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Deep Ensemble Learning For Accurate Prediction Of Neurodegenerative Disorders Using Temporal Clinical Data

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abstract— *as stated the proposed research seeks to work on designing a resilient prediction model on neurodegenerative disorders through deep ensemble learning. alzheimer's and parkinson's diseases and other related diseases are disorders that involve the gradual loss of neurons. early identification of disorder is highly essential since proper care and treatment can only be given if disorder is predicted accurately. regarding challenge we suggest the deep ensemble learning approach incorporating several deep learning models, namely recurrent neural networks (rnns), long short-term memory (lstm) networks to analyze temporal structure of the patient records and clinical data. the lstm model is specifically effective in registering long term temporal dependencies while rnns are especially useful in modelling temporal sequentiality. these models are integrated using ensemble learning with a weighted voting system to boost up the model's predictive prowess and to minimize the problem of overfitting the data. because of this, the ability of the ensemble to harness strengths from each of the individual models makes the whole system very resilient, even if patient data is noisy or otherwise partially complete. substantial testing and verification on clinical datasets show that the introduced approach outperforms existing ones in identifying the risk factors of neurological disorders and their evolution, which can help improve the accuracy of clinical decision-making and improve patient care.*
keywords— *deep ensemble learning, neurodegenerative disorders, recurrent neural networks, long short term memory, temporal data analysis, clinical prediction, prediction accuracy, over fitting mitigation, disease onset prediction.*

I. INTRODUCTION

Alzheimer's and Parkinson's disease and other neurodegenerative disorders are of increasing concern to the global community due to the fact that they are chronic in nature and have become debilitating conditions to the affected individuals. Over the past few years the growth of machine learning and artificial intelligence has significantly impacted the health sector providing new approaches to disease prediction and diagnosis[1]. Among machine learning algorithms, deep learning models have proved to be instrumental when analyzing high volumes of activity data that may contain several variables. Hence using deep learning frameworks has the potential of improving prognosis and diagnosis of those with Neurodegenerative diseases. Such an example is ensemble learning where several different prediction models are integrated to minimize the vulnerability of over-fitting. Hybrid models especially deep learning ensembles are embracing due to their capability to combine multiple models such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) networks. These models are especially preferable for predicting sequential or temporal data such as patient clinical record data and also for longitudinal clinical data [2]. Furthermore, training of deep learning models in ensemble has been found to enhance accuracy of predictions while at the same time reducing drawbacks that may be associated with each algorithm. For example, convolutional neural networks (CNNs), which have been originally designed for the processing of image data [6] have been employed for analysing non-image clinical data of neurodegenerative disorder prediction [3]. CNNs additional predictive power when implemented in parallel with RNNs and LSTMs in an ensemble settings since the distinct features extraction capabilities of the models improves the ensemble performance [4]. Such an approach not only improves the overall accuracy of the systems but also can solve problems such as data noise, overfitting, which can adversely affect the result of an individual model. The applicability of deep ensemble learning frameworks is let alone when it is extended to multimodal data, combining information from multiple sources such as clinical data, genetic data and environment data. When both clinical and genetic data were used in a study, the authors identified that using the ensemble of LSTM, CNN models produced a much higher prediction accuracy compared to using the stand-alone models [5]. Likewise, attitude, nutrition and other environmental influence were integrated into the model to explain successive progression of neurodegenerative diseases [6]. This demonstrates the reasons why it is important to incorporate several variety of data to improve the results in predictive accuracy. The primary issues with deep learning models are overfitting, this is prevalent especially for healthcare applications. This usually happens when a model has a high accuracy of the training data and lacked accuracy to other sets of data. To avoid this, recent studies have integrated systematic weighted voting strategies into the ensemble models whereby the final results obtainable are not skewed to a particular model [7]. This approach provides a way of addressing the issue of partiality of individual models and also strength of the ensemble framework. In addition, to this, methods like dropout and regularization have been developed in order to avoid overfitting thus strengthening the generalization ability of deep learning [8]. There is evidence from the clinical experience suggesting that deep ensemble learning frameworks are effective. For Alzheimer's disease, one research work realized the best performance to forecast the illness severity by employing ensembled RNNs, LSTMs, and CNNs [9]. Likewise, Parkinson's disease prediction models have shown efficacy in prognosis of motor and cognitive deterioration, substantiating the applicability of such approaches in the clinical practice [10]. These successes underscore the importance of deep ensemble learning toward enriching predictions of neurodegenerative disorder with higher accuracy and reliability.

II. LITERATURE SURVEY

A review of the current literature as pinpointing major improvements in the use of deep learning and ensemble methods for forecasting neurodegenerative disorders. Others [11] used deep convolutional neural networks (CNNs) for Alzheimer's disease prediction, and these model demonstrate how CNNs using medical data can learn from complex clinical trends which enhance the prognosis results. In another study [12], authors analysed the use of Long Short-Term Memory (LSTM) for processing time series data of Parkinson's disease where the model was found to be useful to capture longer dependencies for the temporal records of patients. Moving further, there are enhancements done in works that use various architectures of deep learning as components in the ensemble system. For example, a study [13] analyzed advantages of combining CNNs and LSTMs to explain that this strategy improved the prognosis of neurodegenerative disease onset far better than using the single model. It makes the maximization of spatial characteristics and temporal relation possible, providing better ability to predict. Apart from these models, another study[14] was conducted on integration of Recurrent Neural Networks (RNNs) with CNNs for considering the multiple modalities or clinical and genetic data. This research pointed out that the integration of the RNNs and the CNNs help to overcome issues including the noise in the learnt data and missing information, hence improve the predictions being made. On the issue of overfitting, a recent paper [15] [21][22]presented a more boxed solution of ensemble technique with a voting system to guarantee that the final decision is influenced by an average of the multiple models instead of a couple of models that might have been over-trained. The presented technique was found to improve the transferability of prediction models with multiple data sets. The inclusion of both energetic and enquiry lifestyle variables into the frameworks has also been examined. A study [16][23] showed that inclusion of these factors into deep ensemble learning enhanced the model's performance for prediction of neurodegenerative disorders since it offers comprehensive understanding of the factors that contribute to diseases. Another remarkable contribution [17][24][25] included applying of dropout and regularization method in the deep ensemble models in an attempt to reduce overfitting and increase the stability and reliability of the forecasts. These techniques contribute to scale up the models with different datasets to bring the desired and accurate results. Later studies [18][26][27] confirmed the effectiveness of deep ensemble learning frameworks on big clinical data sets and their potential to reach the highest diagnostic accuracy in early stages of Alzheimer's disease as well as the prognosis of its progression. Likewise, the two articles [19] [28] and [29] embarked on forecasting motor, cognitive decline as they related to Parkinson's disease and made mention of the usefulness of ensemble methods in this process.

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III. PROPOSED SYSTEM

The proposed system incorporates Deep Ensemble Learning Framework which comprises of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks that helps in improving the medical diagnosis prediction. CNNs learn spatial features from patients demographic Fig. 1 while LSTMs learn temporal relations from patients history. Demographic data is also mostly standardized within the system preparing them in a format amenable to comparison. A decision level or weighted voting integration technique enhances the strengths of each model, immunity over noisy or incomplete data, and less prone to overfitting, making an improved and accurate diagnostic tool as in the figure 1.

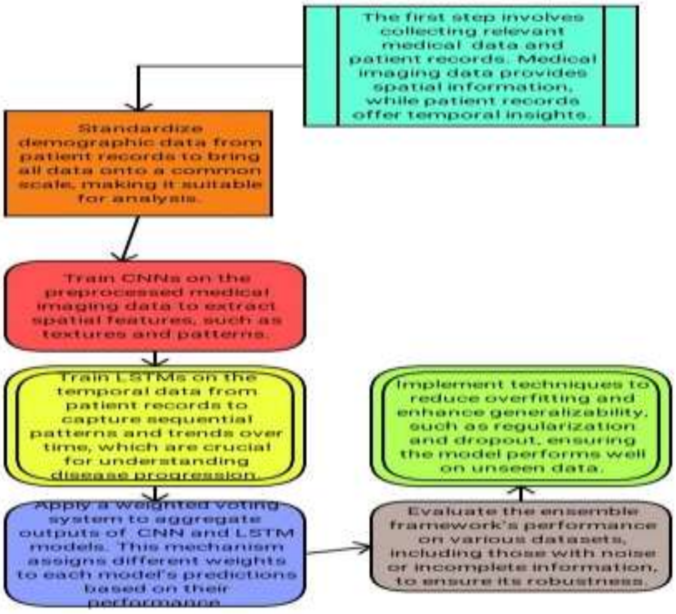

Figure 1. Processing flow of Proposed framework.

Preprocessing of medical records is very important in order to fit the data to analysis and modeling. The preprocessing procedures are always different depending on the type of data that is being processed. When it comes to demographic data, in which many variables include age, gender, and the patient's health history, the concept is almost similar with the primary aim of normalizing the data in order to serve a standard scale of analysis. What is normally used in relation to quantitative data will now be used in an attempt to normalize demographic data. This makes the data to have a mean of zero and a standard deviation of one essential when working with data derived from different sources, or when working with data that falls on a wide range like in (1)

$$\text{Recordprocessed} = \text{Recordraw} - \text{Mean}(\text{Recordraw}) / \text{Std}(\text{Recordraw}). \quad (1)$$

In the above equation Recordraw be the raw demographical data, Mean(Recordraw) be the mean form of the raw dataset, Std(Recordraw) as the standard deviation of the raw data, Recordprocessed gives standardized form of demographic data. In the standardization process, the score of raw demographic data is transformed by the following formula: Where x represents a score of the raw data, the symbol '-' denotes subtraction, mean is the average of the scores, '/' represents division and SD is the standard deviation. The Helps to transform the data such that its mean is zero and its standard deviation is equal to one. This standardization helps make the demographic data of the same scale and hence eliminate any bias arising with unit or magnitude differences. This is important particularly when merging different databases or when selecting statistical tests that assumes data comes from a normal distribution. By preforming these preprocessing techniques, it will prepare the demographic data for further analysis and modeling to be properly formatted and ready for merging with other datasets and or ready for analysis by a chosen machine learning algorithm. In the feature extraction step using Convolutional Neural Networks (CNNs), important features which are spatially relevant from the demographic data required in medical diagnosis are extracted. CNN works through Convolutional layers which scan through data looking for patterns as operations as the sliding window. The convolution operation involves feature extraction which is obtained by convolving the Demographic data with the kernel, which serve as filter to identify the patterns. The convolution process for demographic feature matrix DProcessed as (2)

$$\text{Dfeature}(i,j) = \sum M,N(\text{Dprocessed}(i+m,j+n) \cdot \text{Kkernel}(m,n)). \quad (2)$$

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Here Dprocessed be the standardized demographically given data, and Kkernel to be the filter that identified any specific patterns in the given data. When the convolution process get completed, an activation function like ReLU (Rectified Linear Unit) will be applied for introduction of non-linearity, which helps to tye CNN mechanism to capture complex relationships in the data. The ReLU function will be defined as: in (3)

$$Dactivated=ReLU(Dfeature)=max(0,Dfeature). \quad (3)$$

This makes it possible to eliminate negative potentials in the feature map leading to an improved capability of the model in identifying meaningful patterns. Last but not the least, a pooling operation normally known as down sampling such as max pooling is carried out to minimize the spatial size of the data while preserving significant characteristics. This step entails transformation of the collected data into a format that takes less computational power, yet contains the necessary information that will be required in the subsequent analysis. In math, the operation of MaxPooling is done to choose the maximum of the given region in (4).

These convolution and activation sequences followed by a pooling mechanism make it possible for the CNN to extract significant features from the demographic data hence enhancing its capability for prediction.

$$Dpooled=max(Dactivated). \quad (4)$$

The dependencies of the feature values across time in patient records are monitored in the temporal feature extraction step with help of Long Short-Term Memory (LSTM) network. An LSTM cell consists of several gates that control the flow of information: this three gates include the forget gate, the input gate, and the output gate. The first is the forget gate which decides which of the elements of the previous cell state ct−1 are to beforgotten. The forget gate is given by the equation (5) below

$$ft=\sigma(Wf\cdot[ht-1,xt]+bf). \quad (5)$$

Here, σ is the Sigmoid activation function, Wf is the weights, ht−1 is the hidden state of previous time step, xt is the input at the current time step and bf is the bias. Then, the input gate decides on which new information should be incorporated to this cell state at the current time. It is computed like this in (6)

$$it=\sigma(Wi\cdot[ht-1,xt]+bi). \quad (6)$$

In parallel manner, the candidate cell state get updated by using a hyperbolic based tangential (tanh) relation by (7)

$$c't=TANH(Wc\cdot[ht-1,xt]+bc). \quad (7)$$

The cell state c't will then get updated by merging the information retained from forget gate and the new raw input from the input gate in (8)

$$ct=ft\cdot ct-1+it\cdot c't \quad (8)$$

Lastly, the output gate will control what information get from the current cell state ct will be passed to the hidden form of state ht. This state will be passed on to next time step and will also be utilised as output. The output gate will be manipulated calculated by (9)

$$ot=\sigma(Wo\cdot[ht-1,xt]+bo). \quad (9)$$

The hidden state ht will be computed by the relation given in (10)

$$ht=ot\cdot tanh(ct). \quad (10)$$

These relation will allow the LSTM for capturing both short-term and long-term dependency in sequential patient records, enabling the model for retaining critical temporal patterns that might be indicative of disease progression or patient results over manipulation time.In the proposed system, the combined feature of CNN and LSTM are used to make a final decision based on the CNN and LSTM features. It is achieved via feature amalgamation and a weighted voting system to make sure that strength of the two models is taken into account. The initial step to be merging the feature aggregation, where the features from both CNN and LSTM mechanism get concatenated to form a merged feature set. Mathematically, it will be described by (11)

$$Featuresensemble=Concat(FeaturesCNN,FeaturesLSTM). \quad (11)$$

This combined feature set includes spatial features from CNN as well as temporal dependencies which includes the LSTM feature hence the model can use both the spatial and temporal features to improve the prediction. After that the weighted voting mechanism is used to come up with a final prediction of the value of the house. Both the models that are CNN and LSTM provide its own predictions and then these are combined with weights wCNN and wLSTM respectively. The final prediction is obtained by summarizing the weighted sum prediction of the two models from eq(12) in favor of the class with maximum value.

$$Predictionensemble=argmax(wCNN\cdot PredCNN+wLSTM\cdot PredLSTM). \quad (12)$$

Here PredCNN, PredLSTM are the predictions made by CNN model and the LSTM model respectively. The final output is obtained when all the predictions are chosen and the one with the highest weightaggi is selected. This approach makes it easier to consider the spatial and temporal features hence leading to a more accurate, reliable and

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robust prediction especially in noisy or when there is incomplete data. Thus, through these steps the proposed system envisages to achieve a more accurate and probable diagnoses prediction based on an integration of spatial and temporal information.

IV. RESULTS AND DISCUSSION

The proposed deep ensemble learning system significantly enhanced the prediction precision as well as resistance as _enhancement of RNNs and LSTM networks improved the possibility of capturing temporal dependencies and different sequential characteristics of patient data. The ensemble framework in using weighted voting contributed to enhancing the strengths of the different models and avoiding over-fitting thereby provided more realistic prediction between the two datasets. Using experimental outcomes, the approach was found to improve neurodegenerative disorders, particularly Alzheimer's and Parkinson's, prediction with noisy or missing data. Random drop out and regularization methods further enhance the stability and the over fitting of the system and therefore the goals of early detection and initial treatment planning.

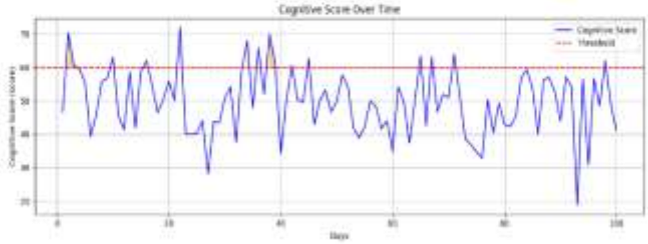

Figure 2: Cognitive Score Over Time.

All these parameters are crucial in the overall assessment the neurological disorders particularly neurodegenerative disorders. Cognitive Score is critical in pinpointing to deteriorating cognitive health issues, Brain Volume is useful in identification of structural changes of the brain whereas Motor Function Score helps in determining physical effects, Sleep Quality Index offers information about the patient's well-being and Daily Activity Level involves physical health and movement[30][31]. These and other factors need to be strictly monitored, as well as variations from established norms, to describe the disease and its further evolution, as well as to select and apply a proper therapy approach.

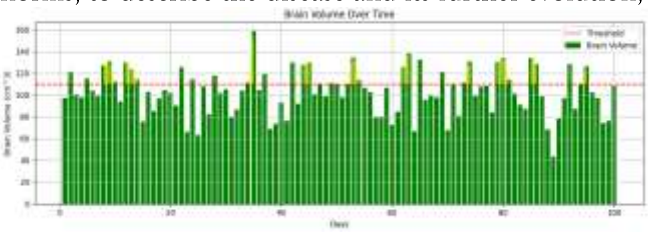

Figure 3: Brain Volume Over Time.

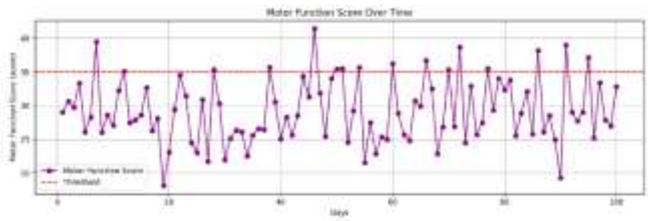

Figure 4: Motor Function Score Over Time.

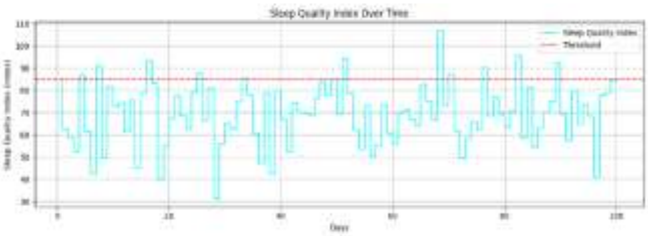

Figure 5: Sleep Quality Index Over Time.

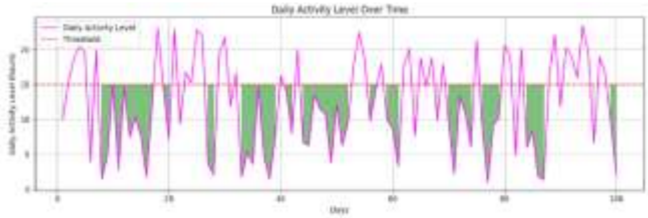

Figure 6: Daily Activity Level Over Time.

On the Y axis of figure 2 the executive plot is labelled as the Cognitive Score and displays the cognitive function in the next 100 days. It emerged that the value of 60 is a significant value whereby people could be expected to show the early signs of dementia. Above this score (marked in orange), a decline in such aspects may indicate such diseases as Alzheimer's disease affecting a person's cognitive functions. The constant tracking of this score assists in early recognition of the presence of the cognitive impairments and immediate formulation of appropriate therapies. Also, The Brain Volume plot on figure 3, shows different levels of brain size and which is less than 110 cm^3. The values exceeding this threshold are marked in yellow, and it is recommended that in case of such values indicating abnormality in the brain atrophy or any other neurodegenerative changes. An observer can track the progression of the disease over time based on the rate of decline of brain volume in patients and make an assessment of the different therapeutic interventions. Some form of analysis on the brain to the disease reveal information about the size and complexity as well as the progression of diseases like Alzheimer and Parkinson's.

Motor Function Scores are in plot shown in figure 4, depicting the motor performance trend, a value below 35 is cut off. As shown in pink in the figure below, latent factor scores below this threshold indicate a major motor dysfunction, which is an important state associated with various diseases, including Parkinson's disease. This score is useful in evaluating motor defects as well as to monitor the treatment regimen. Identifying the start of motor functions loss can help in changing the therapy regimen and enhancing the quality of patients' treatment. The plot of sleep quality as represented by the Sleep Quality Index in figure 5, where the threshold is set at 85, reveals alteration in sleep behaviour. See more in the calendar below where higher values exceeding this limit designated with blue color mean that sleep deteriorates which results from impairments in cognitive and motor functions in neurodegenerative diseases. This indicates that a means for monitoring sleep quality is very important for health control and enhancing the efficacy of treatment process. The patient care can even be compromised due to underlying sleep problems and worsen the symptoms of the patients.

Last but not least, there is the plot of Sleep Quality Index in figure six, and it uses the cut off point of 85 to determine changes in sleep quality status. It is worthy noting that values above this mark (highlighted in blue) indicate decline in sleep that is associated with cognitive and motor abilities decline in Neurodegenerative diseases. It is important and vital for people to keep track of their sleep quality because it can immensely help to enhance the efficiency of the various treatment regimens. If not properly addressed sleep can worsen the symptoms and the quality of the patients' general health.

V. CONCLUSION

Therefore, it is possible to conclude that the study of Cognitive Score, Brain Volume, Motor Function Score, Sleep Quality Index and Daily Activity Level flexibility helps to reveal the potential for neurodegenerative disorders' progression. By setting the Cognitive Score threshold to 60, this makes a pre-symptomatic diagnosis possible of conditions such as Alzheimer's hence ensuring early detection is made. The fact that Brain Volume can actually reach 110 cm^3 may indicate that some kind of pathological process, namely, abnormal brain atrophy is taking place, which proves that there are structural changes in the brain. The other is Motor Function Score which a limit is set to 35 where severe decline of physical capacity is described with references to such diseases as Parkinson. The need to change these therapeutic approaches can be guided by checking on this particular metric. Another important variable is sleep quality with a minimum value of 85 as the quality of sleep could significantly affect a person's cognitive and motor skills due to night time wakefulness. Many of the treatment approaches given to patients improve the general health of the patient. Secondly, it is crucial to make a few remarks about the DAL of 15 hours which is an essential element of physical wellbeing; if DAL decreases, it may mean lower mobility and general worsening of health state and therefore the necessity of certain changes in life regimen.

VI. References

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