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Deep learning and Blockchain-based Essential and Parkinson Tremor Classification Scheme

Jigna J Hathaliya*, Hetav Modi†, Rajesh Gupta‡, *Student Member, IEEE*, Sudeep Tanwar§, *Senior Member, IEEE*
*†‡§Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India
Emails: *19ftphde36@nirmauni.ac.in, †19bce078@nirmauni.ac.in, ‡18ftvphde31@nirmauni.ac.in,
§sudeep.tanwar@nirmauni.ac.in,

***Abstract*—Essential tremor (ET) and Parkinson's tremor (PST) are neurological movement disorders in which ET emerges with body part activation, while PST is recorded in the relaxed position of the patient. The medical symptoms of ET and PST are equivalent, including gait, anxiety, and muscular stiffness. In both disorders, doctors diagnose patients related to clinical evaluations during such hospital visits, leading to misdiagnosis. Machine Learning (ML) is being used to classify the ET and PST using human-based feature extraction to address this issue. Motivated by this, we applied Deep Learning (DL) to overcome the ML issue via automating feature extraction through the model itself. In this paper, we have used the integration of Gated recurrent unit (GRU) and Long short term memory (LSTM) algorithms to predict tremor severity. Initially, accelerometer sensors are used to record tremors in all three axial dimensions for each subject. Further, this data is pre-processed using the standard scalar function and scaled in-unit variance. Furthermore, this data first passed through the GRU model, and later it fed into the LSTM model to improve the model's performance. Moreover, we employed the blockchain (BC) network to validate the performance of the trained model. we have used a smart contract to validate the identity of the researcher. The proposed model outperforms with 80.4% training accuracy and 74.1% testing accuracy. The total communication and computation cost of the proposed scheme is 448 bits and 0.056 ms. The integration of BC and DL makes a system more reliable, transparent, and accurate.**

Index Terms*—Parkinson's disease, Essential Tremor, Parkinson's Tremor, Tremor severity, GRU, LSTM, Blockchain, Smart contract

I. Introduction

ET and PST are tremor-related movement disorders. Tremor is an impulsive, periodic, and repetitive movement that affects human body parts. Tremor is divided into two types: ET and PST. ET occurs while the patient is conducting any type of muscular action, whereas PST occurs when the patient is not performing any type of muscle activity and all of the body parts are in a relaxed state. ET notices the elderly, especially those who are 60 years or older. ET is a movement disorder that manifests as both motor and non-motor symptoms that progresses with time. Medical symptoms such as tremor, rigidity, dystonia, bradykinesia, and gait abnormalities, as well as non-motor symptoms including sleep difficulties, anxiety, cognitive deformity, depression, are similar in both disorders [1].

Currently, during hospital visits, neurologists assess the tremor severity of both subjects including healthy control and Parkinson's disease (PSD) patients. A neurologist conducts a UPDRS III examination, in which patients are asked to complete activities such as resting their arm, extending their arm, and touching their nose with their index finger. Furthermore, a single test often fails to detect the full range of tremors that PSD patients experience daily [2]. This manual diagnosis of the tremor patients is not giving promising results due to similar characteristics of both ET and PST and resulted in a misdiagnosis of the disease. To solve the issue of miss diagnosis, Many authors have used ML and DL techniques to identify the ET and PST from the collected dataset.

Moon *et al.* [3] developed a classification strategy in which ET and PST are classified using ML techniques for an efficient identification. This ML technique is having the issue of human-based feature extraction, that solved using the DL technique. DL can remove the human-based feature extraction method to improve classification results [4][5]. Later on, Hssayeni *et al.* [2] presented a scheme to identify PST using DL-based model. They have used ensemble ML-based gradient boosting and DL-based LSTM model for tremor classification. In this scheme, they have given the comparison of high correlation and ordinary correlation among expected and medical examination tremor scores. Their scheme provides an optimum solution in real-time monitoring of the different tremor-related movements but they have not classified the ET and PST based on characteristics of tremor. To solve this issue, [6] proposed a classification scheme of ET and PST using a convolutional LSTM algorithm. They tested on the merged position of both tremors to improve the performance of the model, but they did not specify the training and testing accuracy of their model to prove the correctness of their model.

To address the aforementioned issues, we have used a DL-based model for the classification of ET and PST. we have used the integration of GRU and LSTM-based model to differentiate the ET and PST. Initially, tremor recording collects from accelerometer sensor named as BioStampRC21 [7]. It provides a PSD accelerometry dataset built using five wearable sensors. It gives information on both HC and PSD patients. The MC 10 BioStamp RC sensors were used to collect the data. The primary prerequisite of the model is preprocessing, in which the raw data is to be converted and normalized before feeding it into the model. We used standard scalar function to normalize and scale the data in a single unit variance. In the model training, this data feed into the GRU model, in which reset gate and update gate can reset and update the memory cell in a specific frame and timestamp. The proposed scheme used 16 consecutive readings for each input to be passed through the GRU model and then fed into the LSTM model for an efficient differentiation on ET and PST. After that, the LSTM layer is followed by the dropout layer, which prevents the overfitting of the model and followed by the dense layer, which generates a result of classification. Moreover, in the data evaluation process, BC is used to evaluate the validity

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of the trained model. It provides transparency of the system, so researchers(connected in the BC network) evaluate the validity of the model. Initially, the anonymity of the researcher is verified using a smart contract, after that they allow to validate the model. This validation helps to improve the performance of the model. After the model evaluation, a model is retrained and achieves 80.4% training accuracy and 74.1% testing accuracy which is better as compared to [8], [9] scheme. Duque *et al* [8] proposed the use of angular velocity boosted by machine learning to classify ET and PST with an accuracy of 77.8%. [9] proposed a classification based on video analytics using machine learning has been implemented to identify PST from ET with the accuracy of 77%. The proposed scheme combined the BC and DL technology to make the system more reliable, transparent, and accurate.

A. Motivation

Currently, It is hard to distinguish between ET and PST due to comparable features of the movement-based disorders. ET is often found in those over the age of 60, whereas PST is seen in PSD patients in a relaxed state. Authors in [3], [8], [9] have employed an ML algorithm to identify ET and PST using accelerometer and wearable sensors. ML is having an issue of human-based feature extraction, that has led to degrading the model's performance. Later on, many researchers solved this issue in their research article [10], [11], [12], [13] by proposing DL based algorithms that would provide automatic feature extraction instead of human-based feature extraction. After that, authors in this [2] [6] presented a LSTM based classification scheme to identify the ET and PST. They compared the expected tremor score and clinical evaluation tremor score using gradient boosting an LSTM. They trained the result with a combined position of tremor, but they have not evaluated their model correctness with providing the training and testing accuracy. Motivated from this, we have proposed the integration of GRU and LSTM to improve the performance of the model. We can also validate our model using blockchain to make a system more reliable, accurate, and transparent.

B. Contribution

The contributions of this paper are as follows:

- We proposed DL-based integration of GRU+LSTM to classify the ET and PST from the accelerometer dataset. The comparative analysis of the proposed scheme with state-of-the-artwork is also given.
- We presented a BC network to evaluate the trained model and validate the performance of the model.
- We employed a smart contract to validate the identity of the researcher. After the validation, a legitimate researcher can evaluate the trained model.
- The security analysis of the BC is computed using communication and computation cost.

C. Organization

The rest of the paper is presented as follows. The system model and problem formulation are described in Section II Proposed architecture and algorithm are presented in Section III. Section IV contains the performance evaluation. Finally, the paper concludes in section V.

II. System Model and Problem Formulation

Fig 1 shows the working process of a system model. Initially, tremor data collect using an accelerometer sensor in tri-axial directions. Further, this tremor data recording is sent to a smartphone using Bluetooth. Now, before the model training, we need to pre-process the data. In data pre-processing, the standard scalar function normalizes and scales the data in unit variance. Afterward, this normalized data is split into two sets named training and testing sets. First, the model training using an integration of GRU and LSTM model over the 3-dimensional tremor data, and tested using testing dataset. To evaluate the validity and performance of the trained model, we have used BC technology and smart contract where BC is used to validate the trained model while smart contract can be used to check the validity of the researcher. In this scheme, a smart contract is used to check the validity of the researcher, only valid users can validate the model. When any connected participant wants to validate the model then, first it verify using a smart contract, and then that authorized researcher can access and validate the data. After the verification, the researchers have evaluated the model and recommend suggestions to improve the training accuracy of the model. This recommendation helps to check the validity of the trained model, retrain the model based on it and provide a promising result of classification with training, testing accuracy, and loss. If any adversarial attack occurs during training time then it was identified using BC and preserved the privacy of the model.

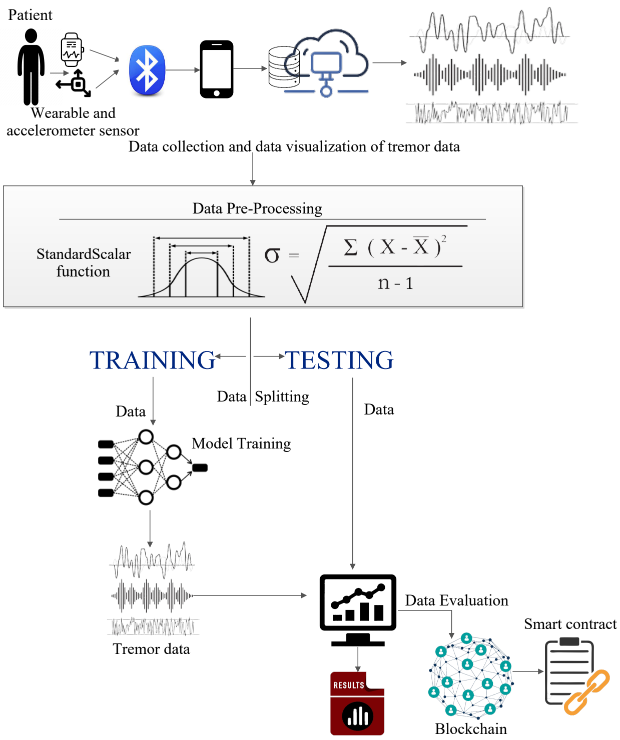

Fig. 1. System Model

A. Problem Formulation

The proposed model integrates the GRU and LSTM algorithms to classify ET and PST from the tremor dataset. The mathematical formulation of GRU and LSTM is as follows:

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TABLE I
DESCRIPTIONS OF SYMBOLS USED

Symbol	Description	Symbol	Description
x_t	Input cell	o_t	Output cell
r_t	Reset gate	$\odot$	Hadamard product
C_t	Memory	B_{curr}	Hash value
$h_t - 1$	Output of preceding cell	h_t	Output of current cell
$\oplus$	XOR	H	Hash function

1) GRU: GRU solves the vanishing gradient problem. It is a variant of LSTM with consisting update and reset gate. These gates control the flow of data in the network. The update gate decides how much information from the past needs to be passed on to the next step. The reset gate removes the values from the memory cell whereas the update gate can update the memory cell at each timestamp. Table I shows the symbol and descriptions of the symbol used for the computation of Equations. The Eqs. of GRU is present as follows:

$$u_t = \sigma(a_u x_t + o_{t-1} We_u + b_u) \tag{1}$$

$$r_t = \sigma(a_r x_t + o_{t-1} We_r + b_r) \tag{2}$$

$$i_t = tanh(a_o x_t + We_o(r_t \odot o_{t-1} + b_o) \tag{3}$$

$$o_t = u_t \odot o_{t-1} + (1 - u_t) \odot i_t) \tag{4}$$

Eqs. [1 - 4] summarize the GRU, where x_t is the input cell of GRU, o_t is the output cell of GRU , u_t is the update gate denoted with u_t, and output gate denotes with o_t, r_t is the reset gate, $\odot$ denotes the Hadamard product and a, We, and b are weights.

2) LSTM: LSTM is a prominent solution to classify, process, and make predictions on time series data. It also identifies the gaps of uncertain duration across critical occurrences. LSTM contains 4 types of gates in the network such as forget gate, input gate, and output gate. After each timestamp, each gate can update its value as per the flow and requirement of the data.

$$in_t = \sigma(x_t a_{in} + h_{t-1} We_{in}) \tag{5}$$

$$f_t = \sigma(x_t a_f + h_{t-1} We_f) \tag{6}$$

$$o_t = \sigma(x_t a_o + h_{t-1} We_o) \tag{7}$$

$$\tilde{C}_t = tanh(x_t a_g + h_{t-1} We_g) \tag{8}$$

$$C_t = \sigma(f_t * C_{t-1} + u_t * \tilde{C}_t) \tag{9}$$

$$h_t = tanh(C_t) * o_t \tag{10}$$

Eqs. [5 - 10] shows the mathematical form of the different gates, where input denotes with x_t, h_{t-1}, is output of preceding cell, Memory of preceding cell describe with C_{t-1}. h_t is a output of current cell, C_t is memory of current cell, and We, a describe the weights.

B. Blockchain

BC contains a chain of blocks that store data as a transaction. Every block is being used with a distinctive hash key H, and calculate a current block B_{curr} hash value using the previous block hash value [14]. Hash is a one-way function which is defined as follows.

$$H : m \to 0, 1^k, \forall m \Sigma M \tag{11}$$

$$H(m) \neq m' \tag{12}$$

$$H(m_x) \neq H(m_y), m_x \neq m_y \tag{13}$$

Eqs. [11 - 13] shows the encryption of message using hash function, where m is a message transfer which belongs to the set of messages M [15]. Hash value of any message is denotes with m'. Thus,the n^{th} block hash is computed as below.

$$H_n = \{H_{n-1} \oplus T_n \oplus Nonce_n\} \tag{14}$$

Eq. 14 presents the n^{th} block hash value which denotes with H_n, H_{n-1} is a value of previous block (n-1). T_n is a timestamp of n^{th} block, and $Nonce_n$ is the value of n^{th} block.

III. The Proposed Model

This section describes the proposed deep learning-based model for the prediction of PSD accurately. Fig. 2 shows the detailed architecture of the proposed model. The input tremor data is provided as input into the GRU cell which is then connected to LSTM cell. Dropout layer follows and the dense layer generates the classification output.

A. Dataset Description

Initially, in the data collection process, accelerometer readings collect using the MC 10 Biostamp RC sensors [7]. The dataset consists of 32 subject from both PSD and control category to distinguish between the tremors associated with parkinsons from essential tremors. The accelerometry recordings are taken for each subject in all the three spatial directions and these readings are calculated with respect to acceleration due to gravity. The recordings are taken at regular divisions of time using the wearable sensors. The recordings are taken from the chest, left and right hand, and left and right thigh.

For the study, we consider the data from the left hand of the subject. These recordings are merged into a comma-separated values (CSV) file consisting of both control and PSD patient time series readings taken at regular intervals of time from the sensors. Each reading is marked against a specific timestamp for each of the recordings from the sensor. The dataset also contains the status of the patient, control patient, or PSD patient. These values are then converted from their categorical representation to encoded numerical form.

B. Data pre-processing

In this phase, tri-axial accelerometer readings are preprocessed so high magnitude readings in one of the axial direction does not impact the model. Scaling of data is done by using the standard scalar. The data is standardized by scaling all the recordings to unit variance. After scaling, the data is prepared to be used as input to train the DL model. The sensor data provides valuable information when observed as time-series data to gain information and make an accurate classification based on readings over a period of time. 16 consecutive readings are combined for each input to be passed to the DL model. We consider overlapping each training input from the previous one to gain the maximum information. Frames for each X, Y, and Z direction for the same time interval are made. The statistical measures are used to assign a common class label of PSD or control to the complete window of 16 recordings. For the proposed model we considered mode as the statistical measure to ensure a good representation of the entire window frame of 16 recordings.

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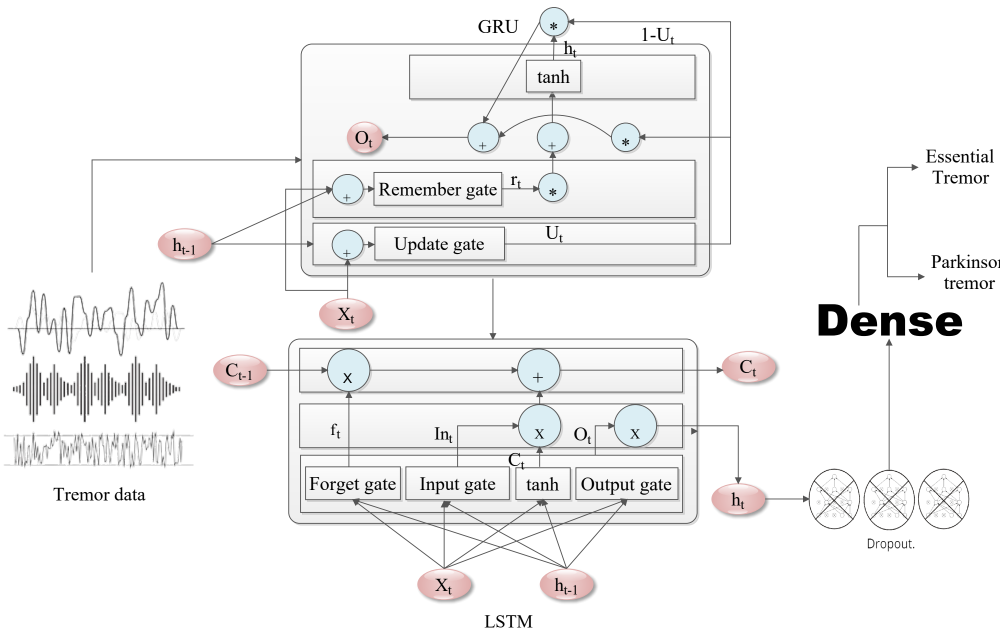

Fig. 2. The Proposed deep learning-based Model.

TABLE II
GRU $\sum$ LSTM MODEL ARCHITECTURE

Layer	Layer Type	No. of Units	Dropout	Return sequence	Output size
1	Input	-	-	-	-
2	GRU	128	-	True	(None,16,128)
3	LSTM	64	-	-	(None,64)
4	Dropout	-	0.2	-	(None,64)
5	Dense	2	-	-	(2)

C. Model Training and Evaluation

The preprocessed data is provided as the input for GRU $\sum$ LSTM model. Table II shows the detailed information of each layer type, neurons, input and output dimensions. The pre-processed data is passed through a GRU model with 128 neurons and then fed into the LSTM layer with 64 neurons to improve the performance of the model. Next, the LSTM layer is followed by a dropout layer to prevent over fitting. The dropout layer randomly sets inputs as 0 during training at a regular frequency to overcome the issue of model over fitting in training data. The output is taken in the final dense layer which gives the classification outcome of a subject as PSD or HC. In this model, the sigmoid function is used as the activation function for the output in the dense layer. This function provides activation to the inputs received from the previous layer and can generate an output to classify the subjects in ET and PST. The model is implemented in python using TensorFlow and Keras library.

The proposed model used Adam (adaptive moment estimation) optimizer to accelerate gradient descent. We tune our proposed model with different learning rates to ensure that the model doesn't diverge or converge while training. The categorical cross-entropy loss is used as the loss function to update the values of the parameters. The validation accuracy is calculated as a parameter to check the correctness of the model's performance. The model is trained for several different combinations of parameters to get a model with high accuracy that generalizes on the unseen data. We train the model for 150 epochs.

D. Algorithm

Algorithm 1 Proposed Algorithm

Input: Multi directional tremor data using BioStampRC21 device
Output: Identify the subject as PSD patient or healthy control

```
procedure PRE-PROCESSING(:)
    M ← Input readings
    M ← Standardscaler(M)
    length ← 4
    Frame ← (length × 4)
    Overlap ← (length × 2)
    for x in (0, Len(M), Overlap) do
        p' ← p[x] to p[x + Frame ]
        q' ← q[x] to q[x + Frame ]
        r' ← r[x] to r[x + Frame ]
        Y ← mode(x to (x + Frame))
    end for
end procedure
procedure MODEL TRAINING(:)
    Sequential ()
    GRU (128, activation = ReLU )
    LSTM (64, activation = ReLU )
    Dropout (0.2)
    Dense (2)
end procedure
procedure COMPILE(:)
    loss ← Sparse_categorical_cross entropy
    Optimizer ← Adam
    Learning rate ← 0.0004
end procedure
procedure EVALUATE(:)
    X ← [p',q',r']
    Test,Train ← X
    Test_size ← 0.2
    Epochs ← 150
end procedure
```

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The working process of the model is present in Algorithm 1. In this algorithm, initially, tremor data is collected using BioStampRC21 device and preprocessed using a standard scalar function to scale the data in three different frames p, q, and r for each of the triaxial directions respectively. The frame component size value is set as 4 timestamps for the proposed model. For each frame, we use 16 consecutive readings for each input to be passed into the LSTM model. In the model training, first, it applies a sequential model, after that GRU layer contains 128 neurons, followed by an LSTM layer with 64 neurons. The next layer is dropout at the value of 0.2. The dropout layer is followed by a dense layer which gives a classification result. After that during compile time, the loss was computed using categorical cross-entropy and optimized the model using Adam optimizer with a 0.0004 learning rate. The model evaluates using 0.2 test size with 150 epochs. To evaluate the validity of the trained model, we have used BC in which each participant can validate the trained model with their knowledge in that field. It helps to improve the overall performance of the model. The time complexity for the data processing portion of the algorithm is O(n^2), where n is the number of accelerometer readings. Estimating the exact time complexity for the deep learning model remains a relatively complex process, we can represent it in terms of parameters like the number of neurons in each layer, number of epochs, number of connections between each layer, and the dropout factor. The space complexity for the proposed approach depends upon the learned parameters during the model training.

IV. Performance Evaluation

We proposed a GRU $\sum$ LSTM based DL model to classify PSD patients from HC based on the tremors recording from the subject accelerometer data. We use the DL network to learn from the time-series data and make the classification based on the sensor data from both subjects. We consider the dataset with 32 subjects and consider their readings to train our model. The PSD is a neurodegenerative disease with its onset usually after the age of 50. The dataset consists of both male and female subjects. The age range of the subject is from 37 being the lowest age and 84 being the highest age part of the dataset subject.

The dataset contains 15 healthy subjects and 17 subjects with PST. We implement the GRU $\sum$ LSTM based model on this dataset and tune the parameters to achieve significant accuracy. The model is implemented by providing input to the GRU layer with 128 neurons, followed by an LSTM layer with 64 neurons. Further, These layers are followed by a dropout layer of 0.2, which helps to eliminate the problem of overfitting. In this model, dropout is used to set some inputs to 0 during the training time. The dropout layer is followed by a dense layer. The dense layer classifies the ET and PST and also differentiates the PSD and HC subjects. The proposed architecture is trained with hyperparameters to achieve the better accuracy of the model. We have used a 0.0004 learning rate which provides high results with adam optimizer. After that, The model weights are updated using the sparse categorical cross-entropy loss function. At Last, the model is compiled after the process of trial and error and the values are selected. This value improves the result of the model when it is trained for 150 epochs.

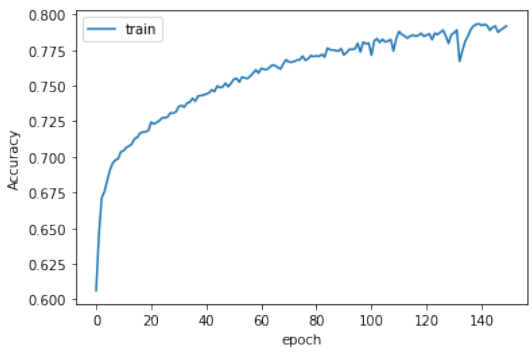

Fig. 3. Accuracy for GRU $\sum$ LSTM model to identify PSD and control patient

Fig. 3 shows the plot of accuracy against the number of epochs for the GRU $\sum$ LSTM proposed model. After choosing the model parameters, the model gives a training accuracy of 80.41%.

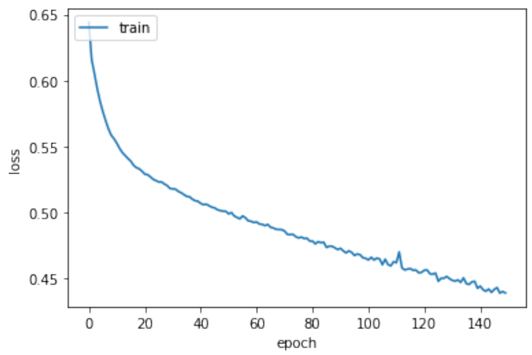

Fig. 4. Loss for GRU $\sum$ LSTM model against the number of epochs

Fig. 4 shows the loss against the numbers of epochs for the proposed GRU $\sum$ LSTM model. We can see that the loss substantially decreases over the epochs while training. The value of loss drops from 0.65 to under 0.41 over while training.

The proposed GRU $\sum$ LSTM model outperforms traditional DL-based models because it can have a high validation accuracy. Fig. 5 shows the comparison of performance in terms of accuracy and loss for the training and validation set. The training set provides an accuracy of 0.804 and a loss of 0.410. The validation set provides an accuracy of 0.741 and a loss of 0.450. The model is able to generalize on the new data and doesn't overfit just on the training set.

Fig. 6 shows the comparison of the performance of the proposed GRU $\sum$ LSTM model with the standalone GRU and LSTM models and other existing works in terms of accuracy. We see that our proposed model outperforms individual models with both higher training and testing accuracy. The proposed model uses manual feature extraction to improve the accuracy in comparison to machine learning models. The proposed GRU $\sum$ LSTM model also shows improvement due to the time series nature of the tremor data which is collected at successive intervals of time, where the DL approach performs better than ML. The values of training and testing accuracy are summarized in Table III. The training accuracy of the

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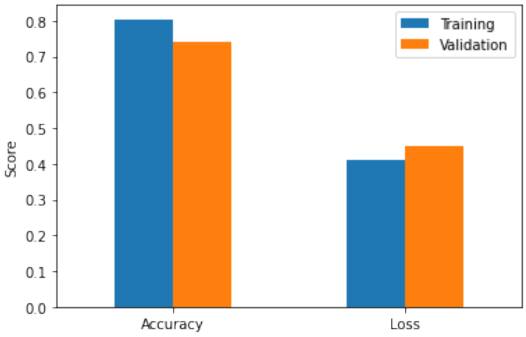

Fig. 5. Accuracy and loss comparison of training and validation set

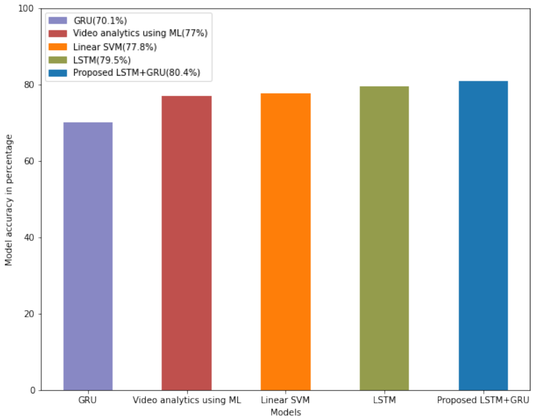

Fig. 6. Accuracy comparison for different models

proposed GRU $\sum$ LSTM model is close to LSTM based model, however, the validation accuracy of the proposed GRU $\sum$ LSTM model outperforms traditional models. The security analysis of the proposed scheme is being described in terms of the communication and computation cost of blockchain storage. The communication cost of the proposed scheme is ID 160 bits, hash output 256 bits and time stamp 32 bits [16], so the total communication cost is 448 bits. The proposed scheme uses a BC network, therefore it requires one hash function which is 0.056 ms [16], thus computation cost is 0.056 ms.

V. Conclusion

We proposed the DL-based integration of GRU and LSTM for the classification of ET and PST. Initially, the PD-BioStampRC21 dataset collects using an accelerometer sensor, which contains the tri-axial tremor recording of the patient. Afterwards, this raw data is being distributed in three frames with a specific timestamp and scaled using a standard scalar function in data pre-processing. The frames are passed into the GRU $\sum$ LSTM model in the model training. This integration performs well and achieves 80.4% and 74.1% accuracy. To validate the model's performance, we employed the BC network to evaluate the trained model. We also used a smart contract to verify the identity of the researcher. After the verification, the researcher can validate the trained model and the performance of the model. The communication and computation cost is 448 bits and 0.056 ms, respectively. Our proposed scheme integrates emerging technologies to make a system more reliable, accurate, and transparent. In the future, we will integrate federated learning with BC to improve the system's reliability and accuracy.

TABLE III
Comparison with other models

Model	Accuracy	Validation accuracy	Loss
LSTM	79.5	64.5	0.59
GRU	70.1	68.3	0.63
Proposed LSTM $\sum$ GRU	80.4	74.1	0.41

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