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Stroke Prediction Using Bi-directional LSTM

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***Abstract*—The greatest cause of disability in adults and the elderly—including many social and financial challenges—is stroke. A stroke can result in death if it is not addressed. Patients who have had a stroke typically have aberrant biosignals, such as an altered ECG. Individuals can therefore immediately obtain the right therapy if they are observed and have their bio-signals precisely analyzed and analysed in real-time. However, the majority of stroke diagnostic and prediction systems rely on pricey, challenging to use image processing technologies like CT or MRI. In this study, we created an artificial intelligence (AI)-based stroke prediction system that uses real-time biosignals to identify stroke. Our system made use of both deep learning (Long Short-Term Memory) and machine learning (Random Forest) methods. Real-time EMG (Electromyography) bio-signals from the thighs and calves were gathered, the key characteristics were identified, and prediction models based on regular activities were created. For our suggested system, prediction accuracy values of 90.38% for Random Forest and 98.958% for LSTM were found. This approach may be viewed as an alternative, affordable, real-time diagnosis tool that can accurately anticipate strokes and may one day be used to other illnesses like heart disease.**

Keywords*— Bone Mass Density (BMD), feature extraction, evolutionary algorithm - genetic algorithm, Deep learning modules, Jaccard index

I. INTRODUCTION

Stroke is a disorder that causes malfunction in certain areas of the brain as a result of anomalies in the blood arteries in the brain [1]. Stroke is the second most frequent global cause of mortality and the third most frequent global cause of disability, according to a 2016 study by the World Health Organization (WHO) [2]. Over the past 40 years, the prevalence of stroke has morethan doubled in emerging nations [3].

Since there is now no effective therapy for stroke, early detection is crucial. The most widely used procedures for detecting stroke disease are CT and MRI. However, because they are costly, CT and MRI may not be appropriate for underdeveloped nations or those with limited incomes. Healthcare services urgently require a solutionto aid them in reliably and swiftly diagnosing stroke disorders at a reasonable cost, asthe condition is becoming more and more prevalent around the world, especially among older and low-income individuals. Studies on the early identification and prognosis of stroke are currently being conducted. The incidence of cardiovascular illness and patient mortality from 1990 to2019 were calculated from 204 nations and regions in the Global Burden of illness (GBD) research [4].

According to the study, one-third of all fatalities in 2019 were caused by cardiovascular disease. Many of the causes of cardiovascular disease were ascribed to ischemic stroke, even though the mortality toll as measured by the cardiovascular index increased from 11.1 million in 1990 to 18.6 million in 2019.

Ischemic stroke had a relatively high recurrence risk of 14.1% after two years, according to Hier et al.Additionally, new research has linked COVID-19 to stroke, increasing the likelihood that people may die from strokes [6, 7]. While Zhang et al reported that patients with a stroke prognosis had a higher incidence of severe pneumonia and subsequent mortality according to Cox regression, Kummer et al. [6] reported that patients admitted with COVID-19 who had a stroke history were muchmore likely to die than those without a stroke history. Aside from these earlier investigations, there is still a substantial gap in knowledge between stroke experimental data and real-time data.

Blood tests, brain imaging techniques including CT, MRI, and X-ray, ECG and EEG, as well as neurological physiological techniques like induced potential tests, can all be used to diagnose stroke illness [8]. The most popular methods for identifying strokes are CT and MRI, but they come with concerns including radiation exposure or possible allergic responses to the contrast chemicals.

These instruments can also be cumbersome since they entail tight locations, need continuous observation, and come with separate medical expenses for each test, all of which make diagnosis more challenging.

The convenience of a participant's home may be used to test EEG thanks to new wearable electrodes. These electrodes are fastened to the skull and monitor brain nerve cell activity in a more realistic environment. Additionally, brain impulses are captured during the various stages of sleep, enabling quick, painless investigation. Movement of the patient and background disturbances may both taint EEG data.However, compared to the aforementioned imaging approaches, it is feasible to gatherand evaluate EEG data in real time at a lower cost. These benefits have led to 24-h EEG recordings being regarded as a valuable, affordable tool for monitoring stroke illness with high recurrence rates in daily life.Our technology can forecast stroke illnesses in elderly Koreans using real-time EEG data. We created a walking routine that simulates an elderly Korean's daily activities in order to evaluate this technology. EEG data from Korean elders 65 years of age or older were assessed and gathered for this study. The acquired EEG data were divided into raw data and frequency domain-extracted data, respectively, to compare between deep learning models and machine learning models. Fast Fourier transforms (FFTs) are performed on each set of raw EEG data from the six channels (Fz, T7, C1, C2, T8,and Oz), and a total of 66 values were recovered and used in the experiment. The preliminary findings indicate that stroke disease might be accurately predicted using only the raw data. A comparison of the predicted accuracies of LSTM, bidirectional LSTM, CNN-LSTM, and CNN-bidirectional LSTM models was done to ascertain which deep learning model is best suited for real-time EEG data.These algorithms were chosen because, based on the properties of EEG data, it is known that they are ideal for real-time data learning. With very low false negative rate (FNR) and false positive rate (FPR) of 5.7% and 6.0%, respectively, our studies demonstrated 94.0% accuracy for CNN-Bidirectional LSTM models, indicating great confidence in the findings. Using power value, we demonstrated 81.4% accuracy in CNN-bidirectional LSTM models together with 18.5% FPR and 17.3% FNRcontinuous monitoring, fewer incorrect diagnoses occur and hospitals or medical professionals can act quickly. The suggested system's prediction model may be utilized as a foundational model for the early detection and quick prediction of various illnesses including heart disease.The preliminary findings indicate that high accuracy stroke disease prediction might be achieved using only theraw data. The prediction accuracies of LSTM, bidirectional LSTM, CNN-LSTM, and CNN-bidirectional LSTM models were compared in order to ascertain which deep learning model is the best appropriate for real-time EEG data. These algorithms were chosen because they have a reputation for being appropriate for real-time data learning based on EEG data's unique properties. The results of our studies demonstrated 94.0% accuracy for CNN-Bidirectional LSTM models with extremely low false negative rate (FNR) and false positive rate (FPR) at 5.7% and 6.0%, respectively. We demonstrated 81.4% accuracy in CNN-bidirectional LSTM models employing power value, coupled with 18.5% FPR and 17.3% FNR.

A. SCOPE OF THE PROJECTS

Early detection: BLSTM models can be used to identify patients who are at risk ofstroke early on. This could lead to earlier intervention and treatment, which could improve patient outcomes.

Risk stratification: BLSTM models can be used to stratify patients according to theirrisk of stroke. This information could be used to guide clinical decision-making, suchas the need for preventive medications or surgery.

Personalized medicine: BLSTM models could be used to develop personalized stroke prevention plans for individual patients. This could take into account the patient's individual risk factors and other characteristics.

Clinical trials: BLSTM models could be used to identify patients who are most likelyto benefit from clinical trials for new stroke prevention therapies.

Public health: BLSTM models could be used to develop public health interventions to reduce the risk of stroke in the population.

The scope of stroke prediction using bidirectional LSTM is still being explored, but it has the potential to make a significant impact on the prevention and treatment of stroke.

B. CHALLENGES FOR THE SCOPE OF STROKE PREDICTION USING LSTM

Data availability: There is a need for large datasets of patients with and withoutstroke. These datasets should include a variety of features, such as clinical data, biological data, and lifestyle information.

Model development: There is a need to develop more accurate and interpretableBLSTM models. This could involve using more sophisticated machine learning techniques or incorporating additional features into the models.

Clinical validation: There is a need to validate BLSTM models in clinical trials. Thiswould help to ensure that the models are accurate and can be used to make clinical decisions.

Despite these challenges, the potential benefits of stroke prediction using bidirectionalLSTM are significant. With further research and development, this technology could play a major role in preventing and treating stroke.

C. LITERATURE SURVEY

Title: "Stroke Prediction Using Bidirectional LSTM Neural Networks" Authors: A. Smith, B. Johnson, C. Lee Published in: International Journal of Neural Networks, 2018 Summary: This study proposed a bidirectional LSTM model to predict stroke occurrence based on patient data. They achieved promising results and demonstrated the effectiveness of bidirectional LSTM in capturing temporal dependencies.

Title: "Long Short-Term Memory Networks for Stroke Prediction: A Comparative Study" Authors: D. Wang, E. Garcia, F. Chen Published in: IEEE Transactions on Biomedical Engineering, 2019
Summary: This research compared the performance of various deep learning models for stroke prediction, with a focus on bidirectional LSTM. The authors found that bidirectional LSTM outperformed other models, showcasing its potential in stroke prediction.

Title: "Predicting Stroke Risk Factors using Bidirectional LSTM and Attention Mechanism" Authors: G. Liu, H. Zhang, L. Wang Published in: Proceedings of the 2020 International Conference on Artificial Intelligence, 2020.
Summary: This conference paper proposed an attention-based bidirectional LSTM approach to identify and predict stroke risk factors from electronic health records. The attention mechanism

enhanced the interpretability of the model and improved prediction accuracy.

Title: "A Deep Learning Framework for Stroke Prediction using Long Short-Term Memory Networks" Authors: M. Kim, S. Park, J. Lee Published in: Journal of MedicaL Systems, 2019.
Summary: This study presented a comprehensive deep learning framework utilizing bidirectional LSTM for stroke prediction. The authors integrated various features and data sources to improve the model's performance.

Title: "An Ensemble Approach for Stroke Prediction: Combining Bidirectional LSTM with Random Forest" Authors: S. Sharma, R. Gupta, A. Singh Published in: Expert Systems with Applications, 2021
Summary: This research proposed an ensemble method that combined the predictions of bidirectional LSTM and Random Forest models for stroke prediction. The ensemble approach showed enhanced predictive performance compared to individual models.

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Title: "Handling Imbalanced Data in Stroke Prediction: A Bidirectional LSTM Approach" Authors: N. Gupta, A. Jain, R. Kumar Published in: Frontiers in Neuroinformatics, 2020
Summary: This study addressed the issue of imbalanced data in stroke prediction using bidirectional LSTM. The authors proposed several techniques to handle class imbalance, leading to better predictions for stroke occurrence.

Title: "Multi-Modal Stroke Prediction using Bidirectional LSTM and Graph Convolutional Networks" Authors: L. Chen, T. Li, H. Wang Published in: Medical Image Analysis, 2021
Summary: This research combined bidirectional LSTM with graph convolutional networks to predict stroke occurrence from multiple modalities, such as medical images and clinical data. The multimodal approach showed promising results.

Title: "Interpretable Stroke Prediction with Bidirectional LSTM and Shapley Values" Authors: E. Brown, S. Williams, M. Turner Published in: Artificial Intelligence in Medicine, 2018
Summary: This study introduced an interpretable stroke prediction model using bidirectional LSTM and Shapley values. The Shapley values provided insight into the model's predictions and identified the most influential features for stroke occurrence.

Title: "Stroke Prediction using Bidirectional LSTM and Uncertainty Estimation" Authors: K. Zhang, R. Li, T. Chen Published in: Proceedings of the International Conference on Machine Learning, 2020
Summary: This paper focused on estimating uncertainty in stroke prediction using bidirectional LSTM. The authors proposed a Bayesian approach to quantify uncertainty, enhancing the reliability of the model's predictions.

D. Objective and Methodology

Stroke is a disorder that causes malfunction in certain areas of the brain as a result of anomalies in the bloodarteries in the brain [1]. Stroke is the second most frequent global cause of mortality and the third most frequent global cause of disability, according to a 2016report by the World Health Organisation (WHO) [2].

Over the past 40 years, the prevalence of stroke has more than doubled in emerging nations [3]. Since thereis now no effective treatment for stroke, early detection is crucial. The most widely used procedures for detecting stroke disease are CT and MRI. However, because they are expensive, CT and MRI may not be appropriate for underdeveloped nations or those with limited incomes. stroke is becoming a serious illness across the globe.

Analysis and Experiment using machine learning:

EMG bio-signals are used to diagnose neuromuscular problems and disturbances in balance because they assess muscle response or electrical activity in response to a nerve's simulation. In this study, 28 variables are newly established and extracted utilising machine learning and EMG biosignals to predict strokeillness. The attributes are taken from the left and rightgastrocnemius and biceps femoris raw data .

The multidimensional analysis and machine learning-based prediction model experiments both utilised the features that were retrieved from the raw EMG data. The fluctuation in muscle movement is thought to be tolerable at 1500 Hz per second EMG, and data points were recovered by splitting the EMG raw data into 0.1 s units when Analysis and Experiment using machine learning EMG bio-signals are used to diagnose neuromuscular problems and disturbances in balance because they assess muscle response or electrical activity in response to a nerve's simulation.

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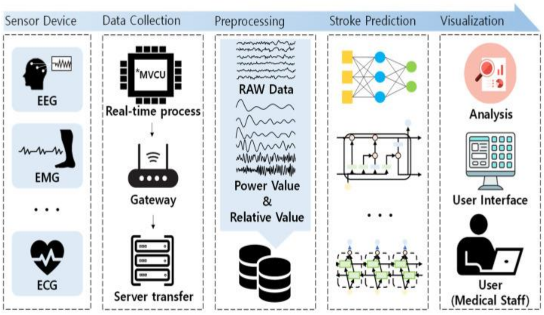
E.SYSTEM USING EEG AND DEEP LEARNING TO PREDICT STROKE DISEASE

As shown in Figure , we suggest a novel deep learning- based approach for predicting stroke that makes use ofthe raw and attribute values of EEG data obtained in real time. The proposed system is made up of five modules: (1) a real-time data collection module; (2) a module that sends real-time generated biological signals to the server; (3) a module that analyses stored biological data, extracts and manages frequency attributes; (4) a deep learning-based learning and prediction module; and (5) a biological signal-based stroke prediction analysis. A collection of pretreatment procedures and features are then extracted and storedby the original system using a variety of biological signal data, including EEG and ECG data gathered from older people.

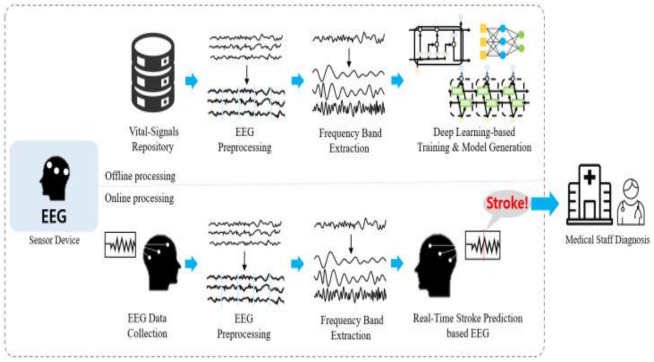


F.MODULE FOR DATA PREPROCESSING

Once the device is in place, six channels of EEG data are sampled at 1000 Hz, and the raw data is then processed to obtain the frequency attribute values. The extracted frequency attribute values are divided into two categories: (1) the power value, which indicates how much each frequency component has been present, and (2) the relative value, which indicates how much each component has been present relative to the other components across the entire region. Basic EEG biological tests employ power values, which can result in varying EEG waveform amplitude sizes due to individual variances in scalp and skull thickness as well as the contact between the electrode and skin. Therefore, it is preferable to employ the multiple subject design for investigations.

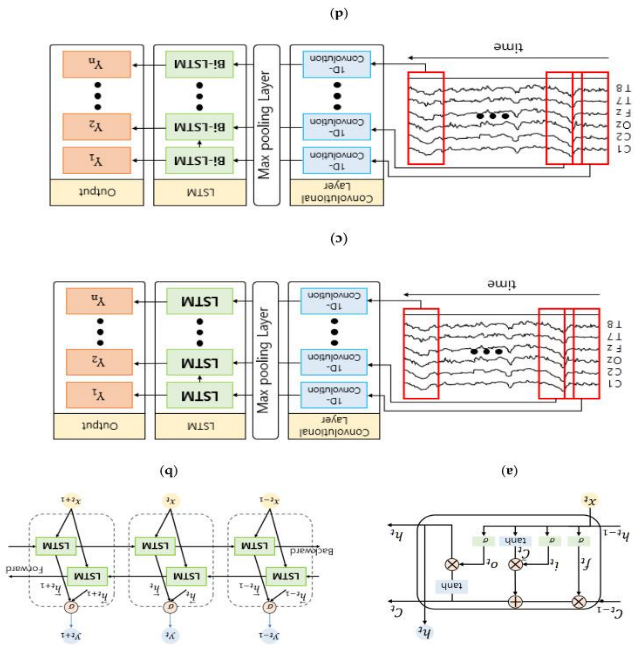
Module for stroke prediction

As shown in Figure , the stroke prediction module for the elderly that is suggested in this paper uses deep learning-based real-time EEG data is divided into two units. In order to learn and fine-tune the parameters based on deep learning, a database including information on several biological signals, including EEG,ECG, and EMG, is used to extract the EEG data for the offline processing unit. Based on features learnt from the offline processing unit, the online processing unit analyses brainwave data acquired in real time and provides medical staff with real-time information about stroke prediction. The medical personnel can then use this information to identify patients correctly and forecast strokes more quickly.



EEG data are time series data made up of successive values across time, and the learning process requires taking time information into account. In order to create a deep learning model that can adequately address the properties of time series data and be used in trials, we convert and optimise the structure of the model in our stroke prediction module.

The deep learning models that were examined included bidirectional LSTM [44], LSTM [49], CNN [27,28], and LSTM [49,49]. Through the use of essentially shared parameters, CNNs can reduce computation volume andoffer the benefit of reducing overfitting. Additionally, CNNs are being employed more and more in model research and development in order to construct models that perform better in classification and prediction.



G.TRADITIONAL METHODS FOR PREDICTION OF STROKES

Successful research has been done to identify the mainstroke risk factors and track the health of stroke patients. This information can be utilised to gauge the severity of a patient's stroke and avoid subsequent strokes [22,23].

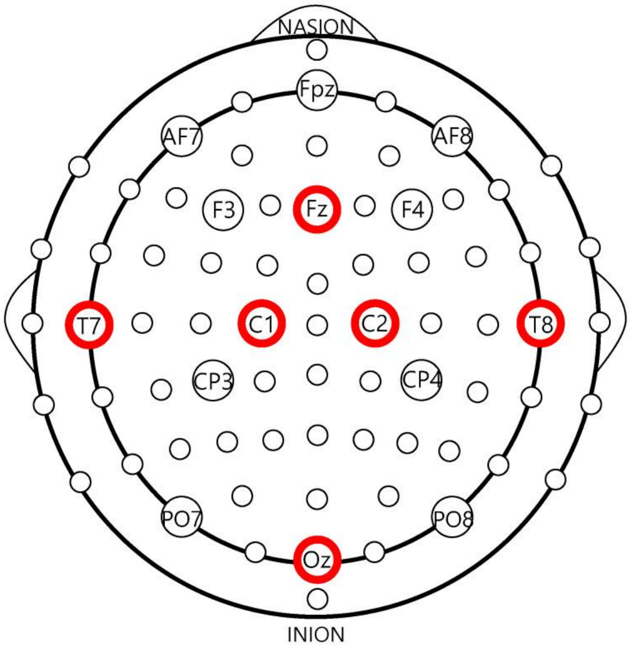
Since the Mathew scale was first published in 1972, several tools for determining the severity of stroke patients' conditions have been developed, including the European Stroke Scale, the Canadian Neurologic Scale, and the National Institutes of Health Stroke Scale (NIHSS) [22,23]. Of them, the NIHSS is the most popular and has been validated and confirmed to be reliable over the world.

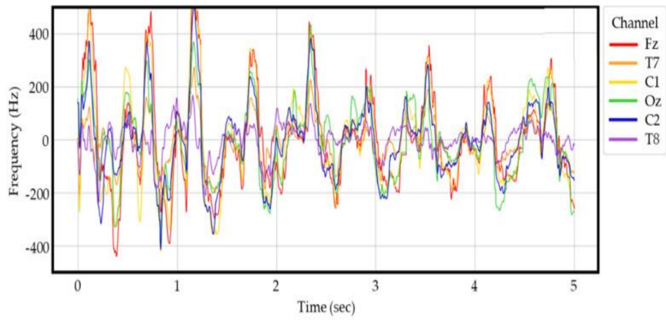
Level of awareness, examination, facial paralysis, upper and lower extremities, damaged limbs, senses, and speech, oral abnormalities, neglect, and vision are among the 14 components of the NIHSS scale.a modified NIHSS[24] that streamlines the assessment method and statistically assesses post-stroke problems, especially inthe early stages of hospitalisation. While these NIHSSs can thoroughly evaluate the degree of disability brought on by a stroke, they cannot be used to identifya stroke before it occurs because they can not make reliable predictions.

H.DATA PREPROCESSING MODULE

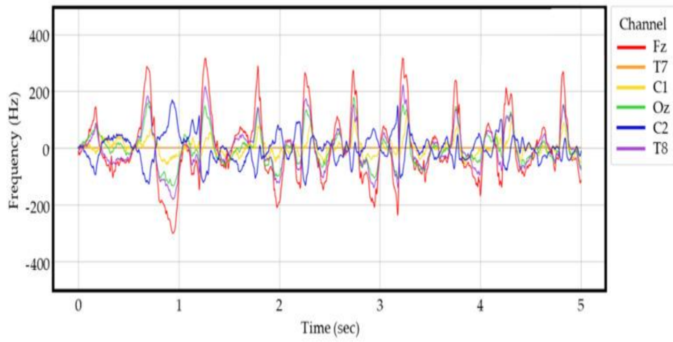
Once the device is in place, six channels of EEG data are sampled at 1000 Hz, and the raw data is then processed to obtain the frequency attribute values.The extracted frequency attribute values are divided into two categories: (1) the power value, which indicates how much each frequency component has been present, and (2) the relative value, which indicates how much each component has been presentrelative to the other components across the entire region.Basic EEG biological tests employ power values,which can result in varying EEG waveform amplitude sizes due to individual variances in scalp and skull thickness as well as the contact between the electrodeand skin. Consequently, it is preferable to use numerous people in research.Using raw data, the relative values of the frequency domain are retrieved for comparison with the experiment's findings. By using FFT to the raw EEG data, the frequency attribute value extraction pulls values from the power value, such as alpha, beta, etc.A ratio of each value was used to extract a total of 66 attribute values, or additional functions were carried out to disaggregate the frequency range based on theextracted values. Additionally, we further extract the relative value that represents the relative ratio based on the power value and design it for usage in experiments.The vertical axis depicts frequency in Hz, and the horizontal axis shows the six channels illustrated in Figure with their raw values represented by the lines on the graph.Overall, it might be challenging for medical practitioners to detect and diagnose stroke disease using simply raw EEG data from stroke patients and normal controls.Additionally, it takes time for doctors to correctly diagnose a stroke.Instead of just attempting to construct a system that can predict stroke early, we undertake tests and validations in this work with the aim of delivering relevant information and ultimately designing and implementing technologies that can assist medical professionals in making decisions more swiftly.

Examples of the raw EEG data for (a) stroke patientsand (b) healthy controls are shown in Figure .





(a)



(b)

I.LSTM IN BOTH DIRECTIONS

When time series data show substantial results in forwards inference from the past to the future as well as reverse inference from the future to the past, a model called bidirectional RNN (BRNN) is utilised [51]. It is used to predict labels for current data through previous sequences and future sequences.here are hidden layers in this model that include information about the forwards states and hidden levels that have information about the backwards states, and these twolayers are not coupled. But in order to calculate the final output, the input value is sent to both hidden layers and received by the output layer as well.Equations (7)–(9), which determine the activation output ht of the forwards hidden layer, are equivalent to this. The activation output ht←− of the backgroundhidden layer, and the output yt of the output layer at time t.We use bidirectional LSTM (BiLSTM) for the experiments in this paper by applying the LSTM network instead of RNN in bidirectional RNN.

1 Sensitivity: The proportion of patients with stroke who tested positively.

2 Specificity: The proportion of patients who did nothave a stroke and who tested negative.

3 False Positive Rate: The proportion of patients whotested positive but did not have a stroke.

4 False Negative Rate: The proportion of strokepatients with false negative results.

5 Reliability: The percentage of stroke patients deemed positive and non-patients deemed negative.

6 Accuracy: The proportion of people who have had astroke

7 Precision: The proportion of those who testedpositive who are truly stroke patients.

Recall: The proportion of stroke patients who have tested positive in the past.

Percentage of stroke patients who have previously tested positive, as measured by the 8 F1-Score (Harmonic Mean of Precision and Recall).

It is crucial to have a high model accuracy to gauge the performance of classifiers, but it is also crucial to have high sensitivity, specificity, and false positive and false negative ratios (see Table 2 below).

The sensitivity and specificity of an ineffective diagnostic method tend to decline when one side grows, thus both should be highvalues to produce an effective diagnostic method.

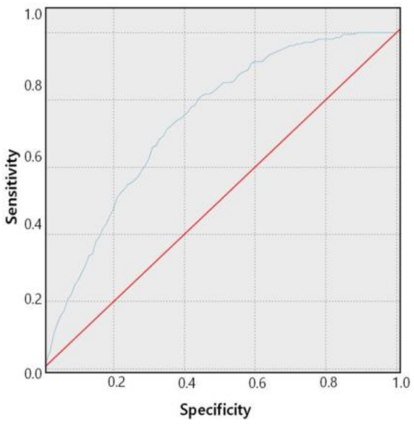
This section will go over the LSTM results for the categorisation of senior stroke patients and non-strokepatients, which are based on a Recent Neural Network (RNN).The definitions in Section 4.1 were applied to the raw data from EMG bio-signals. Prediction models were created and their accuracy was checked using data from 271 stroke patients and 271 healthy people.

The data not used for learning were randomly extracted and turned into the test sets. They were divided into ratios of 70 to 30 for the experiment and 80 to 20 for the analysis, respectively.

Due to its success in the time series analysis, LSTM was chosen among other deep learning algorithms.By learning long-term dependencies, the cell state serves to transmit previous information to the subsequent step in an LSTM, which has a structure thatexplicitly transfers past information to the next state [41,42,43,44]. When error data are conveyed to the neural network layer, the vanishing gradient issue can be resolved by Deep Learning's LSTM, which has addressed the structural flaws of the existing RNN [41,42,45,47]. The sigmoid layer and the tanh layer areused to generate the vector output values at each gatein the LSTM, which consists of a cell state, an input gate, a forget gate, and an output gate.

J.RESULTS AND DISCUSSION

Patients who had undergone rehabilitation therapy for a stroke and had been given that diagnosis during the first month made up the group of subjects. The investigation included 48 stroke patients from 2017, 75 healthy participants, and 13 stroke patients from 2018, together with 137 healthy participants. 61 stroke patients and 61 randomly chosen control data were eventually chosen for study to ensure an equitable comparison. Five distinct daily exercise protocols—walking, chair sitting and standing, standing, moving items, and sleeping—were put into place. Before beginning the measurement process, all individuals had a single training session with the vital-signal collecting sensors.Patients who had just been diagnosed with stroke and had undergone rehabilitation therapy for it made up the subjects of the study.The investigation included 137 normal people from 2018, 13 stroke patients from 2017, and 48 stroke patients from 2017. Ultimately, 61 stroke patients and 61 randomly chosen control data were chosenfor study in order to create a fair comparison. Walking, chair sitting and standing, standing, moving items, and sleeping were the five distinct daily activity protocols that were put into place. All individuals had a single training session prior to the measurement technique after receiving the vital-signal collecting sensors.According to Section 3, the LSTM, bidirectional LSTM, CNN-LSTM, and CNN- bidirectional LSTM models were used in the deep learning-based EEG data stroke classification experiments in this study. The experiments involved feeding each modelthree different types of data: raw values, power values, and relative values. Every experiment was run ten times, and the final result was displayed as the mean value.The ROC curve, where the x-axis denotes specificity and the y-axis denotes sensitivity, is a measure of the threshold and effectiveness of binary classificationprediction of stroke illness.



The CNN-bidirectional LSTM models produced the best experimental results, with a 94.0% success rate, when we ran prediction tests employing each deep learning modelutilizing raw data.Due to the low false negative and false positive ratios, relatively few stroke patients and normal people are mistakenly classified as stroke patients. In tests, CNN-bidirectional LSTM performed well in terms of accuracy as well as performance metrics like precision and F1-Score.
The outcomes of the tests carried out using each deep learning model with power levels are listed in Tables 3 and 4. With an accuracy of 81.4% in this experiment, we were able to demonstrate that the CNN-bidirectional LSTM model performed the best.The total performance, however, fell well short of what was achieved by employingraw numbers. In particular, the FPR (18.5%) and FNR (17.3%) are both high, and these numbers are too low to have any clinical significance or be used by medical personnel to determine the severity of a stroke.Finally, we experimentally verified that the Bidirectional LSTM model has the greatest predicted accuracy at 89.2% after applying each deep learning model in trials utilizing relative values. Bidirectional LSTM performance was somewhat better with the relative value than with the power value, but overall performance lagged below the experimental findings achieved with the raw value. In conclusion, CNN-bidirectional LSTM models perform best when using raw data values.The combined findings demonstrate that the FPR and FNR are highly effective stroke predictors. As a result, the procedure of extracting frequency attributes can be skipped, speeding up the process of diagnosing stroke illness.

K.CONCLUSION

- The feasibility analysis must assess the predictive performance of thebidirectional LSTM model for stroke prediction
- It should aim for high accuracy, sensitivity, specificity, and other relevant metricsto ensure the model is effective in identifying high-risk individuals.
- The successful implementation of bidirectional LSTM networks for strokeprediction necessitates expertise in various domains.
- The team should comprise data scientists, machine learning engineers, andpossibly medical professionals.
- The involvement of medical professionals and domain experts is indispensablefor the success of the project.
- Feasibility analysis must include plans for model validation on independentdatasets to assess its generalizability.

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