A Novel Methodology to Detect Epileptic Seizure Based on EEG Signals Using Deep Learning Assisted Classification Principle

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Abstract: Analyzing the signals generated by neurons in the brain can reveal the presence of epilepsy, a severe and persistent neurological condition. A web of interconnected connections allows neurons to send and receive messages, as well as communicate with other parts of the body. The monitoring of these brain impulses is commonly done using electrocorticography (ECoG) and electroencephalography (EEG) equipment. These complex, noisy, non-linear, and non-stationary signals produce a mountain of data. As a result, detecting seizures and learning about brain-related topics is a challenging endeavor. Using Deep Learning classifiers, EEG data can be efficiently categorized, seizures can be identified, and relevant sensible patterns may be shown. As a result, several approaches to seizure detection have emerged, all utilizing Deep Learning classifiers and statistical data. The biggest challenge is choosing the right classifiers and attributes. The goal of this study is to present a comprehensive experimental review of the many different techniques that have arisen in the field of Deep Learning classifiers and statistical features in the past several years. In this paper, a new algorithm called Neural Classifier with Optimized Learning (NCOL) is presented. It can handle all the scenarios listed above and gives clear results. To test how well the algorithm works, it is cross-validated with the traditional Convolutional Neural Network (CNN) model. Seizure detection and categorization, as well as future research directions, may be better understood with the help of the offered state-of-the-art methodologies and concepts.

1 INTRODUCTION

The ancient Greek and Latin words "epilepsia" meaning "seizure" or "to seize upon" are the etymological roots of the modern English word epilepsy. This neurological condition is quite dangerous and has distinct symptoms, the most prominent of which are repeated seizures. The Babylonians recorded a medical literature including contextual knowledge (Zakareya Lasefr, et al., 2023) about epilepsy almost 3,000 years ago. Apart from other animals, like dogs, cats, rodents, etc., the disease can afflict people as well. The disorder is widespread and prevalent; hence the name "epilepsy" has nothing to suggest about the origin or degree of seizures (Wei Zeng, et al., 2023). A number of hypotheses concerning the origin have been put forth. Malformations, low blood sugar, and an absence of oxygen after delivery are among the causes of electrical activity disruption inside the brain, which is the primary symptom. Roughly 50 million individuals throughout the world deal with epilepsy, and 100 million will experience (Mingkan Shen, et al., 2024) it at some point in their lives. The stated prevalence rate is between half a percent and one percent, and it is responsible for one percent of the global illness burden. Having more than one seizure every day is the most prominent sign of epilepsy. An abrupt disruption or abnormal brain activity (Khati, et al., 2020) triggers an involuntary change in the patient's behavior, feeling, and temporary loss of consciousness. Usually lasting anywhere from few seconds to many minutes, a seizure will not always be accompanied by an aura. From this can come fractures, burns, even death (Afshin Shoeibi, et al., 2021). Based on the symptoms they cause, neurologists divide seizures into two main categories: partial and generalized. Sometimes referred to as a focal seizure, a partial seizure affects only one side of the brain. One knows both simple- and complex-

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partial seizures. A patient in the simple-partial stage is unable to express themselves enough yet does not pass out. The complex-partial is characterized by a "focal impaired awareness seizure," in which the affected individual becomes disoriented and exhibits aberrant behavior such as muttering and chewing. However, with generalized seizures, the entire brain is impacted and entire networks of neurons are damaged rapidly. Convulsive and non-convulsive generalized seizures are the two main classifications of these numerous forms of seizures (Pankaj Kunekar, et al., 2024).

Epilepsy affects almost 50 million people globally, making it one of the most prevalent neurological ailments, according to the World Health Organization. Unpredictable and abrupt seizure activities characterize epilepsy. The quality of life for people affected with epilepsy is greatly diminished. It is characterized by a lifetime of recurring events. Various reasons, including genetic predisposition, malignancies, skull fractures, and other medical conditions, can lead to epileptic seizures (Anis Malekzadeh, et al., 2021). An epileptic seizure is defined as an abrupt and transient disruption of regular brain function, marked by an excess of aberrant electrical activity. Symptoms of this electrical activity can range from mild aches and pains to full-blown seizures and coma, and in rare cases, unanticipated death (Wesley T Kerr, et al., 2024). The precise diagnosis of epilepsy and the development of individualized treatment plans depend on the reliable detection of seizures in individuals with the disorder. Early identification and regular monitoring of seizures can offer a better quality of life and decrease life risks (Afshin Shoeibi, et al., 2021). Examining individuals with a history of seizures allows for the precise diagnosis of seizure type through the analysis of electroencephalogram data, which capture electrical activity in the brain. Intense patterns linked with seizures can be captured by the dynamic depiction of brain activity provided by epileptic EEG recordings. Electrodes placed on the scalp capture electrical activity in the brain. Electrodes like this pick up on the brain's natural electrical signals.

Unprocessed EEG data sometimes includes background noise and other details (Deepa B, et al., 2022). In order to clean and improve the signals, preprocessing processes are used, including filtering, artifact removal, and baseline correction. Classification of electroencephalogram (EEG) signals is an important step in detecting epileptic seizures when preprocessing is complete. The raw signal lacks discriminative information compared to data obtained by extracting pertinent features from signals. Among the many medical uses for machine learning and deep learning is the extraction and classification of significant characteristics, which has tremendous promise for use in epilepsy diagnosis and other areas. The duration, intensity, and appearance of epileptic seizures can range greatly. Regular brain activity is the product of complex neuronal connection via electrical impulses. Seizures occur when neurons in the brain fire inappropriately or too rapidly in those who suffer from epilepsy. Based on their features and the areas of the brain where they start, seizures may be categorized into many categories.

2 RELATED WORKS

For one-fourth of patients with medication-resistant seizures, ongoing maintenance of seizure detection and management is essential to control unplanned episodes (Taeho Kim, et al., 2020). The diagnosis of seizures can benefit from electroencephalogram (EEG), electromyography (EMG), electrocardiogram (ECG), motion detection, oxygen saturation levels, artificial sounds, or visual indications acquired on audio or video recordings of the human head and body. Recent developments in classification algorithms, time-or frequency-domain analysis, and seizure sensor signal processing allow the detection and grouping of seizure phases. We then present a promising future for contemporary, non-invasive brain stimulation technology in seizure treatment. This work reviews the principles of brain stimulation techniques for treating seizures with an eye toward transcranial magnetic stimulation (TMS), transcranial direct current stimulation (tDCS), and transcranial focused ultrasonic stimulation (tFUS). Our goal in writing this review was to provide readers a bird's-eye perspective of the current diagnostic and therapy landscape for seizures. Both new and seasoned researchers would benefit from this information as it would allow them to better track developments in seizure sensing, detection, categorization, and therapy. Finally, we suggest future areas of study that seizure researchers and engineers might be interested in.

Common tool for seizure identification is an electroencephalogram (EEG), which records brain's electrical activity (G. Yogarajan, et al., 2023). The symmetry or asymmetry of the EEG signals guides one to detect epileptic events. Typically, the patterns of an electroencephalogram (EEG) on one side of the brain are identical to those on the other. On the other hand, an asymmetrical EEG signal could be caused by a rapid spike in electrical activity in one cerebral hemisphere during a seizure. The existence of epileptic activity can be revealed by seeing asymmetric spikes or sharp waves in interictal EEG recordings from individuals with epilepsy. As a result, seeing asymmetry or symmetry in EEG data can help with epilepsy diagnosis and treatment. Remember that interpretation of EEG data should always consider the medical background and findings from other diagnostic tests of a patient. We introduce in this study a Deep neural network (DNN) and Binary dragonfly algorithm (BDFA)-based enhanced automated seizure detection system using electroencephalogram (EEG) data. The DNN model learns the characteristics of the EEG signals by using nine different statistical and Hjorth parameters obtained from various levels of decomposed data gathered by the Stationary Wavelet Transform. The next step was to use the BDFA to minimize the extracted features; this would allow the DNN to be trained more quickly and with better performance. With a sensitivity, specificity, and F1 score of 100% in comparison to previous methods, our results suggest that using a subset of characteristics chosen with a 13% success rate helps in correctly differentiating between normal, interictal, and ictal signals.

Automated seizure detection (Paul Vanabelle, et al., 2020) is addressed by using machine learning algorithms applied to clinical electroencephalograms (EEGs) kept in the TUSZ database Temple University Hospital. Results on this complex dataset have therefore so far fallen short of expectations. This experiment aims to discover how much additional data will help to improve the outcomes. We demonstrate that the extracted features aid in accurate discrimination between normal, interictal, and ictal signals using a subset of features picked with a success rate of 13%. Our results outperform prior methodologies with sensitivity, specificity, and F1 score of 100%. The achieved results are comparable to those of deep learning models previously reported in the literature. By sorting performances according to seizure kinds and determining which attributes are most important, we are able to provide context for our findings. Compared to focal seizures, our data shows that generalized seizures are typically far easier to forecast. When trying to differentiate between seizure and background activity in EEG, we find that certain channels and characteristics are more significant than others.

Electroencephalography (Rekha Sahu, et al., 2020) is one method to detect illnesses connected to the electrical activity of the brain seizure conditions. In order to diagnose patients accurately and provide them the right medication, it is necessary to discover patterns of brain activity and how they relate to symptoms and illnesses. In order to better understand and anticipate epileptic seizures, this study seeks to classify electroencephalography data recorded on several channels. The dataset includes 179 pieces of information and 11,500 occurrences derived from electroencephalography recordings. The signs of an epileptic seizure are one of five types of instances. We have demonstrated the efficacy of deep machine learning approaches, classical methods, and ensemble methods in detecting epileptic seizures. It makes use of a one-dimensional convolutional neural network in conjunction with ensemble ML methods such as stacking, boosting (including AdaBoost, gradient boosting, and XG boosting), and bagging. Decision trees, random forests, additional trees, ridge classifiers, logistic regression, K-Nearest Neighbors, Naive Bayes (gaussian), and Kernel Support Vector Machine (polynomial, gaussian) are some of the traditional machine learning techniques used for epileptic seizure classification and prediction. We preprocessed the dataset by removing superfluous characteristics using the Karl Pearson correlation coefficient before using ensemble and conventional methods. Each classifier's Receiver Operating Characteristic Area under the Curve is used to alter the classifiers' classification and prediction accuracy using k-fold cross-validation procedures. Our method sorting and comparing findings demonstrate that the convolutional neural network and extra tree bagging classifiers perform the best among other ensemble and conventional classifiers.

An attribute of the medical condition known as epilepsy, an erratic, too fast firing of neurons in the brain influences the normal electrical activity of the brain (Ferdaus Anam Jibon, et al., 2023). Using electroencephalograms (EEGs), which track electrical activity generated by nerve cells in the cerebral cortex, has become somewhat more common in the diagnosis and treatment of epilepsy during the past few years. Physiological data often has irregular topologies, making it impossible to think about it as a matrix, even though this would be beneficial. This contrasts with present deep learning-based automated seizure detection systems using raw EEG signals, which mostly depend on grid-like data. Graph neural networks have drawn a lot of attention as a way to leverage the implicit information available for seizure detection. Edges link interacting nodes in these networks; anatomical connections or temporal correlations allow one to ascertain the weights of the edges. To get over this drawback, we provide a new hybrid design that uses DenseNet in conjunction with an LGCN to identify epileptic episodes. Improvements in feature propagation across all layers and a solution to the vanishing gradient problem allow DenseNet to outperform earlier deep learning networks in terms of computational accuracy and memory economy. The Stockwell transform (S-transform) is used for the first preprocessing of the raw EEG data. The resulting matrix is subsequently inputted into the LGCN for feature selection by grouping it into time-frequency blocks. Next, Densenet is used for categorization. The proposed hybrid system outperformed the state-of-the-art in seizure detection tasks, achieving 98.60% specificity and 98% accuracy, according to extensive testing conducted on the publicly accessible CHB-MIT EEG dataset.

3 METHODOLOGIES

Deep learning is being used to improve results on health and biological data sets. Improving seizure detection is a top priority for researchers and scientists across disciplines, with a focus on data mining and deep learning. Finding reasonable and significant patterns in various domain datasets has been a major use of deep learning. Numerous fields, including healthcare, rely on it, and it has the ability to solve their difficulties. Seizure detection, epilepsy lateralization, discriminating seizure states, and localization are some of the other uses of deep learning on brain datasets. Several learning classifiers, including ANN, SVM, decision forest, decision trees, and random forests, have accomplished this. Previous studies on seizure detection, applied features, classifiers, and claimed accuracy have definitely mostly overlooked the challenges faced by data scientists investigating datasets related to neurological diseases. This work investigates comprehensively Epileptic seizure detection and related knowledge discovery issues as deep learning applications. The examined papers come from notable journals in related disciplines and also considered other highly acclaimed conference papers. The literature has addressed in great detail the thorough investigation of several features and classifiers applied in EEG datasets for seizure identification. The processes of feature extraction and applying classification methods are both difficult. The use of deep learning classifiers to meaningfully extract patterns from electroencephalogram (EEG) data has recently seen a surge in research, leading to remarkable advancements in our understanding of seizure identification, brain region of origin, and related topics. Jean Gotman, 30 years ago, examined EEG data, used several computational and statistical methods for automatic seizure identification, and developed a model for their practical use. In addition, many data science and signal processing methodologies have been used in the research to improve the results. The suggested technique, Neural Classifier with Optimized Learning (NCOL), outperforms the current method, Convolutional Neural Network (CNN), in classifying epileptic episodes. The following figure 1 shows the system flow diagram and the following figure 2 shows the system architecture.

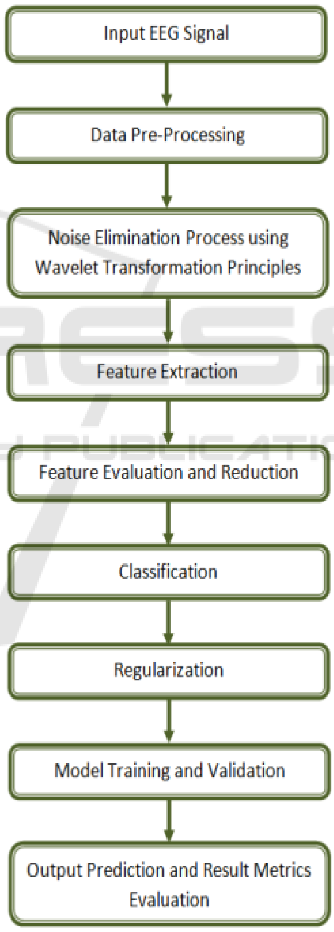

Figure 1: System flow diagram.

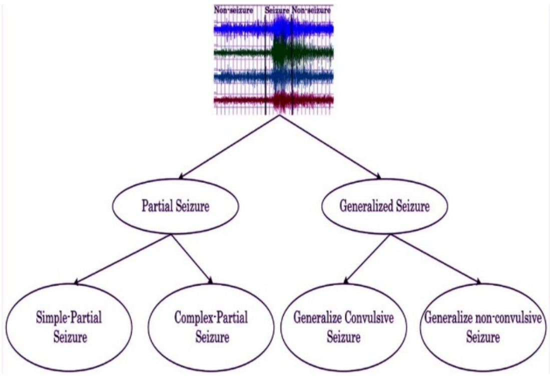

Figure 2: System architecture.

(i) Data Collection: Gathering the dataset of brain signals is the first step. Various monitoring tools are utilized for this purpose. Since the electrodes or channels of EEG and ECoG are often glued to the scalp in accordance with the 10-20 International system at various lobes, these devices are usually the most commonly employed. They are all connected to the EEG equipment and give real-time information on voltage fluctuations and other spatial and temporal characteristics. Electrodes are worn by the patient to record electrical impulses from their brainwaves. The raw data from the EEG monitoring equipment is then shown on a screen. The analyst has also painstakingly recorded these unprocessed signals and classified them as "seizure" or "non-seizure."

(ii) Data Transformation: An important first step after data collecting is turning the signal data to a two-dimensional table form. The goal is to facilitate analysis and supply essential information, such as seizure detection, in this way. Due to the lack of processing, this data is considered raw. Giving relevant information will thus be improper. Different approaches of feature selection have been applied for processing. This procedure also gives possible class-values for the class attribute, therefore guiding the dataset.

(iii) Dataset Preparation: Data processing, a necessary first step in data transformation, is extracting pertinent information from the gathered raw dataset. Several feature extraction methods were therefore applied. Usually, these techniques are implemented on the dataset of extracted EEG signals. Several statistical measure values are abundant in the raw dataset. After feature extraction, the dataset gains additional useful information, which helps the classifier gain a better grasp of the problem. In order to achieve a high rate of accurate seizure identification, various supervised and unsupervised deep learning techniques have been used to explore relevant information from the EEG processed dataset.

(iv) Classification: There are "class attribute" and "non-class attributes" in dataset D, which are used for classification. Since both of them have a high correlation for possible categorization, they are the main components and their relevant information is quite crucial. Defining the target characteristic as the "class attribute," C, it consists of more than one class value—that of seizure and non-seizure among others. Conversely, features are sometimes referred to as "non-class attributes," or predictors. Popularly used classifiers in seizure detection include the ones listed below. In order to identify seizures, the processed EEG data is run through popular classifiers including support vector machines, decision trees, and decision forests.

(v) Performance Evaluation: Various approaches are assessed using the precision of the acquired results. With tenfold cross-valuation, the most popular training approach, the remaining nine segments serve as the training dataset while each fold, or one horizontal segment, is considered the testing dataset. Apart from their accuracy, classifier performance is usually assessed using measures like precision, recall, and f-measure.

4 RESULTS AND DISCUSSION

Recent research has shown that deep learning models can effectively detect epileptic seizures automatically from EEG data, doing away with the necessity for human feature extraction. By comparing it to the conventional deep learning model known as a Convolutional Neural Network (CNN), the suggested Neural Classifier with Optimized Learning (NCOL) model is able to determine how well it performs in identifying epileptic seizures based on the features that have been assessed and the training scenarios that have been set up. This technique improved the efficiency and performance of model training by decomposing EEG signals using the noise elimination strategy to extract statistical and Hjorth parameters, and then by applying the suggested NCOL to minimize feature dimensionality. Frameworks based on NCOL that can handle raw EEG data automatically, without the need for human feature extraction, have also been the subject of research. In order to identify seizures accurately and in a timely manner, these models can differentiate between three states: seizure, preictal, and interictal. Research has looked into ways to make deep learning models more transparent, such as analyzing the frequency patterns learned by NCOL model layers and identifying EEG waveforms that greatly impact seizure predictions, both of which are important for clinical adoption of the models. Building trust and easing the incorporation of deep learning models into clinical practice are the goals of these endeavors. The use of deep learning algorithms to detect epileptic seizures using EEG data has made great strides in the field. Accurate and capable of automating feature extraction; models such as CNN and NCOL have shown themselves. Improving model interpretability and creating hybrid systems to boost detection performance are active areas of research. The accuracy comparison between the NCOL and CNN techniques is depicted in the accompanying image, Figure 3, in order to evaluate the effectiveness of the suggested scheme in a clear manner. As an additional descriptive resource, the accompanying table (Table-1) displays the identical data.

Table 1: Accuracy evaluation between CNN and NCOL.

Epochs	CNN (%)	NCOL (%)
100	92.65	96.67
150	91.47	96.39
200	92.58	97.09
250	91.36	96.56
300	90.12	96.73
350	90.47	96.78
400	89.56	96.80
450	90.45	96.83
500	89.34	96.86
550	90.16	96.89
600	91.77	96.92

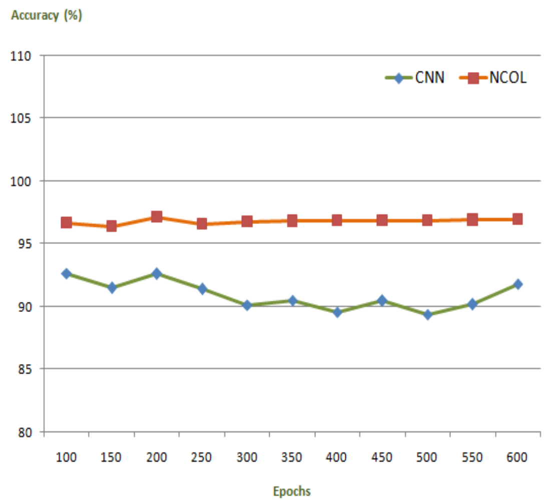

Figure 3: Accuracy analysis.

The precision ratio comparison between the proposed NCOL method and the existing CNN technique is depicted in the accompanying image, Figure 4. This comparison is intended to assess the precision ratio of the proposed scheme in an accurate manner, and Table-2 provides a descriptive representation of the same.

Table 2: Precision comparison between CNN and NCOL.

Epochs	CNN (%)	NCOL (%)
100	91.45	98.59
150	90.67	98.64
200	89.38	97.73
250	90.46	97.48
300	89.52	97.61
350	91.77	97.46
400	89.66	97.39
450	89.75	98.49
500	90.24	98.52
550	91.46	97.47
600	90.17	98.69

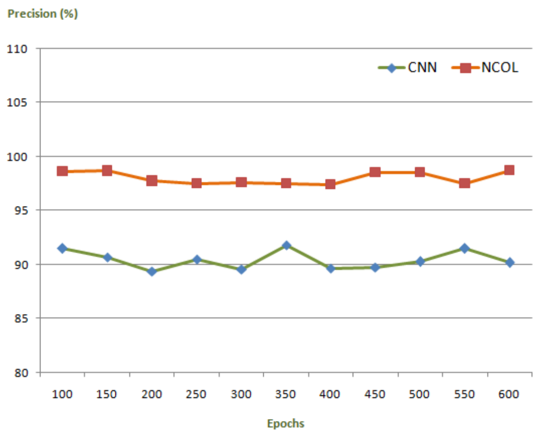

Figure 4: Precision analysis.

The recall ratio comparison between the proposed NCOL technique and the existing CNN strategy is depicted in the accompanying image, Figure 5. This comparison is intended to assess the recall ratio of the proposed scheme in an accurate manner, and Table-3 provides a descriptive representation of the same.

Table 3: Comparison of Recall Between Cnn and Ncol.

Epochs	CNN (%)	NCOL (%)
100	86.17	95.71
150	87.73	96.63
200	87.66	95.59
250	86.27	95.64
300	88.29	96.76
350	89.59	96.73
400	89.47	96.87
450	88.58	95.88
500	88.69	95.57
550	87.27	95.82
600	89.54	96.77

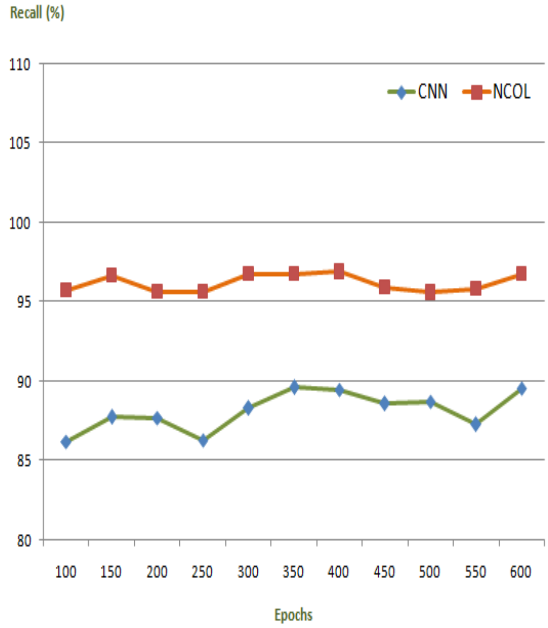

Figure 5: Recall.

The F1-Score ratio comparison between the new NCOL technique and the existing CNN strategy is depicted in the accompanying figure 6. This comparison is made in order to evaluate the F1-Score of the suggested scheme in an accurate manner. The same information is also provided in the following table, Table-4, in a descriptive manner.

Table 4: Comparison of F1-score between CNN and NCOL.

Epochs	CNN (%)	NCOL (%)
100	90.02	97.82
150	91.19	97.63
200	88.72	96.17
250	91.09	96.51
300	87.47	96.59
350	88.16	96.34
400	88.13	96.19
450	87.57	97.29
500	85.44	97.25
550	86.36	96.56
600	87.27	97.45

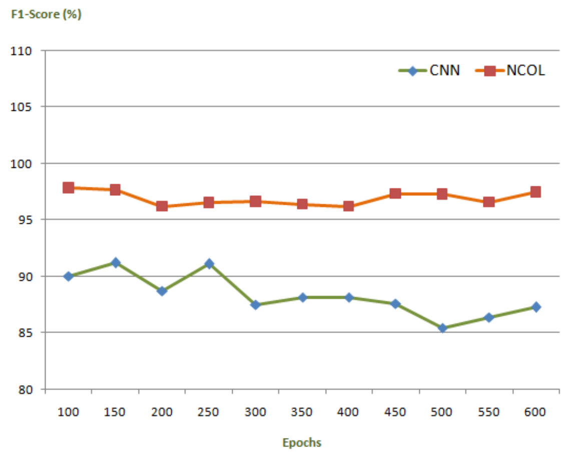

Figure 6: F1-score.

5 CONCLUSION AND FUTURE SCOPE

In summary, this paper suggested a framework that is based on deep learning model and is capable of identifying Epileptic Seizure occurrences from EEG records. The Neural Classifier with Optimized Learning (NCOL) model, which was proposed, effectively extracted perceptive features from raw EEG signals using discrete wavelet transform analysis. NCOL also assisted in the removal of noises and artifacts that were present in the original signal. The presence of these elements presents a significant challenge during the succeeding phases of feature extraction. The dimensionality of the data was substantially reduced by 85% in the first run through feature selection, which led to a remarkable improvement in terms of performance and computation cost. The classifiers were trained in approximately 57% less time when only the pertinent features were used. By combining information from several physiological signals, such as electroencephalography, electrocardiography and others, a more complete picture of a patient's health may be revealed. The specificity and sensitivity of seizure detection can be enhanced by multimodal techniques.

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