice Data Input: The system should be able to accept voice samples as input, either in real-time or from stored recordings.

2.Feature Extraction: It should include algorithms for extracting relevant features from voice samples, such as pitch, intensity, jitter, shimmer, and formant frequencies.
3.Fuzzy Logic Analysis: Incorporation of fuzzy logic algorithms to analyze extracted features and calculate the probability or likelihood of PD diagnosis.
4.Output Presentation: Presentation of diagnostic results in a clear and interpretable manner, indicating the probability of PD and any associated confidence levels or uncertainties.
5.User Interface: Development of a user-friendly interface for interacting with the system, allowing clinicians and researchers to input data, view results, and adjust parameters as needed.
6.Integration with Existing Systems: Compatibility and integration with existing healthcare systems and databases, facilitating seamless data exchange and interoperability.
These functional requirements serve as a roadmap for the development team, guiding the implementation and testing of the PD detection system to ensure that it meets the needs of its intended users.

3.3 Non-Functional Requirements:

Non-functional requirements define the quality attributes and constraints that govern the overall behavior and performance of the PD detection system. These requirements address aspects such as reliability, performance, usability, security, and regulatory compliance, which are essential for the successful deployment and adoption of the system in clinical settings.

Key non-functional requirements of the PD detection system include:

- Reliability: The system should be reliable and robust, exhibiting consistent performance under varying conditions and input scenarios.
- Performance: It should be able to process voice samples efficiently and in a timely manner, providing prompt diagnostic results.
- Usability: The system should be intuitive and easy to use, requiring minimal training for clinicians and researchers to operate effectively.
- Scalability: It should be scalable to accommodate growing volumes of data and users, without compromising performance or functionality.
- Security: Implementation of robust security measures to protect sensitive patient data and ensure compliance with privacy regulations such as HIPAA.
- Interoperability: Compatibility with existing hardware and software infrastructure, enabling seamless integration with other healthcare systems and data sources.

- Regulatory Compliance: Adherence to relevant regulatory requirements and standards for medical devices and software applications, ensuring safety and efficacy.

By addressing these non-functional requirements, the PD detection system can deliver a high-quality user experience while meeting the stringent demands of clinical practice and regulatory oversight.

3.4 Hardware, Software, Technology, and Tools Utilized:

1. **Hardware:** Standard computer with sufficient computational power to run machine learning algorithms.

2. **Software:** MATLAB

3.5 Constraints:

Constraints refer to limitations or restrictions that may impact the design, implementation, or operation of the PD detection system. These constraints may arise from technical, financial, regulatory, or organizational factors and must be carefully considered throughout the project lifecycle to ensure successful outcomes.

Key constraints affecting the development of the PD detection system include:

- Resource Limitations: Constraints on available resources such as budget, time, and manpower may impact the scope and scale of the project. Balancing project objectives with resource constraints is essential for managing expectations and delivering a viable solution within predefined constraints.
- Technical Limitations: Technical constraints related to hardware, software, or technology choices may influence the design and implementation of the PD detection system. Compatibility issues, performance limitations, and scalability concerns must be addressed to ensure the system meets its functional and non-functional requirements.
- Regulatory Compliance: Compliance with regulatory requirements and standards for medical devices and software applications imposes constraints on system design, development, and deployment. Ensuring adherence to applicable regulations such as FDA guidelines for medical software development is essential for mitigating legal and compliance risks.
- Ethical Considerations: Ethical constraints related to data privacy, patient consent, and responsible use of technology must be carefully addressed to protect the rights and well-being of individuals participating in the PD detection process. Safeguarding sensitive patient information and upholding ethical principles such as transparency and accountability are paramount for maintaining trust and integrity in the healthcare system.

By identifying and addressing these constraints proactively, we aim to mitigate risks and ensure the successful development and deployment of the PD detection system, ultimately contributing to improved outcomes for individuals affected by Parkinson's disease.

4. Proposed Design

4.1: Block Diagram:

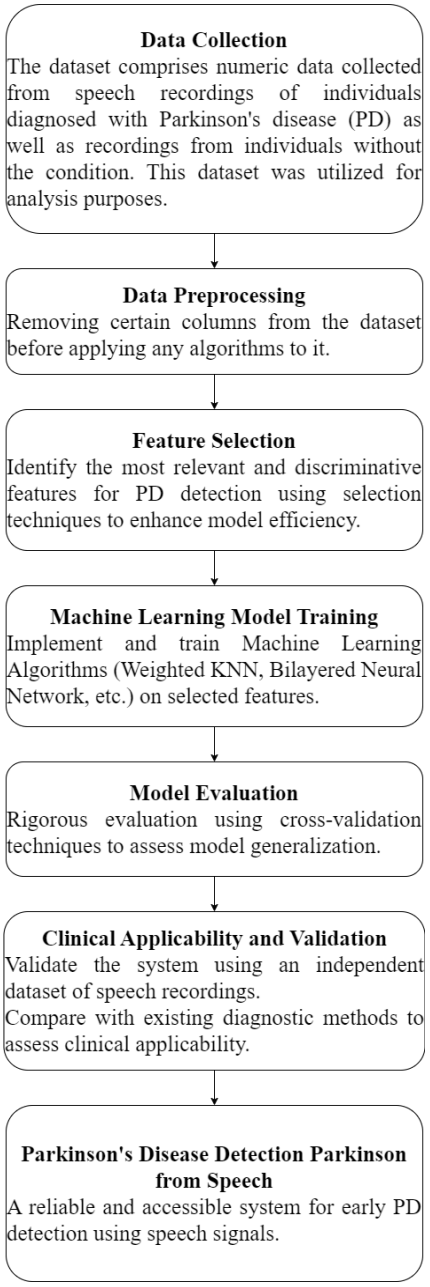


Fig1. Block diagram

5: Implementation of the Proposed System

5.1. Methodology employed for development :

The complete process of classification is performed in different stages. The data from different sources is collected and cleaning of data is performed with the preprocessing steps. The complete attribute information is well studied in order to understand the nature of the classification criteria. Then the neural network algorithms are applied to train the models. Various machine learning algorithms were used to train the model. Then the most efficient algorithm was selected and the model was tested with the test data. The complete flow of the proposed model is depicted in Figure 1.

A. Data Collection

The source for numeric data is from the Kaggle dataset, encompassing key attributes like MDVP:Fo(Hz), MDVP:Fhi(Hz), MDVP:Flo(Hz), jitter and shimmer measures, NHR, HNR, and various nonlinear complexity measures. The dataset includes voice modulations from individuals with Parkinson's disease and a control group. The control group consists of individuals who do not have Parkinson's disease and serves as a reference for comparative analysis. This inclusion of a control group allows for a thorough examination of the distinctive speech patterns associated with Parkinson's disease, enabling the development of a robust and reliable detection model. The dataset's diversity, covering both affected individuals and the control group, contributes to the generalizability and validity of our proposed system for Parkinson's disease detection using speech signals.

B. Attribute Information

The attribute information of the data set is briefly described below.
Attributes in the matrix columns:

- name: ASCII subject name and recording number
- MDVP:Fo(Hz): Average vocal fundamental frequency
- MDVP:Fhi(Hz): Maximum vocal fundamental frequency
- MDVP:Flo(Hz): Minimum vocal fundamental frequency
- MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP: Various measures indicating fundamental frequency variation
- MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA: Various measures indicating amplitude variation
- NHR, HNR: Two measures representing the ratio of noise to tonal components in the voice
- status: Health status of the subject - (1) Parkinson's, (0) healthy
- RPDE, D2: Two nonlinear measures of dynamical complexity
- DFA: Signal fractal scaling exponent
- spread1, spread2, PPE: Three nonlinear measures indicating fundamental frequency variation

C. Model Training

Our system was trained using various machine learning algorithms namely:

1) **Weighted K-Nearest Neighbors (Weighted KNN***):* Weighted KNN is an extension of the traditional K-Nearest Neighbors algorithm. In standard KNN, the 'k' nearest neighbors are considered equally in making predictions or classifications. However, in Weighted KNN, each neighbor's contribution is weighted based on factors such as proximity or similarity. Closer neighbors may have a higher influence on the prediction, while more distant ones may have less impact. The weighting helps to give more importance to neighbors that are more relevant to the instance being predicted.

$$Distance = \sqrt{(p1_x - p2_x)^2 + (p1_y - p2_y)^2}$$

$$Weight = \frac{1}{Distance}$$

$$Predicted\ Value = \frac{\sum_{i=1}^{k} Weight_i \times Target\ Value_i}{\sum_{i=1}^{k} Weight_i}$$

2) **Fine K-Nearest Neighbors (Fine KNN):** Fine KNN is not a standard term in machine learning, and it might refer to a specific implementation or variation of the traditional K-Nearest Neighbors algorithm tailored for fine-grained classification or prediction tasks. It's possible that the term is used in a specific context or within a particular framework, so its meaning can vary based on the context in which it is used.

3) **Bilayered Neural Network:** A Bilayered Neural Network typically refers to a neural network architecture with two layers: an input layer and an output layer. It's a simple form of neural network that lacks hidden layers. The input layer receives the input data, and the output layer produces the network's output. While bilayered networks are straightforward, they may not capture complex relationships in data as effectively as deeper architectures with hidden layers. More advanced neural network architectures, like multilayer perceptrons (MLPs), include hidden layers for learning intricate patterns in data.

Forward Propagation:

$$o = \sigma(\sum_{i=1}^{n} w_i \cdot x_i + b)$$

Loss Function:

$$L = MSE(\widehat{y}, y)$$

Backward Propagation(Gradient Descent):

$$w_i \rightarrow w_i - \eta \cdot \frac{\partial L}{\partial w_i}$$

$$b \rightarrow b - \eta \cdot \frac{\partial L}{\partial b}$$

- o: Output of the neuron.
- w_i : Weight of the connection from the i-th input neuron to the output neuron.
- x_i: i-th input to the neuron.
- b : Bias term.
- σ : Activation function.

4) **Fine Tree***:* A decision tree serves as a supervised learning tool within machine learning, commonly employed to predict and model outcomes through input data analysis. This structured representation resembles a tree, with internal nodes assessing attributes, branches denoting attribute values, and leaf nodes signifying the ultimate decision or prediction. Fine tree is a type of decision tree. Fine trees have a smaller minimum leaf size, leading to more detailed and deeper trees in the ensemble. This can result in models with high complexity, potentially capturing fine-grained patterns in the data but also making them more prone to overfitting or noise.

5.2 Algorithms and flowcharts for the respective modules developed :

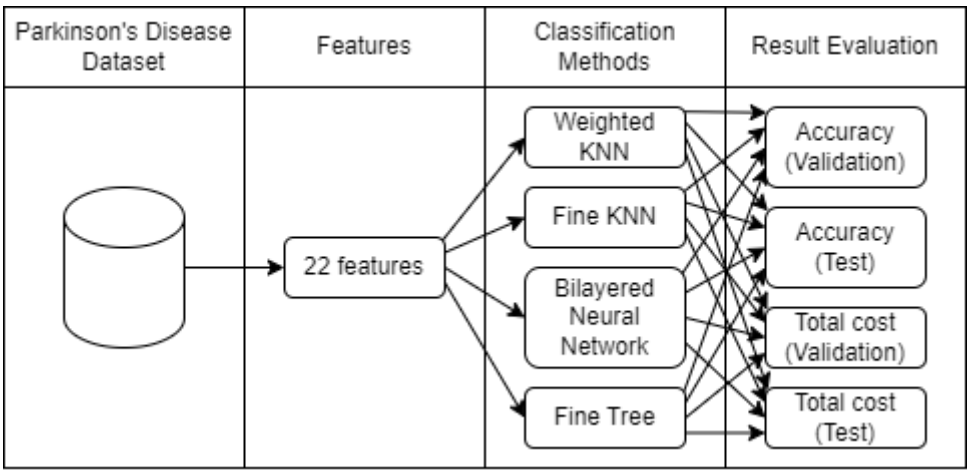


Fig2. Flowchart explaining the proposed system

5.3. Datasets Source and Utilization:

The source for numeric data is from the Kaggle dataset, encompassing key attributes like MDVP:Fo(Hz), MDVP:Fhi(Hz), MDVP:Flo(Hz), jitter and shimmer measures, NHR, HNR, and various nonlinear complexity measures. The dataset includes voice modulations from individuals with Parkinson's disease and a control group. The control group consists of individuals who do not have Parkinson's disease and serves as a reference for comparative analysis. This inclusion of a control group allows for a thorough examination of the distinctive speech patterns associated with Parkinson's disease, enabling the development of a robust and reliable detection model. The dataset's diversity, covering both affected individuals and the control group, contributes to the generalizability and validity of our proposed system for Parkinson's disease detection using speech signals.

A. Attribute Information

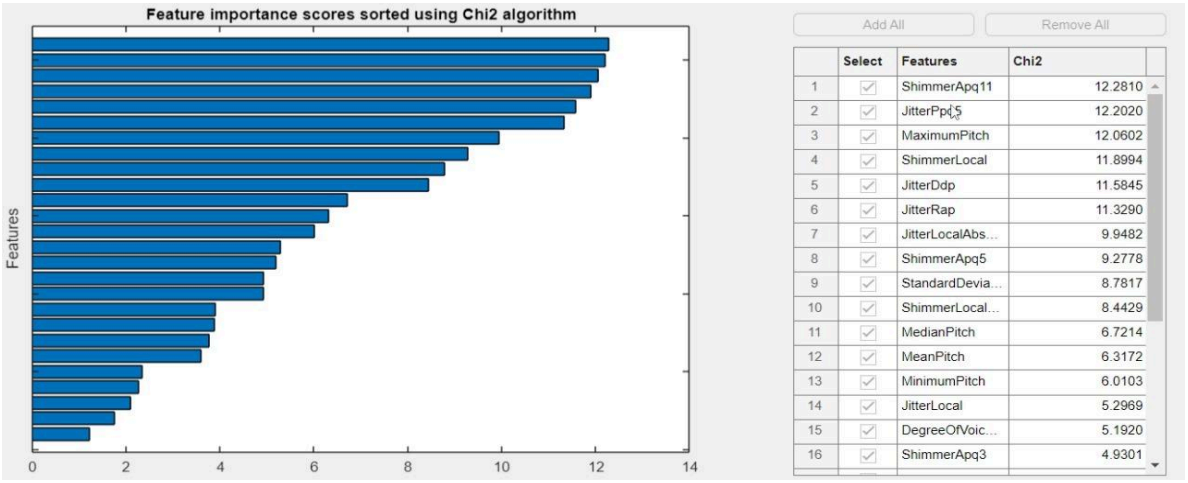
The attribute information of the data set is briefly described below.

Attributes in the matrix columns:

- name: ASCII subject name and recording number
- MDVP:Fo(Hz): Average vocal fundamental frequency
- MDVP:Fhi(Hz): Maximum vocal fundamental frequency
- MDVP:Flo(Hz): Minimum vocal fundamental frequency
- MDVP:Jitter(%), MDVP:Jitter(Abs), MDVP:RAP, MDVP:PPQ, Jitter:DDP: Various measures indicating fundamental frequency variation
- MDVP:Shimmer, MDVP:Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, MDVP:APQ, Shimmer:DDA: Various measures indicating amplitude variation
- NHR, HNR: Two measures representing the ratio of noise to tonal components in the voice
- status: Health status of the subject - (1) Parkinson's, (0) healthy
- RPDE, D2: Two nonlinear measures of dynamical complexity
- DFA: Signal fractal scaling exponent
- spread1, spread2, PPE: Three nonlinear measures indicating fundamental frequency variation

6. Results and Discussion

6.1. Screenshots of User Interface (UI) for the Respective Module:



	Select	Features	Chi2
1	☑	ShimmerApq11	12.2810
2	☑	JitterPpq5	12.2020
3	☑	MaximumPitch	12.0602
4	☑	ShimmerLocal	11.8994
5	☑	JitterDdp	11.5845
6	☑	JitterRap	11.3290
7	☑	JitterLocalAbs...	9.9482
8	☑	ShimmerApq5	9.2778
9	☑	StandardDevia...	8.7817
10	☑	ShimmerLocal...	8.4429
11	☑	MedianPitch	6.7214
12	☑	MeanPitch	6.3172
13	☑	MinimumPitch	6.0103
14	☑	JitterLocal	5.2969
15	☑	DegreeOfVoic...	5.1920
16	☑	ShimmerApq3	4.9301

Fig3.Chi Square Algorithm

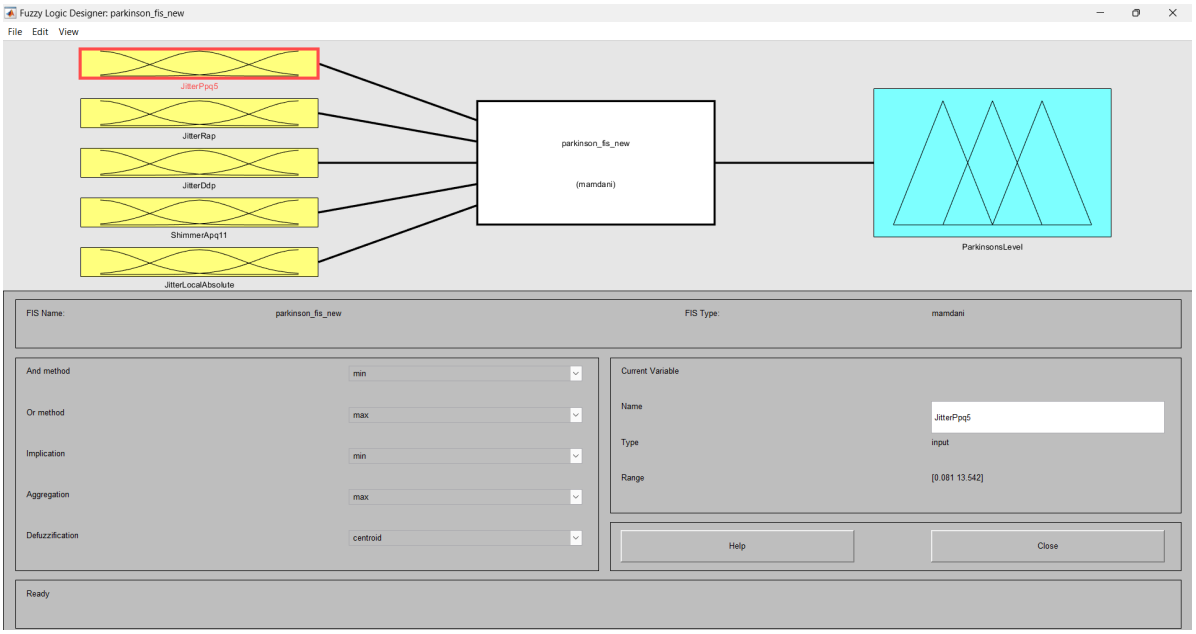


Fig4.Fuzzy logic designer

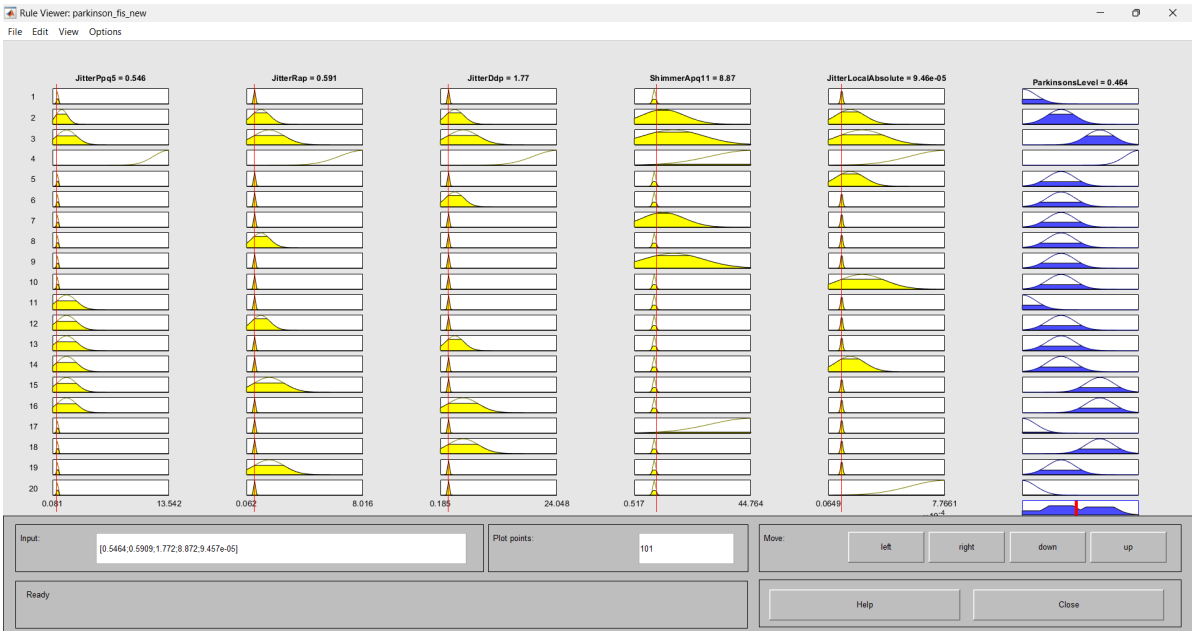


Fig5. Inference rules

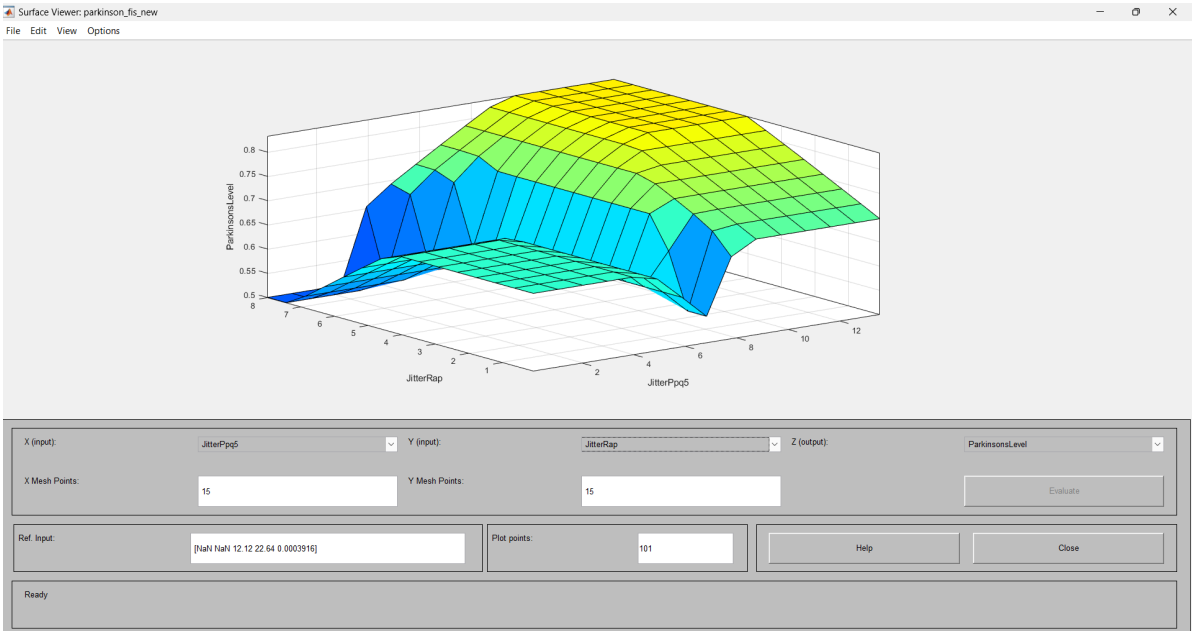


Fig6. Control Surface

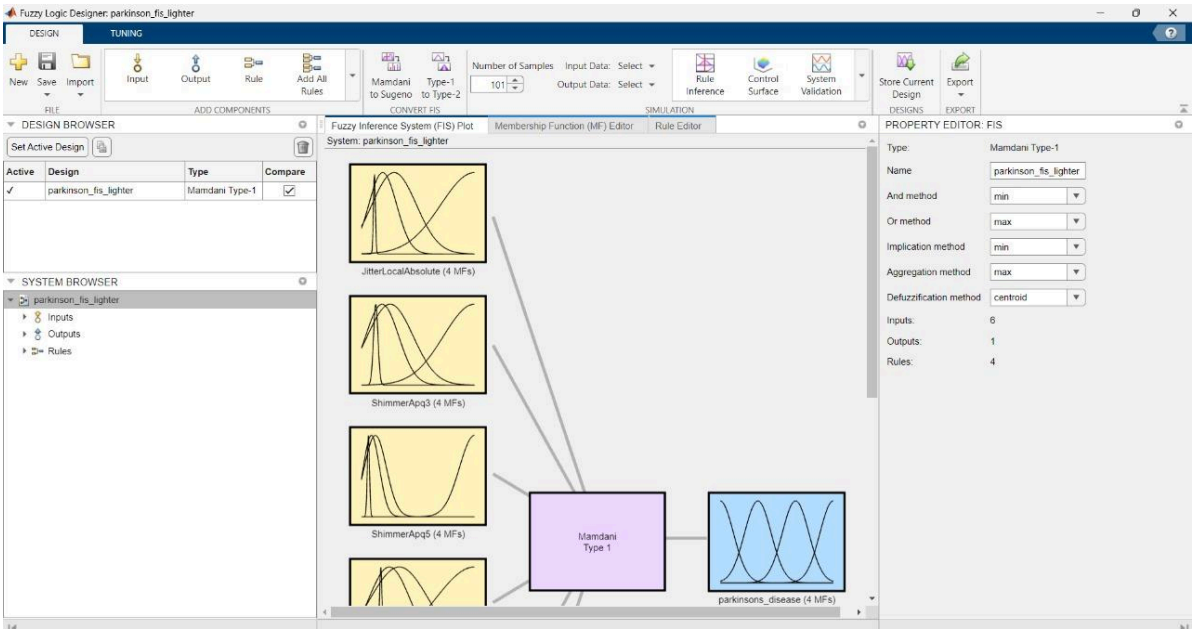


Fig7. Inference rules

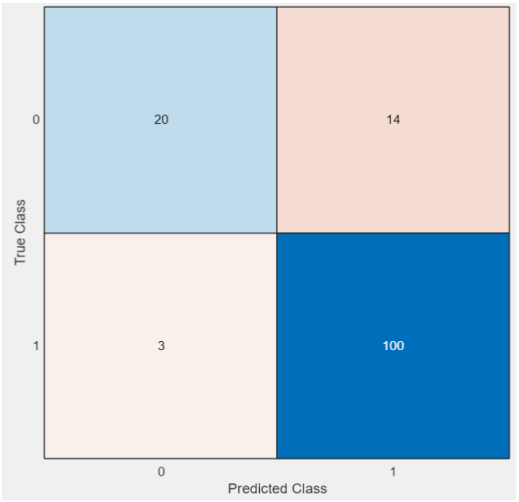


Figure 8: Validation Confusion Matrix (Weighted KNN)

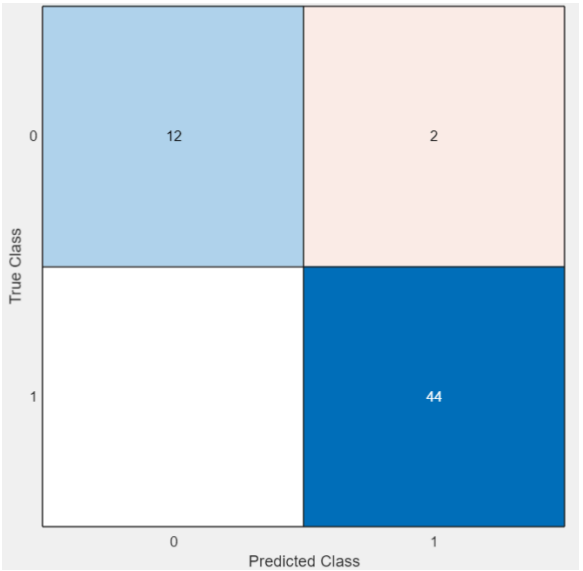


Figure 9: Test Confusion Matrix (Weighted KNN)

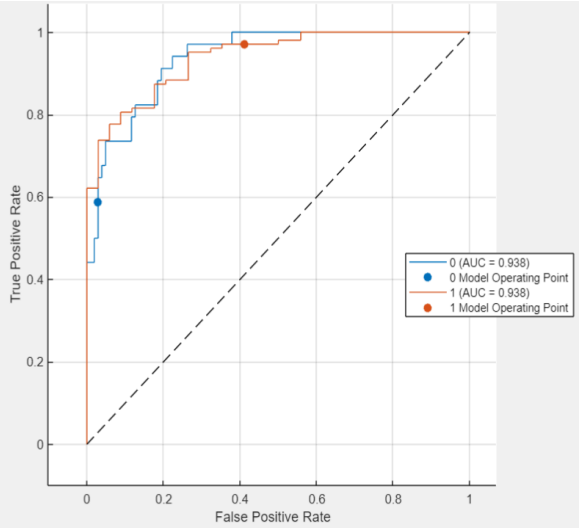


Figure 10: Validation ROC Curve (Weighted KNN)

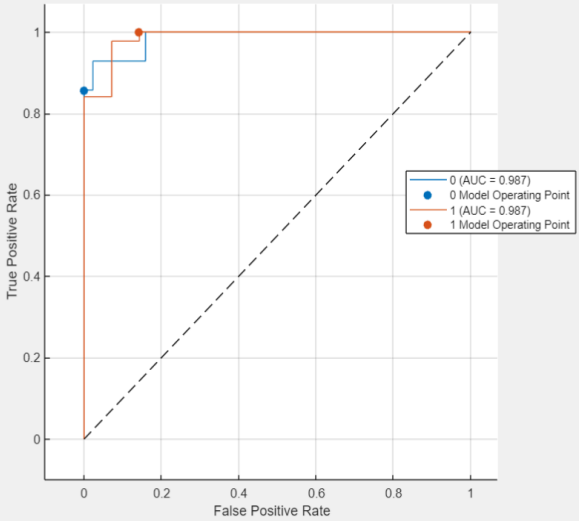


Figure 11: Test ROC Curve (Weighted KNN)

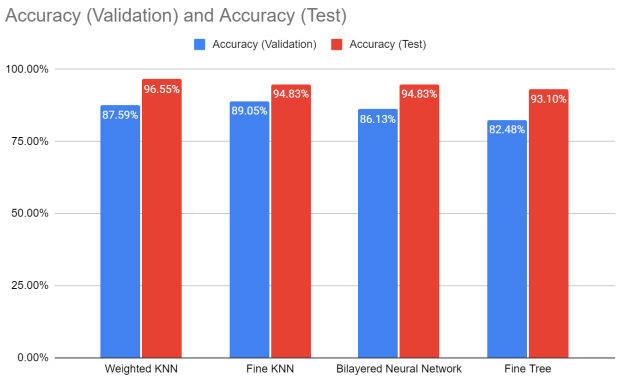


Figure 12: Comparative Accuracy of the Machine Learning

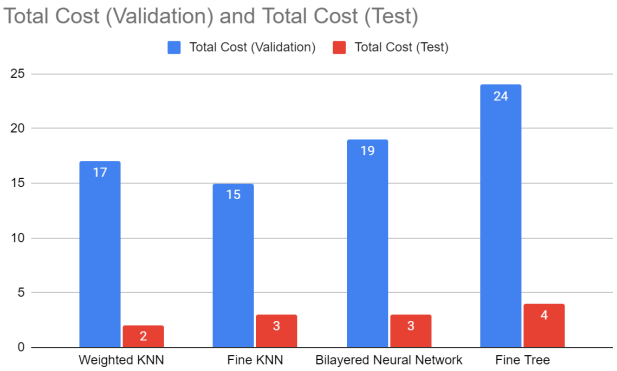


Figure 13: Comparative cost of the Machine Learning Algorithms

	Name	Range	Number of MFs
1	JitterLocalAbsolute	[6.495e-06 0.000776606]	4
2	ShimmerApq3	[0.496 25.82]	4
3	ShimmerApq5	[0.708 72.86]	4
4	ShimmerApq11	[0.517 44.764]	4
5	MeanPitch	[82.363 470.456]	4
6	StandardDeviationOfPeriod	[5.5347e-05 0.0063712]	4

Figure 14:Number of MFs

Name JitterLocalAbsolute

Range [6.495e-06 0.000776606]

Number of MFs: 4

Evenly Distribute MFs

Name	Type	Parameters
very_low	Gaussian	[6.495e-06 9.4926e-05]
low	Gaussian	[9.4926e-05 0.000151373]
med	Gaussian	[0.000151373 0.000229327]
high	Gaussian	[0.000229327 0.000776606]

Figure 15: Mapping of Jitter_Local Absolute

PROPERTY EDITOR: OUTPUT

Name parkinsons_disease

Range [0 1]

Number of MFs: 4

Evenly Distribute MFs

Name	Type	Parameters
no_pd	Gaussian	[0.118 1.735e-18]
low_pd	Gaussian	[0.118 0.3333]
med_pd	Gaussian	[0.118 0.6667]
high_pd	Gaussian	[0.118 1]

Figure 16: Mapping of the Output

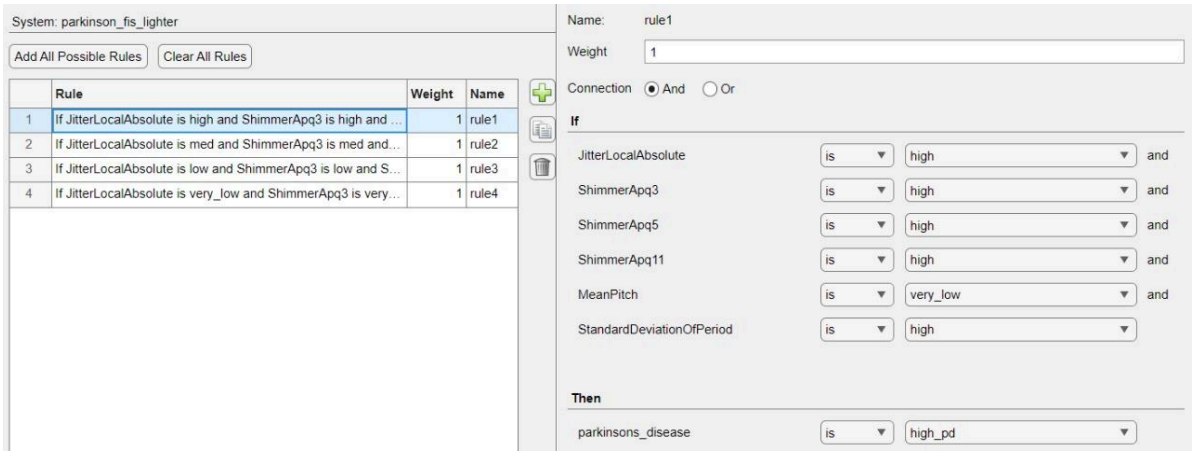


Figure 17. Fuzzy logic rules

6.2. Performance Evaluation Measures:

1. Accuracy = (TP + TN)/(TP+TN+FP+FN)
2. Sensitivity = TP/(TP+FN)
3. Specificity = TN/(TN+TP)
4. Correctness = (TP+TN)/Total

Here:-
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives
Total = Total Number of Samples

Weighted KNN:
Validation:
Accuracy (Validation): 87.59%
Sensitivity (Validation): 97.087%
Specificity (Validation): 58.82%
Correctness (Validation): 87.719%

Testing:
Accuracy (Test): 96.55%
Sensitivity (Test): 100%
Specificity (Test): 85.71%
Correctness (Test): 95.65%

6.3. Input Parameters/Features Considered:

Jitter Local Absolute:

Description: Jitter refers to the cycle-to-cycle variation in the duration of speech signals. Jitter Local Absolute measures short-term frequency variations.

Effect in Parkinson's Disease: Individuals with PD may exhibit increased jitter, indicating irregularities in the timing of vocal fold vibration. This can result in a voice that sounds shaky or jittery.

Shimmer Apq3, Shimmer Apq5, Shimmer Apq11:

Description: Shimmer measures the cycle-to-cycle amplitude variation in speech signals. Shimmer Apq3, Apq5, and Apq11 specifically quantify amplitude perturbations over different time scales.

Effect in Parkinson's Disease: Increased shimmer values suggest greater variability in the loudness of the voice. In PD, this may contribute to a voice that sounds more hoarse, breathy, or strained.

Mean Pitch:

Description: Mean Pitch represents the average fundamental frequency of the voice, indicating the perceived pitch of speech.

Effect in Parkinson's Disease: Individuals with PD may experience a decrease in mean pitch, leading to a voice that sounds monotone or lacks natural intonation. This is known as hypophonia.

Standard Deviation of Period:

Description: Standard Deviation of Period measures the variation in the time between consecutive pitch periods.

Effect in Parkinson's Disease: PD can lead to an increase in the standard deviation of the period, indicating a more irregular pattern of speech. This contributes to a voice that may sound less rhythmic and more unpredictable.

6.4 Comparison of Results with Existing Systems:

The results of the ParkinSense: A Machine Learning approach to classify Parkinson's Disease Project are compared with existing tourism systems to assess its effectiveness, efficiency. Key areas of comparison include:

- Accuracy: The test accuracy achieved is about 96.55% and validation accuracy is about 87.59% for Weighted KNN.

- Responsiveness and Performance: The cost for validation and test is 17 and 2 for Weighted KNN.

6.5 Inferences Drawn:

Metric	Weighted KNN	Fine KNN	Bilayered Neural Network	Fine Tree
Accuracy (Validation)	87.59%	89.05%	86.13%	82.48%
Accuracy (Test)	96.55%	94.83%	94.83%	93.10%
Total Cost (Validation)	17	15	19	24
Total Cost (Test)	2	3	3	4

Table1: Accuracy and Cost

Looking at the accuracy, Weighted KNN stands out, boasting the highest accuracy in the test (96.55%) set. Right behind is Fine KNN with solid numbers, hitting 89.05% on validation and 94.83% on the test set. On the flip side, Bilayered Neural Network and Fine Tree show slightly less accuracy, with Fine Tree at the bottom.

Now, onto the cost, where Weighted KNN shines again, being the most cost-efficient with the lowest total cost for both validation (17) and test (2).

Fine KNN, although a bit cheaper on validation (15) than Weighted KNN, evens out with a decent test cost (3). This chart helps show the balance between Weighted KNN and Fine KNN in terms of costs. Meanwhile, Bilayered Neural Network and Fine Tree end up costing more, with Fine Tree having the highest cost among the bunch. The cost chart gives a quick glance at how each model fares in terms of expenses.

7: Conclusion

7.1 Limitations:

Identifying and acknowledging limitations is crucial for providing a comprehensive understanding of the scope and potential constraints of the PD detection system. While our project endeavors to develop an innovative and effective solution for PD diagnosis, it is essential to recognize the challenges and limitations that may impact its performance and applicability.

1.Data Limitations: One of the primary limitations of our project is the availability and quality of training data. Although efforts were made to collect diverse and representative voice samples from individuals with and without PD, the size and variability of the dataset may impact the robustness and generalizability of the developed model. Future research should focus on expanding and diversifying the dataset to enhance the reliability and accuracy of the PD detection system.

2.Algorithm Complexity: The fuzzy logic-based approach adopted in our project introduces a level of complexity in the modeling and interpretation of diagnostic outcomes. While fuzzy logic offers flexibility in handling uncertainty and imprecision, it may also pose challenges in terms of model interpretability and explainability. Simplifying the algorithmic framework and enhancing transparency in decision-making processes are areas for improvement in future iterations of the PD detection system.

3.Performance Evaluation: Evaluating the performance of the PD detection system presents certain challenges, particularly in the absence of standardized benchmarks and metrics for assessing diagnostic accuracy. While efforts were made to validate the system using cross-validation and independent testing datasets, the lack of consensus on evaluation criteria may introduce variability in performance assessments. Collaborative initiatives and benchmarking studies within the research community are needed to establish a common framework for comparing and benchmarking PD detection algorithms.

4.Clinical Validation: Although our project lays the groundwork for PD detection using voice analysis and fuzzy logic, clinical validation in real-world settings is necessary to demonstrate the system's efficacy and utility in clinical practice. Conducting large-scale clinical trials involving diverse patient populations and healthcare settings is essential for validating the diagnostic performance, reliability, and clinical impact of the PD detection system. Collaboration with healthcare institutions and industry partners is crucial for facilitating the translation of research findings into clinical applications.

5.Deployment Challenges: Deploying the PD detection system in clinical settings may encounter various challenges related to technology adoption, regulatory compliance, and healthcare infrastructure. Integration with existing electronic health record systems, ensuring data security and privacy, and navigating regulatory approval processes are critical considerations for successful deployment. Collaboration with healthcare stakeholders, policymakers, and regulatory authorities is essential for addressing these challenges and facilitating the adoption of the PD detection system in routine clinical practice.

By acknowledging these limitations and challenges, we aim to inform future research directions and facilitate continuous improvement in the development and implementation of PD detection technologies. Despite these challenges, our project represents a significant step towards advancing the state-of-the-art in PD diagnosis and paving the way for personalized and proactive healthcare interventions.

7.2 Conclusion

In conclusion, our project represents a pioneering effort in the development of a PD detection system using fuzzy logic and voice analysis. By leveraging computational techniques and machine learning algorithms, we aim to address the unmet needs and challenges associated with PD diagnosis, enabling early detection and personalized treatment strategies.Through a systematic approach to requirement gathering, algorithm development, and system validation, we have laid the groundwork for a robust and efficient PD detection system. While the journey towards clinical translation and real-world impact may pose certain challenges, we remain committed to advancing the field of PD diagnosis and improving patient outcomes.Moving forward, we envision a future where computational methods and digital technologies play a central role in revolutionizing healthcare delivery and empowering individuals with tools for proactive disease management. By harnessing the power of innovation and collaboration, we can make significant strides towards a world where Parkinson's disease is detected early, treated effectively, and ultimately conquered.

7.3 Future Scope

The future scope of our project encompasses several avenues for further research, development, and implementation. Building upon the foundation laid by our current efforts, future endeavors may focus on the following areas:

- Enhanced Feature Extraction: Exploring advanced signal processing techniques and feature extraction algorithms to capture subtle changes in vocal characteristics associated with PD.

- Model Optimization: Fine-tuning and optimizing fuzzy logic-based models to improve diagnostic accuracy, interpretability, and scalability.

- Clinical Validation: Conducting large-scale clinical trials to validate the performance and clinical utility of the PD detection system in diverse patient populations and healthcare settings.

- Integration with Telehealth Platforms: Integrating the PD detection system with telehealth platforms and wearable devices to enable remote monitoring and early intervention for individuals at risk of PD.

- Longitudinal Monitoring: Developing longitudinal monitoring tools for tracking disease progression and treatment response over time, enabling personalized treatment planning and optimization.

- Patient Engagement and Education: Designing patient-centered tools and educational resources to empower individuals with PD and their caregivers to actively participate in disease management and self-care.

- Collaborative Partnerships: Establishing partnerships with healthcare institutions, industry stakeholders, and regulatory authorities to facilitate the translation and adoption of PD detection technologies in clinical practice.

By pursuing these avenues for future research and collaboration, we can continue to advance the field of PD diagnosis and make meaningful contributions towards improving the lives of individuals affected by Parkinson's disease.

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7. C. Quan, K. Ren and Z. Luo, "A Deep Learning Based Method for Parkinson's Disease Detection Using Dynamic Features of Speech," in IEEE Access, vol. 9, pp. 10239-10252, 2021, doi: 10.1109/ACCESS.2021.3051432.
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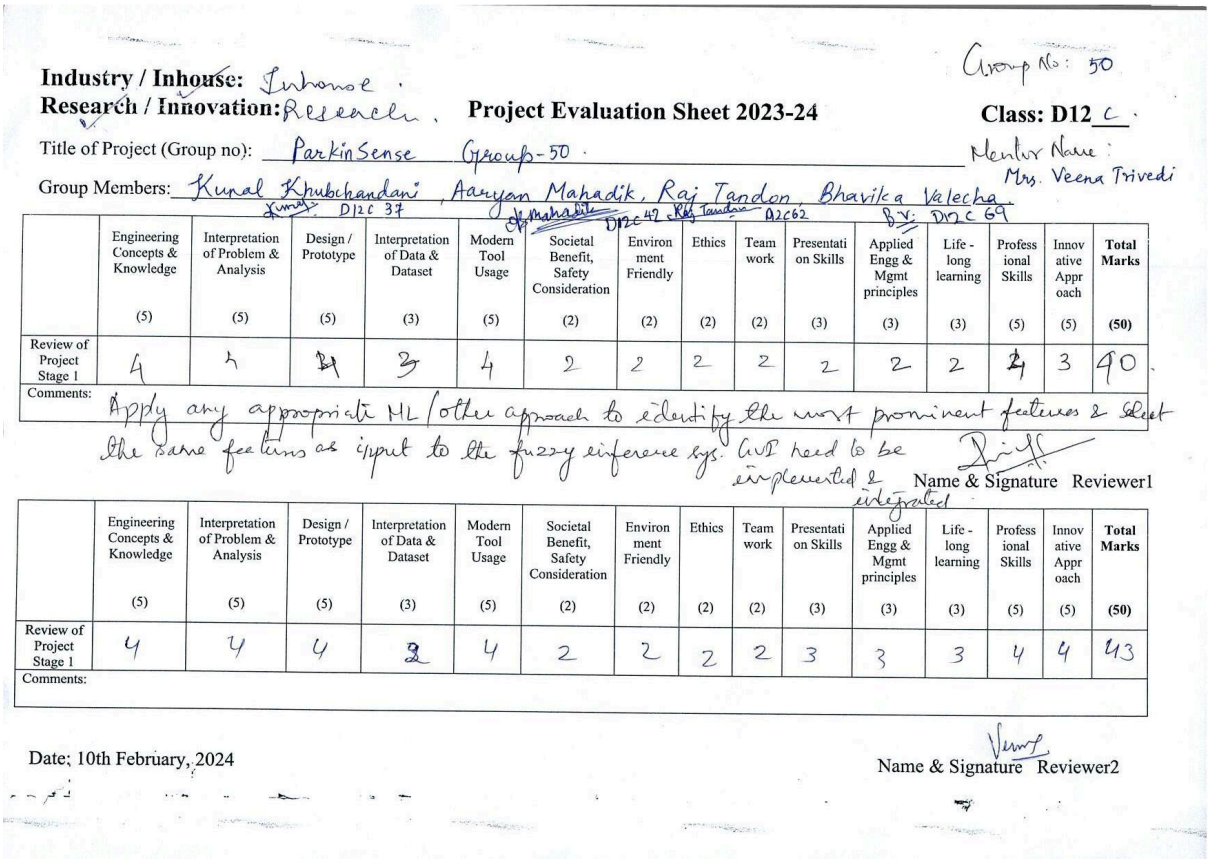
15. J NEUROENG REHABIL; PG: 9; GA: IJ0RY; UT: WOS:000475608600003.

d.Project review sheet

Review-1:



Group No: 50

Industry / Inhouse: Inhouse

Research / Innovation: Research

Project Evaluation Sheet 2023-24

Class: D12_C

Title of Project (Group no): ParkinSense Group-50

Mentor Name: Mrs. Veena Trivedi

Group Members: Kunal Khubchandani D12C 37, Aaryan Mahadik D12C 47, Raj Tandon A2C62, Bhavika Valecha D12C 69

	Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (3)	Applied Engg & Mgmt principles (3)	Life-long learning (3)	Professional Skills (5)	Innovative Approach (5)	**Total Marks (50)**
Review of Project Stage 1	4	4	4	3	4	2	2	2	2	2	2	2	4	3	40

Comments: Apply any appropriate ML/other approach to identify the most prominent features & select the same features as input to the fuzzy inference sys. GUI need to be implemented & integrated

Name & Signature Reviewer1

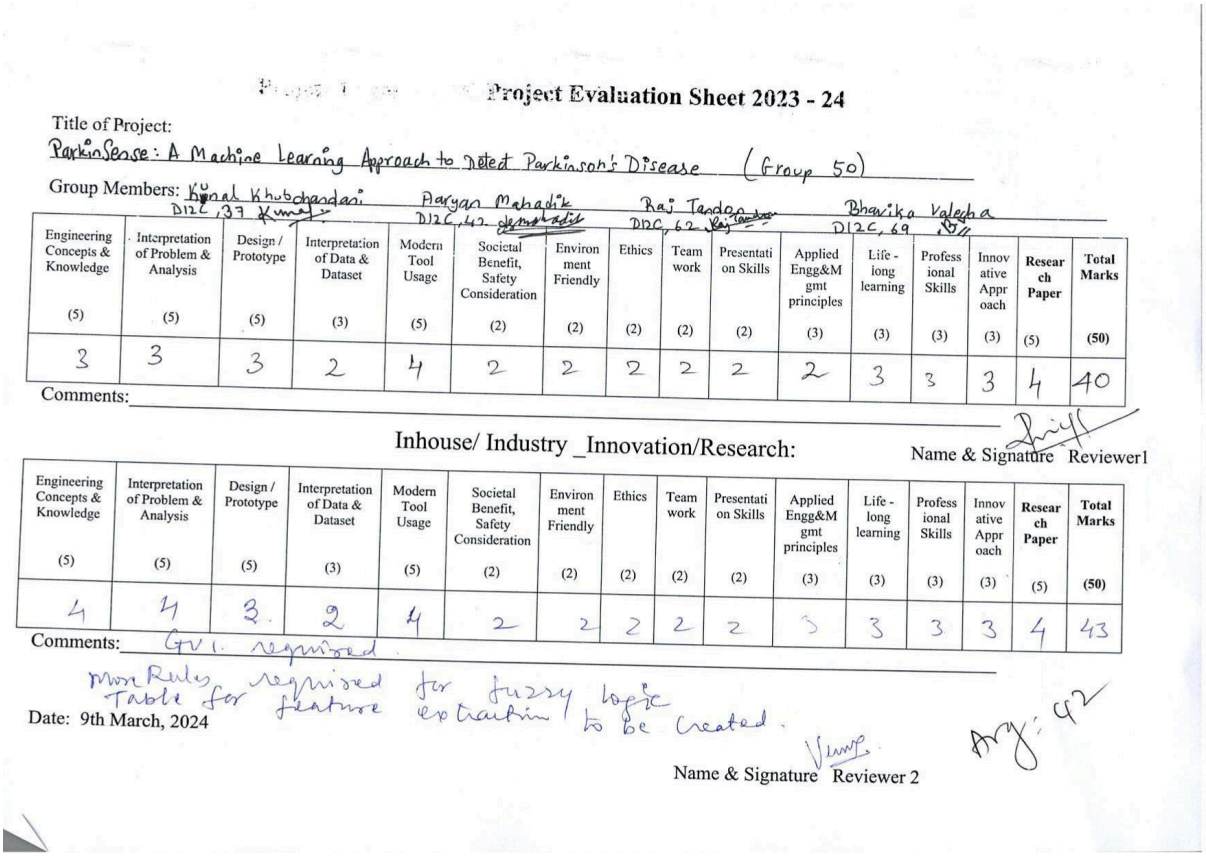
	Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (3)	Applied Engg & Mgmt principles (3)	Life-long learning (3)	Professional Skills (5)	Innovative Approach (5)	**Total Marks (50)**
Review of Project Stage 1	4	4	4	3	4	2	2	2	2	3	3	3	4	4	43

Comments:

Date: 10th February, 2024

Name & Signature Reviewer2

Review 2:



Project Evaluation Sheet 2023 - 24

Title of Project:

ParkinSense: A Machine Learning Approach to Detect Parkinson's Disease (Group 50)

Group Members: Kunal Khubchandani D12C, 37 Aaryan Mahadik D12C, 42 Raj Tandon D12C, 62 Bhavika Valecha D12C, 69

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
3	3	3	2	4	2	2	2	2	2	2	3	3	3	4	40

Comments:

Inhouse/ Industry _Innovation/Research:

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
4	4	3	2	4	2	2	2	2	2	3	3	3	3	4	43

Comments: GUI required

More Rules required for fuzzy logic
Table for feature extraction to be created.

Date: 9th March, 2024

Name & Signature Reviewer 2