www.journalofbabylon.com | ISSN: 2616 - 9916 | Journal.eng@uobabylon.edu.iq | info@journalofbabylon.com

مجلة جامعة بابل للعلوم الهندسية

Brain Stroke Detection Using ANN Based On EEG Signals Using CNN Path

Riyadh Abdulhamza Al-Alwani

Electrical Engineering Department, College of Engineering, University of Babylon, Babylon,Iraq

Email: alwaniriyad@gmail.com

Kasim K. Abdalla

Electrical Engineering Department, College of Engineering, University of Babylon,Babylon, Iraq

Email: kasimkaa.11@gmail.com

Farah Nabil Abbas

Physiology department, Medical college, University of Babylon, Babylon, Iraq

Email: frhnabil@yahoo.com

Received:	16/1/2023	Accepted:	22/2/2023	Published:	26/2/2023

Abstract:

Brain stroke occurs because of a blockage in the artery, which delivers oxygenated blood to the brain. Acute Ischemic Stroke (AIS) is mostly occurred brain stroke. Early detection of brain stroke can be life-saving for patients. Electroencephalography is a technique to analyze electrical activities present in the different parts of the human brain, and using visual trace, it records these activities. EEG provides cost-effective, portable, high-frequency and accurate measurement as compared to other brain wave activity monitoring tools. EEG is used to diagnose AIS. In the proposed research, the convolutional neural network is applied for the classification of stroke severity. In this algorithm, the power spectral density (PSD) of EEG signals is calculated based on the extracted features from the artificial neural network. The feature map was then trained to classify the data into four instances based on the severity of the brain stroke. The effectiveness of the suggested algorithm is examined by comparing it with several similar algorithms., and it is observed that the accuracy of the proposed algorithm is 98.3% and which is better than the existing algorithm for brain stroke detection.

Keywords: Electroencephalogram (EEG), Down sampling, Segmentation, Welch's method for power spectral density, Convolutional Neural Network, Random Forest, SVM.

1.Introduction

Stroke is a condition that has quickly risen to become one of the main causes of mortality around the world. According to the findings of a study that was conducted by the Institute for Health Metrics and Evaluation in 2017 (IHME), it is the leading cause of death and disability

Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.

مجلة جامعة بابل للعلوم الهندسية
info@journalofbabylon.com | Journal.eng@uobabylon.edu.iq | www.journalofbabylon.com ISSN: 2616 - 9916

worldwide. One of the most significant organs in the human body, the brain is one of the primary controllers of both behavior and cognition. The cortex of the human brain is more developed than the brains of other animals. White matter, grey matter, and cerebrospinal fluid, usually known simply as cerebrospinal fluid, are the three components that make up the human brain [1]. Blood is continuously pumped to the brain as part of the body's function in order to provide it with

Nutrients and oxygen. Any condition in which the blood supply is severely reduced or blocked causes a stroke. Both conditions are extremely harmful and can cause serious injury. Serious brain problems, damage, and death are very common with stroke. Accurate stroke detection aids in early detection and diagnosis. However, stroke detection is a challenging and complex task. The heterogeneous nature of stroke texture, shape, and color makes the stroke detection task complex and challenging. Many researchers are working on machine learning techniques to detect brain strokes in s their early stages [2].

A stroke of the brain is a serious medical emergency that may result in death or in permanent or temporary disability. Just like the causes of many other illnesses, age and lifestyle choices play a significant role in the risk of having a stroke. Both the brain and the heart are dependent on an adequate blood flow in order to perform their functions correctly. Brain strokes are often the consequence of the rupture of blood vessels in the brain or of an obstruction in the blood flow to the brain. Ischemic brain stroke and hemorrhagic brain stroke are the two primary classifications that may be used to this condition.

Ischemic Stroke is a kind of brain stroke that happens when there is a blockage in an artery that supplies oxygenated blood to the brain. This may cause the brain to suffer a stroke. The presence of clumps in the brain is the most prevalent cause of arterial blockages, which may lead to an ischemic stroke [3]. Ischemic strokes may be divided into two categories: thrombotic and embolic. Thrombotic strokes are more common than embolic strokes. The difference between a thrombotic stroke and an embolic stroke is that the former is brought on by the presence of blood clots in the artery, while the latter is brought on by the presence of fatty materials or plaques in the artery. Ischemic Strokes are by far the most common cause of mortality, especially when compared to hemorrhagic Strokes. In the instance of a hemorrhagic stroke, an artery in the brain begins to bleed, which is what ultimately leads to the stroke [4]. The most frequent kinds of hemorrhagic brain stroke are known as the subarachnoid stroke and the intracerebral stroke. The location of the blood leak is what differentiates these two kinds of strokes from one another. Both intracerebral hemorrhage and subarachnoid stroke are induced when blood vessels on the surface of the brain rupture, while intracerebral hemorrhage happens when the blood leaks within the vessels. Bleeding was discovered in the middle and inner layer of the brain membranes after this particular stroke. As a result, the pressure of the blood on the skull ultimately rises. Inflammation and a rise in blood pressure can cause harm to the tissues and cells of the brain.

Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.

JOURNAL OF UNIVERSITY OF BABYLON
For ENGINEERING SCIENCES (JUBES)
Vol.31, No.1.| 2023
www.journalofbabylon.com | ISSN: 2616 - 9916
info@journalofbabylon.com | Journal.eng@uobabylon.edu.iq | www.journalofbabylon.com

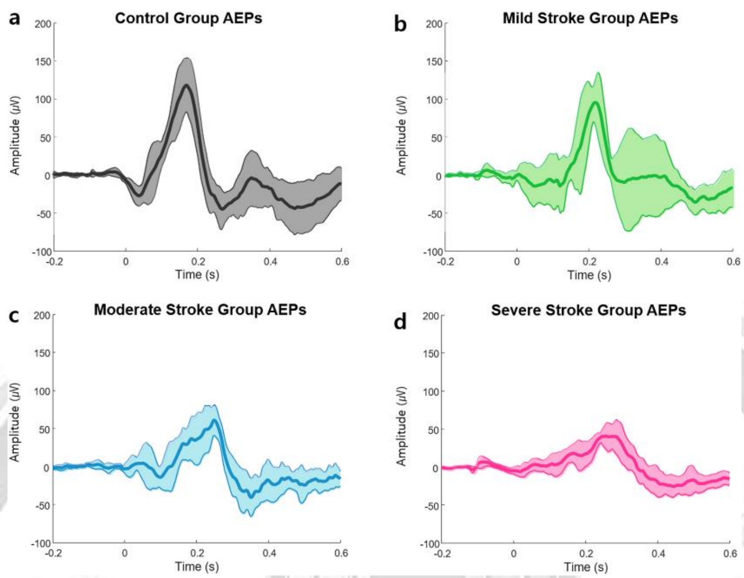


Figure 1: EEG Signal for different type of stroke.

Figure 1 shows the EEG Signal for different type of brain stroke. An early diagnosis of brain stroke can reduce the risk of death or abnormalities for the patients. There are some standard tools which are generally used to diagnose stroke, this as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT-Scan). These techniques are popularly used and provide higher accuracy. However, there are still some worries about it with the direct exposure of x-rays on the patient body. Additionally, in a great number of nations, there is a shortage of these tools or it is expensive to afford this treatment. Alon with that both tools are time-consuming and it takes a lot of time to extract the test result, which can be very dangerous when life is at stake [5].

Hence, an alternate method of diagnosis, such as those provided by MRI and CT scans, is required in order to provide better and more timely therapy. In addition to these technologies, electroencephalography (EEG) is an additional evolving technology that has the potential to identify brain strokes in a more expedient and risk-free way. Electroencephalography (EEG) is a technology that uses a visual trace to capture the electrical activity that is taking place in various areas of the human brain. This approach is used to examine electrical activities. As compared to other methods of monitoring brain wave activity, EEG is superior in terms of its ability to produce reliable measurements while also being portable, high-frequency, and cost-effective. Electrodes in an EEG test are responsible for detecting the minute electrical charges that are produced as a consequence of the activity of brain cells. The interpretation of this extensive EEG data yields a higher degree of accuracy as compared to its use in functional brain imaging.

Journal of University of Babylon for Engineering Sciences by University of Babylon is licensed under a Creative Commons Attribution 4.0 International License.

مجلة جامعة بابل للعلوم الهندسية

info@journalofbabylon.com | Journal.eng@uobabylon.edu.iq | www.journalofbabylon.com ISSN: 2616 - 9916

The next part provides an outline for the research article that has been suggested. In the first section, the fundamental problem, the present technologies, and the need for improvement in the early identification of brain strokes are discussed. In the second section, a summary of the linked work and the prior research on the suggested method is presented. In Part 3, we will discuss the suggested approach for detecting brain strokes by employing artificial neural networks (ANN) and basing it on EEG readings. In the next section, "Section 4," we will conduct an examination of the suggested system's performance by comparing different rates of accuracy. The suggested approach and the derived performance analysis are summarized at the end of Section 5.

2. Related Work

Many scientists are trying to find a way to find brain strokes and brain tumors early and for less time and money. There exist various methods to detect brain stroke, Researchers are working to change all of them so that they can find strokes early on. These methods include Image processing using enhancement, skull stripping and using machine learning algorithms. This section describes few of the related work to brain stroke detection.

Using the brain signals, it is possible to detect the ischemic brain stroke in the patient as the cerebral blood flow in a normal person is 50 to 70 ml, however, it gets reduced to 23-30 ml in the ischemic brain stroke [6]. This dilation can be detected by Electroencephalogram signals, by increasing the slow waveforms of theta and delta frequencies and decreasing the fast waveforms like alpha and beta frequencies [7]. In previous research, the pattern of this signal has been classified into normal strokes and ischemic strokes. For example, Omar et al. in their research used Relative Power Ratio (RPR) beta, alpha, delta and theta to cluster 3 levels of stroke [8]. In another research putter observed the correlation between National Institute of Health Stroke Scale scores (NIHSS) and the Brain Symmetry Index (BSI) [9]. Finnigan et al. found the correlation of relative alpha power and Delta/Alpha Ratio (DAR) measures with NIHSS score using QEEG (Quantitative electroencephalography) [10]. Osmalina used BSI, DTABR and DAR combined [11], however Fitriah implement Principal Component Analysis (PCA) with same features to increases the accuracy with minimum number of channels [12]. Most of this research requires the expertise domain knowledge for the classification purpose. In the proposed research the classification task will be performed without intervention of expertise domain knowledge by using machine learning technique like deep neural network methods.

Deep learning a subset of machine learning, in which networks learn by discovering intricate structures in the data they experience [13]. Deep learning enables to find the hidden pattern and learn from the raw dataset with minor preprocessing techniques. Convolutional neural network (CNN) is one of the mostly used deep learning network [5]. In recent few years, CNN has been used in many research including computer vision fields, as it is able to extract the local features in neighboring elements from an input dataset where there is a high possibility of the same patterns. Using filter kernel, it is possible to minimize the count of learnable parameters

Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.

مـجلـة جـــامعة بـــابـل للعلـــوم الهندسية مـجلـة جـــامعة بـــابـل للعلـــوم الهندسية مـجلـة جـــامعة بـــابـل للعلـــوم الهندسية

info@journalofbabylon.com | Journal.eng@uobabylon.edu.iq | www.journalofbabylon.com ISSN: 2616 - 9916

to the kernel size and it will not be depended on the input datasets, however, in case of normal neural network, the parameter count increases with the size of an input data. Along with that, CNN is not only limited the image dataset, but it can also be used of EEG datasets and other 1-dimensional datasets. There is some existing research in the 1-dimensional CNN on the EEG datasets, this includes feature extraction and classification of epilepsy [14], auto detection and diagnosis of seizure [13], scoring of sleep stages [15] and ischemic stroke detection [16].

3. Proposed Method

In the proposed research dataset collected which was used in the previous research [11,12], in this dataset, 31 data were collected from a normal person without any abnormality while 27 datasets are of patients with acute ischemic stroke. While taking the dataset sampling rate is kept at 512 Hz for all the readings. It took around 30 minutes to take the EEG data from all the samples and all perceptron's with electrode placement by maintaining international standards. The data collected from these sources are stored in the European Data Format file (.edf file).

When compared to a normal individual, a patient suffering from acute ischemic stroke has a reduced volume of cerebral fluid. This causes slower wave frequencies, such as theta and delta, to become more prominent, while higher wave frequencies, such as alpha and beta, become less prominent. There is no need for study in the time domain since this data may be readily recognized via the use of EEG frequency analysis. Because the EEG signals are generated by a stochastic process, power spectral density analysis is favored over basic FFT because it takes into account the average of the signal.

Although there are a number of other suggested approaches for power spectral density analysis, the Welch method is being used in this study. This method has the advantage of robustness, which ensures that there is no invalid frequency in the analysis of density. On the other hand, the disadvantage of this method is its windowing, which leads to distortion of the resulting density. Robustness is an advantage. Robustness ensures that there is no invalid frequency in the analysis of density. The following are the stages that are involved in Welch's method: At first, the signal is split up into multiple overlapping parts. After that, a periodogram is collected for each segment. Finally, the average of all of the section's periodograms is taken into consideration when calculating the spectral estimate.

1. Partition the data sequence:

Dataset $x[0], x[1],..., x[N - 1]$ is segmented into k batches or segments:

Segment 1: $x[0], x[1], \ldots, x[M - 1]$

Segment 2: $x[S], x[S + 1], \ldots, x[M + S - 1]$

..

..

Segment K: $x[N - M], x[N - M + 1], \ldots, x[N - 1]$----------- 1

Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.

In this equation K is count of segments, M is points count in each segment, and S is points require to shift between segments.

2. windowed discrete Fourier transform (DFT) is computed for each segment (K= 1 to K) with frequency v

$xk(v) = \sum_{m}(\text{x[m]w[m] exp }(-\text{j }2\pi\text{vm }))$ --------- 2

Where, m is (k - 1) S, . . . , M + (k-1)S – 1 and w[m] is the window function.

3. From DFT value for modified periodogram for each segment is calculated as:

$$Pk(v) \quad = \frac{1}{W}\,|xk(v)| \text{ ----------3}$$

Where,

$$W \ = \sum_{m=0}^{M}(\text{w[m] }) \text{ ---------4}$$

4. Calculate the average to obtain the power spectral density estimate:

$$sx(v) = \frac{1}{K} + \sum_{K=1}^{K}(\text{pk(v)}) \text{ -------- 5}$$

Where, $sx(v)$ is a PSD estimate using Welch's method

Because the length of the windows that are employed in the segmentation process has an effect on the resolution of the frequencies, utilizing larger windows will result in a peak that is narrower in frequency. Because the frequency bands that are being investigated in this investigation are lower than 20 Hz, down sampling is being done in order to cut down on the needless computing complexity. Through the process of down sampling, a sample rate of 512 Hz may be decreased to 32 Hz. When calculating Welch's power spectral density, 50% overlap, 64 window length, and one second is used as the time value. The estimated spectral density that is produced as a result of this stage is what is ultimately sent into the convolutional neural network model as the raw input. Additionally referred to as the weighted overlapped segment averaging (WOSA) technique and the periodogram averaging method, Welch's approach goes by these names as well.

Before calculating the power spectral density, the EEG is first divided into many portions with short durations and equal lengths. This is done so that a higher quantity of input data may be gathered. This time is changed in order to find the length that is optimal for providing the highest possible accuracy rate. Following the completion of the segmentation process, this input is then splinted into training and testing according to an 80/20 aspect ratio. Figure 2 is an illustration of the process.

www.journalofbabylon.com | ISSN: 2616 - 9916 | Journal.eng@uobabylon.edu.iq | info@journalofbabylon.com

مـجلـة جـامعة بـابل للعلـوم الهندسية مـجلـة جـامعة بـابل للعلـوم الهندسية مـجلـة جـامعة بـابل للعلـوم الهندسية

Journal of University of Babylon for Engineering Sciences by University of Babylon is licensed under a Creative Commons Attribution 4.0 International License.

مجلة جامعة بابل للعلوم الهندسية

www.journalofbabylon.com | ISSN: 2616 - 9916 | Journal.eng@uobabylon.edu.iq | info@journalofbabylon.com

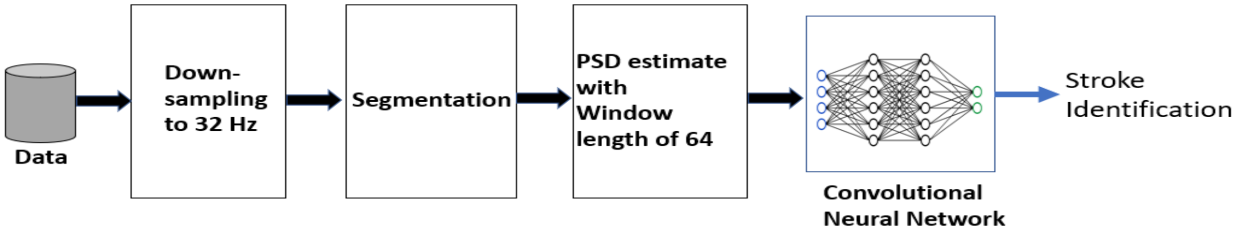


Figure 2: Schematic of proposed system

In the study that was suggested, a convolutional neural network was used in order to carry out feature extraction and classification. On the other hand, in the research that came before, the process of feature extraction required manual calculations and required a certain amount of domain knowledge; in the research that is being proposed, the process of feature extraction is carried out automatically using a machine learning algorithm.

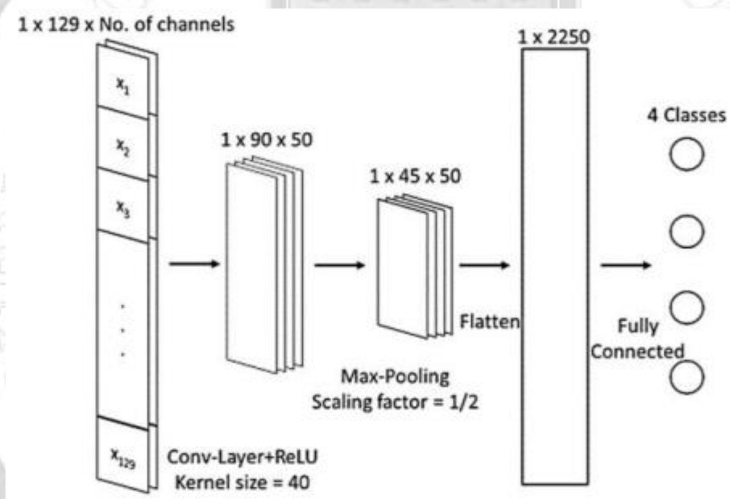


Figure 3: Architecture of Convolutional neural network

The architecture of a convolutional neural network with only one convolutional layer and one pooling layer is seen in Figure 3. The development of feature maps is the responsibility of convolutional layers, which do this by sliding filters over an input picture and identifying patterns that are already present in the image. Pooling layers are in charge of down sampling the feature map in order to introduce translation invariance, which helps to lower the likelihood of the model is overfitting. A convolutional neural network consists of convolutional layers, each of which has 50 filters and a kernel size of 1*120, as well as fully connected (FC) layers and pooling layers with a scaling factor of 1/2. In addition, the network has fully connected layers. In fully-connected layers, sometimes referred to as linear layers, each input neuron links to the other output neuron in the layer. This sort of layer is also referred to as "linear." Training sessions last for three hundred epochs. Model building is accomplished with the help of the Keras Python package. Google has created the Keras library as a tool for the implementation of

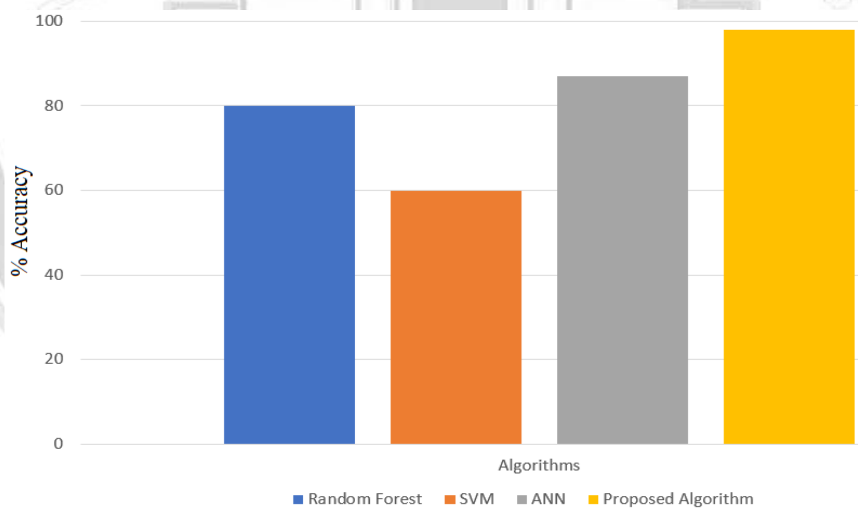
Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.

neural networks. The output is broken down into four separate categories: normal, mild, moderate, and severe brain stroke. The true severity of the brain stroke may be determined based on these output types.

4. Result and Discussion

The data set is divided into 80 and 20 patterns for the purpose of determining the correctness of the proposed model. Twenty percent of the data is utilized for testing the proposed model, while the remaining eighty percent of the data is used to train the trained model. Based on the findings of this experiment, the most effective artificial intelligence or machine learning method might be suggested for use in model construction using the data that was obtained. The accuracy of the proposed model is compared with the Random forest machine learning technique, Support vector machine, and Convolutional neural network without data segmentation in order to evaluate how well the model fits the training data.

For the purpose of the experimental analysis, one thousand samples are gathered and then using the 80-20 split approach, the dataset is partitioned into training data and testing data. Testing data are used in order to determine how accurate the algorithms are. A comparison of the two algorithms' levels of precision is shown in Figure 4. The performance of the suggested method was found to be superior to that of other algorithms.



.Figure 4: Accuracy Comparison of algorithm

Figure 4 shows the accuracy comparison of different machine learning algorithms. It is clearly observed that the accuracy of the proposed algorithm outperforms the accuracy of Random forest, support vector machine and Convolutional neural network without data preprocessing. Because of the linear classification of the Support vector machine, the accuracy seems to be less, however, the ensemble classification algorithm and convolutional neural network improve the accuracy to 80% and 87% respectively. It is observed that, when the downsampling and segmentation is applied, the accuracy of proposed algorithm further improved

www.journalofbabylon.com | ISSN: 2616 - 9916 | Journal.eng@uobabylon.edu.iq | info@journalofbabylon.com
مجلة جامعة بابل للعلوم الهندسية

Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.

to 98.3%. For further analysis and to determine the impact of the proposed algorithm on the real-time data, instead of split test, real datasets are used, and the accuracy is determined. For this purpose, 1000 samples are collected, and its accuracy is measured for normal, mild, moderate and severe. The results are compared with PCA algorithm proposed in previous.

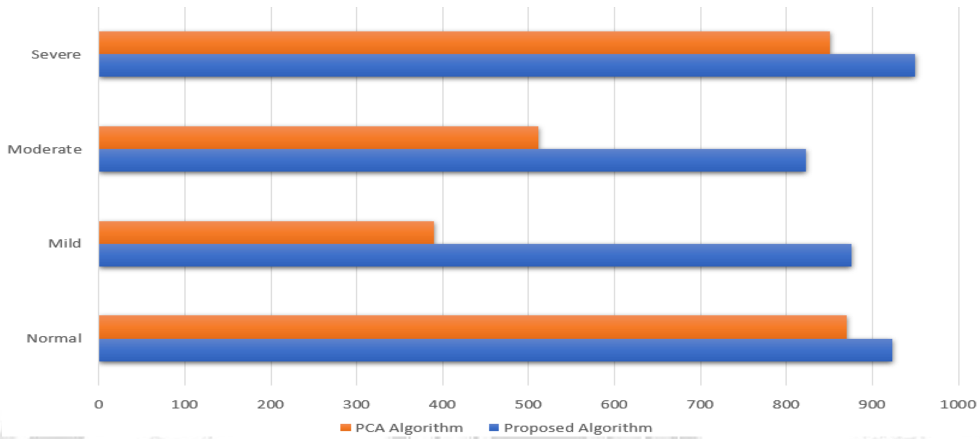


Figure-5-: Accuracy Comparison of PCA & Proposed algorithm with real time data

Figure-5 shows that the accuracy of the proposed algorithm is better than the previously proposed algorithm. The result also emphasizes that the accuracy for previous research more accurate towards determining the results into 2 classes, which are normal or Severe, however,er proposed method determines the normal or Severe classification accurately, along with that the classification of Moderate and Mild stroke is also carried out with higher accuracy, which is not the case for previous research [12].

In light of the fact that the accuracy of the suggested algorithm has been shown to be superior to that of other algorithms, an investigation into the impact of variable segment length has been carried out for the proposed algorithm. In order to identify the optimal segmentation length, several combinations of lengths are evaluated on the available data, and the length that is judged to be the most suited for improving the test result is chosen. In order to accomplish this goal, the length of the segmentation is evaluated relative to variations of 16, 32, 64, 128, 256, 512, and 1024…

Table 1: Accuracy with respect to segment length variation

Segment Length (s)	Training	Testing	Accuracy (%)
16	5300	1325	94.6
32	2305	577	96.8
64	1316	329	98.3
128	644	161	93.8
256	316	79	89.9
512	136	34	79.4
1024	48	12	58.3

Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.

www.journalofbabylon.com | ISSN: 2616 - 9916 | Journal.eng@uobabylon.edu.iq | info@journalofbabylon.com
مـجلـة جـــامعة بـــابـل للعلـــوم الهندسية

The accuracy comparison of the dataset is shown in Table 1, and it is broken down in terms of the variance in segment length. It is clear from looking at table 1 that the proportion of correct answers changes depending on the length of the segments. The amount of accessible training data has a direct correlation to the level of accuracy achieved. The accuracy of the method is at its peak at a length of 64, but beyond that, due to down sampling, it begins to lose precision as the length increases beyond 64 since the smaller segments distort the actual signal.

5.Conclusion

A patient's life may be saved by early diagnosis and treatment of brain stroke, which is caused when an artery in the brain becomes blocked. Electroencephalography (EEG) is a method that uses a visual trace to capture the electrical activity that are taking place in various regions of the human brain. This method is used to examine electrical activities. A convolutional neural network is used in the study that is being suggested for the purpose of stroke severity classification. The power spectral density (PSD) of EEG signals may be determined with the help of this approach by using the characteristics that have been retrieved from an artificial neural network.

In order to evaluate the proposed model's accuracy, the data set is segmented into 80 and 20 patterns. The accuracy of the proposed model is then compared to the results of the machine learning algorithms known as random forest, support vector machine, and convolutional neural network, all of which do not segment the data. It was found that the suggested method performed much better than previous algorithms, with an accuracy of performance of 98.3%. Accuracy comparison of the dataset with regard to the varying segment lengths is necessary for examining the impact of segmentation and selecting the optimal segment length. It was discovered that the accuracy is linearly proportional to the segment length; however, due to down sampling, the accuracy begins to decline after 64 as the shorter segment distorts the true signal. This happens because the shorter segments are more likely to be sampled more often. The optimal result is achieved with a segment length of 64. Based on the analysis of the results, it has been determined that the accuracy of the proposed method is superior to that of the current algorithm for machine learning, and that the segment length of 64 size achieves the highest level of performance accuracy.

References

[1] Bassett, D.S., Wymbs, N.F., Porter, M.A., Mucha, P.J., Carlson, J.M., Grafton, S.T., Dynamic reconfiguration of human brain networks during learning. Proc. Nat. Ac. Sc., 108(18), pp. 7641–7646, 2011.

[2] Bonna Akter; Aditya Rajbongshi; Sadia Sazzad; Rashiduzzaman Shakil; Jahanur Biswas, A Machine Learning Approach to Detect the Brain Stroke Disease, 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2022.

[3] Olympia Karadima; Raquel C. Conceição; Panagiotis Kosmas, Differentiation of brain stroke type by using microwave-based machine learning classification, 2021 International Conference on Electromagnetics in Advanced Applications (ICEAA), Honolulu, HI, USA, 2021

مجلة جامعة بابل للعلوم الهندسية
www.journalofbabylon.com | ISSN: 2616 - 9916
info@journalofbabylon.com | Journal.eng@uobabylon.edu.iq | www.journalofbabylon.com

Journal of University of Babylon for Engineering Sciences by University of Babylon is licensed under a Creative Commons Attribution 4.0 International License.

[4] Xiaoyou Lin; Yifan Chen; Zheng Gong; Hui Zhang, Brain Stroke Classification using a Microwave Transmission Line Approach, IEEE Asia-Pacific Microwave Conference (APMC), Hong Kong, Hong Kong, 2021

[5] M. A. Nielsen, Neural Networks and Deep Learning. San Fransisco: Determination Press, 2015

[6] K. G. Jordan, "Emergency EEG and Continuous EEG Monitoring in Acute Ischemic Stroke," vol. 21, no. 5, pp. 341–352, 2004.

[7] M. A. Nielsen, Neural Networks and Deep Learning. San Fransisco: Determination Press, 2015.

[8] W. R. W. Omar et al., "Acute Ischemic Stroke Brainwave Classification Using Relative Power Ratio Cluster Analysis," Procedia - Soc. Behav. Sci., vol. 97, pp. 546–552, 2013.

[9] M. J. A. M. Van Putten and D. L. J. Tavy, "Continuous quantitative EEG monitoring in hemispheric stroke patients using the brain symmetry index," Stroke, vol. 35, no. 11, pp. 2489–2492, 2004.

[10] S. P. Finnigan, M. Walsh, S. E. Rose, and J. B. Chalk, "Quantitative EEG indices of sub-acute ischemic stroke correlate with clinical outcomes," Clin. Neurophysiol., vol. 118, no. 11, pp. 2525–2532, 2007

[11] O. N. Rahma, S. K. Wijaya, Prawito, and C. Badri, "Electroencephalogram analysis with extreme learning machine as a supporting tool for classifying acute ischemic stroke severity," Proc. - 2017 Int. Semin. Sensor, Instrumentation, Meas. Metrol. Innov. Adv. Compet. Nation, ISSIMM 2017, vol. 2017-Janua, pp. 180–186, 2017.

[12] N. Fitriah, S. K. Wijaya, M. I. Fanany, C. Badri, and M. Rezal, "EEG channels reduction using PCA to increase XGBoost's accuracy for stroke detection," AIP Conf. Proc., vol. 1862, no. July 2017.

[13] I. Ullah, M. Hussain, E. Qazi, and H. Aboalsamh, "An Automated System for Epilepsy Detection using EEG Brain Signals based on Deep Learning Approach Insight Centre for Data Analytics , National University of Ireland , Galway , Ireland Visual Computing Lab , Department of Computer Science , College of Com," Expert Syst. Appl., no. 107, pp. 61–71, 2018.

[14] T. Wen and Z. Zhang, "Deep Convolution Neural Network and Autoencoders-Based Unsupervised Feature Learning of EEG Signals," IEEE Access, vol. 6, pp. 25399–25410, 2018.

[15] O. Tsinalis, P. M. Matthews, Y. Guo, and S. Zafeiriou, "Automatic Sleep Stage Scoring with Single-Channel EEG Using Convolutional Neural Networks," 2016.

[16] E. P. Giri, M. I. Fanany, A. M. Arymurthy, and S. K. Wijaya, "Ischemic stroke identification based on EEG and EOG using ID convolutional neural network and batch normalization," 2016 Int. Conf. Adv. Comput. Sci. Inf. Syst. ICACSIS 2016, pp. 484–491, 2017

info@journalofbabylon.com | Journal.eng@uobabylon.edu.iq | www.journalofbabylon.com ISSN: 2616 - 9916

Journal of University of Babylon for Engineering Sciences by University of Babylon is licensed under a Creative Commons Attribution 4.0 International License.

ARTICLE

JOURNAL OF UNIVERSITY OF BABYLON

For ENGINEERING SCIENCES (JUBES)

Vol.31, No.1.| 2023

ISSN: 2616 - 9916 | www.journalofbabylon.com | Journal.eng@uobabylon.edu.iq | info@journalofbabylon.com

مجلة جامعة بابل للعلوم الهندسية

كشف السكتة الدماغية باستخدام ANN بناءً على إشارات EEG باستخدام مسار سي إن إن

رياض عبد الحمزة العلواني

قسم الهندسة الكهربائية، كلية الهندسة، جامعة بابل، بابل، العراق

البريد الكتروني:alwaniriyad@gmail.com

قاسم كرم عبدالله

قسم الهندسة الكهربائية، كلية الهندسة، جامعة بابل، بابل، العراق

البريد الكتروني:kasimkaa.11@gmail.com

فرح نبيل عباس

قسم علم وظائف الأعضاء، كلية الطب، جامعة بابل، بابل، العراق

البريد الكتروني:frhnabil@yahoo.com

الخلاصة:

تحدث السكتة الدماغية بسبب انسداد في الشريان الذي ينقل الدم المؤكسج إلى الدماغ. السكتة الدماغية الحادة هي السكتة الدماغية الأكثر شيوعًا. يمكن أن يكون الاكتشاف المبكر للسكتة الدماغية منقذاً لحياة المرضى. تخطيط كهربية الدماغ هو تقنية لتحليل الأنشطة الكهربائية الموجودة في الأجزاء المختلفة من الدماغ البشري، وباستخدام التتبع البصري، فإنه يسجل هذه الأنشطة. يوفر EEG قياسات فعالة من حيث التكلفة ومحمولة وعالية التردد ودقيقة مقارنة بأدوات مراقبة نشاط الموجات الدماغية الأخرى. يستخدم مخطط كهربية الدماغ لتشخيص متلازمة حساسية الاندروجين. في البحث المقترح، تم تطبيق الشبكة العصبية التلافيفية لتصنيف شدة السكتة الدماغية. في هذه الخوارزمية ، يتم حساب الكثافة الطيفية للطاقة (PSD) لإشارات مخطط كهربية الدماغ بناءً على الميزات المستخرجة من الشبكة العصبية الاصطناعية. ثم تم تدريب خريطة المعالم لتصنيف البيانات إلى أربع حالات بناءً على شدة السكتة الدماغية. بالنسبة لتحليل الأداء، تتم مقارنة الخوارزمية المقترحة مع الخوارزميات الموجودة، ويلاحظ أن دقة الخوارزمية المقترحة هي 98.3٪، وهي أفضل من الخوارزمية الموجودة للكشف عن السكتة الدماغية.

الكلمات الدالة:– مخطط كهربائية الدماغ، أخذ العينات السفلية، التجزئة، طريقة ويلش لكثافة طيف الطاقة، الشبكة العصبية التلافيفية، الغابة العشوائية..SVM.

Journal of University of Babylon for Engineering Sciences by *University of Babylon* is licensed under a Creative Commons Attribution 4.0 International License.