International Journal of Mathematics, Statistics, and Computer Science
Vol. 2, 2024
ISSN: 2704-1077 eISSN 2704-1069, DOI: 10.59543/ijmscs.v2i.8915

A Comprehensive Review on Advancements in Artificial Intelligence Approaches and Future Perspectives for Early Diagnosis of Parkinson's Disease

Aiesha Mahmoud Ibrahim[1], Mazin Abed Mohammed[2]
[1]Department of College of Computer, College of Computer Science and Information Technology, University of Anbar, Anbar, 31001, Iraq; aie21c1019@uoanbar.edu.iq
[2]Department of Artificial Intelligence, College of Computer Science and Information Technology, University of Anbar, Anbar, 31001, Iraq; mazinalshujeary@uoanbar.edu.iq

ABSTRACT: Parkinson's disease (PD) is a neurological condition that generally strikes people in their average age of onset for PD a neurological disorder, is 55 and up. A wide variety of motor and non-motor symptoms can be observed in patients with PD. The medical community has made great strides in recent years, but Parkinson's disease still has no treatment or cure. Therefore, exploring possible ways for early PD identification is an intriguing scientific endeavor. Full symptoms may not appear for years due to the progressive nature of PD. Thus, early diagnosis is vital to enhance the patient's quality of life. Symptoms will usually worsen with time, so keep that in mind. Several neurodegenerative disorders share very similar symptoms, making early identification crucial for disease prediction. Many people are starting to pay attention to using Artificial Intelligence (AI) methods in medical diagnostics because they can process massive volumes of data and make reliable statistical predictions. This paper covers all the bases when it comes to artificial intelligence (AI) approaches to PD diagnosis, including the many deep and machine learning-based methods that have been deployed and how they have opened new avenues for research. Furthermore, the study explores the current situation and future possibilities of data-driven AI approaches to Parkinson's disease diagnosis. This study is an excellent resource as a review article for researchers interested in creating PD prediction models employing different AI-based modalities.

Keywords: Parkinson's disease, Machine Learning, Artificial Intelligence, Deep Learning, Early Detection.

1. INTRODUCTION

About ten million people throughout the world are affected by Parkinson's disease (PD) every year, making it the most prevalent neurodegenerative ailment [1]. James Parkinson, an English physician, initially characterized Parkinson's disease in 1817 [2]. The characteristic of the condition is neuronal loss in the substantia nigra portion of the brain. The generation of dopamine is a crucial activity of these neurons. This chemical messenger allows the spinal column to transmit information to other body parts, which controls movement. PD significantly impacts human quality of life. It progresses to a chronic condition with motor and non-motor symptoms over time [3]. Researchers utilize the Movement Disorder Society-Unified PD Rating Scale (MDS-UPDRS) to classify the various stages of PD, which vary from 1 to 5 [4]. In addition, the widely used Hoehn & Yahr Scale [5] can be used to assess the severity of a disorder. The time that scores change is an issue with these measurements since it makes monitoring the condition's progression difficult.

For a long time, the foundations of PD diagnosis were the patient's medical records and the doctor's evaluation of symptoms [6]. Neuroimaging techniques such as functional magnetic resonance imaging (fMRI), single photon emission computed tomography (SPECT), and transcranial magnetic resonance angiography (TMR) are utilized in contemporary diagnostic methods that depend on pathophysiological signals [7]. A recent spike in investigating the potential for early detection using mobile health technology has been spurred by researchers' hopeful findings from analyzing data obtained from wearable devices and cell phones [8]. Nearly five percent of outpatients and over 20% of critically sick patients in the US still encounter misdiagnosis, even though PD diagnosis has advanced. The continuous difficulties in precise diagnosis were highlighted by a worldwide burden study that found a 22% rise in the standard incidence of Parkinson's disease from 1990 to 2016 [9].

Recently, medical imaging—and the healthcare industry as a whole—has been dominated by artificial intelligence (AI) [10]. Decisions about the diagnosis of various diseases may now be made more precisely and quickly thanks to machine learning (ML) [11]. There have been recent efforts to use AI—specifically ML and DL algorithms—to make early diagnoses of PD [12]. Machine learning and deep learning techniques are very complex to the size of the training data set, and AI is biased since there is a lack of (i) research verification, (ii) medical assessment of these AI tactics, and (iii) proper structure of massive data [13]. Using symptoms of PD risk factors as input to an AI techniques necessitates a trustworthy, accurate, and bias-free AI network. The primary goal, then, is to find biased AI research automatically. Also, provide all the research into one of three bias categories: low, moderate, or high. It is also essential to learn which AI architectures were employed in this research and how they relate to the AI traits associated with various types of AI bias. Finally, we should find the rules of thumb for reducing the RoB in these AI investigations. Additionally, to show the focus does not include researching potential links between PD and other health issues. The key objectives and contributions of this research are:

- This study reviews the classic machine learning methods and modern technologies, especially those based on deep learning, that can improve PD diagnosis.
- Recognizing the critical role that features extraction and selection methods play in improving PD diagnosis accuracy; the study emphasizes their relevance.
- In addition, it delves into the details related to the amount and kind of datasets used in PD studies. Improving PD diagnosis with ML and DL relies heavily on comprehending these data characteristics.
- This study is an excellent resource as a review article for researchers interested in creating PD prediction models employing different AI-based modalities.

The rest organized of this study is: Section 2 and 3 present a PD diagnosis based on deep learning and machine learning. Section 4 presents challenges and issues. Section 5 presents the future research directions, and Section 6 presents the conclusion.

2. PD DIAGNOSIS BASED ON DEEP LEARNING

Over the last decade, experts in Parkinson's disease have worked tirelessly to develop ML algorithms that can reliably diagnose the early stages of the disease by analyzing a collection of precisely defined criteria. The capacity of these ML algorithms to enhance prediction accuracy when applied to unknown test data was still a significant hurdle. Researchers' interest in algorithms for deep learning (DL) has grown in recent years. Healthcare, computer vision, image identification, audio and speech recognition, and natural language processing were among the many areas that found its uses. In many cases, deep learning approaches outperform traditional ML methods when it comes to analyzing medical images for the diagnosis of PD [14].

Medical image analysis heavily uses Convolutional Neural Networks (CNNs), a popular DL model. This network can retrieve features automatically, unlike conventional ML systems that require human intervention to create features [15]. One notable difference between DL and more traditional machine learning methods is how the data is represented. Still, Structured data is where machine learning shines. The main benefit of DL is its ability to efficiently extract data from raw, unstructured, and unlabeled datasets without the need for human interaction. DL can become a crucial technique for extensive data analysis when datasets are significantly more prominent. Many academics are trying to develop better deep-learning models with more sophisticated architectures to tackle complex real-world challenges [16].

Many studies have been discussed the role and utilization of deep learning models in the PD diagnosis such as Oh et al. introduced a 13-layer Convolutional Neural Network (CNN) to categorize individuals as either Parkinson's disease (PD) patients or controls. This classification is based on analyzing resting-state Electroencephalograms (EEGs) obtained from a group of 20 PD participants and 20 controls [17]. The model attained an accuracy of 88.3%, a sensitivity of 84.7%, and a specificity of 92%. Another study by , Wagh et al. [18] introduced an 8-layer graph convolutional neural network (CNN) that was applied to 86 feature matrices derived from 10-second EEG intervals. The study included 1,385 patients with neurological illnesses, such as Parkinson's disease (PD), as well as 208 healthy people. The feature matrix measures the overall strength of the EEG's six wave. These bands are spread out over eight spatial channels. The model attained an area under the receiver operating characteristic curve (AUC of ROC) of 85% in identifying neurological disorders.

Also, another study by [19], introduced two hybrid models, namely 2D-CNN-RNN and 3D-CNN-RNN, for the purpose of categorizing people into Parkinson's disease (PD) patients and controls. This classification was done using an EEG dataset consisting of 40 PD patients and 30 healthy persons. With an accuracy rating of 82.89%, the 3D-CNN-RNN model outperformed all others. Following the suggestion of [20], a novel hybrid model was created. A Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) are combined in this model. In differentiating between control subjects and those with Parkinson's disease (PD), the model had an accuracy rate of 96.9%. Disease severity and dopaminergic activity levels are two of the clinical features of Parkinson's disease that the model was shown to take on.

Khare et al. [21] analyzed a dataset of resting-state electroencephalograms (EEGs) using several machine learning approaches, comprising the Support Vector Machine (SVM). Five distinct features were retrieved from this dataset's tunable Q-factor wavelet transform (TQWT), which included 15 PD cases and 16 controls.

Differentiating HC from PD participants, with and without medication, was the aim. Results showed a 96% success rate for PD patients not taking medication and a 97.7% success rate for PD patients using medication. Khare et al. transformed two EEG recordings into a smoothed pseudo-Wigner Ville distribution (SPWVD) using a 10-layer Convolutional Neural Network (CNN) in their study [22]. There were 35 PD patients and 36 healthy controls in these databases. Validation accuracy for the control participants was 100%, and for the PD cases, it was 99.9% using CNN. In addition, a resting-state electroencephalogram (EEG) dataset, including 16 healthy controls and 15 PD patients, was processed utilizing a (2D-CNN) on the Gabor transform by Loh et al. Separating the subjects into two groups—healthy controls (HC) and PD patients with and without medication—was the primary goal. A remarkable 99.5% accuracy in categorization was attained [23].

Additionally, a state-of-the-art deep learning framework was created by [24] using three different models of artificial neural networks, each with thirteen layers. An EEG dataset with 32 channels was used to apply these models to the Oz, P8, and FC2 channels when the subject was at rest. Fifteen patients with PD and sixteen healthy controls were part of the study. When using a majority voting strategy, the framework was able to accurately differentiate individuals with Parkinson's disease (PD) from healthy controls (HC) with a test accuracy of 98%, sensitivity of 97%, and specificity of 100%.

The new framework proposed by [25] performed a novel approach to screen de novo PD patients with 76.46% accuracy using DNN applied to 102 MRI data with two views: AXI and SAG data. To prepare the two-view data for further processing, image augmentation methods based on WGANs were used. In addition, the two-view data was processed using a pair of ResNeXt networks; a vector including the hidden layer outputs of both networks was then input into the Softmax classification layer. To detect de novo PD subjects new study by[26] suggested using spatial and density autoencoders based on Diffusion Tensor Imaging (DTI) MRI data from 129 individuals with Parkinson's disease (PD) and 57 healthy individuals. The authors used two clinical indicators, mean diffusivity and fractional variance, and postulated that the reconstruction error would exhibit a notably greater magnitude in PD sufferers compared to healthy controls. The spatial autoencoder obtained the highest Area Under the Curve (AUC) for Receiver Operating Characteristic (ROC) with a score of 83%. Furthermore, another study by [27] investigated the use of pre-tuned VGG-19 to differentiate between PD and controls based on wave and vortex handwriting datasets. The proposed model achieved high accuracy and sensitivity of more than 88% and 86%, respectively.

Using transfer learning, freezing, data augmentation, and fine-tuning together with handwriting data, an AlexNet-based deep learning technique was proposed for selecting professional development themes in research by [28]. When applied to the PaHaW dataset—which included 36 PD sufferers and 36 controls—this technique achieved an accuracy of 98.28%. In their deep learning framework, Kamran et al. [29] used pre-trained networks such as ResNet-50, AlexNet, VGG-16, VGG-19, GoogleNet, and ResNet-101 in addition to the same bottom-up models. The system could distinguish between participants with and without Parkinson's disease. Parkinson graphics, PaHaW, HandPD, and NewHandPD, were the datasets utilized in this investigation. Inversion, illumination, contrast, and thresholding enhanced the data. After running three independent handwritten datasets through AlexNet with fine-tuned parameters, they reached a maximum accuracy of 99.2%. Two deep-learning models were shown to categorize audio data from 188 PD patients and 64 control subjects [30]. A nine-layer CNN gives several attributes gathered from the audio data in the first frame. All speech feature data from the second frame was processed simultaneously using of two convolutional layers before entering a merged layer. A ten-layer CNN was then used to classify the combined data. There were four convolutional layers in the CNN: an output layer, a max pooling layer, a fully connected layer, and two convolutional layers that followed each other. The first frame had an accuracy of 84.5%, and the second frame had an accuracy of 86.8%. The literature review of DL algorithms is summarized in Table 1.

Table 1. The summary review on PD diagnosis based on DL.

Ref	**Main Objective**	**Dataset**	**Algorithms**	**Result (Accuracy)**	**limitation**
[17]	Detection of PD	EEG data from 29 patients with PD and 30 healthy controls.	A CNN with 13 Layers	88.25%	limited dataset, limited performance
[18]	Neurological disease detection, including Parkinson's disease	EEG (208 Healthy and 1385 Diseased Subjects)	A CNN with 8 Layers	AUC: 90%	Not only for Parkinson's disease identification, this dataset was recorded in various settings and with various methods.

[19]	Detection of PD	EEG data was collected from a total of 40 people diagnosed with PD and 30 individuals who were deemed healthy controls	Dimensional Two- and Three-CNN-RNN	81%, 83%	Low performance due to model complexity
[20]	Detection of PD	EEG data was collected from a total of 20 people diagnosed with PD and 22 individuals who were deemed healthy controls.	CNN–LSTM	97%	Limited performance due to model complexity
[21]	Detection of PD	EEG data from 35 patients with PD and 36 healthy controls.	Q-factor tunable LSSVM	97.7%,	Limited performance due to model complexity
[22]	Detection of PD	EEG data from 35 patients with PD and 36 healthy controls.	CNN 2D and SPWVD	99.5%	Limited performance due to model complexity
[23]	Detection of PD	EEG data from 15 patients with PD and 16 healthy controls.	Eight-Layer CNN Based on Gabor Transform	99.5%	Limited performance due to model complexity
[24]	Detection of PD	EEG data from 15 patients with PD and 16 healthy controls.	Wavelet-Based 13-Layer ANN CNN with 12 Layers	98%, 99.9%, 99.9%	Limited performance due to model complexity
[25]	Detection of PD Prodromal	102 MRI AXI/SAG	WGAN with ResNeXt	76.5%	Low performance and a complicated method
[26]	PD Detection by De Novo	DTI MRI (57 controls and 129 PD)	Using Convolutional Autoencoding	AUC: 83%	Low performance and a complicated method
[27]	Detection of PD	102 samples of handwriting, including 55 samples from individuals with PD and 55 samples from healthy individuals.	VGG-19	88%	limited dataset
[28]	Detection of PD	Data on handwriting, including 36 samples with PD and 36 samples Controls.	AlexNet	98.3%	limited dataset and intricate training procedure
[29]	Detection of PD	The data on handwriting is as follows: HandPD (74 PD, 18 Controls), PaHaw (37 PD, 38	ResNet-101, VGG-16, AlexNet, VGG-19,	AlexNet Maximum Accuracy: 99.2%	Model training complexity

		Controls), and NewHandPD (31 PD, 35 Controls)	ResNet-50, GoogleNet.		
[30]	Detection of PD	Speech data from 188 patients with PD and 64 healthy controls.	CNN with 9 layers, 2 convolution layers, 1 merge layer, and 10 layers	84.5%, 86.8%	Low performance and a complicated method

3. PD DIAGNOSIS BASED ON USING MACHINE LEARNING ALGORITHMS

To aid clinicians in making a more accurate preliminary diagnosis of PD and in recognizing the illness at an early stage, ML has demonstrated promising outcomes in detecting and categorizing Parkinson's disease. This might decrease the mistake rate associated with disease diagnoses and the early detection of Parkinson's disease. Vanegas et al. presented three ML models for identifying EEG biomarkers linked with PD, and many publications have examined the importance and usage of ML models in PD diagnosis. The area under the curve (AUC) on the receiver operating characteristic (ROC) curve was 99.4 percent for the first model, the additive tree classifier. To do this, they compared the visual stimulation EEG spectral amplitudes in 29 PD patients and 30 healthy controls. The goal was to identify any differences. Decision tree models generated an ROC score of 86.2% and logistic regression score of 94.9%. The decision nodes in the decision tree and the logistic regression weights worked together to find the frequency bins that were most useful for telling the difference between PD cases and controls [31]. In a separate study he conducted, Koch et al. [32] categorized patients with PD as having excellent or impaired cognition using a random forest model. Using sets of medical and mechanical features obtained from EEG data, the model was trained and evaluated on 20 subjects with normal cognition and 20 with cognitive impairment.

Another study by Prasohn et al.[33] suggested in another study that PD could be detected using DTI MRI and binary SVM and multi-kernel learning (MKL) architectures. Preprocessing a DTI MRI dataset comprising 57 controls and 162 subjects with PD was integral to the methodology, which aimed to ascertain clinical diffusion metrics and compute supplementary distribution metrics. MKL was applied to various series of diffusion metrics and each of the five detected diffusion measures was subjected to bSVM. According to the results, the area under the curve (AUC) for ROC did not go over 60%, and the researchers concluded that DTI-based evaluations are often not suitable for correct PD patient classification. Furthermore, another study [34] used a blend of machine learning methods—including logistic regression, random forest, SVM, light generalized based on statistics (GBS), and a stacked ensemble model—to differentiate wearable sensor-based motor disparities between PD and other neurological disorders. The models were supplied with two distinct sets of features: tremor features only and tremor and bradykinesia feature combined. Utilizing both feature sets resulted in the highest level of accuracy (85%). On the other hand, accuracy fell to 80% when machine learning models were fed only jitter characteristics. In addition, another study [35] showed that the backpropagation with variable adaptive momentum (BPVAM) method might be used for de novo PD identification utilizing audio data from 23 PD cases and eight controls. The audio data was subjected to principal component analysis (PCA) before classification to extract the best features. Achieving 97.5% accuracy was made possible by utilizing the 15 most distinguishing characteristics. However, speech categorization took around seven seconds longer when using PCA and BPVAM on a CPU workstation. Another study [36] suggested using Light Gradient Boosting and Extreme GB to identify PD from 256 auditory features in 40 PD patients and 40 healthy controls. Furthermore, feature analysis techniques were utilized to determine the seven most pertinent features. The approximate accuracy of classification, as determined by the seven most pertinent features, was 82%.

In a different study, the time-frequency characteristics of audio data were used to test a machine learning framework that included a stacked autoencoder and the KNN algorithm. In PD detection, the method demonstrated an accuracy reaching from 94% to 98% using the Oxford and Istanbul datasets [37]. An alternative research conducted by [38] utilized neural network classification, decision tree, and Naïve Bayes techniques to diagnose Parkinson's disease. By autonomously implementing three classification approaches on a PD dataset containing features to identify the human voice disorder, he was able to resolve the issue. Determine which of the three methods is the most effective. The classification outcomes demonstrated that the neural network achieved the lowest accuracy rate of 89.46%, while the decision tree achieved the highest accuracy rate of 91.63%. The results indicate using a decision tree or a neural network with Naive Bayes support for datasets with similar properties. Machine learning techniques based on voice noise assessment and multiple features assessment (MFEA) for a multi-agent system were assessed and categorized by the authors of [39] to improve the precision of Parkinson's disease diagnosis. Pre- and post-voice disturbance analysis Parkinson's disease diagnoses were made using five separate classification schemes: decision tree, naive Bayes, neural network, random forest, and support vector machine. The testing approach uses ten-fold cross-validation to assess the algorithms' learning capacities and track performance variations. To increase the classifiers' performance, MFEA finds the optimal feature set for the multi-agent system. Human gait signals are used to categorize individuals with Parkinson's disease using feature extraction using local binary pattern algorithms in another work by [40]. Local Gradient Pattern (LGP), Local Neighbor Description Pattern, and Local Gradient Pattern (LNGP) were added to the Local Binary Pattern (LBP) for feature extraction from gait data. Following data retrieval and statistical analysis, the Kruskal-Walli’s test was used to identify the most relevant set of attributes; a further step comprised using an ANN for classification. The proposed SWLNGP approach achieves a higher accuracy rate of 96.28% compared to the competitors. This study provides strong evidence that SWLNGP might be an effective method for identifying Parkinson's gait characteristics. Lightweight deep learning (PLDL) methods with dual training were used in the study by [41] to accurately detect patterns in the healthy/PD group's hand drawings. Deep selection of features with a 50% failure rate and binary identification are the last steps in the system's lengthy procedure, including picture pre-processing and data augmentation for improved detection accuracy during dual training. The results of this study show that waveforms might be a valuable tool for PD detection, especially if it is feasible to improve identification accuracy by using the LDLS method and considering both individual and aggregate MobileNet features. An accurate detection rate of 100% was achieved by utilizing the KNN classifier and its intrinsic properties. A study by [42] examined several methods for classifying symptoms of vocal problems as indicators of PD. Data collection, extraction, and selection are all parts of the process. They compared eleven classification methods, looking at how well they did on measures like F1 scores, ROC, MAE, and recall. The research used a MAFT (machine learning methodology) and evaluated the performance of 11 distinct classifier techniques. The findings showed that the HM obtained the greatest level of diagnostic accuracy, reaching an impressive rate of 96.6%. The dataset that underwent filtering showed notable improvements, with the HM and NB algorithms obtaining the most substantial increase in accuracy, amounting to a 3% improvement. The study offers valuable ideas for future research and presents a comprehensive overview of the current state of knowledge. Nevertheless, the constraints include the exclusion of runtime periods and computing effort from the evaluation. Subsequent investigations will prioritize the examination of various medical scenarios and benchmark datasets to authenticate the efficacy of the strategy. The literature review of ML algorithms is summarized in Table 2.

Table 2. The literature review that has used ML.

Ref	Main Objective	Dataset	Algorithms	Result	limitation
[31]	Finding Parkinson's Disease Biomarkers	30 healthy controls and 29 PD patients' electroencephalograms	Decision Tree , Extra Tree and Logistic Regression	94.9% 86.2% 99.4%	For the best outcomes, people should be visually stimulated.
[32]	Detection of PD Cognitive scale	Twenty healthy controls and twenty brain-damaged subjects had their electroencephalograms recorded.	Random Forest	91%	Limited dataset, need for manual feature extraction
[33]	Detection of PD	included 162 individuals with PD and 70 control subjects who underwent DTI MRI scans	bSVM MKL	58% 60%	Low performance
[34]	PD in Comparison to Neurological Conditions	Data collected from 56 patients' senses	Random Forest, Stacked Ensemble Model, Light GBM, and SVM	Best Possible Result: 85%	Limited performance, limited dataset
[35]	Detection of PD	A total of 23 PD patients and 8 healthy controls' voice recordings	BPVAM	97.5%	limited dataset, classification delay

[36]	Detection of PD	Information on the speech of forty people with Parkinson's disease and forty healthy controls	GB, Extreme GB	82%	small dataset, Limited performance
[37]	Detection of PD	Speech Data (Istanbul:20 patients with PD and 20healthy controls)and (Oxford:23 patients with PD and 8healthy controls)	KNN, stacked autoencoder	98% 94%	limited dataset
[40]	Evaluation of classification methods PD	human voice recording for 31 people, 23 diagnosed with PD.	Decision Tree Naïve Bayes Neural Network	91.63% 89.46% 91.01%	Feature selection is not used. limited dataset
[41]	improving the diagnosis of PD	human voice recording for	SVM, Naïve Bayes, Random Forest, Neural Network, and Decision Tree	86.440% 74.111% 87.755% 86.734% 86.294%	small sample size used
[42]	Recognition of PD Based on Gait Signals	Gaitpdb Walking signals for 166 people	SWLNGP SWLBP LNGP LBP LNDP SWLNDP LGP	95.08% 95.50% 94.43% 93.83% 92.38% 93.50% 94.42% 94.64	Small dataset
[43]	Improve PD detection accuracy	Hand-Sketchs for 51 healthy and 51 PD	MobileNet-KNN	100%	small dataset
[44]	diagnosis of PD	vocal symptoms	CN2, , KNN, RF, DT, LR, AdaBoost, SGD, SVM, NN, NB	78.5%, 85.6%, 87.2%, 85.1%, 86.2%, 86.2%, 86.7%, 88.2%, 91.3%, 81.5%	not evaluating runtime periods and computational effort.

4. DISCUSSION

Many of the studies described in the presented literature cover a variety of ML methodologies and data types aiming to PD based on different datasets, including EEG, MRI, handwriting, and speech data. These studies showcase the potential of advanced computational techniques to aid Parkinson's disease diagnosis and monitoring. Studies conducted by[17], [18], [19], [20], [21], [22], [23], [24], used convolutional neural networks (CNNs) and recurrent neural networks. (RNNs), hybrid CNN-RNN models, and other deep learning architectures on EEG data. These models showed high accuracy, sensitivity, and specificity, ranging from 76.46% to 99.9%, in distinguishing PD patients from controls. The use of various EEG features and advanced neural network architectures demonstrates the effectiveness of deep learning in identifying PD-related patterns in brain signals. Research in [25]and [26] focused on MRI data for PD detection. The use of deep neural networks and autoencoder models on MRI data achieved accuracy ranging from 76.46% to 83%. These approaches explored different MRI views, preprocessing techniques, and neural network architectures, suggesting that MRI data can be utilized for PD screening despite moderate accuracy. While [27] [28] and [30] used Handwriting and speech using transfer learning, pre-trained models, and CNN architecture. These studies achieved high accuracy ranging from 84.5% to 99.2%, showcasing the effectiveness of deep learning in distinguishing professional development from controls based on these distinct data modalities.

The studies highlight the potential of machine learning models to identify subtle patterns or biomarkers in various data modalities, including EEG, vocal data, DTI MRI, and wearable sensor data. These biomarkers can aid in distinguishing PD from healthy controls or other neurological disorders. The identification of influential frequency bins in EEG by [31]. and using wearable sensors-related features by[34]. demonstrates the importance of specific data characteristics in discriminating PD from other conditions. While certain models demonstrated high accuracy rates in classifying PD, such as [31] extra tree classifier achieving 99.4% AUC, others faced challenges. [33] DTI-based analysis, for instance, did not yield satisfactory results, raising questions about the applicability of diffusion metrics in PD diagnosis. The computational burden observed in some studies, leading to increased processing times, such as in [35] work, indicates a need for more efficient algorithms or hardware for real-time clinical implementation. Several studies integrated multiple data sources to enhance diagnostic accuracy. For instance, [32]. utilized clinical and automated EEG features, while [37]. employed time–frequency features of vocal data. These integrations underscore the potential benefits of combining diverse data modalities in improving classification performance. Feature selection techniques used in various studies, such as identifying influential frequency bins or relevant vocal features, are crucial for reducing noise and extracting the most informative characteristics for classification purposes.

5. CHALLENGES AND ISSUES

The major goal of this evaluation is to investigate and forecast potential future research directions in PD diagnosis approaches based on AI. Additionally, this review covers all the bases regarding deep learning and standard machine learning methods for PD prediction. We have examined the capabilities of ML and DL methods to process neuroimaging, physiological data, and other diagnostic modalities for Parkinson's disease. Most studies looked at parameters including sensitivity, specificity, and accuracy to validate the performance of the created PD classification algorithms. We also found that physiological markers were the most often employed PD diagnostic modality in this investigation. On the other hand, more studies need to rely on EEG and EMG. Consequently, research into image-based diagnosis is necessary to assist physicians in making better decisions. Similarly, cell phones will be crucial going forward, especially as researchers look at mobile health technologies to track patients' routines at home, which is a promising development. Furthermore, several research studies have advocated for using deep learning techniques in PD diagnosis, with the goal of training prediction models to perform better and reduce computation time. Modern technology has made it possible for anybody, including those without medical training, to make precise illness predictions using deep learning-based algorithms without human interaction.

On the other hand, for the benefit of doctors, this extensive study highlights the results of PD diagnosis. The healthcare industry has more difficulties than other research domains when gathering real-life patient data. When it comes to neurodegenerative diseases, medical statistics are typically skewed.

- Since an unbalanced dataset distorts the results, dealing with it in the current context is challenging, and it takes a lot of work.
- In addition, as deep learning and nature-based methods continue to advance, to improve the accuracy of PD predictions, there is unrealized potential to use multimodal datasets.
- Choose the accurate metrics to measure ML methods efficacy in PD classification is critical, and there's opportunity for development in investigating the various measures.
- Physiological signals have certain limits, such as the fact that EEG signals are contaminated with artifacts and have limited spatial resolution. One example is voice signals, where environmental factors and motion abnormalities can degrade speech quality and lead to a false diagnosis of PD.

6. THE FUTURE DIRECTIONS

Several areas of healthcare, research, and technology will have a role in developing the future of artificial intelligence (AI) for Parkinson's disease classification. Several exciting possibilities for the further development of AI for the PD diagnosis are as follows:

- The accuracy of PD classification models might be improved by future research investigating the integration of different data modalities. These modalities could include clinical, genetic, and imaging data (MRI, PET scans). A deeper understanding of the medical condition can be revealed using multi-modal techniques.

- Analyzing Longitudinal Data: Studies that follow patients over an extended period can aid in understanding how a disease develops. Artificial intelligence models that examine longitudinal data could help forecast the course of PD, which might lead to more targeted interventions and treatments.
- The medical field places a premium on better AI model interpretability, which is why explainable AI (XAI) is essential. The future of AI-assisted diagnostics may lie in creating explainable models that doctors may use better to comprehend the reasoning behind the models' predictions.
- For more varied and robust PD classification models, researchers could investigate federated learning, which allows collaborative model training across numerous institutions without sharing raw data, and transfer learning, which will enable models trained on one dataset to be adapted to another.

7. CONCLUSION

This study summarizes the results of numerous studies examining deep learning and machine learning in PD diagnosing. The accuracy of speech signal-based Parkinson's disease diagnostic models has been the subject of much research utilizing ML methods. It may be necessary to explore alternative methods, such as speech signals, to diagnose PD, though. The results of this study show an opportunity for improvement in several deep learning and machine learning algorithms and that further research is needed to improve accuracy and speed up decision-making. When professional doctors and deep learning-based algorithms work together, early PD detection rates rise. The area of healthcare is currently benefiting from these deep learning models. Enriching them to improve the accuracy of PD diagnosis using deep learning models is recommended. Lastly, other criteria beyond sensitivity and specificity might be implemented to enhance the tools used by specialists in PD diagnosis. It is quite probable that these suggestions will address the obstacles to improving the precision of Parkinson's disease identification.

REFERENCES

[1] Z. Ou et al., “Global Trends in the Incidence, Prevalence, and Years Lived with Disability of Parkinson’s Disease in 204 Countries/Territories From 1990 to 2019,” Front. Public Heal., vol. 9, no. December 2021, doi: 10.3389/fpubh.2021.776847.

[2] J. S. Perlmutter, “Assessment of parkinson disease manifestations,” Curr. Protoc. Neurosci., no. SUPPL.49, pp. 1–16, 2009, doi: 10.1002/0471142301.ns1001s49.

[3] C. Raza, R. Anjum, and N. ul A. Shakeel, “Parkinson’s disease: Mechanisms, translational models and management strategies,” Life Sci., vol. 226, pp. 77–90, 2019, doi: 10.1016/j.lfs.2019.03.057.

[4] Y. Guo, C. G. Goetz, G. T. Stebbins, T. A. Mestre, and S. Luo, “Using Movement Disorder Society Unified Parkinson’s Disease Rating Scale Parts 2 and 3 Simultaneously: Combining the Patient Voice with Clinician Ratings,” vol. 38, no. 3, pp. 453–463, 2023, doi: 10.1002/mds.29308.Using.

[5] S. Sciencedirect, D. R. Scale, and D. Data, “Parkinsonism and Related Disorders Statistical analysis and mapping of the unified Parkinson’ s Disease rating scale to Hoehn and Yahr staging,” vol. 18, pp. 697–699, 2012, doi: 10.1016/j.parkreldis.2012.01.011.

[6] B. R. Bloem, M. S. Okun, and C. Klein, “Parkinson’s disease,” Lancet, vol. 397, no. 10291, pp. 2284–2303, 2021, doi: 10.1016/S0140-6736(21)00218-X.

[7] M. Shaban, “Deep Learning for Parkinson’s Disease Diagnosis: A Short Survey,” Computers, vol. 12, no. 3, 2023, doi: 10.3390/computers12030058.

[8] J. Lee, I. Yeom, M. L. Chung, Y. Kim, S. Yoo, and E. Kim, “Use of Mobile Apps for Self-care in People with Parkinson Disease: Systematic Review.,” JMIR mHealth uHealth, vol. 10, no. 1, p. e33944, Jan. 2022, doi: 10.2196/33944.

[9] J. A. Logemann, H. B. Fisher, B. Boshes, and E. R. Blonsky, “Frequency and cooccurrence of vocal tract dysfunctions in the speech of a large sample of Parkinson patients,” pp. 47–57, 2016.

[10] M. K. Al-thiabi, “The Prediction of COVID - 19 Virus Mutation Using Long Short - Term Memory,” 2022 8th Int. Conf. Contemp. Inf. Technol. Math., pp. 113–118, 2022, doi: 10.1109/ICCITM56309.2022.10032012.

[11] J. G. Richens, C. M. Lee, and S. Johri, “Improving the accuracy of medical diagnosis with causal machine learning,” Nat. Commun., no. 2020, pp. 1–9, doi: 10.1038/s41467-020-17419-7.

[12] S. Paul et al., “Bias Investigation in Artificial Intelligence Systems for Early Detection of Parkinson’s Disease: A Narrative Review.,” Diagnostics (Basel, Switzerland), vol. 12, no. 1, Jan. 2022, doi: 10.3390/diagnostics12010166.

[13] M. A. Gianfrancesco, S. Tamang, J. Yazdany, and G. Schmajuk, “Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data.,” JAMA Intern. Med., vol. 178, no. 11, pp. 1544–1547, Nov. 2018, doi: 10.1001/jamainternmed.2018.3763.

[14] J. G. Lee et al., “Deep learning in medical imaging: General overview,” Korean J. Radiol., vol. 18, no. 4, pp. 570–584, 2017, doi: 10.3348/kjr.2017.18.4.570.

[15] L. Alzubaidi et al., “Review of deep learning: concepts, CNN architectures, challenges, applications, future directions,” J. Big Data, vol. 8, no. 1, p. 53, 2021, doi: 10.1186/s40537-021-00444-8.

[16] M. M. Taye, “Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions,” Computers, vol. 12, no. 5, 2023, doi: 10.3390/computers12050091.

[17] S. L. Oh et al., “A deep learning approach for Parkinson’s disease diagnosis from EEG signals,” Neural Comput. Appl., vol. 32, no. 15, pp. 10927–10933, 2020, doi: 10.1007/s00521-018-3689-5.

[18] N. Wagh and Y. Varatharajah, “EEG-GCNN: Augmenting Electroencephalogram-based Neurological Disease Diagnosis using a Domain-guided Graph Convolutional Neural Network,” Proc. Mach. Learn. Res., vol. 136, pp. 367–378, 2020.

[19] X. Shi, T. Wang, L. Wang, H. Liu, and N. Yan, “Hybrid Convolutional Recurrent Neural Networks Outperform CNN and RNN in Task-state EEG Detection for Parkinson’s Disease,” 2019 Asia-Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. APSIPA

ASC 2019, no. November, pp. 939–944, 2019.
[20] S. Lee, R. Hussein, and M. J. McKeown, “A deep convolutional-recurrent neural network architecture for Parkinson’s disease EEG classification,” Glob. 2019 - 7th IEEE Glob. Conf. Signal Inf. Process. Proc., pp. 14–17, 2019, doi: 10.1109/GlobalSIP45357.2019.8969309.
[21] S. K. Khare, V. Bajaj, and U. R. Acharya, “Detection of Parkinson’s disease using automated tunable Q wavelet transform technique with EEG signals,” Biocybern. Biomed. Eng., vol. 41, no. 2, pp. 679–689, 2021, doi: 10.1016/j.bbe.2021.04.008.
[22] S. K. Khare, V. Bajaj, and U. R. Acharya, “PDCNNet: An Automatic Framework for the Detection of Parkinson’s Disease Using EEG Signals,” IEEE Sens. J., vol. 21, no. 15, pp. 17017–17024, 2021, doi: 10.1109/JSEN.2021.3080135.
[23] H. W. Loh et al., “Gaborpdnet: Gabor transformation and deep neural network for parkinson’s disease detection using eeg signals,” Electron., vol. 10, no. 14, 2021, doi: 10.3390/electronics10141740.
[24] M. Shaban, “Automated screening of Parkinson’s disease using deep learning-based electroencephalography,” Int. IEEE/EMBS Conf. Neural Eng. NER, vol. 2021-May, pp. 158–161, 2021, doi: 10.1109/NER49283.2021.9441065.
[25] I. Yoo, J. Bi, X. Hu, National Science Foundation (U.S.), and Institute of Electrical and Electronics Engineers, “Deep Neural Networks with Broad Views for Parkinson’s Disease Screening,” pp. 1018–1022, 2020.
[26] V. M. Ramirez, V. Kmetzsch, F. Forbes, and M. Dojat, “Deep Learning Models to Study the Early Stages of Parkinson’s Disease,” Proc. - Int. Symp. Biomed. Imaging, vol. 2020-April, pp. 1534–1537, 2020, doi: 10.1109/ISBI45749.2020.9098529.
[27] M. Shaban, “Deep Convolutional Neural Network for Parkinson’s Disease Based Handwriting Screening,” ISBI Work. 2020 - Int. Symp. Biomed. Imaging Work. Proc., pp. 10–13, 2020, doi: 10.1109/ISBIWorkshops50223.2020.9153407.
[28] A. Naseer, M. Rani, S. Naz, M. I. Razzak, M. Imran, and G. Xu, “Refining Parkinson’s neurological disorder identification through deep transfer learning,” Neural Comput. Appl., vol. 32, no. 3, pp. 839–854, 2020, doi: 10.1007/s00521-019-04069-0.
[29] I. Kamran, S. Naz, I. Razzak, and M. Imran, “Handwriting dynamics assessment using deep neural network for early identification of Parkinson’s disease,” Futur. Gener. Comput. Syst., vol. 117, pp. 234–244, 2021, doi: 10.1016/j.future.2020.11.020.
[30] H. Gunduz, “Deep Learning-Based Parkinson’s Disease Classification Using Vocal Feature Sets,” IEEE Access, vol. 7, pp. 115540–115551, 2019, doi: 10.1109/ACCESS.2019.2936564.
[31] F. Expression, “Machine learning for EEG-based biomarkers in Parkinson’s disease,” 2018 IEEE Int. Conf. Bioinforma. Biomed., vol. 2, no. 3, pp. 69–73, 2002.
[32] M. Koch, V. Geraedts, H. Wang, M. Tannemaat, and T. Back, “Automated Machine Learning for EEG-Based Classification of Parkinson’s Disease Patients,” Proc. - 2019 IEEE Int. Conf. Big Data, Big Data 2019, pp. 4845–4852, 2019, doi: 10.1109/BigData47090.2019.9006599.
[33] J. Prasuhn, M. Heldmann, T. F. Münte, and N. Brüggemann, “A machine learning-based classification approach on Parkinson’s disease diffusion tensor imaging datasets,” 2020.
[34] A. Talitckii et al., “Avoiding Misdiagnosis of Parkinson’s Disease with the Use of Wearable Sensors and Artificial Intelligence,” IEEE Sens. J., vol. 21, no. 3, pp. 3738–3747, 2021, doi: 10.1109/JSEN.2020.3027564.
[35] J. Rasheed, A. A. Hameed, N. Ajlouni, A. Jamil, A. Ozyavas, and Z. Orman, “Application of Adaptive Back-Propagation Neural Networks for Parkinson’s Disease Prediction,” 2020 Int. Conf. Data Anal. Bus. Ind. W. Towar. a Sustain. Econ. ICDABI 2020, 2020, doi: 10.1109/ICDABI51230.2020.9325709.
[36] I. Karabayir, S. M. Goldman, S. Pappu, and O. Akbilgic, “Gradient boosting for Parkinson’s disease diagnosis from voice recordings,” BMC Med. Inform. Decis. Mak., vol. 20, no. 1, pp. 1–7, 2020, doi: 10.1186/s12911-020-01250-7.
[37] Y. N. Zhang, “Can a Smartphone Diagnose Parkinson Disease? A Deep Neural Network Method and Telediagnosis System Implementation,” Parkinsons. Dis., vol. 2017, no. 1, 2017, doi: 10.1155/2017/6209703.
[38] S. A. Mostafa, A. Mustapha, and S. H. Khaleefah, “Evaluating the Performance of Three Classification Methods in Diagnosis of Parkinson’ s Disease Evaluating the Performance of Three Classi fi cation Methods in Diagnosis of Parkinson’ s Disease,” no. February 2018, doi: 10.1007/978-3-319-72550-5.
[39] S. A. Mostafa et al., “ScienceDirect Examining multiple feature evaluation and classification methods for improving the diagnosis of Parkinson’ s disease,” Cogn. Syst. Res., vol. 54, pp. 90–99, 2019, doi: 10.1016/j.cogsys.2018.12.004.
[40] S. J. Priya, A. J. Rani, M. S. P. Subathra, and M. A. Mohammed, “Local Pattern Transformation Based Feature Extraction for Recognition of Parkinson’ s Disease Based on Gait Signals,” 2021.
[41] V. Rajinikanth, S. Yassine, S. Ahmad, and C. Bukhari, “Hand-Sketchs based Parkinson’ s disease Screening using Lightweight Deep-Learning with Two-Fold Training and Fused Optimal Features,” vol. 2, no. Ml, 2024, doi: 10.59543/ijmscs.v2i.7821.
[42] M. A. Mohammed, M. Elhoseny, K. H. Abdulkareem, S. A. Mostafa, and M. S. Maashi, “A Multi-agent Feature Selection and Hybrid Classification Model for Parkinson’ s Disease Diagnosis,” vol. 17, no. 2, 2021.