Classification of Alcoholic EEG Signals Using a Deep Learning Method

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Abstract—**Most of the traditional alcoholism detection methods are developed based on machine learning based methods that cannot extract the deep concealed characteristics of Electroencephalogram (EEG) signals from different layers. Hence, this study aims to introduce a deep leaning-based method that can automatically identify alcoholic EEG signals. It also explores if a hand-crafted feature extraction method is worth applying to deep learning techniques for classification of alcoholism. To investigate this, this paper presents two deep learning-based algorithms for classification of alcoholic EEG signals for comparison. In Algorithm 1, Principal Component Analysis (PCA) based feature extraction technique has been applied to extract representative components and then the extracted features are used as input to Artificial neural network (ANN) for classification. In Algorithm 2, the raw EEG data are directly used as inputs to a deep learning method: 'long short-term memory (LSTM)' for detection of alcoholism. The proposed algorithms were tested on a publicly available UCI Alcoholic EEG dataset. The experimental results show that the proposed Algorithm 2 could achieve an average classification accuracy of 93% while this accuracy is 86% for the proposed Algorithm 1. The comparative evaluations with the state-of-the-art algorithms indicate that Algorithm 2 also outperforms other competing algorithms in the literature. Thus deep learning algorithm when applied to raw data, can produce better performance than the combination of the hand-crafted feature method and the deep leaning algorithm. Our proposed system can be used to determine the extent of alcoholism-related changes in EEG signals and the effectiveness of therapeutic plans.**

Index Terms— **Alcoholism; Electroencephalogram (EEG); Feature extraction; Principal Component Analysis (PCA); Artificial neural network (ANN); Long short-term memory (LSTM) network; deep leaning method.**

I. INTRODUCTION

ALCOHOLISM is a severe disorder that affects the functionality of neurons in the central nervous system and alters the behaviour of the affected person [1]. The most common negative effects of excessive alcohol consumption on health are cardiomyopathy, stroke, high blood pressure, cirrhosis, and increased risk of cancer. Alcohol can affect many parts of the body but, it particularly affects the brain, heart, liver, and the immune system. According to the World Health Organization (WHO), globally, 3.3 million deaths every year result from the harmful use of alcohol [2]. It is the third highest risk factor for causing diseases as reported by the World Health Organization (WHO) [3]. Alcoholism causes neurological deficiencies like impairment of decision making, learning and memory deficits, and behavioral changes [4, 5, 6] and may also cause serious accidents while driving or operating machines where alertness and appropriate judgments are required. Long-term consumption of alcohol impairs the development of the human brain [7], whereas short-term consumption causes a number of issues, including of memory impairment, black outs, recklessness, and impaired decision making. According to the national institute on alcohol abuse and alcoholism, chronic consumption of alcoholism causes diminished ability to think, loss of visuospatial abilities, Wernicke–Korsakoff syndrome, memory loss, and loss of attention span [8].

The identification of alcohol in subjects is a challenging task because the standard devices are based on the smell of drink, which is not always accurate. Electroencephalography (EEG) is a powerful and popular technique for measuring brain activity, which reflects the condition of the brain. Recently, it has been demonstrated that EEG signals can be used as a diagnostic tool in the evaluation of subjects with alcoholism. EEG signals provide a record of electrical activity of the brain from the scalp. The measurements given by an EEG are used to confirm or rule out a condition such as alcoholism. Drinking alcohol appears to be related to a specific pattern of brain electrical activity in adults and the brain activity of alcoholics and non-alcoholics differs in some characteristic ways that may reflect the future development of alcoholism [9]. EEG recordings contain huge volumes of data with dynamic characteristics. So far, the EEG data are visually analysed to identify and understand abnormalities within the brain and how they propagate [10]. This manual approach to analysing huge data is an inefficient and inaccurate procedure: it is time and resource-consuming, and human error contributes to reduced decision-making reliability. As yet, there is no reliable way of identifying alcoholism from EEG data automatically, rapidly and accurately. Thus, there is increasing demand for an automatic and efficient EEG data analyser that can produce accurate, up-to-date and robust scientific evidence for reliable decision-making.

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In recent years, many research works have been undertaken on the identification of alcoholism using EEG signals. For example, Bajaj et al. [11] reported a method based Short Time Fourier Transform (STFT) and non-negative least squares classifier (NNLS) for identification of alcoholic EEG signals. In [12] Kousarrizi et al. used Wavelet Transform (WT) based features with Support vector method (SVM) for classification of normal and alcoholic EEG signals. Sun et al. [13] employed Principal Component Analysis (PCA) to preprocess the original data to reduce the dimension of EEG signals. They used WT based features for analysis of alcoholic and control EEG signals. In [14], Correlation dimension based features were used as measures to discriminate alcoholic and normal EEG signals. In [15] Kannathal et al. introduced chaotic measures like correlation dimension (CD), largest Lyapunov exponent (LE) and Hurst exponent (HE) and entropy used as features to classify alcoholic EEG signals from normal EEG signals. Supriya et al. [16] proposed a data analysis method for recognizing alcoholic EEG signals from control signals combining complex network (CN) and machine learning techniques (e.g. Naive Bayes (NB), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), SVM). In [17] Acharya et al. proposed a method where the nonlinear features were used as input to the SVM classifier for classification of alcoholic and normal EEG signals. Faust et al. [18] reported a method based on energy measures which were extracted from wavelet packet decomposition with various machine learning classifiers for identification of alcoholic EEG signals. [19], the fast Fourier transform (FFT) and auto regressive (AR) method based power density were used as features with a machine learning technique for classification of alcoholic and control EEG signals.

From the above literature review, it may be observed that most of the existing research in alcoholism detection from EEGs has been performed in the machine learning area and we could not find any research related to alcoholism detection in the deep learning area. The existing methods are based on hand-crafted feature extraction methods which are manually chosen based on the expert knowledge of the researcher (e.g. WT, Fourier Transform, PCA, CN, Entropy, LE, CD) and traditional machine learning techniques (e.g. SVM, k-nearest neighbour (k-NN), LDA, NB). Existing feature extraction methods cannot extract the deep concealed characteristics of EEG signals from different layers. Again, in the current process, it is hard to select appropriate and effective feature extraction methods for different EEG data and in addition this is both labour-intensive and time-consuming. Traditional machine learning methods consist of shallow architectures having at most one layer of non-liner feature transformation (e.g. SVMs use a shallow linear pattern separation model) [20], which requires more computational elements and hard to model complex concepts and multi-level abstractions. Due to their single layer construction, traditional machine learning methods are unable to detect abnormal points from the deep hidden layer effectively. Moreover, existing methods are limited in their ability to balance the efficiency and accuracy of alcoholism detection.

This study aims to develop a deep learning based data mining algorithm to classify EEG signals into two classes: alcoholic and non-alcoholic, as accurately as possible. This study also intends to explore the significance of the application of hand-crafted feature extraction method (which is manually chosen by the researcher) on applying the deep learning method. For this purpose, this study proposes two deep learning-based algorithms. **Algorithm 1** is based on Principal Component Analysis (PCA) (hand-crafted feature extraction method) and Artificial Neural Network (ANN) (deep learning method). In this algorithm, the PCA method is used to extract important feature values from EEG data which are used as input to the ANN method. **Algorithm 2** is based on the Long Short-Term Memory (LSTM) network where the raw EEG data are directly used as input to LSTM network method. Then the performance of these two algorithms is compared. A comparative study with the proposed method and the existing methods is also reported for the same data set that is used in this study. The experimental results demonstrate that applying raw EEG data to the LSTM network method (**Algorithm 2**) yields a better performance compared to the combined application of the hand-crafted feature extraction method (e.g. PCA) and ANN) (**Algorithm 1**) and also existing machine learning based methods.

The main contributions of this study are: (1) Design and validate a new framework for automatic identification of alcoholic and non-alcoholic subjects as accurately as possible; (2) Explore knowledge of the significance of the application of the feature extraction method on applying a deep leaning algorithm; (3) Investigate a sustainable classification model for the proposed features to differentiate the subject groups; (4) Improve classification accuracy compared to existing methods as the deep learning method automatically optimizes the parameters and requires less prior expert knowledge for the feature extraction procedure to perform effectively; (5) Build a low cost time model. To the best of our knowledge, this is the first work to apply the deep leaning technique with a feature extraction method and without a feature extraction method for classification of alcoholic and non-alcoholic subjects from EEG data.

The rest of the paper is organized as follows: Section II describes dataset used in this study and presents the description of the proposed approach. The experimental procedure and results are discussed in Section III. Finally, Section IV draws the conclusions of the study.

II. DATA AND METHOLOGY

A. Data

The dataset for the current research is from UCI [21], the EEG dataset is from the Neurodynamic Laboratory at the State University of New York. It has a total of 122 subjects with 77 diagnosed with alcoholism and 45 control subjects. For every subject 120 separate trials were performed. If the subject was alcoholic all the trials were labelled as alcoholism. All trials were sampled at 256Hz with 64 electrodes placed on the subjects' scalps for 1 second. The classification method needs to identify whether the subject has been diagnosed with alcoholism or is a control subject. Fig.1 shows the raw data for alcoholic and non-alcoholic participants; for this visualization only one third of the electrodes are displayed. As we see in the plot the data are noisy, with a sudden departure from the mean value. At a brief look there is no obvious difference between alcoholic and non-alcoholic participants.

B. Proposed Methodology

This paper proposes two algorithms based on the deep learning method for classifying alcoholic EEG signals from control signals. **Algorithm 1** is based on the ANN method and **Algorithm 2** is based on the LSTM method. The block diagram of the proposed deep learning methods is shown in Fig.2. In **Algorithm 1**, firstly Principal component analysis (PCA) is employed on the raw EEG data to extract important components and also to reduce the dimension of data from the signals. Then, the extracted components are used as input to the ANN model for classifying alcoholic signals from control signals. In **Algorithm 2**, directly the raw EEG signals are used to the LSTM deep learning model which extracts important features from different layers of the data and then applies those features as input in the model for classification.

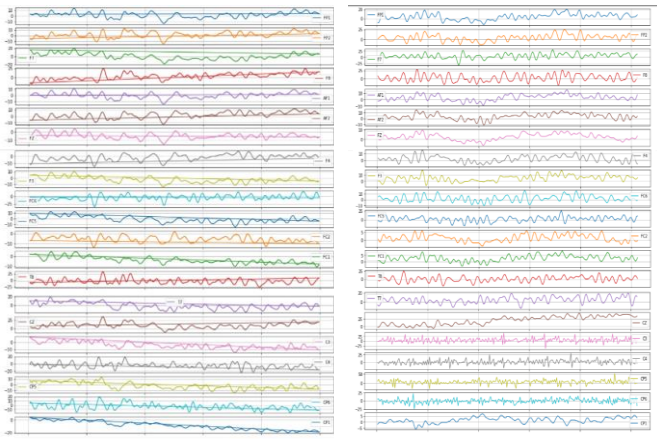

Fig.1. A sample of data for Control participant (left) and alcoholic participant (right)– First 20 channels

The description of the proposed methods with implementation procedure are provided below:

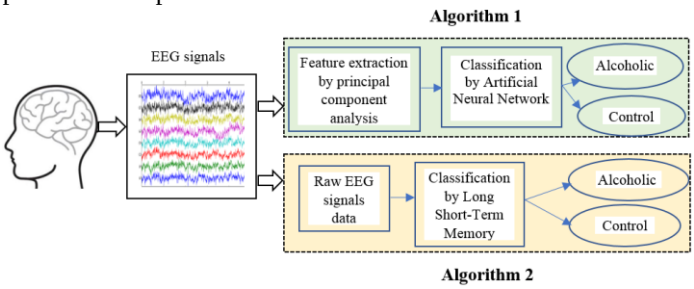

Fig. 2: Block diagram of the proposed methodology for alcoholic EEG signal classification

- Dimension reduction using PCA

Principal component analysis (PCA) is a type of signal analysis method that determines the main components of a multi-dimensional data set and the method uses the principal components to reduce the features of the original data [22]. The main components hold statistically significant insight about the original data and can be defined as the variance in data or the method to identify the components that cover the most variance, and they can recreate the original data set. The result of PCA is that the contribution of the principle components is ranked from high to low, so for example the first component holds the maximum information to the variance in the data. The reason of considering PCA method in this study is that EEG data are always complex and high dimensional that is inappropriate directly to use as input to a classification model. The purpose of reducing the dimension is to allow minimal information loss. After applying PCA, the most of the data come to in the lower dimensional space that is suitable to use them as an input source to a deep learning or a machine learning classifier. In other words, since EEG data contains recordings from multiple locations on the human scalp and the signal recorded consists of mixed brain activity, this method is used to calculate the independent components to help observe the original features of the neuron activity. An essential part of the principal component analysis method is finding how many components are needed to explain the original data [22]. The original data have 64 columns, based on the result of variance ratio analysis, so we use the first 30 components and project 64 from the original data to 30 dimensions. After applying the PCA method and obtaining a new dimension, there is no specific meaning assigned to each principal component. One of the most important applications of the principal component analysis method is increasing the speed of the classifier technique. This study consider these 30 components as the valuable features for representing the characteristics of the original EEG signals. In the following sections, we will look at the implementation of EEG classification that is built on 30 main components.

- ANN for classification

Artificial neural network (ANN) is a brain-inspired system and consists of input layer, intermediate layer and output layer. The nodes in the middle layer can transform the input into something that the output layer can use, so the layers can extract different features until the network recognizes what it is looking for. The process of the ANN training process is relatively faster than other types of deep learning methods. In time series data like EEG signals one of the most common issues with the ANN network is the over-training and the sensitivity to the number of hidden neurons.

ANNs are usually classification methods comprising large numbers of simple interconnected neurons which perform computation tasks. There are several neural network topologies. In this research ANN and LSTM are used in the classification of EEG signals. The Multilayer neural network (MLP) with two or more layers is the most commonly used technique in feedforwarding architecture due to its fast training process and ease of the implementation [23]. The MLP consists of three sequential layers: input layer, hidden layer and output layer (Fig.3) the number of nodes in the first layer (input) is dependent on selected dimensions. This study used 30 principal components from the result of PCA method and then 64 channels from raw EEG dataset in two separate experiments.

The number of neurons in the output layer depends on the number of desired classes. In this study we need to determine if a person is alcoholic or not, so the number of the class is 1. Intermediate or hidden layers are useful to increase the ability of the network; and MLP can have multiple intermediate layers and there are no rules on the number of layers and nodes needed. Large numbers of hidden layers and neurons increase the complexity of the network and execution time and small numbers of layers and nodes lead to errors and low performance and poor generalization. As there are no rules to determine the best topology, therefore, it is only found by trial and error. In

this study we experimented with shallow and deep ANN with 2 and 4-layers topology, using PCA as input and raw data and compared the results of classification in terms of performance and accuracy.

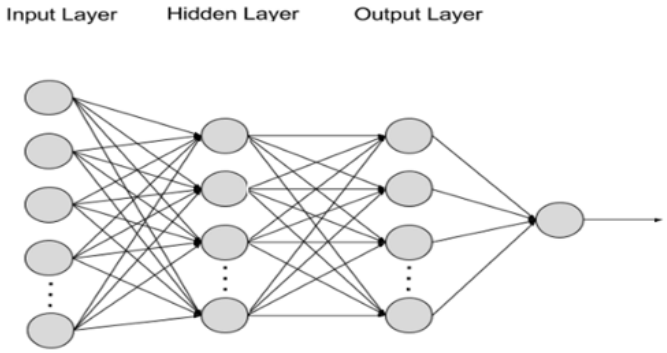

Fig. 3. The structure of MLP model

- Implementation of PCA and ANN proposed method

In this paper, the proposed methods are implemented with the UCI alcoholic EEG data [21]. As discussed in Section 2.1, the UCI EEG data has 64 channels of data with a total of 122 subjects with 77 diagnosed with alcoholism and 45 control subjects. Every channel consists of 2,831,104 data points sampled at 256Hz. In this part of the study, for the classification of two-class EEG signals, ANN is used as a classifier in two separated experiments to distinguish the 30 features obtained through the PCA method and 64 channels from the raw data set.

Model A

The model is combination of the result of PCA plus a simple multi-layer ANN. The first layer contains 30 principal components as input neurons, and there is one intermediate layer containing 50 neurons to learn from the input, with the nodes utilizing a tangent activation function. Finally, there is an output layer with 1 node corresponding to the 1 possible class of alcoholic or not. A sigmoid output layer was used to perform this classification.

Model B

The model is a simple two-layer ANN, feeding from raw EEG data The first layer contains 64 channels as input neurons, and there is one intermediate layer containing 100 neurons to learn from the input, with the nodes utilizing a Relu activation function. Finally, there is an output layer with 1 node corresponding to the 1 possible class of alcoholic or not. A sigmoid output layer was used to perform this classification.

Model C

The model is a four-layer ANN, feeding from raw EEG data. The first layer contains 64 channels as input neurons, and there are three intermediate layers containing 100, 50, or 32 neurons to learn from the input, with the nodes utilizing a Relu activation function. An output layer with 1 node corresponded to the 1 possible class of alcoholic or not. A sigmoid output layer was used to perform this classification. The main reason for using a sigmoid function for the last layer is because the result of this function exists between zero and one, so it is useful for the models where the probability has to be predicted as the result. For the middle layers, ReLU functions perform better overall in our ANN models than tanh as it is less computationally expensive than tanh and Relu accelerates the convergence of the model better compared to the tanh function in this architecture. After setting up the skeleton of the network architecture for each model, we have to define how data flows through out network. The four models are defined and trained in four following stages.

- *Split Data into Training and Test Sets*

Typically, the train test split is 20% test and 80% training data. For the above 3 models we select 0.8 ratio for splitting the EEG dataset. The training set contains a known output as a label which is zero or one, and the model learns from this data in order to be generalized to other data later on. So, we fit the ANN models on the training set only.

- Forward Propagation

In this step, activations are calculated at each layer by calculating the two steps shown below. These activations flow in the forward direction from the input layer to the output layer in order to generate the final output.

z = weight * input + bias

a = Activation Function (z)

So, for the first layer we calculate activation of hidden layer:

$z_1 = X*W_1 + b_1$

$a_1 = Tangh(z_1)$

And for the second layer which is output layer

$z_2 = a_1*W_2 + b_2$

output = Sigmoid (z_2)

- *Loss Computation*

In this step, the loss or error is calculated in the output layer. A simple error function can tell the difference between the actual value and the predicted value. Later, we look at different loss functions available in deep learning framework.

- *Backpropagation*

The goal of this step is to reduce the error in the final or output layer by making marginal changes in the bias and the weights. These changes are computed using the derivatives of the error term. Based on the Calculus principle of the Chain rule, the delta changes are back passed to hidden layers where corresponding changes in their weights and bias are made. This leads to an adjustment in the weights and bias until the error is minimized.

- *Updating the Parameters*

Finally, the weights and bias are updated using the delta changes received from the above backpropagation step. When these steps are executed for a number of epochs with a large number of training examples, the loss is reduced to a minimum value. The final weight and bias values are obtained and can then be used to make predictions on the unseen data. When the maximum number of epochs is reached, which is 100 for our experiments, the training ANN process is stopped, and the model converged, and the goal is reached.

- LSTM for classification

A Recurrent Neural Network (RNN) is a type of multi-layer neural network, used to predict sequential data, such as speech recognition. The method relies on weighted memory and a feedback loop. Exploding or vanishing gradients are a problem with RNN where a large error accumulates in the training process resulting in a very large update to the weights. The Long Short-Term Memory (LSTM) technique is a type of RNN and is very powerful when working with timeseries data such as EEG signals. The motivation behind using the Long Short-

Term Memory (LSTM) in this study is that this model can save important information about previous states and exploit the time dependencies between the data using a memory cell. The ability of LSTM to remember previous data makes this network ideal for EEG tasks. The LSTM is the most successful type of RNNs as this method overcomes the problems of overfitting a recurrent network and has been used on a wide range of applications.

In regular ANN, information flows from one layer to another layer. The layers are stateless, so they do not have any memory of previous states. Loops are introduced by RNNs by allowing output nodes to feedback as input nodes. This make RNNs very effective networks for time series problems, although RNNs are very hard to train and most of the time the model becomes overfit very fast. The LSTM technique is a type of Recurrent neural network, used in order to overcome the problem of long-term dependency and gradient explosion in recurrent networks; this technique was introduced by Hochreiter and Schmidhuber in 1997 [26]. Exploding or vanishing gradients are a problem where a large error accumulates in the training process resulting in very large updates to the weights. Thus, the model is not stable and is not able to learn from data during training processes. As a result, the values of weights can become very large and grow exponentially. Exploding gradients can be reduced by using the LSTM.

The LSTM technique is very powerful when working with timeseries data such as EEG signals, as the model can save information about previous states and exploit the time dependencies between the data using memory cell. These cells decide which information should be save in the memory and which should not, so, the cell memory added to the model enables it to remember previous steps. We assessed different LSTM architectures by testing several parameters on a sample of data such as changing number of layers, nodes per layer, changing loss of function, drop out value and batch size.

- Implementation of the LSTM based method

In this paper, the LSTM deep learning is applied to raw EEG signals of 122 participants to assess whether or not they are alcoholic. Each participant has a matrix of data and labels. Label vector represents the class of each subject by one (alcoholic) or zero (non-alcoholic). Fig. 4 shows the proposed deep learning neural network model. The model consists of two fully connected LSTM layers, one dropout layer, and one dense layer.

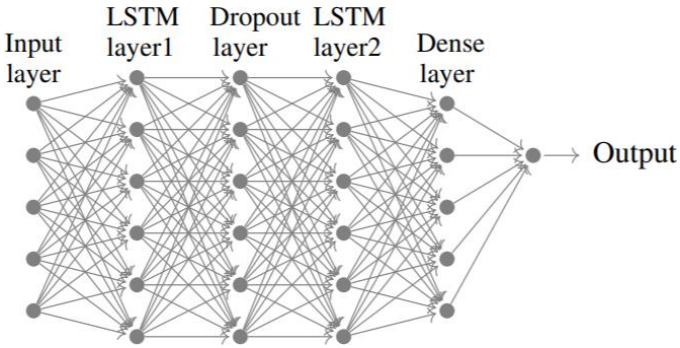

Fig.4. LSTM Neural network model

Dropout works are based on probability. They are constructed by removing inputs to a layer; these may be input features in the first layer from raw data set or activation nodes from a previous layer. This has the impact of transforming a large network to a different, smaller, network structure and, at the result, making the neurons in the network more robust. The LSTM and dropout layers are used to learn 64 features from raw EEG signals and the dense layer is used for final classification.

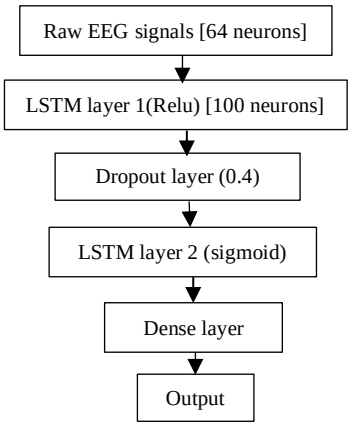

Fig.5. Detailed proposed LSTM model

Each piece of participant data consists of 64 channels and is sampled for one second. The topology of the network in this study consists of the input layer, the first LSTM layer, a dropout layer with a probability of 0.4, a many to one LSTM layer, and a dense layer for classification as shown in Fig.5. The LSTM model is trained on 80% of the data using 100 epoch iterations and tested on 20% of the EEG data. ADAM optimization used with learning ratio of 1e-4. Pytorch [25] library is used to develop the proposed deep learning method.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

As mentioned before, we used a UCI EEG dataset [21] for this study where EEG signals are recorded from 122 subjects. With UCI EEG data, 2,831,104 vectors of 64 dimensions for each method used, where 2,264,883 vectors are utilized as the training set and 566,220 vectors of the same dimensions are utilized as the testing set. For this dataset, five experiments are carried out using different type of deep learning networks. All models are trained with the training set and performance is assessed with the testing data set for different hyper-parameters setting.

A. Classification Performance Evaluation Metrics

We estimated the success of the proposed algorithms, by calculating the classification accuracy, sensitivity and specificity, and tuned the hyperparameters of each model accordingly. Such hyper-parameters include hidden layers, activation function, number of neurons, learning rate, number of epochs to train, batch size and dropout probability. The description and formulas of accuracy, sensitivity and specificity are available in references [27-31].

B. Increase hidden Layers

One of the first features we tried to increase the number of hidden layers as it has been established that many of the functions will converge in a higher level of abstraction. So, it

seems with more layers we have better results; we started from 2 layers of ANN and then increased to 4 layers of architecture.

C. Change Activation function

Changing activation function can be a deal breaker. Firstly, we have tested results with tanh and sigmoid. Most of the time we use sigmoid function. Compared to sigmoid, the gradients of ReLU does not approach zero when x is very big. Our experiment shows that ReLU converges faster than other activation functions. For both ANN (**Algorithm 1**) and LSTM (**Algorithm 2**) we carried out experiments with these functions.

D. Increase number of neurons

The number of neurons is very important as the network will be unable to model complex data if there are not enough nodes in every layer, and the resulting fit will be poor. In the other way the training time may become excessively long, if too many neurons are used, and the network may overfit the data. When overfitting occurs, the network will begin to model random noise in the data. As the result, the model fits the training data very well with a high accuracy rate, but in fact it is not good to the new and unseen data. There is not any specific rule to choose the number of neurons, but there are two common approaches, and we defined the hidden nodes using these rules for all the networks:

Number of hidden neurons = the size of the output layer + $\frac{2}{3} \times$ the size of the input layer

Number of hidden neurons $<$ size of the input layer $\times$ 2

E. Experiment results

We trained LSTM with 100 hidden units. We used Mean Square Error loss function and Adam function as an optimizer (shown in Table 3); we tested different learning rates from 0.0001-0.1 and trained the model in 100 epochs (shown in Table 2). All experiments were performed using the Python and Pytorch package and run on an Intel Core (TM) i7 CPU @ 2.5Gz, 2.59 GHz machine with 16 GB of RAM. The operating system on the machine was Microsoft Windows 10.

Table 1 presents the performance comparison of a proposed deep learning method for different hyper-parameters of two-class EEG signals from UCI for detecting alcoholic and non-alcoholic participants. In most of the cases, the proposed LSTM (**Algorithm 2**) approach achieves higher classification accuracy, compared to the classic machine learning method in the previous study [24] and ANN proposed (**Algorithm 1**) in the current study. The average classification accuracy is calculated using all accuracy values for all epoch. The epoch number tested from 50-500 for ANN and 50-100 for LSTM (shown in Table 2). In this study, the highest classification accuracy was obtained a 93% in the alcoholic EEG signals for the LSTM technique (**Algorithm 2**) and while it was approximately 86% for **Algorithm 1** (seen in Table 1) that was same as the previous study (seen in Table 4).

For each experiment, the execution time of all methods was compared as shown in Table 1. The average execution time was around 8.5 hours for the whole dataset for the LSTM method while it was 6 hours for the ANN method. A longer execution time was shown when we increased the hidden layers in ANN. The LSTM network is not faster than ANN, although it is hard to compare architecture from a time perspective in time series application, as EEG data sets are usually large data sets and have complex structure, so many factors such as a very small or high learning rate, number of epochs to train the model, network depth and batch size could impact the execution time. The batch size is always dependent to the available memory and CPU/GPU. These factors can lead to a slow convergence and increase the overall execution time. As our training process is dependent on the error, accuracy and precision metrics, when we achieved the lowest error, highest accuracy and precision, we took down the training process.

For the LSTM model we identified a reducing learning rate when the model stopped so the convergence has benefits and we have seen more improvements in performance when the learning rate is reduced. We also noticed in the LSTM model that increasing the dropout from 0.2 to 0.4 led to better execution time and avoided over fitting. In our study, LSTM models take longer than even deep ANN to train and score and LSTM could not do that significantly faster than ANN. The results of these experiments are summarized in Table 1.

Table 1. Best Results from ANN and LSTM Models

Proposed algorithm	**Model**	**Loss function error**	**Accuracy (%)**	**Execution time**	**Sensitivity (%)**	**Specificity (%)**
Algorithm 1	PCA + ANN	0.4	75.00	02:44:00	76.00	74.00
	ANN-2	0.35	80.00	03:36:00	81.00	79.00
	ANN-4	0.28	86.00	06:00:00	85.00	84.00
Algorithm 2	LSTM-1	0.25	91.00	08:50:00	90.00	89.00
	LSTM-2	0.23	**93.00**	08:35:00	95.00	92.00

Table 2. ANN, LSTM architecture

Proposed algorithm	**Model**	**Layers**	**Activation Function**	**Topology**	**Epoch**	**Dropout**	**learning ratio**
Algorithm 1	PCA + ANN	2	Tanh, Sigmoid	30-50-1	50-500	0	0.001-0.4
	ANN-2	2	Relu, Sigmoid	64-100-1	50-500	0	0.001-0.4
	ANN-4	4	Relu, Sigmoid	64-100-50- 32-1	50-100	0	0.001-0.4
Algorithm 2	LSTM-1	2	Relu, Sigmoid	64-100-1	100	0.0-02	0.0001-0.1

	LSTM-2	3	Relu, Sigmoid	64-100-32-1	100	0.2-04	0.0001-0.1

Table 3. ANN, LSTM architecture-hyper-Parameters

Proposed algorithm	Model	Optimizer	Batch Size	Loss function
Algorithm 1	PCA + ANN	Adam	250	Mean Squared Error, Binary Cross entropy
	ANN-2	Adam	250	Mean Squared Error, Binary Cross entropy
	ANN-4	Adam	250	Mean Squared Error, Binary Cross entropy
Algorithm 2	LSTM-1	Adam, SGD	50-150	Mean Squared Error, Binary Cross entropy
	LSTM-2	Adam, SGD	50-150	Mean Squared Error, Binary Cross entropy

Based on our results, simple ANNs (by Algorithm 1) proved not to be more powerful than the non-deep learning model developed prior to this study. However, the LSTM model (Algorithm 2) did prove to be more powerful than the regular ANN. Not surprisingly, the ANN (by Algorithm 2) feed-forward on raw EEG signals did manage to outperform the ANN on principal components ((by Algorithm 1)) and the accuracy increased when we fed the classifier with more input feature from 75% to 86% with the best ANN model. As can be seen in Table 2, both the Relu activation function and Adam optimization performed better than the Tanh function and adding more hidden layers plus more neurons in intermediate layers to the ANN proved to be more powerful. Considering the results shown in Table 1, one can observe that proposed LSTM method (**Algorithm 2**) is more capable of classifying the two-class EEG signal than the proposed ANN based method (**Algorithm 1**) and also the classic machine learning.

Table 4. Summarization of 3 machine learners over UCI EEG dataset-Previous study [24]

Classifiers	10-fold cross validation accuracy (%)										Averaged
Bagging	72.8	63.2	64.9	67.5	65.8	69.3	70.2	66.7	63.2	64.0	66.7
Random Forest	86.8	78.9	89.5	81.6	91.2	83.3	87.7	87.7	87.7	85.6	**86.0**
Adaboost	78.1	71.1	71.9	69.3	68.4	71.9	79.8	79.8	75.4	73.0	73.9

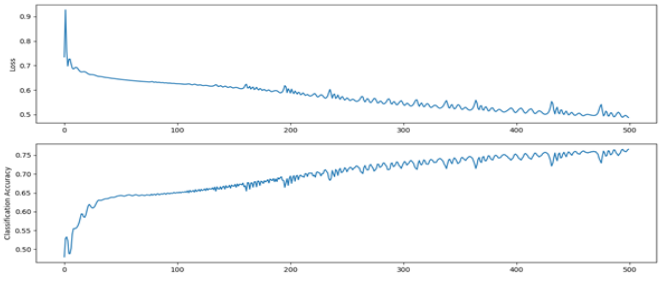

Fig.6. Loss and accuracy for **Algorithm 1** (PCA+ANN) model

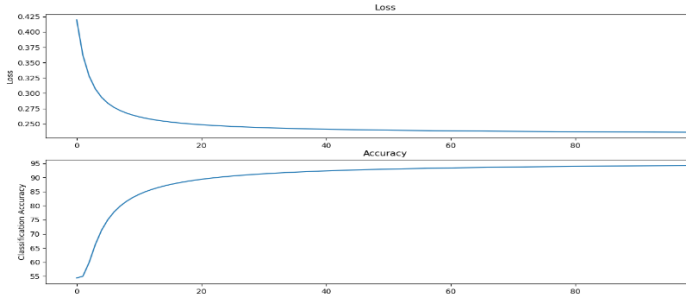

Fig.7. Loss and accuracy for **Algorithm 2 (**LSTM model)

Fig. 7 shows the progression of the loss function during epoch iteration. The data were averaged for the LSTM model. The loss function started from 0.420 and at the end of 100 epoch decreased to 0.236 and the accuracy of the model start from 54% in epoch 1 and converged to achieve 93% at the end of the iteration. As can be seen from Fig. 6 and Fig. 7, the proposed LSTM method is more effective for classifying alcoholism EEG signal compared to the proposed PCA and ANN based method.

In 'Introduction' section, we have already provided a discussion about some research works in the literature [11-19] that were performed on the identification of alcoholic EEG signals in UCI database. In order to further examine the efficiency of our proposed LSTM based algorithm (**Algorithm 2**), a report of comparative study for the same dataset is presented in Table 4. From Table 4, it is clear that the proposed LSTM based algorithm yields the better classification performances (93.00%) in terms of accuracy criteria compared to the reported existing methods in the literature.

Table 5. A comparative report for our proposed approach with the existing methods

Authors	Methods	Reported Accuracy
Ehlers et al. [14]	Correlation dimension (CD) based discriminant analysis	88.00%
Kannathal et al. [15]	CD, Lyapunov exponent, entropy, Hurst's exponent features with Discriminant analysis classifier	90.00%
Acharya et al. [17]	Approximate entropy, SampEn, Lyapunov exponent, Higher order spectra (HOS) features with SVM (poly kernel) classifier	91.70%
Faust et al. [32]	HOS based Fuzzy Sugeno classifier	92.40%
Proposed approach for Algorithm 2	Long short-term memory (LSTM) based deep learning algorithm	93.00%

IV CONCLUSION

This paper aimed to develop an efficient approach that can classify EEG signals into two classes: alcoholic and non-alcoholic as accurately as possible. This study proposed two deep learning-based methods: **Algorithm 1** is based on PCA and ANN algorithm and **Algorithm 2** is based on LSTM networks. The performances of the proposed algorithms were assessed on UCI Alcoholic EEG dataset in terms of Accuracy, sensitivity and specificity**.** Each model was trained and tested with two different architectures. Our study showed that significant improvements have been gained with the LSTM method (**Algorithm 2**) (93.00% accuracy) and show that LSTM is a robust and reliable classifier for EEG signals. The result for the ANN approach (**Algorithm 1**) is clearly worse (86.00% accuracy) than the results for the LSTM approaches (**Algorithm 2**); however, the LSTM was not quicker than ANN and its run time was highest among all the models. The experimental results also revealed that it is not worth applying a deep learning technique with a hand-crafted feature extraction method. This study provides necessary knowledge to apply the hand-crafted feature extraction method with the deep leaning algorithms and also give practical suggestions on the selection of hyperparameters in the deployment of deep learning. It will help researcher in other application of EEG signal processing and analysis in future study. There are two limitations in this study that can be compensated in our future studies: (1) binary classification (2) selection of hyper-parameters of the proposed methods through empirically.

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