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REVIEW ARTICLE

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A Comprehensive Review of Deep Learning Techniques for Identifying Parkinson's Disease from Gait Analysis

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Abstract: A group of neurological disorders that manifests in a wide range of motor and cognitive symptoms, Parkinson's Disease (PD) ranks second among those affecting older adults. Many people mistakenly believe that PD symptoms are caused by other conditions, such as essential tremor or natural aging. There may not be a cure for PD, but there are numerous medications that can help with symptoms. Since gait impairment is a prominent and early sign of PD in a clinical context, doctors typically use visual observations to analyse gait abnormalities as one of many manifestations to determine the severity of PD. Nevertheless, therapists' reliance on their own knowledge and judgment makes gait examination a difficult and subjective process. Extracting useful gait features from various input signals for gait analysis has recently been used Deep Learning (DL) models. Intermediate Medical Unit (IMU) patients with movement problems may benefit from a quick and clinically relevant evaluation of gait abnormalities performed automatically utilizing DL algorithms. Using gait analysis, this study provides a comprehensive overview of various DL frameworks that have been created for the purpose of PD prediction and categorization. At the outset, In the first part of the study, various PD prediction and classification systems that have been developed by various researchers and that rely on DL algorithms via gait analysis are reviewed briefly. To find a better way to identify and categorize the PD, we next undertake a comparative analysis to learn about the shortcomings of those algorithms.

Keywords: Parkinson's disease; deep learning; gait evaluation; gait impairments; intermediate medical unit.

I. INTRODAUCTION

The neurodegenerative PD is characterized by progressive motor impairments [1, 2]. The prevalence of PD ranges from 2% to 3% in the elderly population, placing it second only to Alzheimer's disease among neurodegenerative diseases [3]. Reduced brain dopamine levels due to death of dopaminergic neurons in the substantia nigra are a hallmark of PD, as shown in Fig. 1. Slowness and gait abnormalities are symptoms of a diminished capacity to control one's movements [4]. A α-synuclein protein serves as a biomarker for PD. An essential part of Lewy bodies, Oligomer is generated when the α-synuclein protein's activity is disturbed, leading to the death of brain cells [5]. The exact relationship between neuron loss and PD remains unclear, despite much research into the underlying mechanism.

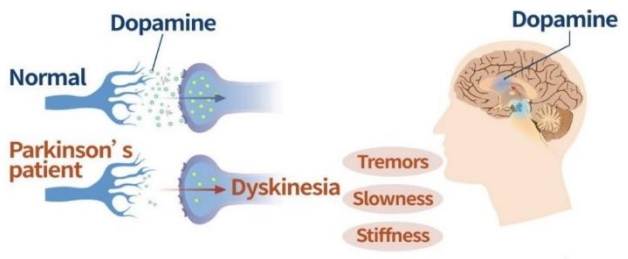

Figure 1. Brain Function between Normal and PD Affected Persons.

So far, PD is thought to be a degenerative disorder associated with aging that can be triggered by both hereditary and environmental variables. The average age is 60 years old, making aging a major factor. Protein metabolisms and mitochondrial capabilities may decline with age, which may cause dopaminergic neurons in the substantia nigra to die off [6].

The percentage of PD patients with a family history is around 15%, and between 5% and 10% have a Mendelian-inherited monogenic variant. Extensive research has identified genetic risk factors and PD variations. Researchers have looked at environmental factors and found that things like coffee consumption and smoking are associated with a higher incidence of PD [7]. Nevertheless, because of the compounding factors' long-term effects, the environmental factors' impact on PD remains unclear. According to Klingelhoefer and Reichmann's [8] theory, PD begins in the olfactory bulb or enteric nervous system, travels via the rostrocranial nerve to the substantia nigra, and then continues to transmit into the central nervous system.

Due to the lack of suitable biomarkers, early symptoms and clinical tests are crucial diagnostic signs for PD [9]. In the early stages of Parkinson's disease, several symptoms can manifest. These include cognitive problems like sadness or worry, movement concerns like slow movement or tremor, stiffness or altered posture and gait, and non-movement symptoms like sleep difficulty or visual degeneration. The use of Magnetic Resonance Imaging (MRI) or clinical scales during physical examinations is standard practice [10].

A person's gait, which includes the cortical regions that are responsible for motor and cognitive functions, can affect their patterns of walking and running [11]. The most prominent symptoms of PD, as mentioned before, are abnormalities and impairments in gait. With the development of more precise quantitative tools, gait analysis has become an important tool in the fight against musculoskeletal and neurological disorders that induce abnormalities in walking and gait [12]. Impairments in gait and other movement-related abnormalities can be caused by three main sources [13]

- **Tremor:** As a general rule, tremors begin in the limbs or hands and tend to happen more frequently when at rest.
- **Slowness of movement:** Patient gait is slower and step length is shorter compared to healthy individuals, which might cause a slowness of movement.
- **Muscular stiffness:** Stiffness in the muscles: When people have tension in their muscles, it makes their posture more rigid, which in turn makes it harder for them to walk steadily.

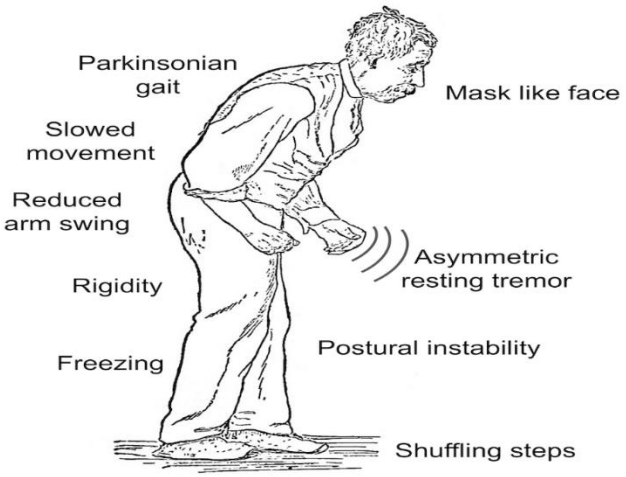

Figure 2. Gait and Postural Symptoms of PD Patients.

And abnormal gait patterns are a marker of non-movement disorders such depression, anxiety, and cognitive impairment [14]. As shown in Fig. 2, the gait patterns of individuals with PD will display a range of impairments and abnormalities due to the impact on both motor and cognitive brain functions. There are three tiers to the description of the gait changes: early, mild-to-moderate, and advanced. Some examples of gait metrics are bradykinesia, postural stability, timing control, and gait planning [14]. Several noticeable alterations in gait characteristics can be utilized to diagnose PD, as shown in Table I.

- **Early Stage:** In the early stages of Parkinson's disease, the patient first exhibits a slow gait speed and short step length. These gait problems are caused by aging or other medical conditions. Reduced arm swing, greater interlimb asymmetry, and smoothness of movement are PD-specific symptoms. During the stance phase, the Range of Motion (ROM) of the lower limb joints decreases, and these deficits are frequently unilateral or bilateral. Dual tasking makes impaired walking patterns more noticeable in PD patients.
- **Mild-To-Moderate Stage:** An increased risk of falling owing to instability in posture and gait planning characterizes the mild-to-moderate stage of Parkinson's disease, which is characterized by severe gait abnormalities in individuals. Common alterations in gait include a less swinging arm, more cadence, shuffling steps, and more dual support. In addition to disintegrating into pieces, some patients may walk with a hunched over position.
- **Advanced Stage:** Freezing of Gait (FOG) is a noticeable and episodic symptom that worsens gait patterns in patients with advanced Parkinson's disease. A number of circumstances, such as those involving movement, perception, thought, and feeling, might set off FOG. We currently lack accurate biomarkers and objective metrics to assess FOG. There is an increase in the likelihood of falling due to impaired balancing, gait planning, and postural stability. Motor function loss from deteriorating muscle control can necessitate the use of wheelchairs or other assistive devices for some patients.

Table I. Physical Disability and Gait Issues

Gait parameters	Indications	Changes with PD
Turning	Postural stability and Gait planning	Fragmentation
Variability and imbalance in gait	Gait planning and postural stability	Increased
Movement velocity	Bradykinesia	Reduced
Duration of dual support	Regulating the Time	Increased
Step/Stride length	Bradykinesia	Reduced
Limb coordination	Postural stability and Gait planning	Reduced
Cadence	Timing Control	Increased
ROM of lower limb joints	Bradykinesia	Reduced
Initiation	Postural stability and Gait planning	Freezing

To move ahead in a rhythm, the human body must control its posture, balance itself, and coordinate its limbs—all while walking on two wheels [15]. Identifying two consecutive gait events—like a heel-strike or toe-off—on the same foot is a crucial way to identify a gait cycle. The two halves of a gait cycle are the stance and the swing. During the walking phase, when both feet touch the floor, this is called dual support.

Fig. 3 shows the gait cycle in PD patients, including the swing and stance phases [16]. A variety of parameters (Table I) can be computed from gait data using various gait analysis tools.

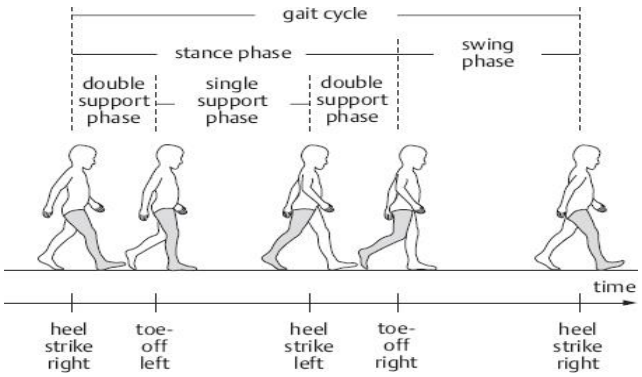

Figure 3. Gait Cycle for PD Patients.

There are a number of popular clinical measures and tests that can be used to evaluate gait in people with PD. There are a number of tests and scales that are specific to PD. These

include the Unified PD Rating Scale (UPDRS), the Hoehn and Yahr (H&Y) Scale, the Freezing of Gait Questionnaire (FOG-Q), and the PD Quality of Life Questionnaire-39 (PDQ-39) [17]. Classification algorithms are created to forecast the severity levels/scales of PD patients based on their gait patterns; in particular, the UPDRS and H&Y scales are often used in PD staging jobs. The transition, gait, and fall risk metrics are commonly measured by many broad scales and tests that assess gait abnormalities [18]. For the purpose of assessing the gait performance of PD patients following targeted gait treatments, several tests/scales can be utilized effectively.

Because gait impairment is one of the first and most noticeable symptoms of PD in a clinical context, doctors typically use visual observations in conjunction with other many manifestations to determine the severity of the disease [19]. Misdiagnosis is possible due to assessment bias, since this type of evaluation relies heavily on the knowledge and skill of the doctors doing it.

Research into PD prediction and classification using gait data has recently advanced to new technologies, namely Artificial Intelligence (AI) [20]. AI encompasses ML and DL models that are utilized to assist in the diagnosis of PD through the analysis of gait metrics. When it comes to diagnosing Parkinson's disease, these models are an intriguing and easily interpretable choice, particularly for use in the early stages of the disease when gait abnormalities manifest and worsen, and for successfully discriminating between the phases of the disease. Fig. 4 shows the DL architecture.

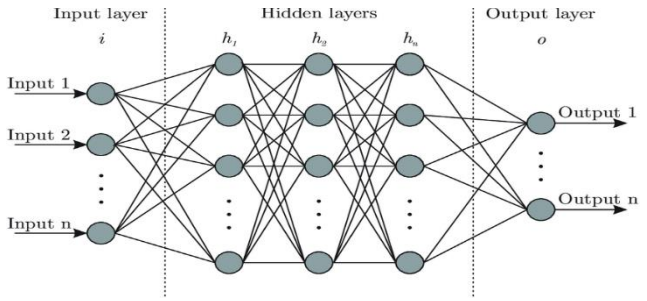

Figure 4. Structure of DL.

The performance of DL models on PD identification and diagnosis is more efficient than that of ML frameworks [21]. With the use of DL algorithms, doctors are able to make more accurate diagnoses based on patient data that has distinctive and important characteristics [22]. For a quantitative evaluation of the severity of PD disease using gait data, DL models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTMs), Deep Belief Networks (DBNs), etc., are useful. The healthcare organization generates a tremendous amount of data, and DL models have proven helpful in making decisions and automated predictions from this data [23]. Multiple DL frameworks for PD classification and prediction have emerged in recent years. There are no linked signs, therefore the particular strategy of preventing a PD is undetermined, despite considerable advancements in detection and prognosis.

A comprehensive review of different DL frameworks for PD detection and diagnosis utilizing gait signals is the main objective of this research. Additionally, to propose future scope, a comparative study is given to address the advantages and disadvantages of those frameworks. What follows is the preparation of the remaining sections: In the second section, we'll look at many frameworks that can identify PD from gait data. A comparison of those models is given in Section III. Part IV provides a synopsis of the full survey as well as suggestions for the forthcoming scope.

II. SURVEY ON DEEP LEARNING MODEL FOR PD SEVERITY DETECTION

The use of CNN and Time-Frequency Representations (TFRs) for multimodal examination of motor abilities in PDs patients was proposed by Vásquez-Correa et al. [24]. This approach simulates the challenges of initiating and terminating skeletal and vocal muscle movements. In addition to accurately assessing the patients' neurological status, this model can also detect the effects of the disease on their ability to speak and any problems with their lower or upper limbs or muscles. Using a CNN model, it can identify when transitions occur in speech, handwriting, and gait. Classification of PD from gait data is assisted by the obtained from CNN models.

To detect PD using vision-based freezing of gait (FOG) research, Hu et al. [25] created a Graph sequence recurrent neural network (GS-RNN). The spatial-temporal data, provided as dynamic graph sequences, was processed using the GS-RNN model. GS-RNN models both the structural and temporal graph patterns simultaneously with its composition of Graph RNN cells and vertex-wise RNN cells. With graph sequences of dynamic structures as inputs, the GS-RNN was trained to learn the FoG patterns using graph recurrent cells. Anatomical joint graphs are helpful for PD severity evaluations because they permit straightforward interpretation of detection results.

A Deep 1D-Convnet was built by El Maachi et al. [26] to accurately diagnose PD and forecast its severity from gait. Foot sensors that measure the vertical ground reaction force (VGRF) provide their inputs to this model. In the initial section of the network, there are 18 input-corresponding parallel 1D-Convnets. Part two is a fully linked network that takes the combined 1D-Convnet outputs and uses them to classify PD.

Using gait analysis, Lu et al. [27] created a model based on automatic vision that may determine the severity of PD motor symptoms. To detect motor deficits in non-intrusive video recordings, the SORT algorithm was employed. Then, from every single frame of the movie, 3D skeletons of the body were retrieved. A CNN was utilized to classify participants over time by training a Hybrid Ordinal Focal method with a Double-Features Double-Motion Network (OF-DDNet). For the purpose of PD evaluations, the bounding boxes and MDS-UPDRS gait scores were employed for movement classification.

To better detect FOG in PD using wearable sensors, Li et al. [28] created a DL model. The technology uses the patient's motion signal to identify FOG with the use of a wearable accelerometer. This system uses 1D-Deep CNN to automatically learn feature representations from multi-channel acceleration signals. Next, the RNN was used to represent the interdependencies between the activations of features over time. This model's detection performance was improved by incorporating the squeeze-and-excitation blocks and attention mechanism. And to make sure that unbalanced datasets didn't affect the PD detection model training, data augmentation was employed.

By utilizing LSTM networks, Balaji et al. [29] developed a system for the autonomous and non-invasive evaluation of PD severity. This model made use of the LSTM structure to make use of the temporal information in the gait sequence. This methodology assesses three distinct walking tasks and uses the UPDRS and the Hoehn & Yahr (H&Y) Scale to determine the degree of severity. Overfitting of the data is

minimized in this model by means of the dropout and L2 regularization techniques. Due to its low memory requirement and small number of hyperparameter tuning options, the Adam optimizer was chosen to solve the cost function for PD diagnosis.

Using a pairwise deep ranking algorithm, Oğul and Özdemir developed a relative evaluation of PD patients based on gait signals [30]. This model's data came from two PD patients who used information from many ground response force sensors. After that, the ranking tasks were performed by RSRNA, which stands for the Siamese Recurrent Network with Attention. This network takes two multivariate time series as inputs and outputs a probability indicating the signal with the higher probability of having a continuous property. An enhanced Long Short Term Memory (LSTM) with an attention mechanism was used to develop the recurrent layer, which captures remote associations in input signals crucial to gait skills.

By utilizing Inflated 3D networks (I3D) derived from movies, Yin et al. [31] created a 3D-CNN model for the purpose of PD severity classification. In this model, the CNN layer was substituted with the temporal relative self-attention block, allowing any 3D network to incorporate Temporal Self-Attention (TSA) for action recognition. During the transfer learning (TL) process, it was used to identify the visual cues that occur over time and to remove the significant difference in motion variations between the PD and non-PD datasets. Using the task assembling method, they were able to extract patient-level severity scores from the MDS-UPDRS, which allowed us to efficiently estimate PD patients' severity using a single score.

Using plantar pressure data, Shalin et al. [32] predicted the FOG in PD using a long short-term memory (LSTM). While walking a predetermined course that causes a freeze, data on plantar pressure was obtained from pressure-sensing insole sensors worn by several PD patients. They balanced and normalized the dataset, and then they extracted FOG instances to use as labeled features. Long short-term memory (LSTM) models were used to classify the observed data as PD.

To use gait dynamics for the prediction of MS and PD, Kaur et al. [33] built a vision and DL pipeline. This model may be applicable to many walking tasks and subjects since it categorizes the strides of People with Multiple Sclerosis (PwMS), Healthy Older Adults (HOA), and People with PDs (PwPD). Before being used to test on walking-while-talking (WT) trials for prediction tasks, the ternary classifiers (HOA, PwMS, or PwPD) were trained on walking trials. The neurological gait analysis' posture estimate block was further enhanced by extracting 3D multi-view fused body keypoint locations from the recorded gait movies.

An auxiliary PD diagnostic system was created by Chen et al. [34] with the help of wearable sensors, a GUI, and a Random Forest classifier refined by Genetic Algorithm. As part of the model, participants record their upper-body motions by wearing wrist sensors. Classifier performance is assessed using Leave-One-Out Cross-Validation (LOOCV), and the GA optimized RF classifier differentiates between PD and non-PD states. With the GUI, neurologists have a better basis for decision-making, which opens up several possibilities for PD auxiliary diagnosis.

To automatically measure the motor severity of PD in finger tapping and postural stability, Yang et al. [35] used a DL model. A pose extraction stage, an extraction stage for domain knowledge, and a classification step make up this model. To estimate the position, DL approaches are used to extract the critical spots for postural stability and finger tapping. Several explicit features, previously specified by seasoned neuro-physicians, were extracted using domain knowledge extraction. Last but not least, a DL classifier was trained to infer the severity of PD using MDSUPDRS.

A model for Parkinson's disease prediction was proposed by Sabo et al. [36] using zeno-instrumented walkways and video-based gait features in individuals with PD. This method included comparing gait characteristics calculated from color video in elderly individuals with PD using 2D human pose-estimation libraries with those obtained from a Zeno-instrumented sidewalk. They used the automated heel-strike detection method to examine the correlations as the subjects walked towards and away from the camera separately. From Zeno and the video, they determined the number of steps and the change in coefficient step width using 2D pose-estimation libraries. When assessing the gait features of persons with PD, they sought for moderate to high positive correlations.

To classify PD from gait analysis according to severity levels, Yang et al. [37] developed a ResNet-based model named PD-ResNet. The input gait features were enhanced in dimensions using a polynomial elevated dimensions approach. The next step was to convert the processed data into 3D format so that PD-ResNet could use it. To make it better at generalizing, they used data augmentation, early stopping technologies, and the Synthetic Minority Over-Sampling Technique (SMOTE). In the end, they built a better focused loss function to train PD-ResNet on the challenging instances and remove the aberrant samples to improve its classification performance.

To predict the severity level of PD using gait analysis, Vidya & Sasikumar [38] built a CNN-LSTM network, which is a mix of CNN and LSTM. The main VGRF signals from the variability analysis were first decomposed using Empirical Mode Decomposition (EMD) to get the important Intrinsic Mode Functions (IMFs) that contained important gait characteristics. The CNN-LSTM classification model was trained using the prominent IMFs recovered from the chosen VGRF signals using power spectral analysis. To solve the issue of data overfitting in the classifier model, this model uses dropout techniques in conjunction with L2 regularization. To reduce tuning and memory requirements for PD diagnosis, the CNN-LSTM network employs the Adam optimizer.

Aşuroğlu and Oğul [39] developed a multi-stage DL method for evaluating the severity of PD. Ground Reaction Force (GRF) signals are processed in this model using a number of time-domain and frequency-domain properties. The UPDRS values were then computed with the use of CNN with Locally Weighted Random Forest (LWRF), which also helps to decrease inter-patient variability in GRF signals. Predictions of PD detection severity levels were made from the UPDRS data.

A hybrid DL method for FOG prediction in PD patients was developed by El-ziaat et al. [40]. The angular axis spectrogram data was used as input data in this model. Subsequently, three max-pooling layers were utilized to extract features from spectrogram images using the Conv-LSTM. Various occurrence cases of fog episodes were utilized to aid in their prediction using the time-series episodes windowing and relay of angular axes feature. The 2D-CNN model was trained using the observed data to predict the FOG of PD patients.

Dong et al. [41] developed static-dynamic temporal networks to evaluate PD severity by gait analysis. Initially, the pressure signals are collected by various sensors on the bottom of the foot, and each signal is assigned a distinct depth attribute. A parallel One-Dimensional CNN (1D-CNN) was used to convolve time series data to extract time-related properties. At each level of the sole, the computed numerous

dynamic time series signals of the force points transfer were analysed using two-dimensional CNN (2D-CNN) parallelization to identify motion features. Finally, the severity prediction and the weights of individual PD sensor inputs were combined using the attention method.

To diagnose PD, Chen et al. [42] built a FuseLGNet model that combines local and global data. One feature extractor uses three convolutional layers to extract spatial information, while the other uses the FuseLGNet model with a self-attention mechanism to focus on relevant data when there are noticeable changes in gait. This method combines the two extractors. down order to extract the local features, the low-level extractor zeroes down on significant gait alterations. The high-level extractor uses the self-attention mechanism of the transformer to acquire global features from the gait image. To detect PD, the data collected from both extractors was pooled.

In their work on PD stage categorization, Pedrero-Sánchez et al. [43] created a two-stage DNN model. Two steps make up this model. The first step was to categorize the participants' actions using a semantic segmentation of the raw sensor information. The biomechanical variables that are deemed clinically relevant for functional assessment are obtained through this activity. Spectrogram images of the sensor signals, raw sensor signals, and biomechanical variables formed the three input branches of the neural network model used in the second step. The DNN model was trained using all this data to identify the initial three stages of PD.

Kwon et al. [44] developed a spatial-temporal graphical CNN to assess FOG in Parkinson's disease patients. The recorded motion capture sequence was first segmented into discrete analysis windows. Then, the AT model and a 4-layer Adaptive temporal-spatial Graphical Convolutional Network (AGCN) were processed. The AGCN model learned attention maps for the movement of individual limbs and joints, but the AT model predicted the most fundamental aspects of motion. Temporal Average Pooling (TAP) processing was applied to the final AGCN layer for the purpose of evaluating the temporal data. Predicting medication status, FOG score, and MDS-UPDRS-III total score will help with PD detection and diagnosis.

Using a skeleton-silhouette fusion convolution network, Zeng et al. [45] created a method for quantifying gait deficits in PD through video analysis. The UPDRS gait scores were predicted using features extracted from the gait movies using the skeleton-silhouette neural network. To learn how each body part-related feature contributed to accurate gait score prediction, they graded the saliency values extracted from the convolutional network. Also, to improve low-resolution clinical rating scales for PD treatments, the additional features were extracted to contribute continuous gait impairment measurements.

III. COMPARATIVE STUDY

In this part, a comparative study is presented according to the benefits and drawbacks for PD detection using different DL methods which are briefly studied in above section are illustrated below Table II.

Table II. Comparison of Different PD Prediction with Different DL Algorithms

Ref No.	Techniques	Merits	Demerits	Performance Evaluation
[24]	TFRs and CNN	To evaluate the onset and offset of each step in the disease evaluation process, a robust technique was developed.	The assessment of motor abilities was plagued by miss-classification mistakes caused by noisy, irrelevant data.	Accuracy = 97.3%
[25]	GS-RNN, Graph RNN and Vertex-wise RNN	Lower computational cost without compromising model learning capacity.	This model produces incorrect predictions due to the key vertices which were not correctly located on patient subjects.	Accuracy = 82.5%; Sensitivity = 83.8%; Specificity = 82.3%
[26]	Deep 1D-Convnet	A large number of older persons have started using this model to track and analyze their gait patterns as they go about their everyday lives	The parameter configuration were not configured well which lowers the classifier's performances	Accuracy = 85.3%;
[27]	SORT algorithm, TCNN, OF-DDNet	Lower computational cost and robustness to analyze between two motion features	This model trains on the small datasets which results in overfitting and uncertainty issues.	F1-score = 0.83; AUC = 0.90; Precision = 0.86
[28]	1D – Deep CNN, RNN, Squeeze-And-Excitation Blocks And Attention Mechanism	High operating efficiency and better convergence rate	Both the processing cost and the difficulty of interpreting the data made this model unsuitable	Sensitivity = 0.951; Specificity = 0.98; AUC = 0.931
[29]	LSTM, Adam optimizer, Dropout and L2 regularization	This model leads to high generazability and avoids over-fitting issues.	This model long training time and high sensitivity to random weight initialization.	Accuracy = 96.6%; Sensitivity = 96.2%; Specificity = 96.08%
[30]	RSRNA, LSTM	In addition to removing the bias that arises from using subjective grading scales, the model provides a more trustworthy and easy-to-understand picture of how the disease is progressing	Unfortunately, this model was unable to evaluate the system's ability to track a single person's development over time due to a lack of data from several samples.	Area Under Curve (AUC) = 0.878; Ranking Accuracy = 81%
[31]	3D-CNN, TSA, TL	This model obtains efficient results on both larger and smaller datasets.	The gathered video samples includes many irrelevant perspectives, scene modification which lowers the severity score prediction.	Average Accuracy = 81.1%; Matthews correlation Coefficient = 0.60
[32]	LSTM	Lower computational time and work	This model was not partially automated and LSTM parameter were not fine-tuned properly	Sensitivity = 84.1%; Specificity = 85.9%

[33]	DL model	This model results in lower computational cost and adaptable to real-time applications	This model's small sample size and gender variations among groups limits the generalized interpretations.	Accuracy = 79.3%; AUC = 0.93
[34]	GA optimized RF, LOOCV, GUI	This model decreases the need for neurologists and minimizing the time length required to diagnose a PD.	The efficiency of this model was limited due to small scale of training data	Accuracy = 94.4%
[35]	DL model, Domain knowledge extraction	This model It increases the interpretability while decreasing the requirement for a large volume of data.	This model results with overfitting issues	F1-Score = 88%;
[36]	Heel-strike detection algorithm, Zeno instrumented walkway	This model does a good job of highlighting the pros and limitations of quantitative gait measurement in PD patients using a consumer-grade camera.	Inconsistent step-to-stride time correlations led to inappropriate detection and increased generalizability error	Sensitivity = 89%
[37]	ResNet, SMOTE, Polynomial elevated dimensions technique, Focal loss function	To minimize the likelihood of error, the movement signal was thoroughly examined throughout the model.	The computational time was high as this method utilizes complex features in the training tasks.	Accuracy = 95.5%; Precision = 94.4%;
[38]	CNN-LSTM, Empirical Mode Decomposition	Lower computational time and memory space	It provides lower efficiency on smaller dataset	Accuracy = 98.52%
[39]	CNN-LWRF	The features were selected with large variance to eliminate the classification problems.	Model trained on limited Parkinson's patient population in gait dataset, addressing heterogeneity in disease severity and lower UPDRS values.	Accuracy = 99.5%; Sensitivity = 98.7%; F1-Score = 99%
[40]	Conv-LSTM, Max-pooling layers, 2D-CNN	Robust to the noisy data and overfitting issues	The parameters of the recommended DL models and windowing sizes were inadequately adjusted	Accuracy = 94%; Precision = 94.85%; Recall = 92.8%;
[41]	1D-CNN, 2D-CNN, Attention mechanism	Because it uses a number of non-linear activation functions, this model is able to handle the gait classification problem	High generalization error and slower convergence rate was resulted	Precision = 92.5%; Recall = 90%
[42]	FuseLGNet, Transformer's self-attention mechanism	This model effectively reduces uncertainty, increases reliability and provides robustness solution for PD prediction issues	This model necessitates large number of parameters and high computational complexity	Accuracy = 98.25%
[43]	DNN, Biomechanical Variables	This model identifies PD initial stages using a 2-minute functional test, making it feasible in clinical context with easy instrumentation requirements.	This model fails to capture temporal signal dynamics and provides insufficient data resolution for analysis.	Accuracy = 99.64%;
[44]	AT model and AGCN, TAP	This model is able to accurately assess FOG automatically because it captures complicated movement patterns in kinematic data	The results were not generalizable, and the severity of FOG was not measured as a continuous outcome	F1-Score = 96.8%;
[45]	Skeleton-silhouette fusion convolution network	This model eliminates the common error accumulation and robust to the noises facts for by skeleton estimation	This model needs to focused on the proximal-distal configuration which provides heavy margin on the skeleton steams	Sensitivity = 92.6%; Spearman Co-efficient = 0.78

Article [45] provides superior gait analysis-based PD prediction results, according to the aforementioned comparison study of articles [24–45]. To anticipate the initial phases of PD by gait analysis, a skeleton-silhouette fusion neural network was built, as described in the publication [45]. Two cell phones were used to record the participant's gaits, one from a sagittal view and one from a coronal view, to identify any gait problems. The videos were analyzed using Mask R-CNN to extract both human silhouettes and skeletal sequences. After that, the sequences of silhouettes were converted to Glei (Lone-Term Gait Energy Image) and the sequences of skeletons were organized into undirected pose graphs. A skeleton stream and a silhouette stream make up the two-stream network, and they both detect aspects of lower-limb motion and parkinsonian gait in terms of space and time. Lastly, to forecast MDS-UPDRS gait scores, all features were fused using completely linked layers.

A number of supplemental features were retrieved to validate the usefulness of the saliency values for the PD detection, and saliency values were derived to identify which body areas contribute more to correct gait prediction.

IV. COMPLICATIONS UNDERTAKEN

It is challenging to diagnose early-stage PDs. People with PDs can greatly enhance their quality of life by receiving treatment early on. Improving the accuracy of early PD diagnoses through the use of deep learning models is the main focus of this effort.

V. CONCLUSION

Many people around the world, especially the elderly, suffer from PD, a devastating disease. In healthcare, determining the exact and early stage of PD is a great challenge. These days, DL algorithms are being used more and more in healthcare for rapid and precise identification, especially when it comes to determining the severity of PD. To tackle the issue of incorrect diagnosis, numerous researchers have proposed various methods in the literature that utilize DL methodologies. This work presents a thorough evaluation of various DL approaches for PD, comparing them based on their abilities, shortcomings, and prediction efficiency. Key access for researchers to construct fully functional models that could improve PD prediction and

diagnosis and give individualized treatments for PD patients is the discussion of the discussed problems and performances. As a result, we will be utilizing state-of-the-art computational models for PD prediction in the near future. These models will analyze the stages of parkinsonian gait with linear interpolation and proximal-distal configuration adjustments.

VI. REFERENCES

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