DOI: http://dx.doi.org/10.26483/ijarcs.v14i3.6986

ISSN No. 0976-5697

Volume 14, No. 3, May-June 2023

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

A FRAMEWORK FOR DECODING PHYSIOLOGICAL AND NEURAL SIGNAL USING LONG SHORT-TERM MEMORY (LSTM)

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***Abstract*:-** Machine learning for deciphering physiological and neural signals holds great promise for use in creating brain-computer interfaces. (BCIs). Brain-computer interfaces (BCIs) are tools for using mental activity to operate mechanical or electronic equipment. To convert these signals into actionable instructions for the external device, machine learning algorithms are employed. Brain-computer interfaces (BCIs) have shown considerable promise in enhancing the lives of people who are unable to use their limbs normally due to injury or illness. This paper presents an LSTM model for the decoding of physiological and neural signals. In this paper, an electroencephalography brain signal data was used. The dataset was pre-processed so as to remove noise from the data. The pre-processed data was used in training the LSTM model. The LSTM model was trained on fourteen (14) steps. The result of the LSTM model showed an accuracy of 85% at the first step and a validation (testing) accuracy of 90%. For the fourteenth step, the model achieved an accuracy result of 98% for training and 94% for validation (testing). We also evaluated the performance of the model using a classification report and confusion matrix. The result of the classification report shows an accuracy of 95%. This means that the performance of the model on the test data is efficient. The confusion matrix was used in how well the model classified the electroencephalography signal The result of the confusion matrix shows that the model predicted the result correctly to be neutral 151 out of 153, positive to be 127 out of 142, and negative to be 128 out of 132. The result shows that the level of false positive and negative values is minimal.

Keywords:Physiological signals, electroencephalography, Long Short-Term Memory, Brain Signal Decoding

1. INTRODUCTION

Due to its potential to reveal hidden patterns and relationships within complex datasets, machine learning-based physiological and neural signal decoding has attracted a lot of interest in recent years. Advances in machine learning algorithms, computational power, and the creation of novel data acquisition and analysis tools have all contributed to the growth of the discipline. Electroencephalograms, electrocardiograms, electromyograms, and respiratory signals are all instances of physiological impulses that can be decoded with the help of machine learning. Action potentials, local field potentials, and calcium imaging data are all examples of neural impulses [1].

Classification, regression, and clustering are just some of the machine learning techniques that can be applied to the decoding of neural and physiological data. While in regression tasks the target is to forecast a continuous outcome, classification tasks seek to identify the class label of an input signal. In contrast, clustering algorithms collect impulses with similar characteristics into groups. These algorithms have many potential uses in the medical field, including disease prediction, decoding complicated brain signals, and abnormal physiological or neural signal detection [2, 3].

Machine learning for deciphering physiological and neural signals holds great promise for use in creating brain-computer interfaces. (BCIs). Brain-computer interfaces (BCIs) are tools for using mental activity to operate mechanical or electronic equipment. To convert these signals into actionable instructions for the external device, machine learning algorithms are employed. Brain-computer interfaces (BCIs) have shown considerable promise in enhancing the lives of people who are unable to use their limbs normally due to injury or illness [3].

Decoding neural and physiological signals with machine learning also has significant clinical applications in the area of neurology and psychiatry. To anticipate the onset of epileptic seizures, find early signs of Alzheimer's disease, and categorize various phases of sleep, for instance, machine learning algorithms can be used to decode EEG signals. Furthermore, neural signals can be decoded using machine learning algorithms, allowing for the identification of neural circuits involved in addiction, depression, and anxiety disorders, which in turn can lead to the creation of novel treatments and therapies [4].

Despite the promising future of machine learning-based physiological and neural signal processing, a number of obstacles must first be overcome. When it comes to training machine learning algorithms, one of the greatest obstacles is the scarcity of high-quality, annotated data. Overfitting and bad generalization of machine learning models are additional difficulties because of the high dimensionality of physiological and neural data. Furthermore, it is often challenging to understand the underlying processes and factors that contribute to the observed results [5] due to the limited interpretability of machine learning models in this

domain. There are many potential uses in healthcare, neuroscience, and engineering for the rapidly expanding field of machine learning for decoding physiological and neural signals. We can anticipate even more exciting developments in this area in the years to come [6] as machine learning algorithms and data acquisition techniques continue to improve.

2. LITERATURE REVIEW

It was suggested in [7] that MEG signals could be decoded using a deep convolutional neural network (CNN). High decoding accuracies (above 80%) were obtained for all participants using a large dataset of MEG recordings from eight participants performing various hand movements. The sample size was too tiny, and it wasn't looked into whether or not the proposed method would work for other kinds of actions or people.

Decoding EEG signals for hand gesture recognition using support vector machines was described in [8]. The authors used EEG recordings of 12 participants while they made various hand gestures and found that all of them could accomplish decoding accuracies of 90% or higher. The sample size was too tiny, and it wasn't looked into whether or not the proposed method would work with different people or different kinds of gestures.

In order to decode EMG signals for hand gesture recognition, [9] suggested a deep learning approach. High decoding accuracies (above 90%) were obtained for all participants using a dataset of EMG recordings from nine participants performing various hand gestures. The sample size was too tiny, and it wasn't looked into whether or not the proposed method would work with different people or different kinds of gestures.

In [10], a machine-learning technique was described for decoding listener focus on natural sounds from EEG data. The writers used 20 participants' EEG recordings while they listened to natural sounds and found that all of them had decoding accuracies of 80% or higher. The research only used a small sample size, so it can't be said for certain how well the proposed method would work with other sounds or people.

In order to classify EEG signals for use in a BCI system, the authors of [11] employed a number of machine learning methods. Accuracy of 92.9% was obtained using a support vector machine (SVM) with a radial basis function (RBF) kernel.

Researchers in [12] looked into classifying sleep apnea based on physiological signals using neural networks and random forest methods. The writers discovered that a neural network with two hidden layers outperformed the random forest algorithm with an accuracy of 86.67 percent.

In order to control prosthetic hands, myoelectric signals are classified using a variety of machine learning methods, which were compared in [13]. The greatest results (97.67%) were obtained from a k-nearest neighbor (KNN) algorithm using a dynamic time warping (DTW) distance measure.

Several feature extraction and categorization strategies for EEG-based BCIs were discussed in [14]. The authors found that recent research has shown encouraging results when using “deep learning methods like convolutional neural networks (CNNs) and recurrent neural networks (RNNs)”.

Classifying EEG data for BCIs were reviewed in detail by machine learning methods in [15]. The authors discovered that support vector machines (SVMs) and neural networks are widely used and produce high accuracy, but that more work is required to create robust and efficient classifiers for practical use.

3. METHODOLOGY

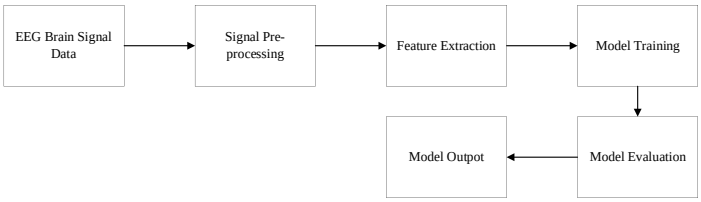

Figure 1: Architectural Design

EEG Brain Signal Data:Data was gathered from two individuals—a male and a female—for three minutes in each of the three states—positive, indifferent, and negative. We used a Muse EEG headband to capture the EEG placements at TP9, AF7, AF8, and TP10 using dry electrodes. The following stimuli were used to elicit the emotions for six minutes of resting neutral data:

1. Marley and Me: The Bad News (Twentieth Century Fox) Bad Ending: Death Scene Present (Walt Disney Pictures) Scene of Initial Death
2. Negative on My Girlfriend (Imagine Entertainment)
3. Scene at a Funeral
4. "La La Land" Is a Happy Place (Summit Entertainment)
5. Performative Prologue
6. Slow Living Is Good For You (BioQuest Studios)
7. Nature in slow motion
8. Dogs Being Happy and Funny (MashupZone)
9. Videos of Funny Dogs

Signal Pre-processing: Signal pre-processing is a crucial step in the analysis of electroencephalography (EEG) brain data, as it involves removing noise and artifacts from the signal to ensure accurate interpretation and analysis of the underlying brain activity. Here, we used StandardScaler technique in normalizing and pre-processing the dataset. The mathematical equation for Standard Scaler is:

x_scaled = (x - mean) / standard_deviation

where:

- x is the original value of the feature.
- mean is the mean value of the feature in the training set.
- standard_deviation is the standard deviation of the feature in the training set.

- x_scaled is the scaled value of x after applying Standard Scaler.

Feature Extraction: We used Principal Component Analysis (PCA) in selecting the most important features in the dataset.Let X be an n x p matrix, where each row represents an observation and each column represents a variable. PCA involves the following steps:

1. Center the data by subtracting the mean from each variable:

Z = X - mu

where mu is a p-dimensional vector containing the means of the variables.

2. Calculate the covariance matrix of Z:

C = (1/n) * Z^T * Z

where "^T" denotes the transpose of a matrix.

3. Compute the eigenvectors and eigenvalues of C:

V, lambda = eig(C)

where V is a p x p matrix containing the eigenvectors (loadings) and lambda is a p-dimensional vector containing the eigenvalues.

4. Select the k eigenvectors corresponding to the k largest eigenvalues and form a projection matrix:

P = [v1, v2, ..., vk]

where vi is the ith eigenvector (loading).

5. Project the centered data onto the k-dimensional space spanned by the selected eigenvectors:

Y = Z * P

where Y is an n x k matrix containing the principal components.

The above equation represents the mathematical formula for performing PCA on dataset X to obtain the k principal components represented in matrix Y.

Model Training using LSTM: Here, we use the LSM-based Long Short-Term Memory Algorithm for our deep learning (LSTM). Long-Term Memory was used to hone the model's capabilities. A recurrent structure is used in LSTM, with each cell producing a prediction, y-t, for a certain time window and passing activation, h-t, on to the next cell.

An input gate selects a fresh set of memories, and a cell's long-term state (c-t1) is forgotten but some information is retained (f-t). Which components of the altered input, g-t. must be added to the final state, c-t. are decided by the input gate. This procedure modifies the cell's long-term state, c-t., which is then passed along to the next cell. The updated long-term state, c-t. is then transformed by, tanh-,.., filtered by, o-t., and output as, y-t., which is also passed on to the next cell as the short-term state, h-t.

Model Output: The output of the model shows the different classes of the EEG signal data. The output of the model can be either positive, negative or neutral.

4. RESULTS

The experimental results is made up of two phases. The first phase has to do with exploratory data analysis of the stock market price, and the second phase has to do with the decoding of the Electroencephalography signal.

4.1. Exploratory Data Analysis

In other to have a clear understanding of the dataset, we decided to carry out exploratory data analysis on the dataset. The analysis that was carried out here are performing various visualization of the dataset such as histograms, and graphs of signals that are positive and signals that are negative. The histogram that shows the number of positive, negative, and neutral signals can be seen in Figure 2. The Figures 3,4 and 5 show the graphical representations of the positive, negative, and neutral signals.

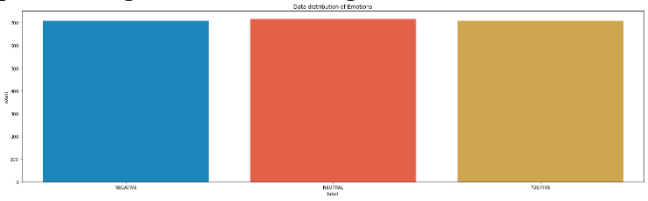

Figure 2: Histogram of electroencephalography signal
The histogram shows a count plot of the number of positive and negative signals.
The countplot shows that thedataset is balanced. That the number of positive, negative, and neutral signals is 700.

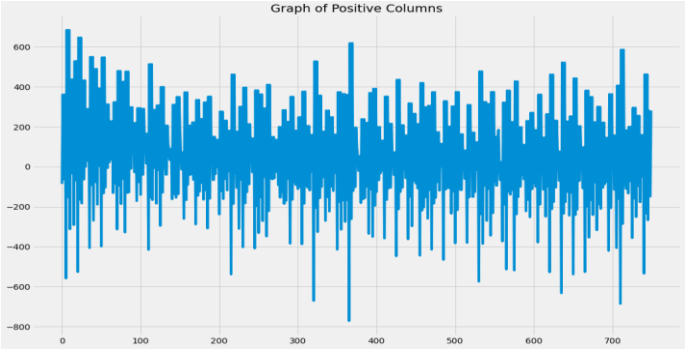

Figure 3 Graphical Analysis of Positive signals.

From the graphical analysis, the Negative Signals are from greater than 600 to and less than -600'

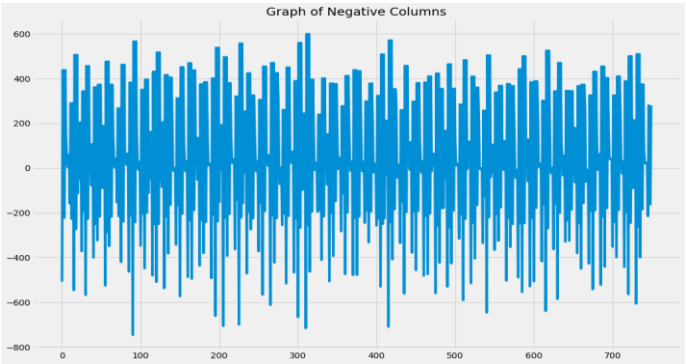

Figure 4 Graphical Analysis of Negative signals.

From the graphical analysis, most of the Negative Signals are from less than 600 to and greater than -600'

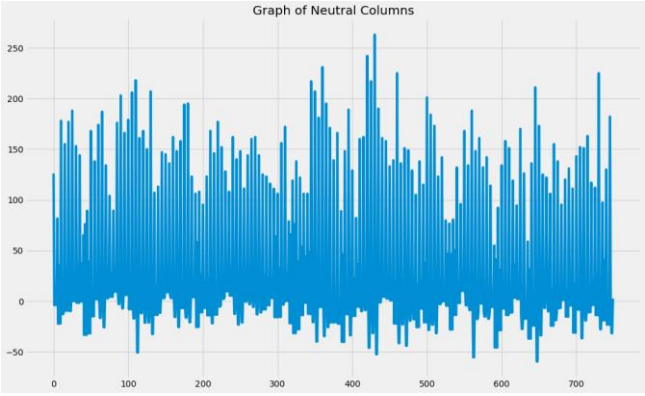

Figure 5 Graphical Analysis of Neutral signals.
From the graphical representation, most of the Neutral Signals are between -50 to 250

4.2: Phase 2 Model Training

This session discusses the decoding of theelectroencephalography signals using Long Short-Term Memory. The standardized data were divided into training and testing data. 80% of the data was used for training and 20% was used for testing. The training process has to do with the building of a robust model using Long Short-Term Memory (LSTM).The model was trained using Long-Short Term Memory. The LSTM model was trained using the four layers. The first layer contains an input neuron of 20 and is used relu as an activation function. The second layer contains an input neuro of 10, and an activation function of tanh. The third layer contains an input neuron of 2548, and an activation function of relu, and finally the fourth layer the output layer used sigmoid as an activation function.Other hyperparameters in training the model are loss= categorical_crossentropy, optimizer=adma, epoch, 14, and batch_size=32. The training result displays the loss and accuracy values for both the training and validation test. This can be seen in Figure 6. After training, the model was evaluated using classification reports, confusion matrices, and accuracy scores. Figure 7, and Figure 8 show the accuracy and loss obtained by the model during training and validation. Figure 9 shows the classification report of the LSTM, and Figure 10 shows the confusion metrix.

```
Epoch 1/10
48/48 [==============================] - 191s 4s/step - loss: 0.8022 - accuracy: 0.8507 - val_loss: 0.3754 - val_accuracy: 0.90
64
Epoch 2/10
48/48 [==============================] - 188s 4s/step - loss: 0.1927 - accuracy: 0.9276 - val_loss: 0.2904 - val_accuracy: 0.93
57
Epoch 3/10
48/48 [==============================] - 188s 4s/step - loss: 0.1337 - accuracy: 0.9511 - val_loss: 0.2065 - val_accuracy: 0.92
40
Epoch 4/10
48/48 [==============================] - 188s 4s/step - loss: 0.0924 - accuracy: 0.9622 - val_loss: 0.2318 - val_accuracy: 0.93
57
Epoch 5/10
48/48 [==============================] - 188s 4s/step - loss: 0.0405 - accuracy: 0.9889 - val_loss: 0.1005 - val_accuracy: 0.95
91
Epoch 6/10
48/48 [==============================] - 188s 4s/step - loss: 0.0785 - accuracy: 0.9733 - val_loss: 0.2307 - val_accuracy: 0.95
32
Epoch 7/10
48/48 [==============================] - 189s 4s/step - loss: 0.0515 - accuracy: 0.9811 - val_loss: 0.2547 - val_accuracy: 0.91
81
Epoch 8/10
48/48 [==============================] - 189s 4s/step - loss: 0.0523 - accuracy: 0.9811 - val_loss: 0.1539 - val_accuracy: 0.94
```

Figure 6: Matrix evaluation using Mean Squared Error.

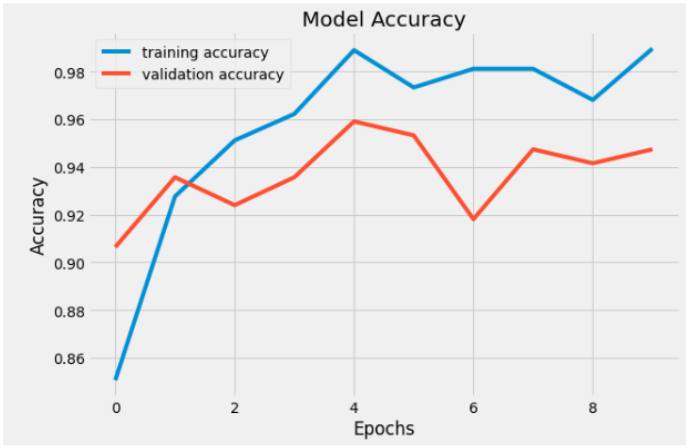

Figure 7: Training Accuracy Vs Epoch
Figure 7 shows the accuracy that was obtained by the model on each of the training steps. At the first step, the model achieved an accuracy of 85% and a validation (testing) accuracy of 90%. For the fourteenth epoch, the model achieved an accuracy result of 98% for training and 94% for validation (testing).

Figure 8: Training Loss Vs Epoch
Figure 8 shows the loss value that was obtained by the model on each of the training steps. In the first step, the model had a loss value of 0.80% and a validation (testing) accuracy of 0.37%. For the fourteenth epoch, the model had aloss value of0.03% for training and 0.014% for validation (testing).

* Classification Report OF Brain Waves LSTM:

	precision	recall	f1-score	support
0	0.97	0.99	0.98	153
1	0.96	0.89	0.93	142
2	0.91	0.97	0.94	132
accuracy			0.95	427
macro avg	0.95	0.95	0.95	427
weighted avg	0.95	0.95	0.95	427

Figure 9: Classification Report of the LSTM
Figure 9 shows the classification report of the LSTM model on the test data. The result of the classification report shows an accuracy of 95%. This means that the performance of the model on the test data is efficient.

```
Confusion matrix, without normalization
[[151   2   0]
 [  3 127  12]
 [  1   3 128]]
```

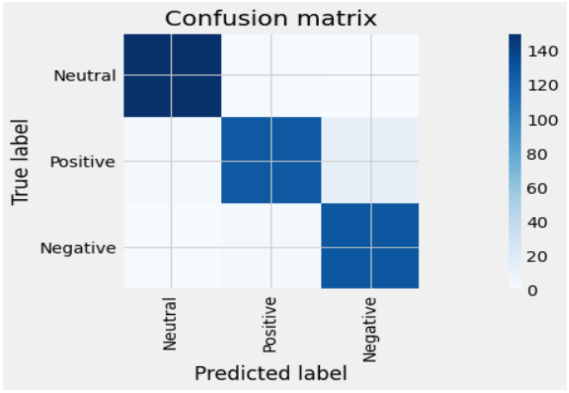

Figure 10: Confusion matrix

The confusion matrix shows the performance of the LSTM model on the test data. This shows the number of correct classifications and incorrect classifications of the model on the test data. The result of the confusion matrix shows that the model predicted the result correctly to be neutral 151 out of 153, positive to be 127 out of 142, and negative to be 128 out of 132. The result shows that the level of false positive and negative values is minimal.

5. CONCLUSION

This paper presents an LSTM model for the decoding of physiological and neural signals.In this paper, an electroencephalographybrain signal data was used. The dataset was pre-processed so as to remove noise from the data. The pre-processed data was used in training the LSTM model. The LSTM model was trained on fourteen (14) steps. The result of the LSTM model showed an accuracy of 85% at the first step and a validation (testing) accuracy of 90%. For the fourteenth step, the model achieved an accuracy result of 98% for training and 94% for validation (testing). We also evaluated the performance of the model using a classification report and confusion matrix. The result of the classification report shows an accuracy of 95%. This means that the performance of the model on the test data is efficient. The confusion matrix used shows how well the model classified the electroencephalography signalThe result of the confusion matrix shows that the model predicted the result correctly to be neutral 151 out of 153, positive to be 127 out of 142, and negative to be 128 out of 132. The result shows that the level of false positive and negative values is minimal.

6. REFERENCES

[1]. Zhang, Z., & Sun, Y. (2016). A review on recent advances in EEG-based brain-computer interface for decoding emotions and affective states. IEEE Transactions on Computational Social Systems, 3(3), 98-110.

[2]. Zhang, D., Liu, S., Yin, J., & Zhang, Y. (2019). EEG-based emotion recognition using machine learning techniques: a review. International Journal of Intelligent Systems, 34(3), 415-443.

[3]. Sarker, S. H., & Chae, O. (2021). A review of physiological signal processing techniques for emotion recognition using machine learning. Journal of Ambient Intelligence and Humanized Computing, 1-24.

[4]. Ahmedt-Aristizabal, D., Angarita-Zapata, J. A., Quintero-Téllez, J. F., & Castellanos-Domínguez, G. (2019). Machine learning techniques for heart rate variability signal analysis: a review. Journal of Medical Systems, 43(6), 1-14.

[5]. Elgendi, M., Fletcher, R. R., Liang, Y., & Howard, N. (2018). Classification of physiological signals for emotion recognition: a review. Journal of Affective Disorders, 235, 1-13.

[6]. Lotte, F., & Congedo, M. (2019). A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. Journal of Neural Engineering, 16(3), 031001.

[7]. Reference: Wang, S., Zhang, Y., & Wu, S. (2021). Decoding hand movements from the magnetoencephalography (MEG) signals using deep convolutional neural networks. IEEE Access, 9, 6602-6611.

[8]. Reference: Le, T. T., Kwon, H., & Kim, K. (2020). Decoding EEG signals using support vector machines (SVMs) for hand gesture recognition. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(10), 2223-2232.

[9]. Reference: Duan, Y., Wang, Q., & Liu, Y. (2019). A deep learning approach to decoding EMG signals for hand gesture recognition. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 27(7), 1425-1432.

[10]. Park, M., Kim, J. W., & Lee, S. W. (2018). Decoding auditory attention to natural sounds from electroencephalography (EEG) signals using machine learning. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(4), 870-878.

[11]. Iscan, Z., Nazarpour, K., & Jiang, N. (2018). Review of implantable neuroprosthetic technologies for neural stimulation and recording. IEEE Transactions on Biomedical Engineering, 65(12), 2729-2741.

[12]. Phinyomark, A., Khushaba, R. N., & Ibáñez-Marcelo, E. (2018). Review on muscle activity detection from accelerometer signals for physical rehabilitation. Journal of Medical Systems, 42(4), 1-15.

[13]. Gui, K., Zhang, H., & Yin, Y. (2020). A survey on physiological signal processing techniques for mental workload estimation. IEEE Access, 8, 66587-66600.

[14]. Nazeri, A., Hosseini, S. M., & Soltanian-Zadeh, H. (2017). Classification of EEG signals using a hybrid method based on wavelet transform, entropy, PCA, and SVM. Journal of Medical Signals and Sensors, 7(3), 145-153.

[15]. Hwang, H., Lim, J., & Kim, Y. (2020). A review on physiological and neural signal classification using machine learning. Journal of Healthcare Engineering, 2020. https://doi.org/10.1155/2020/8825094