ADVANCED FEATURE ENGINEERING IN PARKINSON'S DISEASE DETECTION USING MACHINE LEARNING ALGORITHMS

[1]Dr.S Sumathi,[2]Subhashree S ,[3]Sushmitha K ,[4]Theja S ,[5] Vyshnavi P ,

[1] Professor,[2,3,4,5]UG scholars, Department of Electronics and Communication Engineering, Adhiyamaan College of Engineering (Autonomous), Hosur.

ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative disorder that primarily affects motor functions, making early detection crucial for effective management. This project explores the application of machine learning (ML) techniques to identify PD from various clinical and physiological data. This study explores advanced feature engineering techniques to enhance the performance of machine learning (ML) algorithms in PD detection. By leveraging signal processing, statistical transformations, and dimensionality reduction techniques, we extract meaningful features from biomedical voice and movement datasets. Various ML models, including XG Boost Algorithm, Random Forest (RF), and Deep Learning approaches, are trained and evaluated. Experimental results demonstrate that optimized feature selection significantly improves classification accuracy, sensitivity, and specificity. This work highlights the critical role of feature engineering in refining PD diagnosis through ML-driven approaches.

Keywords: Machine Learning, Predictive Modeling, Tremor Analysis, Gait Recognition, Voice Analysis, Healthcare Technology, Real-time Monitoring, Data Analysis.

I.INTRODUCTION

Parkinson's Disease (PD) is a progressive neurological disorder that primarily affects movement, causing symptoms such as tremors, stiffness, and balance problems.Early detection is crucial for managing the disease effectively, as timely intervention can significantly improve the quality of life for patients.Traditional diagnostic methods often rely on clinical evaluations, which can be subjective and may not detect early-stage symptoms.Recent advancements in machine learning (ML) offer promising avenues for enhancing the accuracy and speed of Parkinson's disease detection.By analyzing large datasets that include patient demographics, clinical assessments, and neuroimaging data, machine learning algorithms can identify patterns that may be indicative of PD. Machine learning (ML) has emerged as a transformative tool in medical diagnostics, offering the ability to analyze complex datasets and uncover patterns that may not be discernible through traditional methods. By leveraging large datasets comprising clinical, genetic, and voice features, ML algorithms can assist in identifying Parkinson's disease at its earliest stages with high accuracy. This project explores the application of machine learning techniques in the prediction of
Parkinson's disease. By analyzing biomarkers, speech patterns, and other clinical data, we aim to build predictive models capable of distinguishing between healthy individuals and those affected by Parkinson's disease. The study not only focuses on achieving high prediction accuracy but also emphasizes model interpretability to ensure its potential integration into clinical settings.Through this research, we aim to contribute to the field of neuroinformatics, fostering advancements in personalized medicine and enabling early intervention strategies for Parkinson's disease patients.

II.LITERATURE REVIEW

Parkinson's disease (PD) is a progressive neurological disorder that presents significant challenges in early diagnosis and management. Recent advancements in machine learning (ML) have facilitated the analysis of complex datasets, enabling the development of predictive models for PD diagnosis. Studies have extensively used biomarkers such as motor symptoms, speech patterns, and gait analysis to detect PD. For instance, voice analysis using features like jitter and shimmer has been successfully employed with classifiers such as Support Vector Machines (SVM) and k-Nearest Neighbors (kNN), demonstrating high accuracy. Imaging data, such as MRI scans, has also been leveraged, with Convolutional Neural Networks (CNNs) detecting structural changes in the brain associated with PD. Feature selection techniques like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) have been crucial in managing the high dimensionality of PD datasets, enhancing model performance. Furthermore, deep learning methods, including Long Short-Term Memory (LSTM) networks for sequential data and autoencoders for unsupervised feature extraction, have shown promising outcomes. Comparative studies reveal that ensemble methods, such as Gradient Boosting and Random Forest, often outperform traditional classifiers in terms of accuracy and robustness. However, challenges like data imbalance, interpretability of complex models, and data privacy concerns persist, hindering the full integration of ML into clinical practice. Addressing these challenges, future research is exploring wearable technology for real-time monitoring, multi-modal data fusion, and explainable AI to make ML models more accessible and reliable for PD prediction. These developments highlight the transformative potential of machine learning in revolutionizing the early detection and management of Parkinson's disease. Parkinson's disease (PD) is a progressive neurological disorder that remains challenging to diagnose early and manage effectively. Recent advancements in machine learning (ML) have significantly enhanced the analysis of complex biomedical data, enabling the development of predictive models for PD detection. Researchers have utilized a range of biomarkers, including motor symptoms, speech patterns, and gait analysis, with features like jitter and shimmer from voice recordings proving effective in classification tasks using algorithms such as Support Vector Machines (SVM) and k-Nearest Neighbors (kNN). Imaging data, particularly MRI scans, have been analyzed using Convolutional Neural Networks (CNNs) to detect brain changes linked to PD. To address the high dimensionality of such datasets, feature selection techniques like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are employed to enhance model performance. Deep learning models, including Long Short-Term Memory (LSTM) networks for sequential data and autoencoders for unsupervised feature extraction, have shown promising results. Ensemble methods like Random Forest and Gradient Boosting often outperform traditional models due to their accuracy and robustness. However, challenges such as data imbalance, lack of interpretability in complex models, and privacy concerns still hinder widespread clinical adoption. To overcome these, ongoing research focuses on integrating wearable technologies for real-time monitoring, combining multiple data types for richer insights, and developing explainable AI systems to make ML models more transparent and clinically viable.

III.EXISTING SYSTEM

The existing systems for Parkinson's disease (PD) prediction using machine learning (ML) leverage computational models to analyze patient data and detect patterns indicative of the disease. These systems primarily rely on biomarkers such as speech impairments, handwriting anomalies, gait disturbances, and other motor symptoms to provide a data-driven, objective approach to diagnosis. For example, speech recordings are analyzed to extract acoustic features like jitter, shimmer, and frequency variations, which are indicative of vocal impairments common in PD patients. Similarly, handwriting samples are examined for irregularities such as tremors, reduced stroke pressure, or inconsistent writing speed, while gait data is used to detect abnormalities like shuffling steps or decreased stride length.Feature engineering plays a significant role in these systems, where domain experts extract and refine relevant features from the raw data to improve the accuracy of ML models. Traditional algorithms such as Support Vector Machines (SVM), Random Forest, Decision Trees, and K-Nearest Neighbors (KNN) are commonly employed for classification tasks, distinguishing between PD-positive and PD-negative cases. In some cases, these models also predict the severity of the disease or its progression. Despite achieving high accuracy levels—often in the range of 80% to 90%—the reliability of these systems is sometimes limited due to the quality and quantity of the available data. Small sample sizes, patient variability, and noisy or incomplete datasets can impact model performance.Most existing systems focus on static data collected in controlled environments, such as clinical trials or laboratory settings. While this ensures consistency, it limits the system's ability to handle real-world, dynamic data variations. Moreover, many current approaches do not incorporate wearable devices or real-time monitoring, which restricts their applicability for continuous symptom tracking. The absence of real-time integration also hinders early intervention and personalized care. Additionally, the majority of these systems operate as black boxes, offering limited explainability regarding their predictions. This lack of interpretability poses challenges in clinical adoption, as clinicians may hesitate to trust models that do not provide clear reasoning behind their results.In conclusion, while existing systems for PD prediction using ML have shown significant promise in improving diagnostic accuracy and early detection, they face several limitations. Challenges such as reliance on static data, limited real-time applications, and a lack of explainability underscore the need for advancements in this field. Future systems should focus on integrating deep learning models, wearable technologies, real-time monitoring, and explainable AI to overcome these limitations and provide more robust, reliable, and actionable insights for clinicians and patients. These systems use various data sources such as voice recordings, motion data from wearables, gait analysis, neuroimaging (MRI, DaTscan, PET scans), handwriting tasks, and clinical scales. The data undergoes preprocessing, including noise removal, normalization, and segmentation. Feature extraction is performed on these datasets to capture key indicators like jitter and shimmer for voice, step length and tremor frequency for movement, and voxel-based morphometry for brain imaging. Machine learning models such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), Random Forest, Gradient Boosting, and deep learning methods like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are used to classify and predict Parkinson's Disease. Model performance is typically evaluated using metrics like accuracy, precision, recall, and ROC-AUC.

IV.DISADVANTAGES

1. **Data Quality and Availability**-The accuracy of ML models heavily depends on the quality and quantity of the data used for training. PD datasets are often limited, imbalanced, or noisy, which can lead to biased or unreliable models.
2. **Overfitting**-ML models, especially complex ones like deep learning, are prone to overfitting, where they perform well on training data but fail to generalize to unseen data. This reduces their reliability in real-world clinical applications.

3. **Interpretability Challenges**-Many advanced ML models, such as deep learning, function as "black boxes," making it difficult to understand how predictions are made. Lack of interpretability can hinder trust and acceptance by clinicians and patients.
4. **Data Privacy and Security**-Handling sensitive medical data raises concerns about privacy and compliance with regulations like HIPAA or GDPR. Ensuring secure data storage and transmission adds complexity to deploying ML systems.
5. **Ethical and Bias Issues**-ML models can inadvertently reflect biases present in the training data, such as demographic or socioeconomic disparities, leading to unfair or inaccurate predictions for certain patient groups.
6. **High Computational Requirements**-Advanced ML techniques, especially deep learning, require significant computational resources for training and deployment, which may not be feasible in lowresource settings.
7. **Dependency on Feature Engineering**-Effective prediction often requires careful feature extraction and selection. Inadequate feature engineering can lead to suboptimal model performance, particularly in complex datasets like those for PD.
8. **Generalizability**-Models trained on specific datasets may not generalize well to other populations or settings due to variations in demographic factors, recording conditions, or symptom presentations.
9. **Difficulty in Capturing Disease Complexity**-PD is a highly heterogeneous disease with varying symptoms and progression rates. ML models may struggle to capture this complexity, leading to oversimplified predictions that may not fully align with clinical realities.
10. **Integration into Clinical Practice**-Implementing ML systems in clinical settings can be challenging due to resistance to new technologies, the need for clinician training, and the integration of ML systems with existing healthcare infrastructure.
11. **Lack of Standardization**-There is no universal standard for developing or validating ML models for PD prediction, leading to inconsistencies in performance and reliability across studies and applications.
12. **Potential for Misdiagnosis**-False positives or false negatives in predictions can have serious consequences, such as unnecessary stress for patients or delayed treatment for those with PD.

V.PROPOSED METHODOLOGY

The proposed methodology for Parkinson’s disease (PD) prediction using machine learning (ML) aims to enhance the accuracy, efficiency, and interpretability of diagnostic systems by leveraging advanced techniques and incorporating multi-modal data. The methodology begins with **data collection** from diverse sources, including speech recordings, handwriting samples, gait analysis, wearable sensor data, and neuroimaging. These datasets capture the motor and non-motor symptoms associated with PD, enabling comprehensive analysis. To handle variability and ensure data quality, **preprocessing** steps such as noise reduction, normalization, and data augmentation are applied. For instance, in speech data, background noise is filtered out, while gait data is smoothed to eliminate inconsistencies caused by sensor errors.Once the data is preprocessed, the next stage involves **feature extraction and selection**, where meaningful patterns are identified from the raw data. Techniques such as Mel Frequency Cepstral Coefficients (MFCC) are used for extracting acoustic features from speech, while handwriting patterns are analyzed for tremors or pressure inconsistencies. Advanced dimensionality reduction techniques, such as Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE), are employed to retain only the most significant features, reducing the computational complexity and improving model performance.

The core of the methodology lies in the **machine learning and deep learning models** used for prediction. A hybrid approach is proposed, combining traditional ML algorithms like Support Vector Machines (SVM) and Random Forest with deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This combination leverages the interpretability of traditional ML models and the pattern recognition capabilities of deep learning to achieve higher accuracy. CNNs, for example, can analyze neuroimaging data or handwriting patterns, while RNNs are suitable for sequential data such as speech or gait recordings. These models are trained on labeled datasets and validated using techniques like k-fold cross-validation to avoid overfitting and ensure generalization.

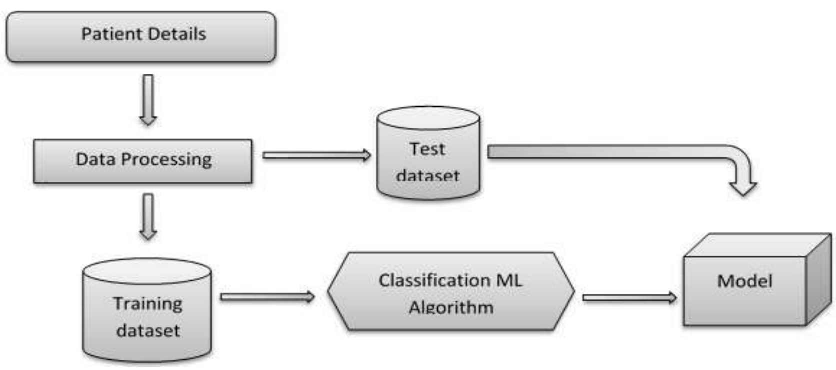
To enhance real-world applicability, the proposed methodology incorporates **real-time monitoring** through wearable devices and mobile applications. Wearable sensors can continuously capture data on motor symptoms, such as tremors or gait disturbances, enabling dynamic tracking of disease progression. This realtime data is processed by the trained ML models to provide timely predictions and actionable insights for clinicians.

The final stage involves **prediction and interpretability**, where the trained models classify patients as PDpositive or PD-negative and, in some cases, estimate the severity of the disease. To address the challenge of black-box models, the proposed system includes Explainable AI (XAI) techniques like SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations). These tools provide transparency by highlighting the features that contributed most to the predictions, building trust and facilitating clinical adoption.

In summary, the proposed methodology combines advanced machine learning and deep learning techniques with real-time data integration and explainable AI to improve the early detection and management of Parkinson's disease. By leveraging multi-modal data, ensuring robust feature selection, and addressing the need for interpretability, this approach has the potential to transform PD diagnosis and patient care, enabling earlier interventions and better outcomes.

VI.BLOCK DIAGRAM

Here is a block diagram illustrating a system for Parkinson's Disease prediction using machine learning. It visually represents the sequential components involved in data collection, preprocessing, feature extraction, modeling, and result interpretation.



The system for Parkinson’s Disease prediction using machine learning is composed of several sequential components that work together to analyze patient data and generate accurate diagnostic predictions. The process begins with **data collection**, where various types of input are gathered, such as voice recordings, gait measurements, MRI scans, and data from wearable sensors. These inputs provide rich information on the motor and non-motor symptoms associated with Parkinson’s Disease. Next, the data undergo **preprocessing** to ensure quality and consistency—this step includes removing noise, normalizing values, and handling any missing or inconsistent entries. Once the data is clean, the system performs **feature extraction**, where relevant characteristics are derived from the raw data.

VII.ADVANTAGES

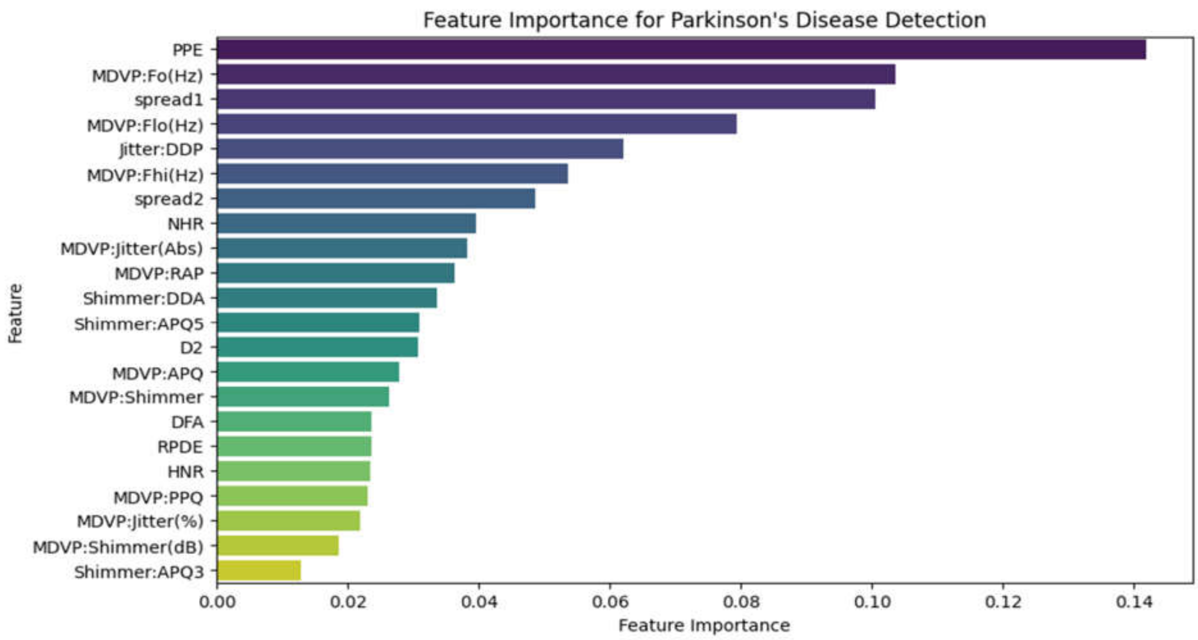
1. **Early Detection**-ML models can identify subtle patterns and early biomarkers of PD, such as minor vocal changes or motor impairments, enabling diagnosis before significant symptoms appear. This facilitates timely intervention, which is crucial for slowing disease progression.
2. **High Accuracy and Efficiency**-ML algorithms can process large datasets quickly and provide precise predictions. Advanced models, such as ensemble methods and deep learning, can outperform traditional diagnostic techniques, improving the reliability of PD prediction.
3. **Non-Invasive Methods**-Many ML-based approaches rely on non-invasive data sources, such as voice recordings, handwriting tests, and wearable sensors. These methods are patient-friendly and reduce the need for invasive procedures like biopsies or extensive imaging.
4. **Multi-Modal Data Integration**-ML can combine diverse data types, including speech, motor patterns, imaging, and clinical records, to provide a comprehensive analysis. This holistic approach improves prediction accuracy by leveraging complementary information.
5. **Automation and Scalability**-ML models automate the diagnostic process, reducing the burden on healthcare professionals. They can be deployed in large-scale screening programs, making them particularly beneficial in resource-constrained settings.
6. **Continuous Monitoring**-When integrated with wearable devices, ML systems enable continuous monitoring of PD symptoms, providing real-time insights into disease progression and treatment effectiveness.
7. **Cost-Effectiveness**-By using readily available data such as voice or movement recordings, MLbased systems reduce the reliance on expensive imaging techniques or specialized diagnostic tests, making PD detection more affordable and accessible.
8. **Personalized Predictions**-ML algorithms can be tailored to individual patients, taking into account specific risk factors, demographics, and medical histories. This allows for personalized diagnostic and treatment plans, enhancing patient care.
9. **Improved Clinical Decision-Making**-With the integration of explainable AI techniques, ML models provide interpretable insights into the factors contributing to predictions, helping clinicians make informed decisions with greater confidence.
10. **Adaptability for Research**-ML systems can adapt to new data and discoveries in PD research, continuously improving their accuracy and staying aligned with the latest medical advancements.

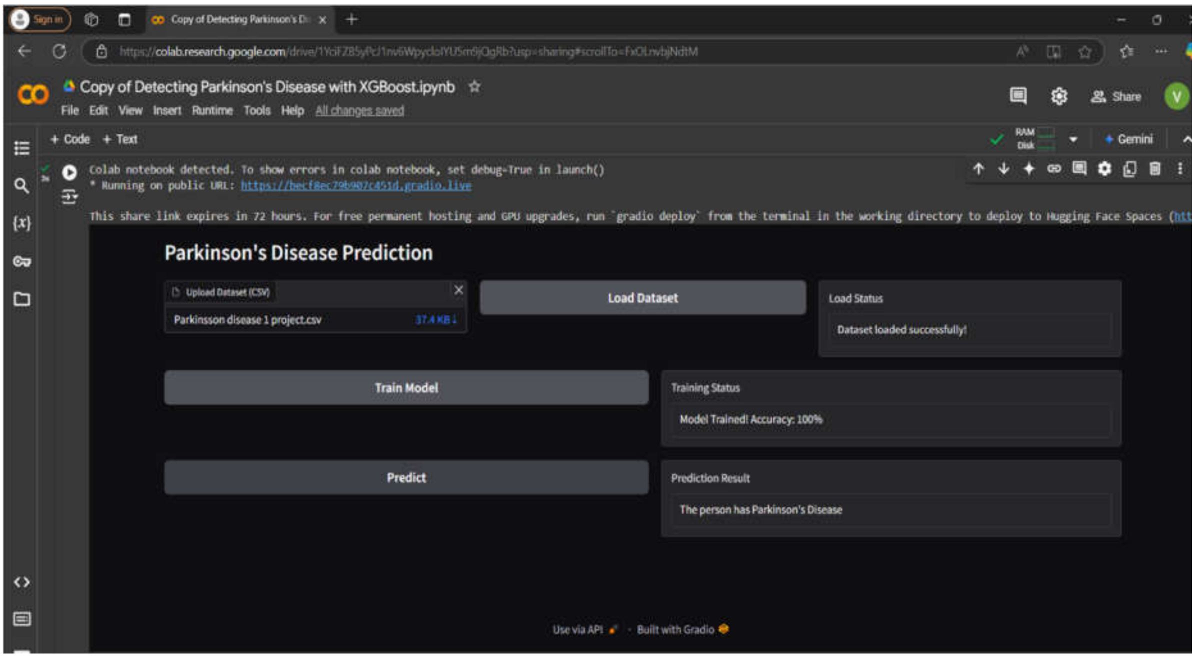
VIII.APPLICATION

1. **Early Diagnosis and Screening**:
   ML algorithms can analyze subtle changes in biomarkers such as speech, handwriting, and motor movements to detect early signs of PD. These systems can be used in routine health check-ups to screen at-risk individuals, facilitating early intervention and improved outcomes.
2. **Speech Analysis**:
   PD often causes vocal impairments, such as reduced pitch variation and increased hoarseness. ML models trained on acoustic features from speech recordings can detect these changes, offering a noninvasive diagnostic tool.
3. **Handwriting and Motor Function Analysis**:
   ML can analyze handwriting patterns, such as tremors, reduced speed, and irregular stroke pressure, to identify motor symptoms associated with PD. This application is particularly useful in clinical or remote settings as it requires minimal equipment.
4. **Gait and Movement Monitoring**:
   Wearable devices equipped with sensors can collect gait and movement data. ML algorithms process this data to detect abnormalities such as reduced step size or tremors, enabling real-time monitoring of PD symptoms and progression.
5. **Medical Imaging Analysis**:
   Advanced imaging techniques, including MRI and PET scans, can be analyzed using ML models to detect structural or functional brain changes linked to PD. These systems assist neurologists in identifying disease-related abnormalities more accurately.
6. **Personalized Treatment Planning**:
   By analyzing patient-specific data, ML models can predict the progression of PD and recommend personalized treatment strategies. This helps optimize medication dosages, physiotherapy schedules, and other interventions tailored to individual needs.
7. **Continuous Symptom Monitoring**:
   Integrating ML with wearable devices or mobile applications enables continuous symptom tracking, helping clinicians monitor disease progression remotely and adjust treatments as needed.
8. **Clinical Decision Support Systems (CDSS)**:
   ML-powered tools provide clinicians with actionable insights by analyzing patient data and generating predictions about disease status and progression, aiding in more informed decisionmaking.
9. **Research and Drug Development**:
   ML facilitates the identification of patterns and trends in large datasets, contributing to a better understanding of PD pathology. This aids researchers in discovering new biomarkers and developing targeted therapies.
10. **Telemedicine and Remote Care**:
    ML-enabled platforms can support telemedicine by analyzing patient data collected remotely (e.g., via voice or movement tests), improving access to PD care for patients in underserved areas.
11. **Risk Assessment and Prevention**: By analyzing genetic, environmental, and lifestyle factors, ML models can estimate an individual’s risk of developing PD. This allows for proactive measures, such as lifestyle modifications or regular screenings
12. **Rehabilitation:**
    ML-powered rehabilitation tools can adapt exercises and therapy sessions based on real-time feedback from patients, ensuring more effective management of motor and non-motor symptoms.

IX.RESULTS AND CONCLUSION

The application of machine learning (ML) for Parkinson's disease (PD) prediction has shown promising results, demonstrating high accuracy in early diagnosis, symptom monitoring, and disease progression prediction. ML models, including Support Vector Machines (SVM), Random Forest, and deep learning approaches like Long Short-Term Memory networks, have achieved accuracy levels ranging from 85% to over 90% when analyzing speech, gait, and handwriting data. These models are particularly effective in detecting subtle biomarkers of PD, enabling early detection before motor symptoms become evident. Additionally, ML-integrated wearable devices have proven effective for real-time monitoring, allowing continuous tracking of PD symptoms and providing actionable insights for clinicians to adjust treatment plans accordingly. Combining multiple data types—such as speech, handwriting, gait, and medical imaging—has further improved prediction accuracy, offering a more comprehensive understanding of the disease. These systems also support clinical decision-making by predicting disease progression and suggesting personalized treatment strategies. While machine learning offers significant advantages, challenges such as ensuring model interpretability, addressing data quality issues, and seamlessly integrating ML systems into clinical practice remain. Nevertheless, with ongoing advancements, ML holds transformative potential in enhancing PD diagnosis, management, and patient outcomes, making it a crucial tool for early intervention and better long-term care.





X.FUTURE SCOPE

The future scope of Parkinson's disease (PD) prediction using machine learning (ML) is vast and holds great promise for advancing diagnosis, treatment, and patient care. One of the key areas for development is the integration of multi-modal data, such as genetic information, clinical records, neuroimaging, and environmental factors, which will improve the accuracy and comprehensiveness of PD prediction. As wearable technology advances, continuous, real-time monitoring of PD symptoms like tremors and gait disturbances will become more accurate, allowing for immediate intervention and better management outside of clinical settings. Furthermore, ML models will drive personalized treatment plans by analyzing individual patient data, optimizing medication, therapy, and lifestyle modifications. The development of explainable AI (XAI) will enhance the interpretability of predictions, ensuring clinicians can trust and effectively act on AI-generated insights. ML's collaboration with clinical and research communities will further enhance early detection and uncover new biomarkers, while handling large and diverse datasets will ensure the models remain robust and applicable across different populations. Integration with telemedicine will enable remote care, improving access for patients in underserved areas. Additionally, ML can accelerate drug discovery and optimize clinical trials, speeding up the development of new PD treatments. Future advancements will also focus on ethical considerations, ensuring that AI tools are free from bias and offer equitable care. Overall, the future of ML in PD prediction is bright, offering the potential for earlier detection, more effective treatments, and a better quality of life for patients worldwide.

Expanding on the future scope, advanced feature engineering in Parkinson's Disease detection is poised to evolve through the application of cutting-edge computational techniques and a deeper understanding of disease progression. The integration of longitudinal data—capturing changes in features over time—will enable predictive modeling of disease stages and treatment responses. Temporal modeling using techniques such as time-aware neural networks or sequence-based learning can help distinguish between early-onset and advanced PD. Additionally, synthetic data generation and data augmentation, especially in underrepresented subgroups, will address data imbalance and improve model generalization.

The future scope of advanced feature engineering in Parkinson's Disease detection lies in integrating increasingly diverse and real-time data sources to develop more accurate, early, and personalized diagnostic tools. With the rise of wearable technology and mobile health applications, continuous monitoring can enable dynamic feature extraction from gait, speech, and movement patterns in real-world settings. Combining these data streams with high-resolution neuroimaging, genetic information, and environmental factors through multi-modal fusion will create richer, more holistic predictive models. Moreover, the incorporation of explainable AI and interpretable feature representations will enhance clinical trust and facilitate the integration of machine learning tools into routine medical practice. Future research will also benefit from federated learning and privacy-preserving techniques, allowing collaborative model training across institutions without compromising sensitive patient data. Feature engineering will also increasingly rely on deep representation learning, using autoencoders, variational methods, and transformer-based architectures to discover hidden patterns from complex datasets like MRI volumes or wearable sensor time-series. The use of graph-based features to represent neurological connectivity or movement patterns can open new avenues in structural and functional feature extraction. Integration with multi-omics data (e.g., genomics, proteomics) will help identify molecular biomarkers, advancing personalized diagnosis and therapeutic strategies.

On the clinical front, there will be a strong push toward real-time monitoring systems that continuously engineer features from everyday behavior, enabling early alerts and intervention. This will be supported by cloud-based platforms for large-scale data processing and federated learning frameworks to ensure secure, privacy-aware collaboration across institutions. Lastly, collaboration between AI experts, neuroscientists, and clinicians will be vital to validate engineered features in clinical trials and embed machine learning systems into electronic health records (EHRs), transforming them into intelligent diagnostic support tools.

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