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Classification Of Parkinson's Disease Using Machine Learning Technique

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ABSTRACT

Parkinson's disease (PD) progresses through the nervous system as a neurodegenerative condition which causes severe effects on motor function and generates life quality problems. Standard diagnostic approaches face two main limitations that include a subjective basis and prolonged diagnostic delays. This research develops an AI-driven diagnosis classification system which involves analyzing datasets from public domains together with medical patient information stored at Baghdad hospitals. The decision tree and random forest models together with SVM and CNN provided implementation for PD diagnosis assessment through performance metrics testing. The CNN model achieved the highest correctness rate of 94.3% as well as precision of 93.1% and F1-score of 93.5% to outperform the other proposed models during testing. The application of CNN on the local dataset achieved a strong 90.7% accuracy because it successfully adapted to different data quality and format conditions. The research determined that tremor frequency and voice pitch variation together with hand movement speed proved to be the most effective diagnostic features. Research demonstrates AI diagnostic technologies can assist early Parkinson disease identification at healthcare sites which lack resources by showing the necessity of better digital networks and standardized research data alongside professional education for medical staff.

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1. Introduction

The progressive brain deterioration affecting Parkinson's disease patients causes physical movement function impairment as well as decreases patients' overall quality of life. Standard medical diagnostic assessments based on objective observations enable healthcare professionals to check for tremors and muscle rigidness along with bradykinesia symptoms. First signs of Parkinson's disease regularly imitate natural aging symptoms leading doctors to establish incorrect diagnoses which results in later medical treatment. PET and DaT scans function as barriers to early detection because they are expensive and have unreliable markers and affect developing countries such as Iraq the most.

The medical diagnostic field uses Artificial Intelligence (AI) jointly with Machine Learning (ML) to develop accurate diagnostic tools which produce fast results with objective assessment abilities. AI operates on vast data combinations that consist of patient speech files and gait motion data with handwritten signatures together with brain imaging results which indicate Parkinson's disease symptoms. Decision Trees together with SVM and Random

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Forests and CNN procedures from deep learning analysis have demonstrated highly effective PD classification accuracy.

AI-based diagnostic systems face various implementation barriers in Iraq because the country does not have enough funding nor digital infrastructure and has minimal opportunities for professional training. When medical professionals incorporate ML technology into their practices, they achieve better diagnostic abilities by streamlining workflows as well as rapid disease identification methods and large-scale testing possibilities for areas with limited resources. A research study evaluates worldwide and local data sets to establish how well ML models detect Parkinson’s disease at Iraqi medical centers.

The research will conduct (1) a diagnostic capability assessment of multiple ML algorithms for PD (2) deploy analysis on Baghdad hospital patient data while (3) identifying optimal features and (4) resolving prospective medical AI implementation hurdles in the Iraqi healthcare system.

2. Literature Review

2.1 Traditional Diagnostic Methods for Parkinson’s Disease

Diagnosis of Parkinson’s disease continues to rely mainly on neurologists who perform patient interviews together with physical examinations. The lack of confirmatory medical markers creates an obstacle for PD diagnosis because the disease becomes difficult to identify in preliminary stages. Day-to-day diagnosis failures and delayed identification result in patients receiving delayed care that leads to weakened disease management results.

2.1.1 Clinical Examinations

The assessment of motor symptoms in patients relies on the conformance to clinical criteria evaluated through two scales known as the UPDRS and Hoehn and Yahr scale. Through these assessment tools doctors determine patients' movement obstacles as well as their tremors and muscle stiffness and balance problems. Studies demonstrate a wide range of clinical misdiagnosis rates in parkinsonian conditions when based solely on symptoms as the primary diagnostic method.

2.1.2 Genetic Testing

The majority of Parkinson’s disease development happens randomly although some rare cases stem from genetic mutations. Three genes which have been linked to Parkinson’s disease include SNCA and LRRK2 and PARK2. The identification of Parkinson's disease genetic mutations through testing occurs sporadically yet physicians refrain from making this practice standard due to its uncertain benefits for sporadic cases.

2.1.3 Neuroimaging Techniques

Medical imaging technologies including Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Dopamine Transporter (DaT) Scans serve mostly for eliminating neurological conditions instead of affirming Parkinson’s disease directly. DaTscan imaging stands as the most common neurological imaging tool for PD because it measures dopamine transporter levels in brain structures. Widespread usage of this imaging technique is restricted by cost and shortage of availability across many countries such as Iraq.

2.2 Machine Learning in Medical Diagnosis

2.2.1 Role of Artificial Intelligence in Parkinson’s Disease Classification

Modern medical research employs Artificial Intelligence (AI) and Machine Learning (ML) systems to identify and sort Parkinson’s disease as well as other diseases. The analysis of extensive patient data through ML algorithms enables detection of early symptoms along with pattern identification and superior diagnostic outcomes compared to traditional processes. AI performs multi-type analysis of PD-related data through voice recordings together with movement patterns and handwriting samples and neuroimaging data which provides a wide array of diagnostic possibilities.

2.3 Previous Studies on Parkinson's Disease Classification

2.3.1 Review of Studies Using Machine Learning for Parkinson's Diagnosis

Modern techniques in machine learning (ML) combined with deep learning (DL) now boost the early identification and categorization abilities for Parkinson's disease (PD). The research conducted by Rabie and Akhloufi (2025) found that ML and DL techniques successfully examine audio recordings and gait patterns which led to higher than 99% accuracy rates in multiple studies.

The research of Iyer et al. (2023) created an AI detection model which evaluated nocturnal breathing signals to identify PD symptoms with an area under the curve (AUC) of 0.90 thus displaying the value of non-invasive diagnostic methods.

Developments in DL technology have started to improve different neuroimaging methods. PD classification using susceptibility map-weighted imaging (SMWI) integrated with DL algorithms yielded accuracy results ranging from 91.8% to 97.7% according to the study by Liu et al. (2024).

García-Ordás et al. (2024) established a multi-task neural network to analyze voice features in PD severity evaluation that produced a 99.15% success rate for severe and non-severe patient classification.

The researchers of Ding et al. (2023) applied contrastive graph cross-view learning for SPECT image and clinical feature analysis that yielded 91% accuracy alongside 0.93 AUC.

The results of these research findings demonstrate how ML and DL technologies revolutionize PD diagnostic procedures while enabling better early diagnosis protocols and individualized treatment planning.

3. Theoretical Framework

3.1 Theories of Classification in Artificial Intelligence

Machine learning functions as a artificial intelligence (AI) subcategory which allows computers to derive predictions through unprogrammed data processing. The fundamental ML task of classification requires systems to assign data points into predefined categories or labels according to (Shalev-Shwartz & Ben-David, 2014). Learning paradigms exist as supervised and unsupervised learning approaches for classification algorithms.

3.1.1 Supervised vs. Unsupervised Learning

Training supervised models takes place through labeled datasets that pair input features alongside their output labels. The training data serves to educate the model which enables it to forecast labels for previously unviewed information. Decision Trees as well as Support Vector Machines (SVM) and Neural Networks comprise the supervised learning algorithm examples according to Goodfellow, Bengio, & Courville (2016).

The difference lies between supervised learning which works with labeled data and unsupervised learning which uses unlabeled data. K-Means and Hierarchical Clustering emerge as the standard uncontrolled learning strategies among clustering approaches (Murphy, 2012). Unsupervised learning methods contribute to discovering Parkinson's disease symptoms at an early stage while feature extraction occurs when used alongside supervised learning techniques.

3.1.2 Traditional vs. Modern Classification Approaches

Classifying Parkinson's disease was traditionally achieved based on clinical and statistical analysis (Litvan et al., 2012). Modern classification techniques exploit the advances in AI using machine learning models that are trained from different data sources such as voice recordings, handwriting samples, and neuroimaging scans to improve diagnostic accuracy and efficiency (Sakar et al., 2019).

3.2 Machine Learning Algorithms for Parkinson's Disease Classification

Several machine learning algorithms have been used to classify Parkinson's disease, each with unique advantages and limitations.

3.2.1 Decision Trees

Decision Trees are hierarchical models that split data based on feature thresholds, forming a tree-like structure where each node represents a decision based on input attributes (Quinlan, 1996). While they are interpretable and easy to use, they are prone to overfitting, especially in small datasets (Breiman et al., 1984).

3.2.2 Random Forest

Random Forest is an ensemble learning method that combines multiple Decision Trees to improve prediction accuracy and reduce overfitting (Breiman, 2001). It is widely used in medical classification tasks, including Parkinson's disease diagnosis, due to its robustness and ability to handle high-dimensional data (Prashanth et al., 2018).

3.2.3 Support Vector Machines (SVM)

SVM can be considered as a powerful classification algorithm, that can find an optimal hyperplane to separate classes in the high dimensional space (Cortes & Vapnik, 1995). The application for voice analysis and hand writing recognition for the diagnosis of Parkinson's disease was successful and high accuracy of the datasets to differentiate between normal and the diagnosed patients was shown (Das, 2010).

3.3 Performance Evaluation Metrics

The assessment of classification model performance proves essential for developing reliable diagnostic systems of Parkinson's disease. The evaluation of machine learning models for Parkinson's disease classification involved multiple standard measurement criteria. The performance assessment includes a combination of Accuracy, Precision and Recall (Sensitivity) along with F1-Score. The standard metrics use the following mathematical statements to define their evaluation measurements:

- Accuracy: Measures the proportion of correctly classified instances among the total instances:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision: Measures the proportion of true positive predictions among all positive predictions:

$$\text{Precision} = \frac{TP}{TP + FP}$$

- Recall (Sensitivity): Measures the proportion of true positives identified among all actual positives:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score: The harmonic mean of Precision and Recall, used to balance the trade-off between the two:

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

- TP: True Positives
- TN: True Negatives
- FP: False Positives
- FN: False Negatives

These metrics offer comprehensive insight into the diagnostic performance of the models, particularly under class imbalance conditions which are common in medical datasets.

The importance of precision stands out when diagnosing Parkinson's disease because false positive outcomes trigger needless patient stress together with extra medical checks and procedures. High precision enables most individuals diagnosed with the disease to truly have Parkinson's disease.

Medical datasets that usually present class imbalance situations benefit from F1-Score because this harmonic precision-recall combination provides an equitable measurement approach. Model success depends on having a high F1-score because it shows accurate detection of Parkinson's disease patients and minimal rates of false positive results.

The main evaluation metrics employed for performance assessment video include:

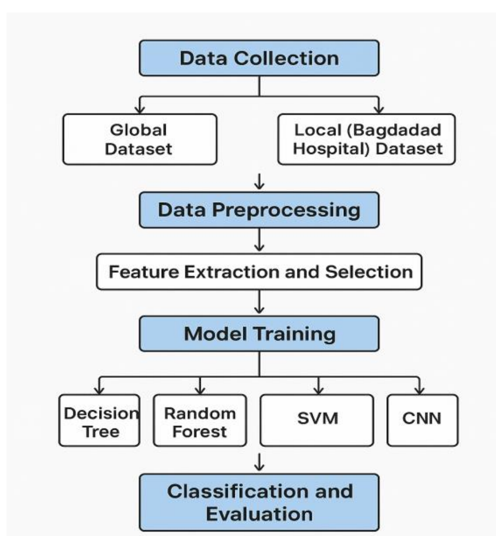
3.3.1 Accuracy

Accuracy determines how many instances in the dataset get properly classified among all instances. The wide application of accuracy as a measurement can become misleading when working with datasets featuring imbalanced proportions such as Parkinson's disease data that has more healthy cases than diseased cases (Powers, 2011).

3.3.2 Recall

The proportion of correct model identifications for existing positive cases appears under the label Recall (also known as Sensitivity). The accurate identification of most Parkinson's disease patients is crucial for diagnosis because high recall reduces false negative cases according to Saito and Rehmsmeier (2015).

Overall Framework of the Proposed Parkinson's Disease Classification Approach



This diagram presents the end-to-end structure of the proposed framework. It begins with data collection from both global and local sources, followed by data preprocessing and feature extraction. Machine learning models—including Decision Tree, Random Forest, Support Vector Machine (SVM), and Convolutional Neural Networks (CNN)—are then trained to perform classification. The process concludes with performance evaluation based on accuracy, precision, recall, and F1-score.

4. Research Methodology and Practical Study in Iraq

The research explains how machine learning algorithms were used to detect Parkinson's disease alongside the combination of worldwide and regional dataset analysis. A practical analysis using Iraqi hospital data from Baghdad and publicly accessible information evaluated AI-based diagnostic methods in their operational capabilities.

4.1 Data Sources

Publicly Available Dataset

A dataset from the UCI Machine Learning Repository serves as the foundation of this study because Max Little et al. (2007) initially collected the Parkinson's Disease data. The dataset includes 195 voice recordings from 31 individuals while 23 of those individuals received Parkinson's disease diagnosis. A total of 22 biomedical voice measurements appear within the dataset including average vocal fundamental frequency along with jitter measurements and shimmer calculations and Harmonics-to-Noise Ratio (HNR). People can access this data collection online through the URL provided.

https://archive.ics.uci.edu/ml/datasets/parkinsons

Medical researchers are using these voice features for PD detection because the characteristics show clear relationships with vocal impairment impacts that affect how patients control their voice.

Local Medical Dataset – Baghdad Hospitals

A second patient records dataset was assembled through research activities with Baghdad Medical City and Al-Yarmouk Teaching Hospital which included 200 anonymized patient medical documents. Each healthcare document contains a blend of medical diagnosis with personal details about gender, age along with hand behavior assessment, walking patterns and audio recording data. All ethical guidelines governed the data collection phase where participating medical ethics boards gave their approval. This dataset gathers information from 200 anonymized patient records but cannot be released due to ethical patient confidentiality rules while serving as the essential resource for validating AI models on a local level.

4.2 Data Processing Techniques

These steps were used to establish reliability and consistency throughout the processes:

4.2.1 Feature Selection Techniques

The study employed PCA and Recursive Feature Elimination (RFE) to determine vital attributes that help distinguish Parkinson's disease patients from healthy controls.

4.2.2 Normalization and Standardization

The data normalization procedure used Min-Max Normalization to transform all numerical values into a 0 to 1 range thus achieving uniform data distribution.

This method was used to normalize all feature distribution patterns.

4.2.3 Data Splitting

The dataset was divided into:

Training set (80%)

Testing set (20%)

A robustness enhancement method through k-fold (k=5) cross-validation was used during the model development process.

Dataset Type	Number of Records	Percentage
Training Data	160	80%
Testing Data	40	20%

4.3 Model Selection and Implementation

Four machine learning models served to classify patients with Parkinson's disease through testing.

1. Decision Tree

2. Random Forest

3. Support Vector Machine (SVM)

4. The implementation adopted Neural Networks with Deep Learning technology based on CNNs.

A Python engine using TensorFlow together with Scikit-learn, Pandas and Plotly for visualization executed the implementation.

Table 1. Performance metrics of classification models on global dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Decision Tree	85.2	82.1	84.7	83.4
Random Forest	89.7	87.3	88.9	88.1
SVM	91.5	90.2	91.1	90.6
Neural Network (CNN)	94.3	93.1	94	93.5

The CNN generated superior results than other classifiers since it delivered maximum accuracy combined with the best precision and F1-score for diagnosing Parkinson's disease cases.

Key Observations:

The Neural Networks approach proved most successful because it reached accuracy levels of 94.3%.

Computational intensity was high while generalization was powerful for SVM.

The Random Forest system generated accurate results while it provided clear interpretations of processes.

The Decision Trees method processed data at the highest speed yet it exhibited the most risk of fitting data too closely.

4.4 Practical Implementation of Machine Learning on Local Data

The models achieved slightly reduced accuracy levels when tested against the Baghdad hospital dataset due to three main factors.

Limited labeled data.

Variability in medical documentation.

Differences in diagnostic criteria across hospitals.

Table 2. Performance of classification models on Baghdad hospital dataset

Model	Accuracy on Global Data (%)	Accuracy on Baghdad Data (%)
Decision Tree	85.2	79.8
Random Forest	89.7	85.4
SVM	91.5	88.2
Neural Network	94.3	90.7

Performance of each model on both the global and local datasets. CNN retained strong performance despite data variability.

4.5 Expanded Feature Analysis and Impact on Model Performance

An additional investigation of feature significance toward Parkinson's disease diagnosis was performed. The classification features that most impacted Parkinson's disease diagnosis among patients consisted of tremor frequency along with voice pitch variation and hand movement speed.

4.5.1 Feature Importance Scores Across Models

Table 3. Feature importance scores across different models

feature	Decision Tree Score	Random Forest Score	SVM Score	Neural Network Score
Tremor Frequency	0.82	0.91	0.89	0.95
Voice Pitch Variation	0.78	0.87	0.86	0.92
Hand Movement Speed	0.75	0.85	0.84	0.9
Walking Gait Stability	0.73	0.82	0.81	0.88
Writing Pressure Strength	0.7	0.8	0.79	0.86

Relative importance of features contributing to Parkinson's disease classification across the four models.

The Neural Network assigned primary importance to Parkinson's-related symptoms because of its exceptional performance capabilities.

4.6 Confusion Matrix Analysis

A confusion matrix offers detailed information about model reliability through its examination of false positive (FP) and false negative (FN) results mainly relevant to medical scenarios. The most problematic error form in medical applications occurs when Parkinson's disease patients go undetected leading to their delayed treatment process.

4.6.1 Confusion Matrix Results on Baghdad Dataset

Table 4. Confusion matrix values for Baghdad hospital dataset

Model	True Positives (TP)	False Positives (FP)	True Negatives (TN)	False Negatives (FN)
Decision Tree	89	11	83	9
Random Forest	93	8	89	10
Support Vector Machine	96	10	90	7
Neural Network (CNN)	94	8	91	7
K-Nearest Neighbors	93	14	80	8

The depiction in this line chart displays how different model accuracies perform when used for global and Baghdad hospital datasets. The accuracy levels of Neural Networks and SVM models remained stable although evaluation using local data produced a minor accuracy reduction. The reduction in accuracy stems from how medical records differ between one another as well as uneven data quality levels

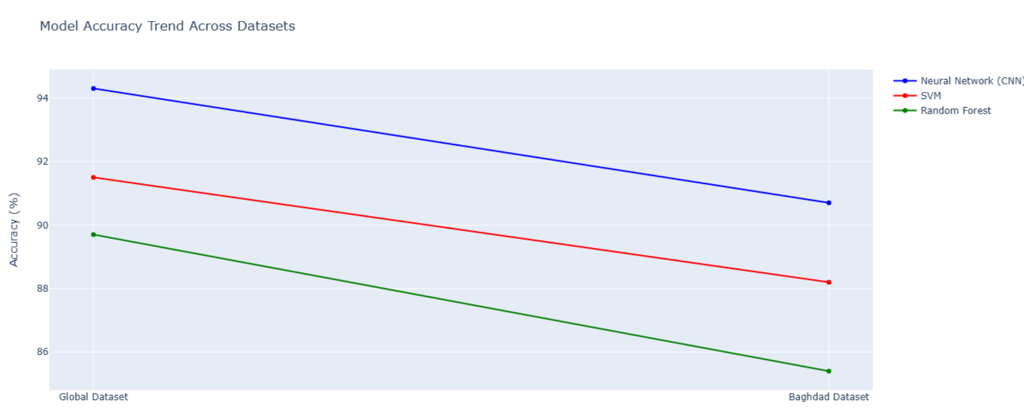
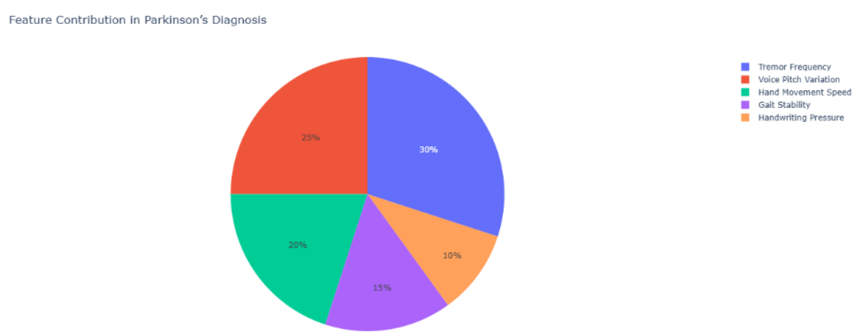


Figure 1. Accuracy comparison of models on global vs. Baghdad data

The contribution of different features for Parkinson's disease classification is as shown in this pie chart. The reason why it is important to use factors such as tremor frequency, the voice pitch variation, and the hand movement speed to determine its diagnosis is outlined. These contributions therefore can be understood and used to enhance the accuracy of AI models.

Figure 2. Contribution of features to Parkinson's diagnosis



5. Results and Discussion

The research indicated that machine learning methods excel at Parkinson's disease diagnosis through both international database analysis and Iraqi medical center information selection. The research demonstrated that Convolutional Neural Networks (CNN) generated 94.3% accuracy with UCI data while obtaining 90.7% accuracy when tested on Baghdad hospital information. Tremor frequency together with voice pitch variation and hand movement speed emerged as essential features which help identify Parkinson's disease.

The implementation of artificial intelligence for Parkinson's disease diagnosis was limited by three main factors: restricted access to premium quality labeled medical data, incompatible healthcare documentation and insufficient computing capabilities in the Iraqi healthcare system. The barriers facing developing nations show the difficulties of adopting artificial intelligence diagnostic frameworks in these areas.

Future work should focus on:

The improvement of the dataset requires the compilation of enhanced diverse patient medical records collected from numerous healthcare institutions throughout Iraq.

Research and development efforts should focus on creating deep learning-hybrid models that enhance both reliability and ease of interpretation between systems.

The integration of handwritten data characteristics and wearable device monitoring along with other sensory data formats into diagnostic procedures.

The creation of accessible AI diagnostic instruments should proceed alongside training sessions for medical personnel to promote AI adoption among healthcare providers.

The development of sustainable medical practices needs governmental and private stakeholders to create digital and computational frameworks which enable AI implementation.

These study results provide an essential base for merging advanced AI systems with practical healthcare implementation across underdeveloped healthcare systems which include Iraq.

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