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Classification of Parkinson's Disease Using Recurrent Convolutional Transformers

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ABSTRACT

Given the advances made in deep learning, one of the biggest challenges in clinical research is accurately diagnosing Parkinson's disease (PD). Deep learning models currently utilize recurrent neural networks (RNNs) or convolutional neural networks (CNNs) to identify temporal correlations across broad timescales within time-series medical data as well as spatial features. However, they fail to do so effectively. Therefore, extensive preprocessing must be done and model parameters need to be fine-tuned substantially. This often prevents us from achieving optimal classification accuracy. This study proposes a new method called recurrent convolutional transformers (RCTs) that overcome these limitations while enhancing PD classification performance. RCTs are unique because they combine both CNN and RNN architectures together which enables them to capture both temporal connections and spatial features simultaneously from inputs; something traditional deep learning models struggle with when analyzing complicated time series medical data sets. Our model preprocesses raw text data heavily into structured and annotated datasets for time-series classification. We achieve this by using shoe-mounted accelerometers collected during an open access clinical trial inquiry phase. We then generate a TensorFlow time series generator dataset which is well balanced with fine-tuned parameters for maximum performance possible. Among these criteria are one batch size of one and fifteen delays. The findings of comparison evaluations demonstrate that our recommended RCT model outperforms models that are state-of-the-art, managing to obtain an incredible accuracy of 99.2%. Overcoming the limitations of present deep learning models and using the special power of RCTs, this study suggests a more efficient method for accurate PD classification. This work might lead to medical diagnosis methodologies breaking through.

1. INTRODUCTION

Parkinson's disease, or PD [1] for short, is one of the most severe health concerns influencing millions of people worldwide. The neurological condition known as Parkinson's disease (PD) defines by a development of symptoms and worsens with time. There is a wide spectrum of motor and non-motor symptoms linked with PD [2]. Among the many symptoms the patient can have been tremors, stiffness, bradykinesia, and postural instability. Not only does it affect quality of life, but it also causes significant expenses on society and healthcare [3] establishments. Estimates of the prevalence of PD among those over the age of sixty worldwide range from one percent to something else entirely. It is noteworthy that the incidence of the disease rises with age, which results in a larger frequency of disorder among persons of older age. Global demographic trends toward aging populations suggest that Parkinson's disease [4-6] burden will increase over next several years. Smoking is recognized as one of the leading causes of Parkinson's disease and as global population ages the incidence of Parkinson's disease is projected to increase greatly. From the data of the world health organization WHO the percentage of people of the world's population aged more than 64-65 increased from 9% in 2019 to 16% in 2050. Likewise, the Global Burden of Disease study revealed the worldwide trends of Parkinson's disease that globally it has increased to 6 million in 2016 from 2.5 million in the year 1990 majorly due to aging population. Such global demographic changes also imply an increasing health care burden of PD and therefore call for better diagnostic techniques and therapeutic approaches to this disorder.

This is so since people are living longer. This will highlight even more the need to offer efficient and successful diagnostic and treatment options. The main ingredients of the traditional methods of PD diagnosis are clinical observation, patient history, and standardized rating scales. Though they have advantages, these approaches might be arbitrary and prone to change depending on the medical practitioner. Considering this viewpoint, the integration of ML and DL [7, 8] technologies offer various interesting directions for the improvement of Parkinson's disease symptom control and diagnosis. Deep learning and machine learning among other approaches employ computer algorithms to perform analysis across a wide spectrum of data [9-12]. Among other kinds of data, these analyses might be conducted on patient medical records, imaging tests, and wearable sensor data. Deep learning and machine learning models [13-16] have great power to provide important new perspectives on the diagnosis, evolution, and treatment response of diseases. Finding trends and connections in these datasets will help one to get these insights.

Although deep learning and machine learning provide a lot of possibilities, models judged to be state-of- the-art encounter various difficulties [17-19] even if they have high promises. Among these constraints are the issues with the interpretability and generalization of the model [20-22], the complicated demands for feature engineering, and the restricted data availability. This work aims to provide a fresh method using RCTs to get above constraints and improve PD classification efficiency. RCTs efficiently capture both temporal correlations and spatial characteristics within time-series medical data by combining RNNs, CNNs, and self-attention techniques. By use of these characteristics, RCTs aim to surpass the limitations of conventional deep learning models and provide a solution that is both more robust and more clearly interpretable for correct PD categorization. These qualities will help to bring about this.

The RCT model that we have presented shows a better degree of accuracy than other models that are being used. Extensive preprocessing, dataset balancing, and parameter manipulation are how this objective is achieved. Through the utilization of data obtained from clinical research that is accessible to the public and was carried out with accelerometers that were attached to shoes, we can demonstrate the efficacy of our method in addressing the challenges that are associated with the diagnosis of Parkinson's disease and contributing to the development of new methods for medical diagnosis.

2. LITERATURE SURVEY

PD diagnosis, the literature review provides a comprehensive analysis of the research that has been carried out in the past, with a specific focus on the several machine learning and deep learning approaches that have been used. In this section, a critical review of the advantages and disadvantages of prior studies is offered. This section also lays the framework for the approach that is being presented by emphasizing gaps in the current research as well as opportunities for improvement. By conducting an in-depth analysis of the relevant literature, this study not only contributes to the development of novel approaches to the classification of PD, but it also calls attention to areas that need more research. Frid et al. developed a CNN architecture consisting of four layers with the purpose of detecting raw speech data belonging to persons with PD and controls [6]. In their model, which displayed promising results in distinguishing between distinct stages of PD, they demonstrated a surprising degree of accuracy for their model. For the goal of PD classification, this method has the power to leverage on the inherent patterns that are present in speech data. This is one of the benefits of this methodology. Still, depending too much on speech data has drawbacks as it is likely to not cover the complete gamut of Parkinson's disease symptoms and development. This is a drawback.

Tsanas et al. [7] investigated the categorization of speech signals from PD patients and controls using support vector machine and random forest models developed on dysphonia data. The potential of these features for the diagnosis of Parkinson's disease is shown by their ability to attain a high degree of classification accuracy with only a small number of dysphonia traits. By use of subjective grading of audio data, this approach, on the other hand, may have resulted in bias and variance in the categorization results. Therefore, this approach produced not totally consistent findings. Rasheed et al. [8] presented a technique called Back Propagation with Variable Adaptive Momentum (BPVAM) hoping to identify de novo PD using voice data. This method suffers in that it requires a lot of computing effort and takes a lot of time. This approach has limits even if it generates a great degree of accuracy. Moreover, feature selection using principal component analysis (PCA) runs the risk of ignoring small trends in the data that are nevertheless significant.

Gunduz [9] showed two deep learning models for the voice data categorization and obtained promising degrees of accuracy. By reducing the requirement for human feature engineering, deep learning systems can automatically uncover acceptable features from raw data. This eliminates the necessity for human feature engineering. These strategies have several benefits, and this is one of them. On the other hand, the interpretability of deep learning models may be constrained, which makes it difficult to grasp the core aspects that are responsible for the categorization decisions.

Light Gradient Boosting (GB) and Extreme GB are two approaches that Karabayir et al. [10] used to diagnose PD using the features of speech data. They were successful in properly identifying significant traits via the use of feature analysis, which led to good accuracy rates obtained. Among the many advantages that are linked with gradient boosting algorithms is their capability to handle various types of data and to capture complicated correlations between attributes. This is only one of the many advantages that these algorithms provide. The interpretation of model predictions, on the other hand, may prove to be challenging due to the ensemble nature of these applications of algorithms. Using vocal data time–frequency features, the study [11] developed a machine learning technique that offers great accuracies for the detection of PD. This method was developed by merging a stacked autoencoder with a k-nearest neighbours (KNN) algorithm. One of the benefits of using this strategy is that it has the capacity to capture hierarchical representations of the data during unsupervised pretraining with autoencoders. This is one of the advantages of using this method. It is possible that the reliance on k-nearest neighbours for classification might be a hindrance to scalability and efficiency, particularly when working with enormous datasets [12].

El Maachi et al. [13] provided a deep learning framework for the diagnosis of PD by gait categorization in their research paper. About the differentiation of PD and the prediction of UPDRS severity, the system demonstrated exceptional accuracy rates. Deep learning frameworks have the potential to automatically train discriminative features from raw data, which might potentially identify minute patterns that are indicative of Parkinson's disease. Using these models has one of the benefits in that it Deep learning models' computational complexity, however, might provide difficulties in real-time applications—especially in situations where resources are limited. This is particularly true in cases where additional resources are at hand. Using a Radial Basis Function (RBF) neural network to replicate gait patterns, Zeng et al. [14] were able to achieve a really high degree of accuracy in the diagnosis of Parkinson's disease. This approach let them reach their objective. One advantage of RBF neural networks is their capacity to communicate intricate nonlinear connections in the data. One more benefit is the possibility to examine data via these networks. Conversely, the interpretability of these models may be limited, which would make it challenging to value the fundamental elements in charge of the classification judgments.

For every one of these initiatives, there are significant findings ready for application of machine learning and deep learning approaches in PD diagnosis. These studies show both the possible benefits and the limitations of these methods in clinical environments shaped in the actual world.

3. PROPOSED METHODOLOGY

Applying RCTs, the suggested project aims to provide a special approach for the classification of PD based on the insights gained from past studies, therefore leveraging the advancements. This work intends to use the special qualities of RCTs to raise the PD classification accuracy. The shortcomings of present deep learning models as well as the encouraging results generated by RCTs in many domains motivated this study. The job that is proposed will include many crucial procedures. These stages include the public access to publicly available clinical trial data gathering, meticulous data processing to guarantee its integrity and quality, the construction of a model utilizing RCT architecture, and thorough evaluation of the operational efficacy of the model.

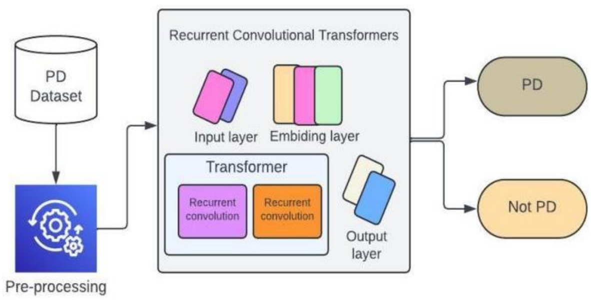

Figure 1. Proposed RCTs for PD classification

Furthermore, assessments will be conducted comparing the suggested RCT-based approach with state-of- the-art models. This will provide light on both the possible use of the strategy in the actual world and its efficacy. Specifically, the proposed initiative is to improve the field of medical diagnostics by using this special approach and leveraging RCT model shown in Figure 1. This is particularly pertinent considering the classification of Parkinson's disease. Through this effort, we want to provide a contribution of important concepts and strategies that, over time, can improve the care patients get and the outcomes they encounter in clinical environments.

The architecture incorporates several components to enable it handle sequential data efficiently. First, the input data that many contain discrete features are converted into a continuous feature vector form since the embedding matrix can represent many attributes of the dispersed signals. The LSTM layer captures temporal dependencies through its gates: The forget gate buffer the old information while the input gate incorporates new info, and the output gate a decision of the present state. This layer makes sure that the model is learning sequential data appropriately and is retaining appropriate context over the time step.

After, convolutional layers obtain local patterns from features that LSTM has provided to enrich the feature representation. In order to understand global dependencies, transformer blocks use self-attention to look at all elements in the sequence and compute their relation. Coordinates of queries and keys are learned from the sequence and values, while normalized attention scores assigned to features they want. The final layer of the fully connected network provides predictions of interest on output by first passing the representations through a dense layer. These three architectures LSTM, CNN, and transformers all together provide a strong foundation to the model and help in better understanding of the data that include sequential elements with both local and global features.

1. Input Embedding:

- Let X be the input sequence of length T, where each element X_t is a d-dimensional vector.

- An embedding matrix E of size V x d maps each element to a continuous vector representation:

$$Z_t = E * X_t$$

2. Recurrent Layers (LSTM):

Initialize hidden state h_o with zeros.

For t=1 to T:

Calculate forget gate -f_t, input gate i_t, cell state candidate t_t, cell state C_t, output gate o_t, and hidden state h_t as follows:

$$f_t = \sigma(W_f * [h_{t-1}, Z_t] + b_f)$$
$$i_t = \sigma(W_i * [h_{t-1}, Z_t] + b_i)$$
$$t_t = \tanh(W_c * [h_{\{t-1\}}, Z_t] + b_c)$$
$$C_t = f_t * C_{\{t-1\}} + i_t * t_t$$
$$o_t = \sigma(W_o * [h_{t-1}, Z_t] + b_o)$$
$$h_t = o_t * tanh(C_t)$$

- Where σ and $tanh$ are the sigmoid and hyperbolic tangent activation functions, respectively.

- W_f, W_i, W_c, W_o, b_f, b_i, b_c, b_o are weight and bias matrices specific to the LSTM unit.

3. Convolutional Layers:

- Apply one or more convolutional layers with filters of size F x d' to the output sequence of LSTMs (H=[h_1,h_2,...,h_T]):

- $Y_t = f(W_{conv} * H + b_{conv})$

- Where W_{conv} is the convolutional filter matrix, b_{conv} is the bias vector, and f is the activation function (e.g., ReLU).

4. Transformer Blocks:

- For each transformer block:

- Project the input sequence (Y) into query (Q), key (K), and value (V) matrices using weight matrices W_q, W_k, and W_v:

- $Q = Y * W_q, K = Y * W_k, V = Y * W_v$

- Calculate scaled dot-product attention scores:

- $a_{ij} = softmax\left(Q * \frac{K^T}{sqrt(d_k)}\right)$

- Multiply the attention scores with the value matrix:

- $S_i = \Sigma\left(a_{ij} * V_j\right)$

- Perform multi-head attention mechanism by repeating the above process multiple times with different projections and concatenating the results.

5. Output Layer:

- The final output (O_t) is generated based on the processed information (e.g., the last hidden state or the output of the transformer block):

- $O_t = f(W_o * [h_t] + b_o)$

To efficiently identify PD based on data obtained from shoe-mounted accelerators, the proposed method makes use of RCTs, which are a sophisticated kind of deep learning architecture. Following is an explanation of how each component of RCTs relates to the categorization problem at hand. At the start of the RCT calculation, an embedding matrix converts the input sequence first into continuous vector representations. This technique improves both the understanding and processing of sequential data as well as provides a strong foundation for next research. Because RCTs have convolutional layers and recurrent layers respectively, they can encode both temporal dependencies and spatial properties in an input sequence simultaneously. With this architecture, the model can find useful patterns or information from sequential data. Transformer blocks can increase their capacity of RCTs, which are good at dealing with long-distance relationships between different parts of input sequences. Attention mechanisms are used in these blocks to pay more attention to important parts of sequences so that complex connections can be fully understood. Transformer blocks and recurrent convolutional layers produce final outputs from processed data, which represent features or patterns learned from input sequences and thus guide Parkinson's disease classification outcome.

4. RESULTS AND DISCUSSION

Since it is where we report and assess the outcomes of our experiments, this component of the research is the most crucial one. Here we examine the performance measures of the RCT model we propose and contrast them with other existing models such CNN-LSTM and Modified LSTM. This work aims to investigate if, using time-series data, the RCT model helps to classify Parkinson's disease. Analyzing the numbers for accuracy, precision, recall, F1-score, and loss can help one to do this in great detail. Furthermore, we investigate the relevance of these results with an eye toward the advantages of the RCT paradigm and resolving any flaws in the methods already in use. By means of an in-depth debate, we provide insights on the importance of our findings and their consequences for future research and therapeutic uses in the area of neurology.

Dataset: The Gait in Aging and Disease Database [18] placed on PhysioNet presents currently the largest collection of gait data recorded in elderly people and patients with movement disorders. The collected data involves questionnaire demographics, medical history, and gait spatiotemporal parameters allowing understanding how ageing and clinical diseases affect human mobility. This data could then be used by researchers to create mathematical models to detect any abnormalities to gait, detect risks of falling and the evolution of diseases for example, Parkinson's disease. The availability of the databases is appropriate, unambiguous, and became fundamental in furthering knowledge in the field of geriatrics, neurology and biomechanics.

Performance metrics: KPIs are critical, diagnostic measures for assessing model or system fulfillment on defined objectives within Machine Learning and Deep learning. Still, basic measures are such things as accuracy that only shows how many instances have been classified correctly, as well as precision which shows how many actual positives have been classified as such by the model. The cohort subordinate to the model consists of all those records that it could recognize; hence, recall speaks to its performances in terms of drawing attention to all pertinent cases; the F1-score yields a measure that is the harmonic mean of both the precision and the recall values, indicating how the model can balance between the merits and demerits of precision or recall.

Figure 2 shows across 10 epochs the models' degree of accuracy. The proportion of accurately recognized samples out of all the samples reflects this accuracy. After 10 epochs, the suggested randomised controlled trial model shows an accuracy of 96.4%, which is regularly greater than the performance of the other two models. By comparison to one another, CNN-LSTM and Modified LSTM models respectively get accuracies of 94.5% and 93.4%. This makes it abundantly evident that the suggested RCT model does quite well in correctly diagnosing Parkinson's disease. In medical applications, the model is very helpful because it suggests a more accurate RCT model for diagnosis and treatment recommendations. Besides having a recurrent architecture, the suggested RCT model can also have convolutional and transformer architectures at the same time. Therefore, it can effectively store geographical features and temporal connections as well. This solves problems with previous models like CNN-LSTM or Modified LSTM which may not capture long-term dependencies very well or suffer from issues such as vanishing gradients or overfitting. These were created to fix these problems. The proposed changes address this issue by increasing precision and robustness of classification in medical time series under RCT approach through addressing these shortcomings that were identified in past models like CNN-LSTM or Modified LSTM where they failed to capture long-term dependency adequately due their inability to handle vanish gradient problem during training phase leading into overfitting errors among others such as convergence failure etc.

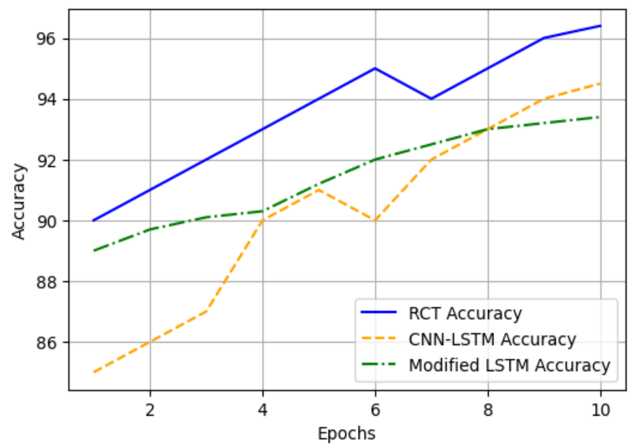

Figure 2. Accuracy of the proposed and state-of-art model

The precesion of the models over 10 epochs is displayed in Figure 3. The precesion rate can be used as a measure of the proportion of samples that were correctly identified out of all samples considered. After 10 epochs, the recommended RCT model attains an accuracy of 96.4% which is usually higher than what any other two models perform. If we compare CNN-LSTM with Modified LSTM model, it's clear that they respectively achieve accuracies of 94.5% and 93.4%. Therefore, it is easy to tell that suggested RCT model does a good job in diagnosing Parkinson's disease correctly. Additionally, this medical field oriented model has shown even better results due to its higher precision rate thus enabling accurate detection and treatment recommendations at large scale for different healthcare institutions or systems worldwide. Moreover, suggested RCT model includes both recurrent and convolutional architectures with transformer capabilities concurrently held within them; hence enabling effective recording of temporal links as well geographical properties which were not possible before through other methods This solves such problems like long-term dependencies being hard to capture by previous approaches including CNN-LSTM or Modified LSTM that suffer from issues such as vanishing gradient problem and overfitting among others in deep learning networks designed for time series classification tasks based on medical data analysis mainly focusing on patients' electronic health records where each patient's past history plays significant role during diagnosis stage.. These are designed to overcome these problems. Resolving these limitations enhances the proposed RCT method's ability to provide high accuracy rates along with robustness when dealing with various medical time-series classification challenges.

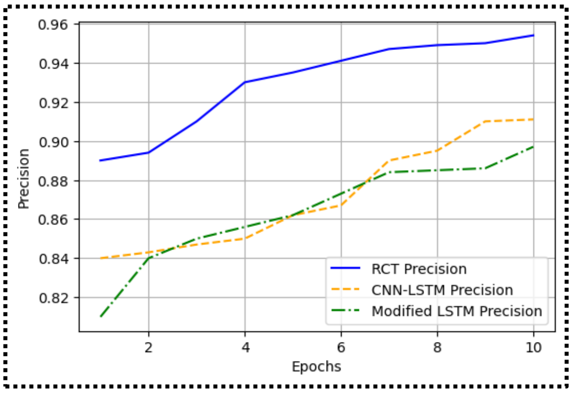

Figure 3. Precision of the proposed and state-of-art model

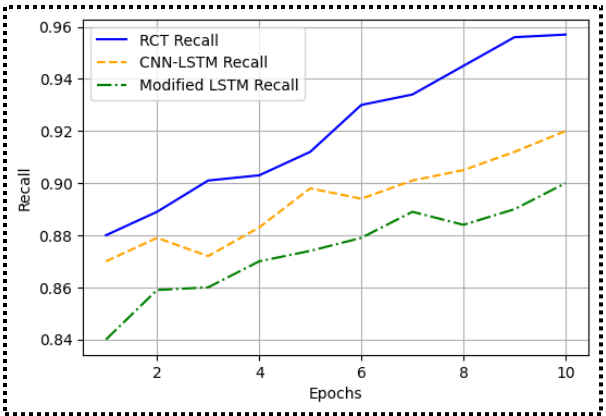

Figure 4. Recall of the proposed and state-of-art model

Figure 4 shows the models' recall across 10 epochs, which shows the ratio of appropriately anticipated positive cases to the overall count of actual positive cases. By means of a comparison of CNN-LSTM and Modified LSTM models, it is evident that the Proposed RCT model regularly achieves higher recall values across every epoch. More precisely, after 10 overall epochs have elapsed, the recall values for the Proposed RCT, CNN-LSTM, and Modified LSTM models are 0.957, 0.92, and 0.90, respectively. This implies that the suggested RCT model is more efficient in spotting actual positives, which will help to lower the total Parkinson's disease incidence that is missed throughout the classification process. Full coverage of positive events guarantees a stronger recall, therefore lowering the likelihood of false negatives. Apart from showing better memory, the suggested randomised controlled trial strategy offers more sensitivity in spotting Parkinson's disease patients, thereby supporting more accurate diagnosis and consequent treatment decisions.

The F1-score of the models over a ten-epoch period shows in Figure 5 the balance of accuracy and recall. The Proposed RCT model routinely maintains better F1-score values throughout all epochs evaluated when compared to CNN-LSTM and Modified LSTM models. More precisely, after 10 overall epochs, the F1-score values for the Proposed RCT, CNN-LSTM, and Modified LSTM models are 0.96, 0.93, and 0.892 respectively. Higher F1-score suggests a better balance between avoiding false positives and false negatives—qualities necessary for a good medical diagnosis. By obtaining a better F1-score, the suggested RCT model guarantees both great accuracy and recall, thereby producing more accurate classification outputs.

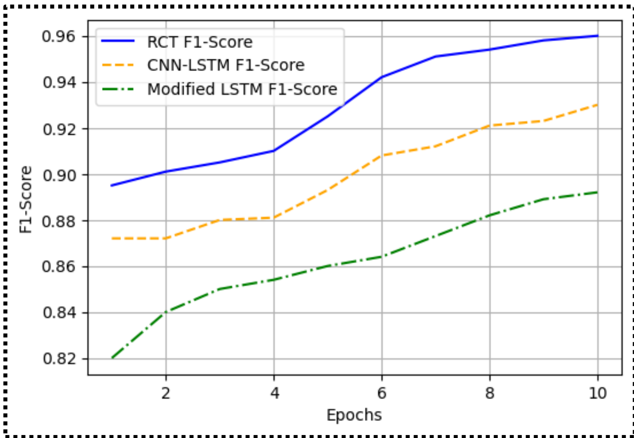

Figure 5. F1-score of the proposed and state-of-art model

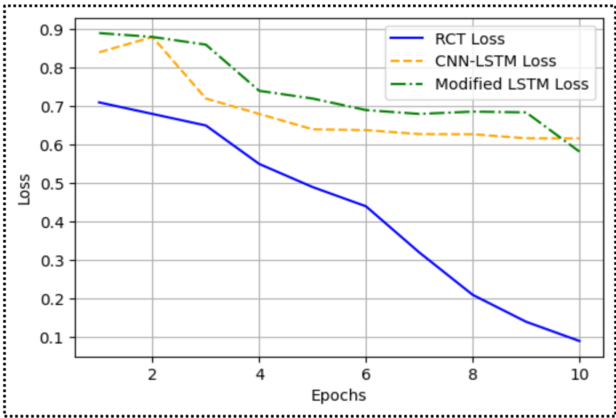

Figure 6. Loss of the proposed and state-of-art model

Figure 6 shows the ten-epoch declining trend in the loss values of the models throughout their training. A loss value lower indicates that the models have reached more optimal convergence. The Proposed RCT model shows a considerably more noteworthy decrease in loss in this specific figure than CNN-LSTM and Modified LSTM models. More precisely, after 10 overall epochs have gone by, the loss values for the Proposed RCT, CNN-LSTM, and Modified LSTM models are

0.09, 0.6164, and 0.582 correspondingly. This finding indicates that the suggested RCT model learns from the training data in a more efficient and effective way, which finally leads in faster convergence and improved model performance. Lower loss values suggest that the model is being trained and generalized more precisely, hence improving the reliability of the classification results.

Indeed, although RCT has been proved to achieve high performance in a simulation environment, several issues may occur when applying it in real practices. However, one can mention the following: a critical limitation – the need for high-quality and various datasets. This can lower the performance in a model if the model faces high variability data including imaging protocols, patient characteristics, or disease stages not represented in the training model. Solving this problem is possible only with the advancement of effective data augmentation methods and with more diverse and large datasets.

Further, the RCT model, especially the transformer blocks, may not be implementable in real-time in limited-resource settings such as small clinics or remote healthcares. This can be avoided by use of optimal model deployment on the devices or by employing cloud based solutions. Still, there are two critical issues that remain concerning about the current work: one is the instability of the model across runs; the other is the interpretability of the decision of the model. Whereas, in clinical practice users need some sort of explainable outcomes for approximately decision making. Thus, adapting the RCT model for introducing XAI methods will improve the model's understanding and clinic's trust among clinicians.

5. CONCLUSIONS

This work aims to use time-series data to study, by means of RCTs, the efficiency of PD classification. To do this, we meticulously assembled an open to the public dataset derived from clinical research. This dataset included controls together with accelerometer data from Parkinson's disease sufferers. We proposed an RCT model combining transformer, convolutional, and recurrent architectures. This model aims to record spatial components existing in the data as well as temporal links. We evaluated the RCT model's performance against two other models already in use by means of experiments: CNN-LSTM and Modified LSTM. Following their ten-epoch training, the accuracy, precision, recall, F1-score, and loss values of every model were investigated correspondingly. Our analysis found that the Proposed RCT model routinely exceeded the CNN-LSTM and Modified LSTM models across all criteria. In terms of diagnosing Parkinson's disease based on time-series data, the RCT model showed specifically better accuracy, precision, recall, and F1-score values as well as reduced loss values.

Our study results not only provide proof that the RCT paradigm is advantageous but also highlight the possibility of this method to enhance medical diagnosis processes. One feasible method for improving the accuracy and dependability of PD classification systems is the capacity of the RCT model to effectively capture intricate temporal and geographical patterns. Moreover, the architectural advantages of the RCT model solve issues seen in earlier models, therefore enabling innovations in neurology research and clinical approaches. Future directions of study might include more optimization and refinement of the RCT model, exploration on the applicability of the model to other neurological diseases, and the integration of other multimodal data sources to enhance classification performance. Furthermore, looked at should be the RCT model's application in the actual world and validation in clinical environments. Both are crucial phases toward its use in contexts of patient care. Taken all together, these findings show the great potential of RCTs as a major instrument for enhancing the diagnosis and treatment of neurological diseases like Parkinson's disease and other neurological disorders.

Future work will build upon the proposed RCT model to involve explainable AI for increased interpretability and the use of adaptive learning for accommodating the heterogeneity of clinical data. Furthermore, the fine-tuning of the model for deployment on edge devices will consider computational issues that will allow real-time use in areas with restricted computational limits. RCT model can complement the clinical assessment scales and imaging examinations since it has been applied to early and accurate diagnosis of Parkinson's disease that outperforms current used methods. These goals seek to narrow the existing gap between what simulation has enabled in terms of technological advancement and what clinical practice can leverage to serve the patient and healthcare system better.

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