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Parkinson's illness Deep Learning Diagnosis: An Innovative LSTM-Based Method for Freezing Gait Detection

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----------**ABSTRACT**----------

By uncovering hidden patterns in big clinical datasets, deep learning has great promise for the medical industry in terms of aiding in the diagnosis of a wide range of diseases. A deterioration in brain function is a hallmark of Parkinson's disease (PD), a neurodegenerative condition. Early automated detection of Parkinson's disease is challenging due to the behavioral similarities between those with the disease and healthy individuals. Our objective is to offer a practical model that can facilitate the early detection of Parkinson's disease. We utilized the VGRF gait signal dataset, which was acquired via Physionet, to distinguish between individuals with Parkinson's disease and healthy individuals. A novel deep learning architecture based on LSTM networks is presented in this study to automatically detect freezing of gait episodes in Parkinson's disease. Unlike typical machine learning techniques, this method effectively captures long-term temporal correlations in gait patterns and eliminates the requirement for human feature engineering, improving the diagnosis of Parkinson's disease. To avoid the issue of vanishing gradients and enable optimal information absorption, the LSTM network uses memory blocks instead of self-connected hidden units. Methods such as L2 regularization and dropout have been employed to prevent overfitting. Adam, an optimizer based on stochastic gradients, is also used in the optimization process. The results demonstrate that our proposed approach, with 97.71% accuracy, 99% sensitivity, 98% precision, and 96% specificity, surpasses the state-of-the-art models in FOG episode recognition. This demonstrates how promising it is as an improved classification method for Parkinson's disease diagnosis.

Keywords - **Deep Learning, Freezing of Gait, LSTM, Parkinson’s Disease**

1.INTRODUCTION

In the substantia nigra, a specific area of the brain, a deficiency of dopamine neurons causes Parkinson's disease. In 2020, the Parkinson's Foundation reported that approximately one million Americans suffered from Parkinson's disease (PD) [1]. The majority of Parkinson's disease diagnoses are based on motor symptoms, such as tremors, stiffness, and difficulty walking. Therapy and medicine are used to manage the symptoms of Parkinson's disease, even though there is presently no recognized cure. On the other hand, early disease detection can aid in the development of suitable treatments or drugs to the disease's progression. Today's medical sciences rely primarily on clinician observations to diagnose Parkinson's disease (PD), which can occasionally lead to false positives.

DL algorithms are becoming increasingly valuable in bioinformatics because of their ability to handle massive datasets and identify biomarkers, which not only results in more accurate predictions but also reduces the time required for diagnosis. A number of physiological markers, including tremor, handwriting samples, speech signals, and gait patterns, are used to identify Parkinson's disease.

Speech analysis can be used to identify non-motor symptoms of Parkinson's disease (PD), and sustained vowel and word phonation can be used to differentiate between people with and without PD

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[2–4]. Potential biomarkers include handwriting's kinesthetic, cognitive, and perceptual-motor elements.

Handwriting is a possible biomarker that includes perceptual motor, cognitive, and kinesthetic components. Using an LCD display and graphics tablet, this includes tests including the dynamic spiral test, stability test, and static spiral test. [5–8] have reported notable machine learning outcomes in this field.

Additionally, ML models have been essential for deciphering the pathophysiology of Parkinson's disease by examining intricate genomic and transcriptome data [9–12]. Because structural magnetic resonance imaging offers high-resolution imaging of brain tissues, it is one of the brain imaging modalities that offers valuable insights for computer-based PD diagnosis. For the diagnosis of Parkinson's disease, methods such as DatScan are also employed.

Dopamine levels in the brain have been identified using MRI scans and machine learning techniques [13–15].

A simple and affordable method of identifying motor symptom impairments is the gait-based categorization [16]. Interestingly, the gait cycle has unique traits like periodicity, deterministic behavior, and spatiotemporal aspects. Gait analysis enables the evaluation of motor functions and aids in determining the severity of the individuals' condition, in contrast to approaches that exclusively address non-motor functions, such as speech or handwriting [17]. Clinicians are therefore able to suggest suitable therapeutic measures to impede the advancement of the condition.

In recent years, great progress has been made in applying deep learning algorithms to predict the stages of Parkinson's disease based on gait data. An overview of the contributions made by this effort is provided below:

i.The study employs an LSTM classifier to tackle the binary class classification problem in Parkinson's disease by effectively leveraging temporal information inside gait sequences.

ii. In this study, dropout and L2 regularization techniques are employed to guarantee the model's generalizability and avoid data overfitting.

iii. The Adam optimizer's minimal memory requirements and minimal hyperparameter tweaking make it a popular choice for optimization aimed at improving model training efficiency.

The following is how the paper is organized: There have been numerous attempts to identify freezing of gait, which are discussed in Section 2. In section three, the recommended methodology is presented.

2. RELATED WORK

An interpretable end-to-end deep learning system was presented by Alharthi et al. [18] in order to integrate raw gait data and create a model for PD detection and classification. This model's F1 score average was 95.5%, with a low standard error of 0.28%. The Layer-wise Relevance Propagation (LRP) method was used for interpretation in order to obtain a better understanding of the model's decision-making process.

Using the MDS-UPDRS scale to measure PD motor deficits is an issue that is addressed in this research [19]. A novel ordinal focus network was proposed by the authors to estimate MDS-UPDRS scores. Additionally, they suggested rater confusion estimation (RCE), a regularization technique, to deal with inter-rater variabilities. Their method was used to analyze video recordings of finger tapping and walking. According to results on a clinical dataset, the classification accuracy was 72% when using majority vote ground truth and 84% when anticipating the score of at least one rater. Even when clinical professionals disagree, this shows how computer-assisted technology can be used to track the motor deficits of PD patients.

The main focus of this study [20] was on Parkinsonism in older persons caused by drugs. The researchers used video data and ST-GCN to predict clinical scores related to parkinsonism. They performed temporal convolutional network baselines and a comparative study between ST-GCN models and traditional regression models. This required using various pose estimation libraries and the Microsoft Kinect device to extract joint trajectories from video. Using 3D joint trajectories, the results consistently showed that the suggested model performed better than alternative approaches. However, it is still difficult to predict Parkinsonism scores in fresh patients; the best models obtained F1-scores of 0.40 ± 0.02 for SAS-gait and 0.53 ± 0.03 for UPDRS.

3.METHODOLOGY

3.1 LSTM Architecture

In order to solve the exploding and vanishing gradient issues that plagued vanilla RNN, Hochreiter and Schmidhuber developed LSTM. Long-term dependencies in sequential data are particularly well-suited for LSTM [26, 27] LSTM uses memory cells instead of traditional

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nodes in the buried layer, unlike RNN. This enables knowledge to be retained and recalled for extended periods of time. A graphic illustration of the LSTM architecture can be found in Fig. 1 (B). Three gates

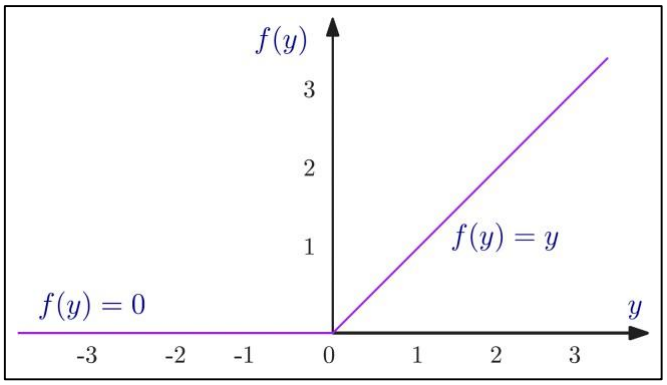

Fig. 1: Proposed workflow for FOG detection in Parkinson's subjects: Detailed LSTM architecture.

comprise the memory block. These are the forget, output, and input gates. Irrelevant inputs are reduced in impact by using multiplicative gate units [28]. The suggested process for identifying Freezing of Gait (FOG) in Parkinson's patients is shown in Fig. 1.

The forget gate determines how much information is retained from the previous state and is computed as follows:

$$ft = \sigma(Whf\, ht{-}1 + Wxf\, xt + bf) \quad (1)$$

Wxf and Whf represent the weight matrices corresponding to the input vector of the current cell and the output vector of the previous cell, respectively, where ht−1 is the output of the previous block, xt is the input sequence, and b is the bias vector. Using the current input vector as a guide, the input layer chooses which data is saved. In the current time step, the output gate computes the output. Here is a definition of the equations:

$$it = \sigma\,(Whiht{-}1 + Wxixt + bi) \quad (2)$$

$$ot = \sigma\,(Whoht{-}1 + Wxoxt + bo) \quad (3)$$

Combining the forget and input gate, the equation for the current cell state is given as:

$$Ct = ft \odot Ct{-}1 + it \odot C't \quad (4)$$

Where, at time step t Ct = cell state and ⊙ = element-wise multiplication. ft ⊙ Ct−1 and it ⊙ C′t determine the information taken from the preceding cell state and current input [34]. Using the tanh activation function, the C′t is calculated as:

$$C't = \tanh\,(WhCht{-}1 + WxC\, xt + bC) \quad (5)$$

The value of the hidden state is calculated as:

$$ot = ht \odot \tanh\,(Ct) \quad (6)$$

3.1.1 Activation Function-ReLU

ReLU is one of the most widely used activation functions in deep neural networks. Because it is parameter-free and non-saturating, it is favored because it accelerates the convergence of stochastic gradient descent (SGD) [29]. Comparing ReLU to saturated activation functions like sigmoid and tanh, LSTM performance has shown notable improvements. It converges faster and more precisely by keeping positive values and removing negative inputs. This enables efficient propagation of gradients during training. ReLU also solves the vanishing gradient problem and provides a straightforward operation because the derivative remains constant on the positive side.

Fig. 1.Graphical representation of ReLU activation function.

3.1.2 L2 regularization

In order to reduce generalization error, this strategy modifies the loss function to apply penalties on excessive weight values. By preventing the weights from growing excessively, this modification helps keep the deep neural network from becoming more susceptible to noise. With L2 regularization, the cost function is provided by:

$$\tilde{l}(w, X) = l(w, X) + \lambda R(w) = l(w, X) + \lambda \sum i\, |w2| \quad (7)$$

Here, λ represents the regularization strength, (w, X) and $R(w)$ are cross-entropy loss function and a convex function respectively.

3.1.3 Dropout

With a probability of p, dropout randomly eliminates neurons from the network, altering the connections within it in contrast to L2 regularization, which penalizes large weight coefficients. In order to promote more robust learning, this method seeks to stop co-adaptation among the deep neural network's hidden nodes [30]. The fundamental idea behind dropout is to randomly deactivate parts of the model at each training cycle. This is the expression for the dropout function:

$$qj = \sum i\, WijVixi + bi \quad (8)$$

Here, Vi = Bernoulli random variables independent vector. For Vi = zero, its corresponding input node xi is excluded from the computation.

3.1.4 Adam optimizer

An extensively used technique for deep neural network training is the Adam optimizer, which combines the RMSProp and momentum-based gradient descent algorithms [31, 32]. In order to update the weights in a

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DNN, it can successfully replace the conventional SGD technique. This technique simply needs a few hyperparameters to be adjusted, and it uses less RAM.

Additionally, updates to the parameters ensure a bounded norm. As a result, Adam optimization finds extensive application across various deep neural network tasks [33].

3.1.5 Softmax layer

Determining the likelihood that an input belongs to a specific class is the responsibility of the final layer in the DNN. It measures the difference between the true label (p) and the predicted label (q) during training using the cross-entropy loss function. This function is used as follows in order to update the weights w and biases b:

$$h(p, q) = -\sum i\, p(x) log q(x) \ldots \quad .(9)$$

4. RESULTS AND DISCUSSIONS

To train the LSTM network, several parameters were systematically changed to maximize performance throughout both training and testing. This experiment involved a number of trials to evaluate the performance of the proposed model. During the evaluation phase, we made improvements to our system by modifying a few parameters, including the hidden layer configuration, epoch count, batch size, and initial learning rate (LR).

Reliability was evaluated using precision, sensitivity, specificity, and accuracy. The input layer in a three-layer model (input layer, one hidden layer, and output layer) maintains a fixed number of nodes

5. CONCLUSION

In this work, an LSTM network based on gait patterns is presented for the early and noninvasive diagnosis of Parkinson's disease. The LSTM is adept at identifying long-term dependencies in time series data and is ideally suited for sequential data processing.

The sample sizes for the inputs vary, so we divided the input frame into two parts to normalize it for the LSTM network. Data overfitting is successfully reduced by incorporating dropout in addition to L2 Regularization techniques, as demonstrated by accuracy and loss charts. PD detection is treated as a binary classification problem in the study by classifying PD and healthy participants using an Adam optimizer. The performance of the LSTM classifier is assessed using key metrics, including precision, sensitivity, specificity, and accuracy. It outperforms SOTA in the diagnosis of Parkinson's disease based on gait.Because of its exceptional sensitivity of 99%, which indicates a very low percentage of false negatives, the suggested LSTM-based model performs exceptionally well. Additionally, the overall accuracy is 97.71%, which is remarkably high, and a specifity 96%.

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