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DEEP LEARNING NETWORK WITH LONG SHORT-TERM MEMORY FOR THE PREDICTION OF EPILEPTIC SEIZURE USING ELECTROENCEPHALOGRAM SIGNALS

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Abstract

Early prediction of seizures can help epileptic patients manage their crises before they occur. A new automated system Combining the process of features extraction and classification solution. The input to deep learning models is a EEG signal, Consequently, fewer computations are needed. An electroencephalogram (EEG), it records and measures the electrical activity of the brain, is now a common component, the range of tools available for studying neural disorders. As a result, these models extract the most discriminative features, Prediction time can be reduced while classification accuracy is improved. This method extracts spatial characteristics from various scalp positions using the LSTM technique. The expressed seizure features from EEG data were studied by using Deep Convolutional Variational Auto - encoder, and a tunable Q-factor wavelet transform has been employed for pre-processing. A suggested channel selection technique makes it suitable for use in real-time. To make sure the data gathered is accurate, a trustworthy test procedure is employed. One of the most prevalent neurological conditions in the world is epilepsy. In the lives of epileptic patients, early seizure prediction has a significant impact. This study proposes a unique deep learning-based method for predicting seizures in individual patients using long-term scalp EEG records. Accurately identifying the preictal brain state, separating it from the dominant interictal state as early as possible, and making it acceptable for real-time are the objectives. A single automated system combines the procedures of feature extraction and categorization. The system considers the raw EEG signal, which has not undergone any preprocessing, as its input, which further streamlines computations. The strongest discriminative characteristics that improve classification accuracy and prediction are extracted using four deep learning models. Convolutional neural networks are used to extract important spatial characteristics from various scalp sites in the proposed method, while recurrent neural networks are used to predict the occurrence of seizures earlier than current techniques. To better solve the optimisation problem, a semi-supervised method based on transfer learning methodology is developed. The most pertinent EEG channels are chosen using a suggested channel selection technique, making the suggested system a strong option for real-time use. Robustness is guaranteed via an efficient test methodology. The proposed method is the most effective on the market today due to the 99.6% accuracy achieved, the low false alarm rate of 0.004 h 1, and the hour-early seizure forecast time.

KEYWORDS: LSTM technique, seizures prediction, EEG Signals, Deep learning models, classification, deep learning, epilepsy, EEG, interictal, preictal, seizure prediction

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INTRODUCTION:

Amount of information being generated in medical field is rapidly increasing. As a result, accurate analysis on medical data has become increasingly important in the field of patient care. By analyzing disease data, we found a pattern in the health care system that can be used to predict patients' risk of death. Data mining, like analytics and business intelligence, refers to a wide variety of techniques that thuge data sets should be evaluated in order to find patterns, then utilized in order to forecast or forecast future the likely hood of upcoming events. Repeated seizures are the main feature of the immobilising neurological condition known as epilepsy [1]. However, it has been identified because if patients have had seizures, they would likely have subsequent seizures in more than 30% of instances that they cannot control with current treatments. Patients can be treated with medications or with surgical procedures.

Due to the unpredictability of epileptic seizures, it is important for doctors to be able to predict when and where the seizures will occur. This can be done by observing electrical brain activity as measured by an electroencephalogram (EEG). Signals from EEG electrodes applied over the scalp are called scalp EEG signals, in contrast to signals from electrodes implanted outside the brain, which are called extracranial EEG (ECoG) signals, signals from electrodes embedded

Intracranial EEG (iEEG) signals are those that originate inside the brain. It can be inferred from EEG recordings that any sudden change in the brain's neurons signals, recorded during a neurological disorder, is attributed to the diseased state of brain. Recurrent seizures (ictal state, the time between seizures) are a neurological condition known as epilepsy. 30 minutes before a seizure actually occurs, exhibits symptoms that may be used for diagnosis. The ictal state, or seizure, typically lasts 3-4 minutes and is followed by a post- clincal state which lasts anywhere from 20 minutes to an hour and a half. There are around two million new cases of epilepsy each year, and the disorder affects 50 million individuals globally. Anti-epileptic drugs (AED) can control up to 70% of epileptic patients, while the remaining 30% are uncontrollable [2]. The electrical recording of brain activity known as an electroencephalogram, or EEG, is thought to be the most effective diagnostic and research tool for epilepsy. According to EEG recordings, doctors divide the brain activity of epileptic patients into four states: preictal state, which refers to the period just before the seizure, ictal state, which is the time period during the seizure occurrence, postictal state, which is assigned to the period after the seizure occurred, and interictal state, which refers to the interval between seizures other than the states mentioned previously [3], In addition to being a potentially fatal disease, epilepsy has a significant psychological and social impact due to its unpredictable seizure times. As a result, the ability to predict epileptic seizures would significantly improve the quality of life for epileptic patients in many ways, such as by raising an alarm prior to the seizure to give people time to take the appropriate action, creating new treatment options, and establishing new strategies to better understand the nature of the disease. The seizure prediction problem could be seen as a classification task between the preictal and interictal brain states in light of the aforementioned description of the epileptic patient's brain activities.

Figures 1 show The amplitude and frequency of 10-second epochs varied between the interictal, preictal, and ictal states of a multi-channel EEG signal. These observations motivate us to attempt classifying interictal and preictal signals for seizure prediction.

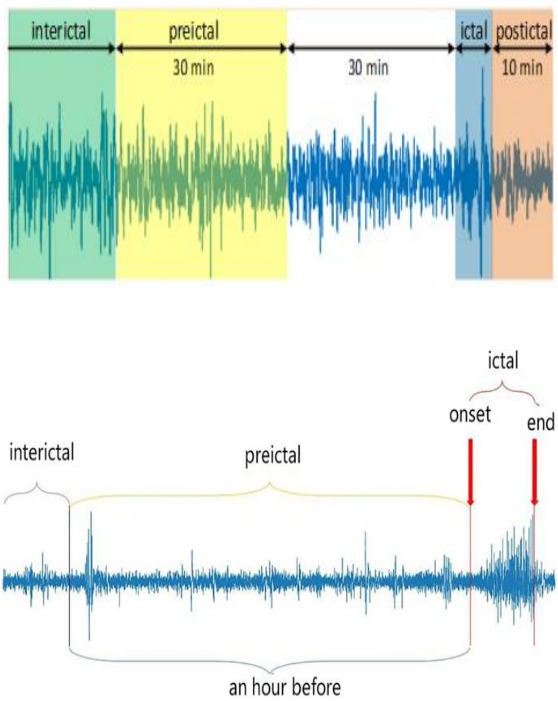

FIGURE 1 Amplitude and frequency response for seizure prediction

A neurologist uses an EEG headset, which can sample brainwaves at frequencies between 200 and 5000 hertz. The beginning of a seizure can be signaled by a sudden and sustained increase in the frequency of brain waves called beta rhythms. Research has shown that distinguishing between the interictal state, Wahich lasts between seizures, and the preictal state, which ends 30 to 90 minutes before a seizure begins, is critical in developing targeted treatments for epilepsy. Preprocessing reduces noise in continuing to increase the Signal-to-Noise ratio with EEG signals (SNR).One commonly used spatial filter is the optimized spatial filter.

EEG signals can be improved by decomposing them into intrinsic mode functions, which are low-frequency components which improves the Signal-to-noise-ratio. Using We can reconfigure EEG signals before putting them into a convolutional neural network using Fourier and wavelet transforms. This is followed by noise removal, the extraction of features, and the selection of appropriate variables for prediction. Many researchers have used both spectral and temporal features to predict epileptic seizures, including Hjorth parameters, Entropy, its first four statistical moments, estimate entropy, and Lyapunov exponents, spectral moments, and power spectral density.

METHODOLOGY:

Software programme for predicting seizures, using scalp EEG signals, aims to predict epileptic seizures. Most seizure prediction methods involve EEG signal preprocessing, semantic segmentation, and distinction between preictal and interictal phases are the three steps.

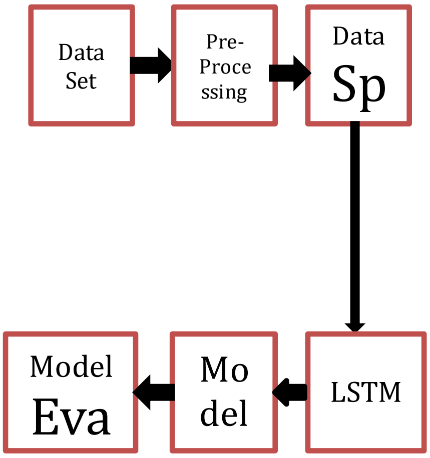

FIGURE 2 Proposed Block diagram

Seizures were labelled as either clinical or clinically comparable. All 10 patients who were a part of Cook and colleagues' prospective experiment were included in this investigation, and their data were utilised (Cook et al., 2013). 2817 seizures and 16.29 years' worth of iEEG data were used in the analysis. The data will soon be made available in sections for public use.

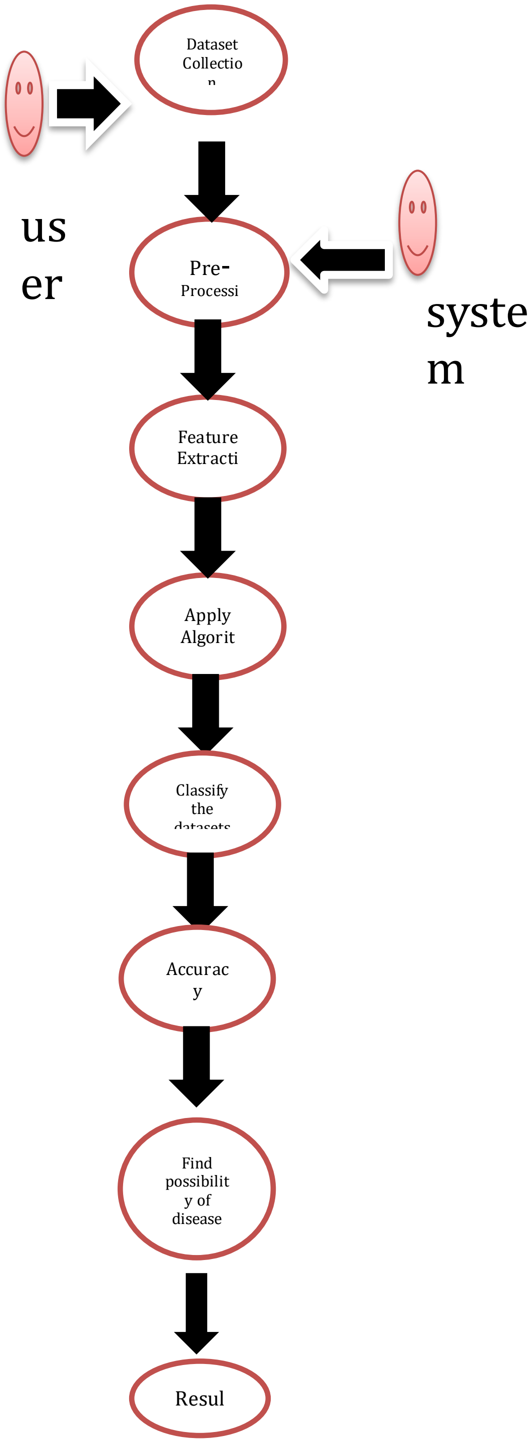

FIGURE 3 UML Diagram – Use Case Diagram

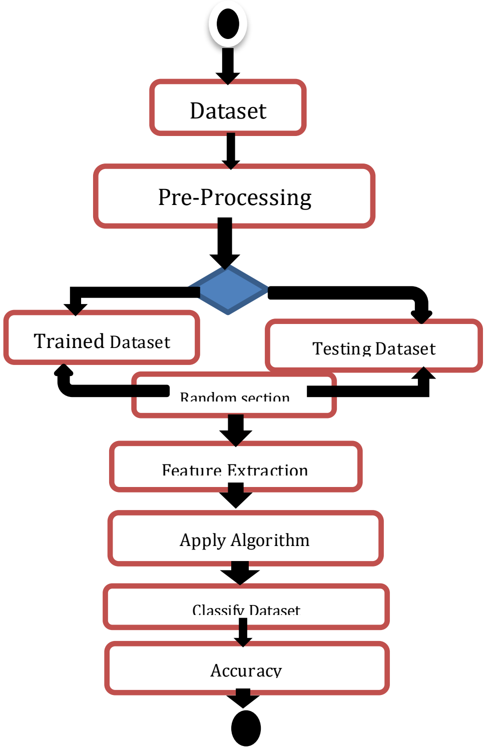

FIGURE 4 proposed flowchart diagram

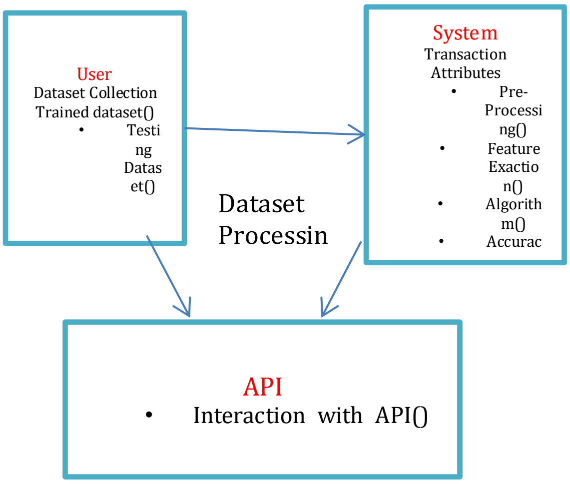

FIGURE 5 Class diagram

Data:

For the investigation, information was gathered from a prior clinical test of an implanted seizure advisory system (Cook et al., 2013). An implanted 16-electrode iEEG system was used to continually record the iEEG of the enrolled patients for up to two years. All seizures were annotated, and the data were evaluated by knowledgeable investigators. For a thorough discussion of the data, see Cook et

PREPROCESSING:

To increase the clarity of the ECG signal, it is processed with filters. These filters, however, are not perfect and the result is that ECG noise may still be present. This noise can affect the classification of interictal and preictal states into different classes resulting in poor performance .The type of noise that affects ECG is base line due to multiple electrodes and electrical activity including eye movements and heart pulse. To attempt to clean remove the noise in the EEG readings, researchers have used various preprocessing techniques. The band pass /band-stop filtering technique can be used to remove power line noise, and the low-pass/high-pass filtering technique can be used to remove other types of noise. In this research, four deep learning-based models are put forth with the goal of early and accurate seizure prediction while taking real-time operation into consideration. A real alarm is taken into account when the preictal condition is recognised within the predetermined preictal interval, as illustrated in Fig. 1. The seizure prediction issue is formulated as a classification job between interictal and preictal brain states. Despite the extensive study on seizure prediction, there is no established time frame for the preictal state. Like in [15], the preictal duration in our trials was set at one hour prior to the commencement of the seizure, and the interictal duration was fixed at at least four hours prior to or following any seizure. be at least four hours prior to or following any seizure, as described in [15]. All of the models start with raw EEG data that hasn't been processed in any way or had any handcrafted characteristics extracted. To minimise overhead and expedite the classification operation, the discriminative features are automatically developed using deep learning algorithms. There is an imbalance between the preictal and interictal samples because each patient only has a limited number of seizures. Naturally, there are much more interictal examples than preictal samples, and classifiers are typically more accurate for the class that has more training samples [16]. Since we obtained the results from the literature, the comparison of CPU time between algorithms is not possible. In addition, the run time of algorithms depends highly on the implementation and the programming language employed. In order to provide a fair comparison, the algorithms are compared based on their computational complexity. The computational complexity of WOA-CM is of O(t(n*p + Cof*p)) where t shows the number of iterations, n is the number of variables, p is the number of solutions, and cof indicates the cost of objective function. This computation complexity is equal to that of PSO. However, the computational complexity of GA and ALO is of O(t* (n*p + Cof*p + p*log(p))) in the best case and O(t* (n*p + Cof*p + p2) in the worst case. This shows that the computational complexity of GA and ALO is worse than those of WOA-CM and PSO due to the need to sort the solutions in each iteration.

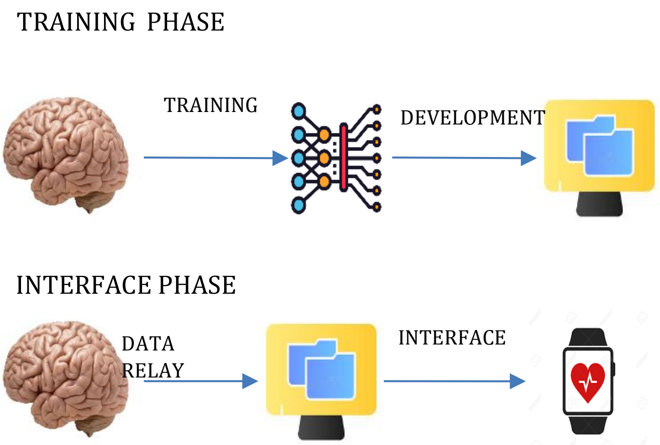

FIGURE 6 System Design Justification

The creation, application, and assessment of a therapeutically applicable seizure prediction system are the goals of this project. We established the following objectives in order for a system to be beneficial to patients while still being manageable by clinicians:

G1. The system must operate effectively and consistently among patients. G2. The system must be able to function independently over extended periods of time without the need for expert maintenance or reconfiguration. G3. The system must enable patients to define.
For the first time, the Whale Optimization Algorithm is utilised for feature selection.G4 A low-power platform must be used for the system to operate in real-time.

Fig. 6: Seizure advisory system concept EEG data is acquired using intracranial electrodes during the training phase, and recordings are sent to a deep learning network (magenta circles show a potential configuration) (green network graph). The model is then put into operation on a TrueNorth chip. b) The inference phase: the intracranial electrodes (magenta circles) record the iEEG signal, and the data are sent to the TrueNorth chip. On a wearable gadget, the patient is given a seizure prediction.

We used deep learning, a method that, in contrast to a more conventional feature engineering approach, does not rely on data analysis experts for the monitoring and adaption of models, to address performance (G1) and long-term viability (G2). Deep learning algorithms learn from examples to automatically distinguish between several classes of signals, in contrast to standard computing systems that learn by instructions or explicit programming. This enables the algorithm to distinguish between preictal and interictal data segments in the context of a seizure prediction system. A system using an artificial neural network cannot only adapt to the unique brain signals of each patient, but also to short- and long-term changes in the recording, due to the nature of the technology. Additionally, it enables the incorporation of other patient-specific factors, such as time of day data, that have been demonstrated to vary with seizure likelihood. A deep neural network can also automatically learn to distinguish between various data classes, such as preictal and interictal in this case. To improve the exploitation property of the WOA algorithm, crossover and mutation are applied. Tournament selection is used to improve the WOA algorithm's exploration. The experiments show that the suggested ways perform better. A recently developed method called "WOA" has not yet been used to solve the feature selection challenge. Two binary variations of the WOA algorithm are presented in this study.a first-ever suggestion was made to look for the ideal feature subsets for categorization purposes. In the first, we want to examine the effects of utilising a roulette wheel or tournament selection system in place of a random operator. The second strategy makes better use of the WOA algorithm by using crossover and mutation operators. A classification neural network, like the one we employed in our study, typically classifies the signal sample-by-sample, which could result in brief but highly frequent alerts. So, in a real-time system, an additional processing layer is needed to balance the system's sensitivity, the quantity, and the duration of alarms. Additionally, it enables the incorporation of other patient-specific factors, such as time of day data, that have been demonstrated to vary with seizure likelihood. A deep neural network can also automatically learn to distinguish between various data classes, such as preictal and interictal in this case. A classification neural network, like the one we employed in our study, typically classifies the signal sample-by-sample, which could result in brief but highly frequent alerts. So, in a real-time system, an additional processing layer is needed to balance the system's sensitivity, the quantity, and the duration of alarms. and the TrueNorth chip receives recordings. On a wearable gadget, the patient is given a seizure prediction.

Performance Evaluation:

We used the measures introduced to assess seizure prediction performance. Sensitivity (the true positive seizure prediction rate), time in warning (TiW, the total duration of a red-light indication), and sensitivity improvement over chance were these (IoC). IoC is determined by contrasting our system with a random predictor, which spends the same amount of time computing the attained sensitivities' difference and issuing warnings. These measurements offer a performance indication that is therapeutically applicable. After a brief first phase of data collection, we report mean prediction scores as well as monthly performance in this work. According to Section 2.2, three independent runs of the results were obtained, and for each run, we present the mean performance as well as the 95% confidence interval.

FEATURE EXTRACTION:

To support classification of epilepsy seizure stages, features should be extracted from electroencephalography (EEG) signals by using either hand-crafted or deep learning methods. Although deep learning methods typically analyze data in the time domain, hand-crafted Both the time and frequency domains contain characteristics. The statistical characteristics of a time series can be described using statistical moments, mean, variance, skewness, and kurtosis. Some of the features you should look for when making predictions about a time series are Bag of waves, zero-crossings intervals, and spectral characteristics.

Seizure prediction techniques have made use of these characteristics. Position and velocity are the two vectors used in PSO. The primary vector that takes into account the best outcome so far found by the particle and the entire swarm is the velocity vector. The location vector is calculated for each solution using the velocity vector. The position of each solution in a search space is, however, only stored in one vector in WOA. Additionally, the solutions are updated either randomly in the search space using Eq. 2 or using a spiral equation (Eq. 6) towards a good solution. Since this algorithm only stores the best estimate of the global optimum in each iteration, the WOA is more memory-efficient than the PSO. PSO, however, keeps track of each particle's best solution and personal best.

More so than PSO, WOA relies on random answers to guide the search. As a result, when compared to PSO, this algorithm exhibits better exploratory tendencies. WOA may be able to avoid these solutions better than PSO because the feature selection problem includes many local solutions. Moreover, WOA has adaptive mechanisms and can speed up exploitation in direct proportion to the number of iterations. In contrast to GA with crossover operators, which abruptly varies the answers throughout the optimisation process, this increases the likelihood of obtaining more accurate solutions to feature selection issues.

Several in-depth experiments have been conducted using various values of the algorithm's key parameters, including the number of search agents (n), the maximum number of iterations (t), and the vector an in Eq. (5), in order to examine the effects of the conventional WOA parameters. To evaluate the various combinations of these factors, three datasets—one small dataset, one medium dataset, and one large dataset—were arbitrarily chosen. The last parameter (vector a) is altered linearly in three different intervals: [0, 1], [0, 2], and [0, 3]. The number of search agents (n) parameter can take one of six possible values: 5, 10, 20, 30, 40, or 50. The t parameter can take one of five possible values: 20, 30, 50, 70, or 100.

CLASSIFICATION:

It is possible for machine learning or deep learning to be used to classify EEG signals as interictal or preictal. Caps nets has proved to be highly accurate in seizure prediction. the classification accuracy obtained utilising complete datasets and using the chosen features from all feature selection methods. The best outcomes are bolded to draw attention to them. The outcomes of algorithms that show differences from the best algorithms that are more than or equal to a 0.05 p-value are also highlighted. The table shows that incorporating every feature in a dataset results in the worst classification accuracy. Also, the table shows that the proposed strategy (WOA-CM) fared better on most datasets than competing approaches (fourteen out of eighteen datasets). This outcome demonstrates the suggested approach's capability to effectively explore the search space and identify the best redacts that result in higher categorization. In this work, various WOA algorithm variants were researched and created. To the best of our knowledge, this was the first instance of the feature selection problem being solved using WOA. The ongoing iteration of WOA was converted to binary by simply invoking the WOA's fundamental operators and swapping them out for binary ones. Here, the WOA-T, WOA-R, and WOA-CM algorithms were proposed as three upgrades to the original WOA algorithm. The feature selection domain was utilised to test the suggested methodologies. Future research may propose the WOA algorithm as a filter feature selection method in an effort to assess the generality of the chosen features and investigate classification accuracy using classifiers other than the KNN used in this report. Using the WOA-CM algorithm to datasets with significantly higher dimensions will be a valuable contribution to the investigation of its performance. Also, a study on the impact of small samples and high dimensionality.

LSTM:

To comprehend the LSTM design, consider how a news team would cover a murder investigation. In these situations, the news is based on facts, proof, and assertions made by numerous persons. You perform one of the following three actions each time a fresh event happens:

Assume that poisoning was used to commit the murder. Yet, the autopsy report states that a head injury was the cause of death. When you work for this journalistic organization, you quickly forget the death's cause and any supporting tales.

Why not your account of the incident included a new suspect, someone who had an interest in the victim and could conceivably be the one who killed him? Would you post this information in your Newsfeeds?

Now that your investigation is still in its early stages, you will need to summarize the information you have gathered and provide it to your audience in a way that will be most effective. You might choose to present “XYZ seems like the prime suspect in this case” or “The suspects are as follows: XYZ, ZYX, YXZ and XZY.”

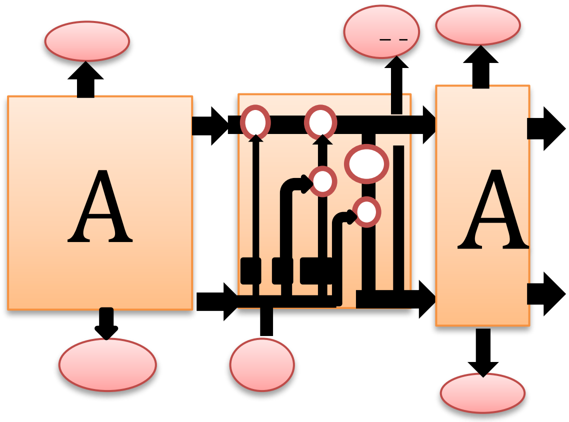

FIGURE 7 LTSM RNN in tensor flow

In the figure above, four neural network layers are depicted as yellow boxes, while pointwise operators, input, and cell states are shown as green and yellow circles, correspondingly. With the aid of three gates and a cell state, the LSTM module may selectively learn, unlearn, or retain data from each of its units. As LSTM networks only provide a limited number of linear interactions between units, the cell state is advantageous for information flow. An input, output, and forget gate is included in each unit and has the ability to add or remove data from the cell state. The forget gate decides which information from the previous cell state should be forgotten for which it uses a sigmoid function. By combining the input gate and the forget gate, we can control the information flow to specific parts of the current cell state. Finally, the output gate decides whether new information should be passed on to the next state. This served as the driving force behind our efforts to analyse the effectiveness of the recently put forth Whale Optimization Algorithm (WOA) [45] in the context of feature selection. An evolutionary algorithm called WOA imitates the foraging process the humpback whales' natural behaviour.

In order to identify the smallest feature subsets, a wrapper feature selection method based on WOA is suggested in this study. While the original version of this algorithm was developed to handle binary problems, the proposed method uses the main operators of WOA but modifications some of them to tackle other types of problems. The proposal of the binary form of WOA and the incorporation of numerous evolutionary operators (selection, crossover, and mutation) that have been utilised to enhance both exploration and exploitation of this algorithm are the paper's contributions. The outcomes demonstrated that the WOA algorithm (WOA-CM) performs better than other methods when the cross over and mutation operators are used. Using many small, medium, and large size datasets, the proposed WOA-CM algorithm's effectiveness is tested and compared with three nature-inspired algorithms, namely GA, PSO, and ALO. Enabling Real-time Tunability:

The deep neural network categorises each segment of incoming data as preictal or interictal throughout system operation. An artificial leaky integrate-and-fire neuron was used to assess whether any given sample should cause the patient to sound an alarm. This made sure that alarms would only go off if many preictal forecasts were made near together in time. The firing threshold, neuron leak, and alert length parameters for this processing layer were optimised to produce the highest performance as measured by an objective that could be specified automatically or by a human. A patient or physician may be able to choose the measure they want to prioritise thanks to this layer. To guarantee optimal performance as indicated below, settings were optimised unless otherwise noted. After each month's worth of incoming data, settings were modified during pseudoprospective optimisation.

RESULTS ANALYSIS:

In order to make an early prediction of epileptic seizures, we classified the scalp EEG data from participants into interictal and preictal states using our suggested technique. Our average specificity was 90.8%, while sensitivity was 92.7% on average. Our 21-minute waiting period was typical. Our suggested method outperforms cutting-edge approaches in terms of sensitivity and specificity for predicting epileptic seizures. Since the preictal class is seen as positive, it is crucial to have a high true positive rate with a low false positive rate.

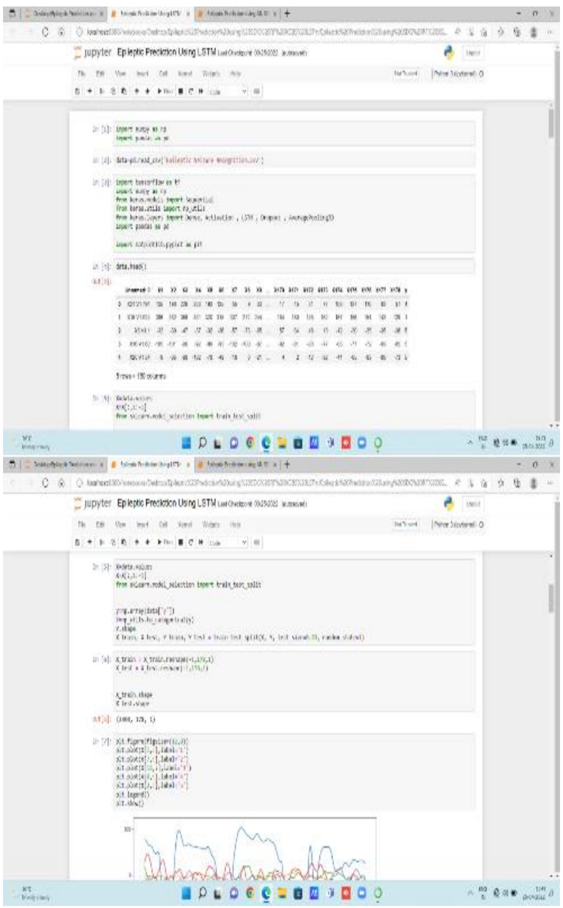

FIGURE 8 Plot on categories of person with epilepsy in input data

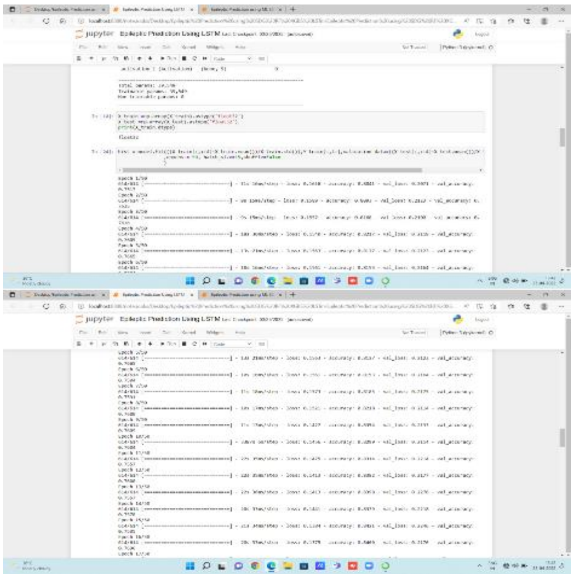

FIGURE 9 Displaying input data and splitting all the input data

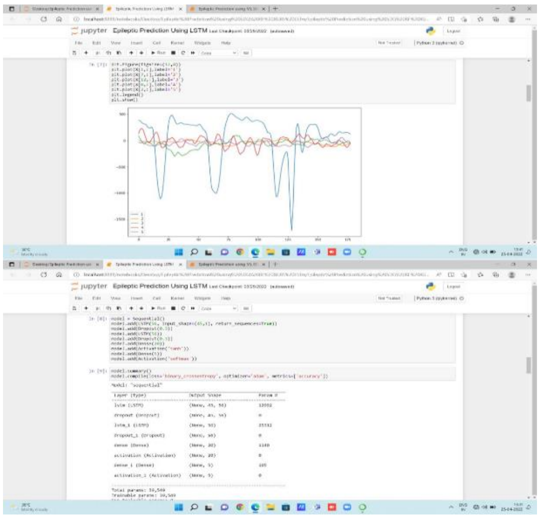

FIGURE 10 Processing of 50 epochs to determine the validation accuracy and validation loss

CONCLUSION:

We have proposed a method for predicting epileptic seizures. Patients affected by epilepsy risk their lives if they cannot keep track of their seizures. Our proposed method extracts feature from devices monitoring a patient's vital signs and uses machine learning classifiers to anticipate when an epileptic episode will start. The neural network model still requires refinement in a number of areas, though. In the future, we plan to improve our model by extending the preprocessing steps to rise the SNR Ratio’s, as well as exploring methods to decrease the more no of parameters. We developed a model that provides accurate seizure predictions, but the future will hopefully bring about more patient-specific methods. These results, however, demonstrate the exploitation capability provided by Eq. (7), which enables the search agents to proceed in the direction of the best search agent thus far. Also, the employment of various selection procedures enhances the performance of the WOA algorithm for almost half of the datasets. One explanation could be the possibility of selecting subpar solutions during the discovery phase thanks to the roulette wheel and tournament selection procedures.

Also, based on the three criteria indicated earlier, Table 3 summarises the outcomes of WOA-CM and the native WOA algorithm. For all examined datasets, the upgraded technique exhibits very good performance. Except for one dataset where the two techniques produced identical results, WOA-CM surpassed WOA in terms of minimal reductions and classification accuracy. These findings demonstrate the need for a careful balance between exploration and exploitation when utilising global search algorithms as WOA. The WOA algorithm's performance has been proven to be enhanced by the mutation operator. The table displays the amount of computing time needed by the two approaches. On every criterion of evaluation, the WOA-CM findings are far superior than those of the native technique. This is due to the crossover and mutation operators, which decreased the amount of time needed for computation in the WOA-CM technique.

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