Deep Learning-Based Classification of Neurodegenerative Diseases Using Gait Dataset: A Comparative Study

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ABSTRACT

Neuro-degenerative diseases pose a significant health concern for human society, especially among the elderly population. Given their high prevalence and the limited availability of clinical expertise and services, there is an urgent requirement for the integration of artificial intelligence (AI) systems to support healthcare professionals in addressing this issue. This paper presents a comparative analysis of seven deep learning architectures for neuro-degenerative disease classification by using a gait dynamics dataset. The models used in the analysis include LSTM, GRU, InceptionTime, ResNet, FCN, TST, and PatchTST. The models are extensively evaluated for different classification tasks. The findings of the study suggest that deep learning techniques have the potential to diagnose and classify different neurodegenerative diseases effectively. It can be inferred that ResNet exhibits superior performance compared to other models in tasks involving the classification of healthy controls (HC) and class of individuals with all neuro-degenerative diseases (NDDs), and classification of healthy controls (HC) from individuals with Parkinson's disease (PD). TST demonstrates the highest level of performance among all models in tasks involving distinguishing between Amyotrophic Lateral Sclerosis (ALS) and healthy controls (HC), as well as Huntington's disease (HD) and healthy controls (HC).

KEYWORDS

Gait analysis, Neuro-degenerative diseases, Deep learning, Time series, Comparative Analysis

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1 INTRODUCTION

The nervous system, comprising of the brain and spinal cord, plays a crucial role in facilitating cognitive processes such as thinking and memory retention, as well as enabling the acquisition of new information through learning [1]. However, the nervous system is susceptible to various diseases, which can disrupt the body's functionality and cause the person discomfort [2]. Nervous system disorders, such as neurodegenerative diseases can potentially alter the behaviour of the nervous system and its response to environmental stimuli [3]. In recent years, the prevalence of neurodegenerative diseases (NDDs) has increased rapidly. Typical NDDs include Parkinson's disease, Huntington's disease, Alzheimer's disease, and Amyotrophic Lateral Sclerosis.

Parkinson's disease (PD) is a type of NDD that primarily affects older individuals and some adults, with the onset of symptoms typically occurring in the middle to late life. Gait impairments are the most common and disabling symptoms of PD, with symptoms including tremors in the arms or hands when at rest or tired, stiffness in muscle movement that limits motion, shuffling steps, walking asymmetry with periods of freezing when moving, and balance problems. Additionally, it also affects the autonomic nervous system and causes symptoms such as orthostatic hypotension, sexual

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dysfunctions, urinary incontinence, constipation, and gastrointestinal problems [4] [5]. Huntington's disease (HD) is a rare, inherited, progressive disease that causes cognitive decline, motor impairments and neurobehavioral symptoms [6]. Amyotrophic lateral sclerosis (ALS) typically affects both lower and upper motor neurons, causing message transmission to be disrupted and muscles to gradually deteriorate [7]. Early clinical symptoms of ALS include trouble in speaking or swallowing, twitching and cramping of legs and arms, and exhaustion [8].

Accurate detection of neurodegenerative disease necessitates a high level of expertise and knowledge. However, manual diagnosis can be costly and time-consuming, especially when early detection is critical for mitigating the effects of an untreatable disease at later stages. The manual process is expensive, prone to human mistake, and test inquiries can cause delays. Hence, artificial intelligence based detection of neurodegenerative diseases has become increasingly popular, making this tedious and costly process short and easily accessible to more people [9]. In diagnosing neurodegenerative diseases, symptoms from a patient, such as rapid eye movement, irregular walking patterns, tremors in hand movement when writing, and voice and speech data can be effectively utilized. Gait analysis has gained popularity as a non-invasive, cost-effective method for diagnosing NDDs. Most of the research on gait analysis has been developed, focusing on various temporal/spatial aspects and pressure measures. These include examining time series of stance, swing, or stride intervals, as well as assessing foot force and ground reaction force (GRF). These patterns can detect early signs of the disease and monitor its progression.

The field of medical diagnosis has dramatically benefited from the advancements in artificial intelligence [10–12]. In the recent years, the studies on NDD classification have focused on statistical analysis or machine learning. Zeng et al. [13] used deterministic learning theory to classify different NDDs. Xia et al. [14] extracted different statistical features for gait rhythm signals and employed popular machine learning methods to diagnose NDDs. Wu et al. [15] measured irregularities in gait rhythms using symbolic entropy, approximate entropy, and signal turns count. They use these parameters for classification using general linear models and support vector machine. Bilgin [16] extracted features from the timeseries data using a wavelet technique which were evaluated by using a Naïve Bayesian Classifier and Linear Discriminant Analysis. Recently, Fraiwan et al. [17] applied decision tree-based ensemble classification to recognise to recognize and classify NDDs based on gait fluctuations.

This paper focuses on deep learning based neurodegenerative diseases classification using gait rhythm data. Deep learning models have demonstrated the ability to achieve high levels of accuracy in a variety of tasks [18–20]. Recently, several advancements [21–23] have been made to automate the identification of neurodegenerative diseases by leveraging deep learning algorithms. Lin et al. [21] implemented a deep-learning-based model that utilizes recurrence plot of vertical GRF data to diagnose NDDs. Berke Erdas et al. [22] presented a robust and efficient disease severity grading system for NDDs based on a convolutional neural network (CNN)-based approach that uses quick response data converted from gait rhythm data. Similarly, Setiawan et al. [23] proposed a model that uses CNN and wavelet coherence spectrogram to specifically identify gait abnormalities associated with neurodegenerative diseases, such as PD, HD, and ALS. In this paper, a comprehensive analysis of various deep learning approaches towards automated NDD classification has been performed. For this, comparative analysis of recurrence-based methods, convolution-based methods and transformers-based methods on gait rhythm data have been included.

This paper makes the following contributions:

- This paper investigates the classification performance of different deep learning architectures on the statistical features of gait rhythm timeseries signals.
- A comprehensive comparative analysis of the results with practical recommendations for the effective use of deep learning in neuro-degenerative disease classification is presented.

The rest of the paper is structured as follows: Section 2 details a description of the methodology, including the research database, the gait cycle, and the workflow. Section 3 presents the results and discussion of the comparative analysis. Section 4 provides the study's conclusion, including a summary of the main findings, limitations, and future work.

2 METHODOLOGY

Numerous deep learning models were employed in this study, all of which were applied to a single dataset. The dataset was meticulously prepared and utilized to train these models. The performance of these trained models was evaluated and differentiated based on the different metrics.

2.1 Gait Dataset

The Gait Dynamics in Neurodegenerative disease dataset [24] was used in the paper, which includes 15,092 data samples collected from a healthy control group (n=16) and participants with NDDs such as Parkinson's disease (n=15), Huntington's disease (n=20), and amyotrophic lateral sclerosis (n=13). The raw data in the dataset is in the form of one-dimensional time-series data collected over a 77-meter hallway for a duration of five minutes, using force-sensitive resistors. The sensors were placed in the insole of the participants' shoes and on the anterior portion of the insole, beneath the toes and metatarsals, as well as on the heel, to provide information about the force underneath the foot of the participant. The readings were later converted from analog to digital and analysed by software [25].

Gait data signifies the manner or style of walking, which can be interpreted to diagnose various neurodegenerative diseases and musculoskeletal injuries or disease processes. It is important to understand the gait terminology to break down the meaning of the indexed data content for the participants in the dataset and analyse the data correctly to make trainable machine learning models. A normal gait cycle consists of steps and strides in a repetitive pattern and consists of two Stance and swing phases, as shown in below. The data set records the steps and strides pattern in the gait cycle for each participant while calculating the double support (on both feet) and single support (on single feet during motion) for the patient to analyse the walking pattern—any abnormality in the reading help in identifying the onset of neurodegenerative disease in the participant. Figure 1 shows the overview of the proposed methodology.

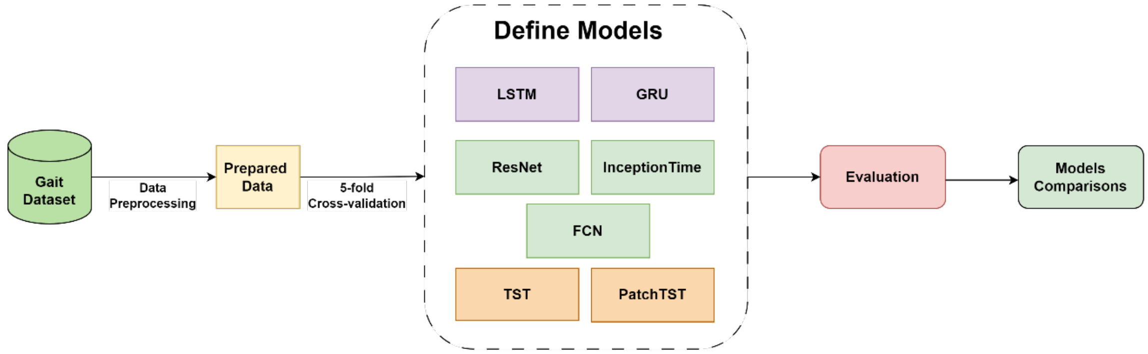

Figure 1: An overview of the proposed methodology

Next, we detail the most widely used deep learning models for time series classification used in our comparative analysis.

2.2 Models

2.2.1 Long Short -Term Memory. Long Short-term memory (LSTM) [26] was introduced to solve the problem of vanishing gradients faced by Vanilla RNNs while learning the temporal changes in sequential data. It works like an extended version of RNN, which can exhibit characteristics of learning long-term dependency information for the given time series data [27]. The recurring Tanh layers in an RNN model allow it to retain information and learn to predict; the LSTM increases the ability to store information for a longer time compared to the RNN model. Each primary cell inside the LSTM model has a cell state and many units, which have three gates to be used for input of data, output from trained, and the forgettable variable. Each unit in the model supports a pointwise multiplication operation and sigmoid activation function. These gates selectively learn and adapt information from each of the inputs. Having a cell state allows the information to remain unaltered as it passes through these units, and only permits a few linear operations for minute changes in the LSTM model.

2.2.2 Gated Recurrent Unit. Gated recurrent units (GRUs) [28] are an improved version of standard RNNs. The GRU introduces a gating mechanism composed of reset gate and update gate. The reset gate controls the extent to which past information should be forgotten. It enables each recurrent unit to capture dependencies in an adaptive manner across multiple time steps. Meanwhile, the update gate performs similar to the input gate and forget gate. It determines how much data the front memory information may continue to retain to the present moment. However, GRU does not possess separate memory cells which are present in LSTM. The structure of GRU is simpler and has fewer number of parameters as compared to LSTM.

2.2.3 InceptionTime. InceptionTime model [29] is a newly proposed deep learning module based on the ensemble of deep convolution neural network models and is heavily inspired by Google Net Module. However, it adds residual connections at every third inception module. The inception Time model has proven to be on par with the current CNN models available when handling time series and is much more scalable and functions by identifying the local and global shape patterns from the low-level and high-level features of the time series data [30].

2.2.4 Residual Network. ResNet [31] is famous for having structured networks with a night number of layers, making them very deep, as well as the ability to solve the vanishing gradient problem faced by many other deep neural networks by doing residual or less amount of function. ResNet, as the name suggests, is better at dropping redundant information than other models using skip connections to skip training for problem-solving layers in the module to produce the output.

2.2.5 Fully Convolutional Network. Fully Convolutional Networks (FCNs) [31] are a popular model for semantic classification due to their ability to detect both temporal and spatial patterns in images with filters and label them based on their importance for selection [18]. These networks rely on locally connected layers of convolution, batch normalisation, pooling, and up-sampling to perform interference and learning while avoiding dense layers, thus reducing the number of parameters needed. FCNs have traditionally been used for image classification and segmentation, but recent research has also shown their competitive accuracy and reliability for detection in time series datasets [30]. In fact, FCNs have been shown to outperform ResNet in tests for prediction on the UCR dataset.

2.2.6 Time Series Transformer. The time series Transformer (TST) is a newly proposed transformer-based framework that is a potential solution for handling unsupervised representation in multivariate time series. Earlier TST has shown promising results when used for univariate time series data. The proposed code in the study experiments with TST on labelled time series data [32]. In TST, attention training is utilised, and linear complexity is employed for the feature vector. Additionally, parallel computation of a sequence is employed in contrast to sequential computation, which is commonly utilised in other neural network models. The authors of this model claim that it is comparable to, or surpasses, current state-of-the-art deep learning techniques such as ResNet.

2.2.7 Patch Time Series Transformer. Patch time series Transformer (PatchTST) is a global Transformer with patched inputs. PatchTST employs continuous segments of time series as input to a vanilla Transformer. It also uses a channel-independence setting. This design allows for the sharing of same embeddings and Transformer

Table 1: Comparison of different deep learning models for HC vs NDD classification task

Method	Precision	Recall	F1-score	Accuracy
LSTM	0.798	0.908	0.850	0.765
GRU	0.773	0.940	0.848	0.754
InceptionTime	0.861	0.898	0.878	0.818
ResNet	**0.875**	**0.909**	**0.890**	**0.833**
FCN	0.835	0.908	0.869	0.801
TST	0.801	0.963	0.871	0.789
PatchTST	0.851	0.871	0.861	0.794

weights across all series within a channel, promoting efficient information processing and consistency. It makes the model less susceptible to overfitting and more robust to noise.

3 EXPERIMENTS

3.1 Implementation Settings

For baseline experiments, we trained seven deep learning models, including LSTM, GRU, Inception Time, ResNet, FCN, TST, and PatchTST for the prediction task. The models are trained and evaluated using 5-fold cross validation technique. The training process was configured with a maximum of 100 epochs, while the initial learning rate was set to 0.0001. This study used different model settings. The hardware configuration used to train the networks was an Intel Xeon E-2288G 3.7GHz and a Quadro RTX 6000 24GB GPU. The software configuration used Pytorch framework.

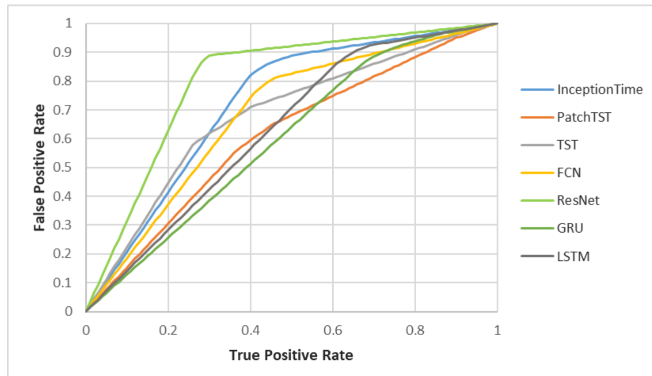

Figure 2: ROC Curve for seven deep learning models for HC vs NDD task

3.2 Results

Table 1 presents accuracy, recall, precision, and F1-scores achieved for the different models on the PhysioNet Gait Dynamics in Neurodegenerative disease dataset for the classification task of healthy control (HC) vs neuro-degenerative disease (NDD). NDD class contains combined classes of patients from amyotrophic lateral sclerosis (ALS), Huntington's disease (HD), and Parkinson's disease (PD). The highest accuracy and F1-score of 0.833 and 0.890 respectively is achieved for ResNet model followed by InceptionTime, which achieved the accuracy and F1-score of 0.818 and 0.878 respectively. F1-score of ResNet differs with InceptionTime by 0.012. The ability to capture complex patterns in sequential data likely contributed to the ResNet model's high accuracy and F1 scores in this study. Additionally, ResNet is known to be highly robust and flexible, making them well-suited for the applications, including time-series classification tasks. The next best performing models were TST, PatchTST, and FCN, reporting an accuracy score in the range 0.789-0.801. GRU achieved the lowest accuracy score and precision score of 0.754 and 0.773 respectively.

As described in Figure 2, the ROC curve data for each model showed a TPR range from 0 to 1 with a corresponding FPR range from 0 to 1. The estimated AUC scores for the models were 0.824 for the LSTM model, 0.812 for the GRU model, 0.851 for the InceptionTime model, 0.902 for the ResNet model, 0.837 for the FCN model, 0.829 for the TST model, and 0.813 for the PatchTST model. The results demonstrate that FCN has a much higher AUC score than PatchTST, even though there is no significant different between their accuracies. This discrepancy can be attributed to the fact that the AUC score only considers the ranking of the predicted probabilities. In contrast, the accuracy score considers both the ranking and the threshold for classification. In some cases, a model with a higher accuracy score may not have a better ROC curve and, thus, a lower AUC score.

Table 2 presents the outcomes of seven different models applied to three classification tasks, specifically distinguishing HC vs ALS, HC vs HD, and HC vs PD. For HC vs ALS, TST achieved the highest accuracy and F1-score of 0.936 and 0.918 respectively, followed by ResNet with accuracy and F1-score of 0.920 and 0.901 respectively. RNN based models such as LSTM and GRU demonstrated the lowest scores across all metrics. For HC vs HD, Transformer based models performed better than the CNN and RNN models. The highest F1-score of 0.810 was achieved on TST model whereas lowest F1-score of 0.644 was achieved on GRU model. For HC vs PD, CNN-based models demonstrated superior performance, followed by comparable performance of Transformer models. ResNet showed the highest F1-score and accuracy of 0. 829 and 0.841 respectively whereas TST achieved accuracy and F1-score of 0.822 and 0.829 respectively. GRU reported the lowest precision, recall, F1-score, and accuracy.

It can be observed that the Transformer based models for time series achieved superior performances. It is attributed to its ability to capture long-range dependencies. Although the PatchTST model has a lower number of parameters, this reduction in parameter count did not translate into better performance than the TST model.

Table 2: Comparison of deep learning models for different classification tasks, i.e., HC vs ALS, HC vs HD, and HC vs PD

Method	HC vs ALS				HC vs HD				HC vs PD			
	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score	Accuracy
LSTM	0.739	0.686	0.711	0.786	0.779	0.566	0.655	0.676	0.749	0.669	0.706	0.736
GRU	0.751	0.667	0.706	0.787	0.726	0.582	0.644	0.652	0.755	0.673	0.711	0.740
InceptionTime	0.858	0.928	0.891	0.913	0.712	0.839	0.747	0.680	0.838	0.707	0.767	0.796
ResNet	0.860	0.947	0.901	0.920	0.781	0.820	0.785	0.746	**0.846**	**0.813**	**0.829**	**0.841**
FCN	0.858	0.928	0.891	0.913	0.712	0.839	0.747	0.680	0.838	0.707	0.767	0.796
TST	**0.909**	**0.928**	**0.918**	**0.936**	**0.809**	**0.817**	**0.810**	**0.789**	0.826	0.823	0.822	0.829
PatchTST	0.734	0.953	0.826	0.843	0.821	0.676	0.741	0.744	0.854	0.677	0.755	0.791

RNN based models performed the worst for all the classification tasks. Learning from long sequences of data may have resulted in poor performance. The sequential processing of input data and the difficulties involved in back-propagation through time cause a number of limitations for LSTM and GRU. Transformers effectively overcome the challenges by employing positional encoding and self-attention techniques. It enables them to simultaneously encode and attend to the sequential order information while analyzing the present data points in the time series. In our experiments, deep CNNs consistently outperformed both RNN models across all tasks. Additionally, the performance of deep CNNs was comparable to that of Transformers, and in certain tasks, it even outperformed the Transformer models. Here, the success of convolutions in classification tasks is attributed to the high generalization power. CNNs excel at learning spatially invariant features in two-dimensional spaces. As a result, it is logical to assume that uncovering patterns in a one-dimensional space, such as time, would be a relatively simpler task for CNNs.

4 CONCLUSION

This paper presents an in-depth study of different deep learning techniques for the classification of neuro-degenerative diseases. The study was conducted using a research database that consisted of gait cycle data. Our results demonstrate the superiority of deep learning models even when the available data is limited. This paper makes a valuable contribution to the advancement of automated medical diagnosis of neuro-degenerative diseases by highlighting the efficacy of these techniques in the field. In future work, we plan to validate our conclusions on other neuro-degenerative diseases databases and investigate the combination of multiple bio-signals for efficient diagnosis.

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