Hybrid Attention-Based Transformers-CNN Model for Seizure Prediction Through Electronic Health Records

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Abstract*—Seizures are a serious neurological disease, and proper prognosis by electroencephalography (EEG) dramatically enhances patient outcomes. Current seizure prediction methods fail to deal with big data and usually need intensive preprocessing. Recent breakthroughs in deep learning can automatically extract features and detect seizures. This work suggests a CNN-Transformer model for epileptic seizure prediction from EEG data with the goal of increasing precision and prediction rates by investigating spatial and temporal relationships within data. The innovation is in employing CNN for spatial feature extraction and a Transformer-based architecture for temporal dependencies over the long term. In contrast to conventional methods that depend on hand-crafted features, this method uses an optimization approach to enhance predictive performance for large-scale EEG datasets. The dataset, which was obtained from Kaggle, consists of EEG signals from 500 subjects with 4097 data points per subject in 23.6 seconds. CNN layers extract spatial characteristics, while the Transformer takes temporal sequences in through a Self-Attention Profiler to process EEG's temporality. The suggested CNN-Transformer model also performs well with 98.3% accuracy, 97.9% precision, 98.73% F1-score, 98.21% specificity, and 98.5% sensitivity. These outcomes show how the model identifies seizures while being low on false positives. The results indicate how the hybrid CNN-Transformer model is effective at utilizing spatiotemporal EEG features in seizure prediction. Its high sensitivity and accuracy indicate important clinical promise for early intervention, enhancing treatment for epilepsy patients. This method improves seizure prediction, allowing for better management and early therapeutic response in the clinic.

Keywords*—*Epileptic seizure prediction; EEG signal analysis; CNN-Transformer model; deep learning in healthcare; spatiotemporal feature extraction; neural network optimization

I. Introduction

The word, epilepsy is derived from the Greek word “epilambanein” which translates to grabbing or attacking. Epilepsy also known as Epileptic Seizure (ES) is a leading neurological disorder in which the neurons in the cerebral cortex experience seeds of unusual discharge. This can cause sudden seizures or fits [1]. A sudden change in brain activity causes a seizure that cannot be controlled. Some usual signs of ES are: uncontrollable jerking movements, feeling dizzy, tingling sensations, seeing flashes of light, losing awareness, and changes in how things taste, sound, smell, or feel [2]. It can affect anybody, although common in childhood and often, it develops in people with over 65 years. Treating epilepsy is complicated and depends on several things, like what type of epilepsy you have, how bad it is, how old the patient is, any other health issues they might have, and how well they respond to medications. Sadly, even with improvements in medicine, some patients still have trouble controlling their seizures [3]. One reason for this could be that antiepileptic drugs don't work well for some patients. There are many seizure medications, but it can be hard to find the right one or the right amount for each person. EEG and iEEG signals are used to diagnose epilepsy and help predict and detect seizures. EEG is a way to check the brain's electrical activity without any surgery. iEEG is a method that requires putting electrodes inside the skull, which is more invasive. In both situations, recording the brain's electrical signals helps us study changes in brain cells and shows us when seizures happen. iEEG allows for better recording of brain activity, making it easier to find the exact part of the brain where seizures happen [4].

A study has been done to look at how people with epilepsy use ASM medications, using data from Sweden's population register. The study showed that there are only a few medicine options for most new patients. They include Randomized effectiveness trials, Cohort studies, Case-control studies and Cross-sectional studies on how drugs are used, using ambulatory electronic health records and insurance claims from different countries are available in Observational Health Data Sciences and Informatics (OHDSI) community [5]. OHDSI has a centralized research infrastructure where data is categorized and standardized to coincide with the Observational Medical Outcomes Partnership Common Data Model (OMOP-CDM). This model helps to present healthcare information from different sources in a clear and uniform manner [6]. A shared way to organize and show data helps create standard tools for analyzing it. The CDM has been designed to acquire scientific data from various kinds of information and to join in major studies utilizing these data types. It found that there were different treatment paths depending on the data source used [7].

In the past, the features of genetic epilepsy were mainly identified by closely watching small groups of people. More recently EHRs have been used to assist with all of the data that is present today. With non-problematic and interchanged words, systematic annotation processes, and logical reasoning as ingredients, this method has been made possible and mitigating some of the problems posed by large real-world data [8]. Detailed analysis of traits has significantly improved our knowledge of the range of disorders linked to changes in genes like SCN2A and STXBP1, among others. People who have genetic epilepsy that starts in childhood show a variety of symptoms and often have high rates of mental health issues and physical health problems. Pettus et al. [9] do not fully understand how their condition changes from childhood to teenage years or how it affects their use of healthcare services and medical treatment.

Earlier research has found that predicting seizures in newborns is difficult, and medical tests and brain wave readings usually do not do a good job of predicting these seizures. Signs and symptoms alone can't tell us if a newborn will have seizures. EEG studies show that while a normal brain wave pattern can reliably indicate that there are no seizures, an abnormal pattern does not necessarily mean that seizures are happening [10]. Models that predict seizures using EEG data, which are created by examining EEG segments, checking EEG reports, or analyzing EEG recordings directly, have faced problems because they often involve small groups of participants or only look at short time periods. Additionally, only a few of these models have been tested on newborns. Because doctors need to look at charts or EEG readings by hand, the current models can't be easily used in regular patient care [11]. Scientists have created programs that use brain signals from EEG and iEEG to find and predict when epileptic seizures will happen. These algorithms use different ways to study signals, like looking at their frequency and how they change over time. These devices can constantly record EEG signals and warn the patient before a seizure happens. Using EEG and iEEG signals to find and predict seizures can really help people with epilepsy live better lives and lower the costs of their treatment and healthcare [12]. The major contributions of this study was given below:

- The study introduces a novel hybrid model that combines Convolutional Neural Networks (CNN) for spatial feature extraction in EEG data, enhancing the model's ability to predict epileptic seizures effectively.
- This approach automatically extracts meaningful features from raw EEG data, reducing the need for extensive preprocessing and enabling more scalable solutions.
- The model effectively handles large-scale EEG time-series and leverage the self-attention mechanism in Transformers, allowing the model to capture both local and global patterns in the data.
- The architecture is designed with flexibility, making it applicable to other forms of neurological or time-series medical data.
- This research demonstrates how the hybrid CNN-Transformer model surpasses conventional methods by providing better performance in seizure prediction, setting a new benchmark for EEG-based epileptic seizure detection.

This rest of the work focuses as follows: Section II reviews the related works for the prediction of seizure, Section III describes the problems in existing methods, Section IV demonstrates the method for the prediction of seizure using deep learning techniques, Section V evaluates the results and discussions, and Section VI concludes the research.

II. Literature Work

Seizures caused by epilepsy are a common neurological disorder that affects a huge amount of people worldwide. Up to 70% of those who receive prompt and accurate identification remain free from seizures. In order to do this, medical practitioners urgently need intelligent, automated solutions to help them accurately detect neurological problems. Previously, attempts have been made to identify behaviours in epilepsy patients using machine learning algorithms and raw electroencephalography (EEG) data. However, in order to extract features from these investigations, clinical knowledge in areas such as radiology and clinical procedures was necessary. Performance was constrained by the human feature engineering used in traditional machine learning for categorization. Automated feature learning from raw data without human intervention is where deep learning shines. To detect seizures, for instance, deep neural networks are currently showing promise in processing raw EEG data, doing away with the need for extensive clinical or engineering requirements. While preliminary research is still in its infancy, it already shows promising applications in various medical fields. However, in this work, the investigation of model explainability is not part of the ResNet-BiGRU-ECA strategy. The data' clinical relevance and interpretability may be hampered by this omission. Mekruksavanich and Jitpattanakul [13] present ResNet-BiGRU-ECA, a novel deep residual model that uses EEG data to accurately diagnose epileptic seizures by examining brain activity. The effectiveness of our suggested deep learning model was assessed using an epilepsy benchmark dataset that was made available to the public. The performance of the proposed deep learning model was evaluated with the epilepsy benchmark dataset that was released to the public. The experiments conducted by us proved that our proposed model outperformed the basic model as well as state-of-the-art deep learning models by obtaining a high accuracy of 0. 998 and the highest of the F1-score of 0. 998. Nevertheless, the current approach ResNet-BiGRU-ECA does not consider the factor of model explainability. This omission might affect comprehensibility of the results obtained from the models.

Millions of humans worldwide suffer from epilepsy, and prompt seizure diagnosis is essential for both improved health and efficient treatment. The study of electroencephalograms (EEGs) provides a non-invasive option, but it takes a lot of time and effort to interpret the data visually. Many current efforts do not take account of the computational complexity of their models or processing speed, instead concentrating only on acquiring competitive levels of accuracy. The goal of this work was to create an automated approach for detecting epileptic seizures in EEG data by using analytic techniques. The main objectives of the efforts have been to reduce computing complexity and offer high accuracy effects by just using a small portion of the signal's frequency spectrum. In this paper, Urbina Fredes et al. [14] combined machine learning and signal processing methods to provide a novel automated method for seizure detection. The suggested approach consists of four steps: (1) Savitzky-Golay filter preprocessing: this eliminates background noise. (2) Decomposition: to recover spontaneous alpha and beta frequency bands, use discrete wavelet transform (DWT). (3) Feature extraction: The following six metrics are determined for each frequency band mean, Standard Deviation, Skewness, Kurtosis, Energy, and entropy. (4) Classification: Signals are classified as either normal or seizure-containing using the support vector machine (SVM) approach. Two publicly available EEG datasets were used for the evaluation of the approach reported in this paper. An accuracy of 92.82% was obtained in the alpha band and 90.55% in the beta band, which is reasonably adequate to resolve seizures. Moreover, the low computing cost that was found points to a possible useful use in circumstances involving real-time evaluation. The findings collected show that it might be a useful tool for both patient monitoring and epilepsy diagnosis. For clinical validation and possible real-time implementation, more research is required. A drawback of this study is that even as future research studies areas to improve signal processing methods may advance, the study does not examine the use of these methods beyond EEG signals. This may limit their applicability of the findings with other types of data.

A neurological condition called epilepsy results in recurrent seizures. Multiple factors can be extracted in order to identify and forecast a seizure, as electroencephalogram (EEG) patterns vary between pre-ictal, ictal, and inter-ictal stages. Nevertheless, little research has been done on the two-dimensional brain connection network. The goal of Tian et al. [15]was to examine how well it works for seizure prediction and detection. To extract image-like features, the two time-window length and five frequency bands and five connectivity measures were adopted. They were then used to train a CMT classifier for SIM and CSM, and a support vector machine for SSM.. Ultimately, studies of efficiency and selecting features were carried out. According to the CHB-MIT dataset's classification findings, a longer window denoted superior performance. SSM, SIM, and CSM had the best detection accuracies, which were 100.00, 99.98, and 99.27%, in that order. The three highest forecast accuracy values were 86.17%, 99.38, and 99.72, in that order. Furthermore, excellent performance and great efficiency were demonstrated by the Phase Lock Value and Pearson Correlation Coefficient connection in the β and γ bands. In order to identify and forecast seizures automatically, the suggested brain connection characteristics shown strong dependability and usefulness, which bodes well for the development of portable real-time monitoring devices. This paper has three restrictions. They are as follows: Despite the distance between bipolar montage and volume conduction, this issue is too severe to be resolved fully. Furthermore, because certain brain connection metrics, like PLV, are sensitive to volume conduction, they should be handled carefully when EEG recordings utilize referential (or unipolar) montage. The unsatisfactory performance of the cross-subject model in seizure prediction suggests that the heterogeneity was not adequately minimized. Other network topologies, including graph neural networks, will be investigated in the upcoming work to address this issue. The CHB-MIT sample size is modest, which may have an impact on deep learning network efficiency. As a result, our partner clinic will continue to gather medical information in the future for categorization.

A computer-assisted diagnostic system (CADS) for the automated identification of seizures caused by epilepsy in EEG data is presented in this study by, Malekzadeh et al. [16]. Three parts make up the suggested method: preprocessing, feature extraction, and classification. The simulations are carried out using the Bonn and Freiburg datasets. First, employed a band-pass filter with a cut-off frequency of 0.5–40 Hz to remove EEG dataset aberrations. The Tunable-Q Wavelet Transform (TQWT) is employed in the breakdown of EEG signals. Different linear and nonlinear characteristics are taken out of TQWT sub-bands in the second stage. Various statistical, frequency, and nonlinear properties are taken out of the sub-bands in this stage. The nonlinear characteristics that are employed are grounded in theories of unpredictability and fractal sizes (FDs). Various methods based on deep learning (DL) and traditional machine learning (ML) are described for the categorizing stage. This stage involves using a CNN-RNN-based deep learning technique with the suggested number of layers. Remarkable outcomes have been observed when the retrieved characteristics are fed into the suggested CNN-RNN model. To illustrate the efficacy of the suggested CNN-RNN classification process, the K-fold cross-validation with $k = 10$ is utilized in the classification stage. The accuracy of the suggested CNN-RNN approach for the Bonn and Freiburg datasets was 99.71% and 99.13%, respectively, according to the results. The study's shortcomings are spoken about As previously said, there are several forms of epileptic seizures, and prompt identification is crucial. To date, there is no dataset available on the different kinds of epileptic seizures. As a result, scholars are unable to do meaningful study in this area. Furthermore, there is restricted usage of the existing EEG datasets for epileptic seizure diagnosing; as a result, true and accurate epileptic seizure detection based on AI algorithms will not be achievable. The lack of a dataset of EEG signals that highlights the preictal, ictal, and interictal periods is another drawback to using EEG signals to diagnose epileptic seizures. With regard to these shortcomings, it is feasible to employ more developed and rather recent DL models for the identification of the various types of epileptic seizures.

To achieve better seizure detection for patients, Wang et al (2023) propose a new structure for MBdMGC-CWTFFNet, a multi-branch dynamic multi-graph convolution based channel-weighted transformer feature fusion network.). In other words, both temporal, spatial and spectral information from the epileptic EEG are initially integrated through a multibranch (MB) feature extractor. Subsequently, to effectively learn dynamic and deep graph structures and extract prerequisite features from the multi-domain graph, build a point-wise dynamic multi-graph convolutional network (dMGCN). Thus, the final chosen method for fusing the multi-domain graph features is called the channel-weighted transformer feature fusion network (CWTFFNet) based on the integration of the local and global channel-weighted techniques with the multi-head self-attention technique. The experimental results concluded that the proposed method delivers superior prediction accuracy to the state of art methods, and hence, indicates the potentiality of the method as an efficient resource for patient-specific seizure prediction. The proposed MB-dMGC-CWTFFNet is evaluated on the CHB-MIT public EEG dataset and a private intracranial sEEG data set. Although the suggested predictions framework performs satisfactorily in terms of seizure detection, the investigation still has shortcoming, MB-dMGC-CWTFFNet is capable of providing an end-to-end seizure warning without the need for laborious EEG pre-processing. However, in real-world warning scenarios, artifacts from epileptiform discharges and perhaps problematic channels might interfere with the predictor and result in some false positives. Shi and Liu [17] propose a novel bi-level coding detection approach named B2-ViT Net in the current research to obtain new generalized spatio-temporal long-range correlation features. These features can be used to model the inter-channel relations in the space domain and express the temporal long-range dependencies which are important for seizure detection. In addition, due to the ability of deep and wide feature search, the proposed model can learn the generalized seizure prediction features in the large space. Thus, only two public datasets, namely the Kaggle dataset and the CHB-MIT dataset, offer enough data to perform enough experiments. Our suggested model offers some interpretability and has demonstrated encouraging results in automatic seizure prediction tests in comparison with different approaches already in use. There remain certain shortcomings in present works. On the one hand, the results were not verified by neuronal tests since there was inadequate data available regarding the person's epileptogenic zone and associated biomarkers. Above two papers share the same limitations. However, the approach is based on individual patients which means that both the test and training sets originate from the same patient. A model generated by one individual cannot be easily transferred to a different person for client-independent seizures detection activities. This is mostly due to the fact that our approach is unable to deal with the disparity in distributions among the test and training sets.

III. Problem Statement

The area of focus in this study is the difficulty of the classification of epileptic seizures from EEG which is a important process for the early detection of epilepsy patients. Epilepsy is a neurological disorder whose symptoms are caused by sudden recurrent episodes of abnormal brain electrical activity in the form of epileptic seizures detectable in EEG data. Most machine learning models employed in this field are obstructed by the volume and comprehensiveness of the EEG data. Additionally, most previous works are categorized under the binary classification and do not consider the temporal distribution of features, thereby having lower prediction rates. Large-scale data sources include databases and repositories with numbers of EEGs and with complex structures and features, making necessary a more sophisticated method that can enhance meaningful features selection and raise the seizure detection rate. This study aims at resolve the mentioned issues using a hybrid CNN-Transformer model designed based on the utilization of CNNs for spatial feature extraction while Transformers for modeling long-term temporal dependencies to make the seizure prediction more accurate and efficient.

IV. Proposed Hybrid Attention-based Transformers-CNN Model

This work employs a systematic method to design and assess a dual CNN-Transformer model for epileptic seizure forecast based on the EEG data. Recruiting subjects entails one of the key stages of the research method in the course of data collection. The EEG dataset I have download from Kaggle has data from 500 people and 4097 values per person, which reflects 23.6 sec of EEG records. Following data loading, a number of data pre-processing steps of data cleaning, handling of missing values and normalization are performed. The data set is then split into 1-second segments, which yields 11500 samples – each of the segments has 178 samples in it. Every sample is then categorized into one of five categories depending on the level of brain activity. The proposed model architecture known as Hybrid Model is comprised of ConvNet and Self-Attention under the category of Transformer mechanisms. The CNN layers are intended for detecting spatial patterns in the EEG while isolated singular areas of the signal are scrutinized and deep local features are extracted, more information about temporal relationships is processed in the Transformer block which employs self-attention techniques. This integration makes it possible for the model o scan through the time series data in a way that checks for any specific structure of the data at a given time or space. This partial EEG data is used for training the aforementioned model, and all the testing is done through cross validation. Metrics like accuracy, precision, F1 measure, specificity and sensitivity are calculated in order to assess the performance of the model. Importantly, hyperparameter tuning is also performed in order to achieve maximum model performance. The last output is then compared to the baseline traditional machine learning algorithms to show the efficiency of the developed hybrid CNN-Transformer model for early seizures' epileptic prediction. The workflow of proposed model is depicted in Fig. 1.

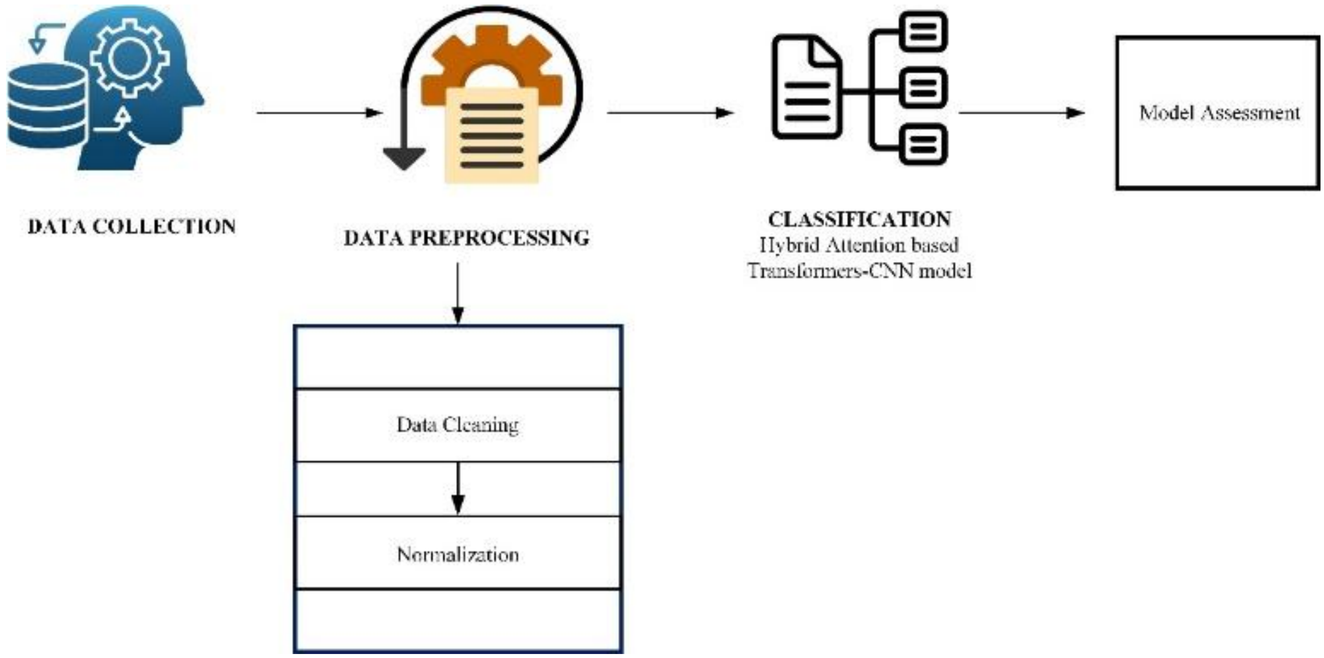

Fig. 1. Workflow of proposed model.

A. Dataset Collection

The data for this study is obtained from an open source Kaggle dataset that has EEG recordings of brain activity from 500 people. The EEG activity of each participant is recorded within 23.6 seconds with time series split into 4097 data points. For the purpose of easy handling and better understanding the dataset was divided into 23 parts and each part has 1 second recording with 178 data points for each second. This lead to a dataset of 11,500 rows, however each row represents 1 second of EEG recordings of an individual. The last column of the dataset, y, represents the response variable, indicating one of five categories of brain activity: She underwent five studies for video-EEG monitoring after being treated for her epilepsy: (1) during an epileptic seizure, (2) EEG recorded from the electrode over the tumor area, (3) EEG from the non-lesion area although she has a brain tumor, (4) eyes close and (5) eyes open. Despite the fact, the provided dataset includes five classes, the majority of researchers are interested in binary classification, in which the first class corresponds to epilepsy seizure, while the other classes consist of different non-seizure patterns. After this pre-processing of data, the dataset is saved in CSV format, where there are 178 numerical features besides a single quantitative aim variable and improving the legibility of the data to prepare for machine learning tasks for the identification of epileptic seizures [18].

B. Data Preprocessing

EEG data preprocessing is an extremely important part of the overall process because the machine learning model has to operate precisely and as fast as possible. Due to the high dimensionality and volume of data originating from EEG records, such data must be pre-processed and cleaned incorporating a structured methodology for normalization and transformation processes. The following is the data cleaning mechanism, normalization, and missing data to help to prepare the dataset with suitable features for the training model and the test model.

1) Data cleaning: The first process involved entails reading in the EEG dataset from the CSV file in order to have an understanding of the factors involved or the variables used in cleaning and if there are any issues with some of them. The first check of the data allows to say if there are any outliers in the data set, meaning that there are either corrupted or new, not expected values, as can be seen with high or low values of the EEG signal that can indicate the malfunctioning of the sensors. To identify such problems, descriptive measures like mean, median and size of standard deviation are applied for cases that show irregularities in the distribution. Dealing with outliers is often mission important because they can skew the result. Anomalies or extraordinary values markedly separated from the principal data sequence are mostly identified using the Min-Max methods, which are statistical. Once an organization identifies these cases, there are different ways to deal with them: omitting the cases, limiting the values to some threshold (for instance, 99% of the maximum value), or using some averaging techniques including a moving average to reduce the impact of the outliers. Also, the content of the data must remain consistent, which is one major goal of consistency. All EEG signals must be normalized and preprocessed, and each chunk must contain one second of data with 178 data points in each data block. The dataset may contain multiple copies of the same 1-second EEG segment; therefore, all such rows have to be deleted to avoid biases in the subsequent analysis and modeling steps.

2) Normalization: The amplitude and signal intensities in the EEG data are significantly variable across subjects making it necessary to normalize it. These differences may pose challenges to the correct interpretation to machine learning models as some of the features may dwarf the others in size. The data is first normalized, so each feature (X1 to X178) has equal weights in order to avoid biasing of the model by any particular feature. In these models normalization enables them to learn faster, have higher accuracy and generality since the input data is well balanced for all features. Another popular method is called Min-Max scaling, it just scales the values of the input features to the range between 0 and 1. It helps the models to be processed by the methods of data processing in such a way that all features are presented at the same scale. The formula for Min-Max scaling is shown in Eq. (1) as follows,

$$X' = \frac{X - Xmin}{Xmax - Xmin} \quad (1)$$

In which X is the first value, X′ is the normalized value, Xmin is the minimum value and $Xmax$ is the maximum value.

C. Feature Extraction using-CNN Model

Detection of seizure among humans is done using the Hybrid Attention based Transformers-CNNs model as proposed. Fig. 2 depicts the architecture diagram of proposed model. Convolutional Neural Network is used for image feature extraction for the dataset. There is still a deep learning method that comes under CNN method. The CNN is the most famous and used algorithm in the field of DL The CNN in comparison to other algorithms has an advantage of not requiring human supervision to fix on which features matter The CNN is constructed from a number of layers which include the input layer, convolutional layers, pooling layer, fully connected layers as well as the output layer. These layers helps to extract the features and classify the seizure as seen in the following.

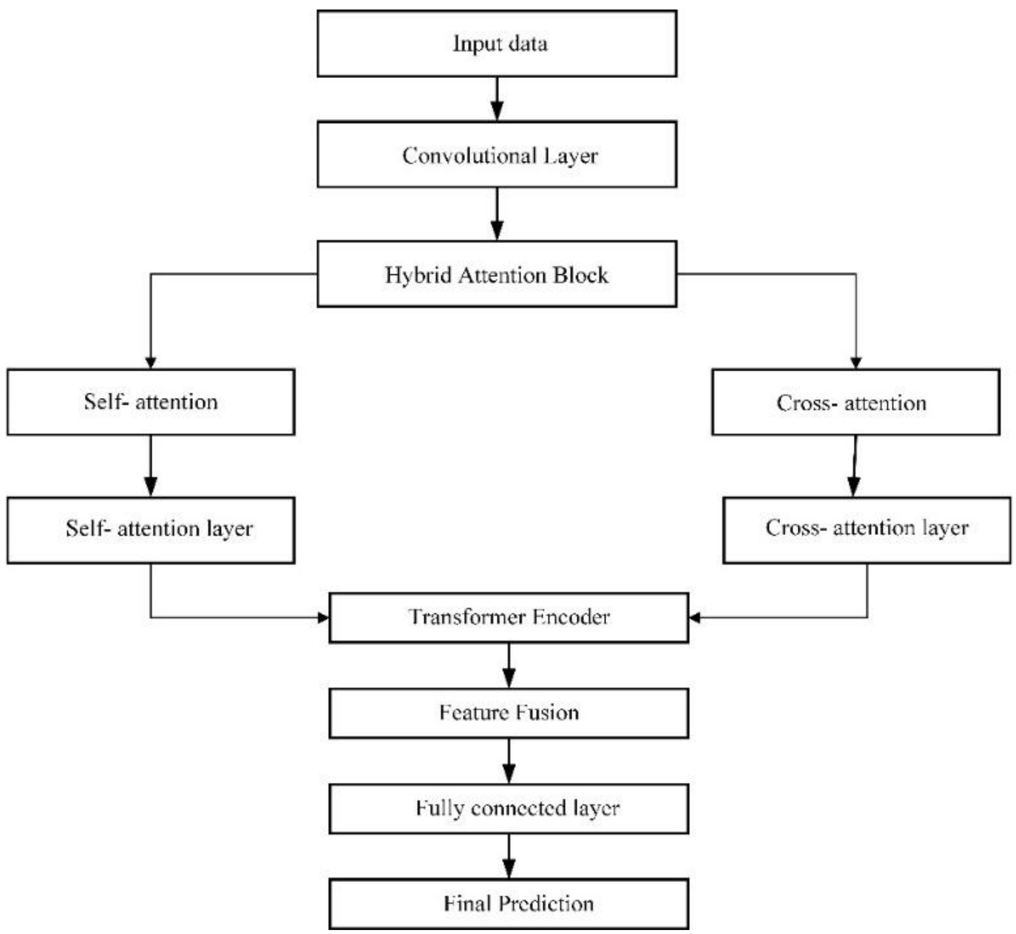

Fig. 2. The architecture diagram of proposed model.

1) Input layer: The topmost layer in CNN architecture is the input layer. In this layer the data is represented as multi-dimensional. The input it receives is EHR; it comprises EEG and patient It accepts the processed data and passes it on to the subsequent layer of the model.

2) Convolutional layer: Convolution layers are the fundamental components as constituent block of the network and exist in hierarchical form. Basically, Convolutional data is used to extract features on the input data to be processed for its main function. The other thing which needs to be added after having the feature maps in CNN is the pooling or the sub-sampling layer following a convolution layer.

3) Activation layer: The activation function has a very significant role in CNN layers. The output of the filter is passed to another mathematical operation known as the activation function. ReLu, which is an abbreviation for rectified linear unit, is the most commonly used activation function in CNN feature extraction most of the time. It converts all negative entries into zero and all positive entries into values which cannot be changed.

D. Hybrid Attention-Based Transformers-CNN Framework

Hybrid Attention-based Transformers-CNNs integrate the performance of the Convolutional Neural Networks (CNNs) and Transformers models to deliver satisfactory performance.

1) Attention mechanism: The attention mechanism is a type of resource allocation mechanism and is developed to imitate the human brain's attention. When the human brain processes things, it directs attention towards areas that is required, while minimizing or in some cases excluding other areas, to obtain specific details which may requires attention. It has often been seen that long-term dependencies pose a problem for attention mechanisms; however, for very long sequences, it is quite helpful. With the help of attention mechanisms, it is possible to enhance the information that is learned by CNN and other neural network models.

2) Transformer: In the current architecture of transformers, an encoder-decoder framework is used, in which the encoder part is responsible for the encoding of the input sequence into a representation while the decoder part is used to decode the output sequence using the information of the input sequence representation. In fact, each encoder and decoder layer of a transformer includes numerous self-attenuating heads as well as feed-forward neural networks. The major element at the core of transformers is the 'Attention' mechanism that enables the model to pay attention to the various parts of the input sequence during predictions. This attention mechanism assists the transformers in capturing the information of the previous and the subsequent words within a given sentence thus they make it easy for the transformers to represent the input data as desirable.

3) Fully connected layer: Finally, there is the necessity for feature classification for the purpose of predicting actual types of the input data. The last fully connected layer must ideally contain neurons it is equal to the number of output classes which we are going to predict. The fully connected layer will take the attention-weighted or feature-extracted signal as input and output classification decision to permit superior tuning of weights and learning anterior to an yield

4) Output layer: The output from the fully connected layers is then put through another activation function for classification like sigmoid or softmax this quantizes the output of each class to probability of score of class. It predicts the output as seizure or no seizure.

V. Results and Discussion

In this section, present the result and analyse the performance of Hybrid Attention-based Transformers-CNN model for seizure prediction using EHR. The proposed model was trained and tested using Python along with deep learning libraries such as CNNs for local spatial feature extraction and Transformer-based attention mechanism for capturing sequential dependencies in EHR. This model's main objective is to improve the reliability of seizure prediction by examining prevailing patterns within EHRs including the EEG signals. The integrated hybrid model builds upon the CNN's outstanding features of processing spatial content and the value of the Transformer in preserving temporal relations crucial for making accurate forecasts based on content. The following results that are the capsules of basic performance aspects like accuracy, precision, F1 score, specificity, and sensitivity metrics were assessed comparatively in terms of training and testing data. These findings consider the Hybrid Attention-based Transformers-CNN model as an improved method for seizure prediction, thus advancing the study of computational healthcare.

A. Seizure Prediction Analysis

The Fig. 3 illustrates the comparison of the recorded EEG signals during the seizure event and normal EEG status. The column on the left side with labels in red presents seizure EEG signals as the right column with labels in blue presents normal EEG signal. In the seizure EEG signals, the following characteristics can be observed; spikes, papery, high amplitude typical of high activity of neurons. These signals contain sharp waves and high-frequency oscillations of voltage which characteristic of broadly epilepsy. On the other hand normal EEG produces more physiological rhythmic, lower amplitude waveforms as compared to the abnormal ones. These relatively stable oscillations represent the normal, non-pathological electrical organization of the brain. This way, the contrast achieved between the seizure and normal EEG patterns shows that while in seizure, neuronal activity is much more violent and irregular compared to normal EEG with its regular and rhythmic activity.

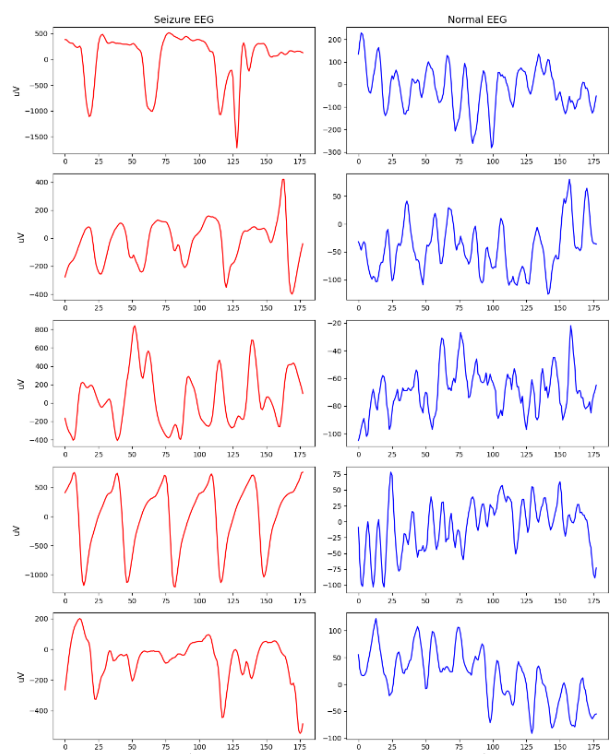

Fig. 3. Seizure analysis.

B. Training and Testing Accuracy

In Fig. 4, the Testing and training accuracy graph shows the accuracies of a machine learning model, Hybrid Attention-based CNN-Transformer model across the number of epochs at 120. Explore the journey follows an upward trend in the training accuracy based on the epochs based on the blue line as shown below. This shows that the model is actually training well from the training data, adapting each time to discern one pattern or the other well enough to make a good prediction wrongly. Therefore, a CNN can capture the local version of the data, while the Transformer can capture the global version with almost maximal internal attention, and thus see its training accuracy improve dramatically. The orange line also increases representing the testing accuracy once the weight accumulated is tested to the unseen data set it is much lower than the training accuracy at the initial stages. The first thing that stands out is a big divide between the training accuracy and the testing accuracy a characteristic that shows that the model, rather than testing it, was better at preparing the data. Worth to be pointed out is that two lines indicate the discrepancy at the quite early steps of training and as training progresses, these lines get closer to each other which is positive. This means that the proposed Hybrid Attention-based CNN-Transformer model is experiencing less overfitting as it can generalise better. From the training as well as testing accuracy plots, there is a gradual improvement in the training and testing database resulting to development of an effective model. While the training of the model progresses, the hybrid architecture provides optimal CNN for spatial features learning and optimal transformer for long-range dependencies features learning, which in turn improves accuracy of both training and testing sets. Slowly, the generality is enhanced as the difference in the accuracies is narrowed even if there could still be some further refining or optimization of the final ratings to make them as close to each other as possible without memorizing the data. This overall trend well characterizes the capability of the Hybrid Attention-based CNN-Transformer model to handle such data and enhance generalization.

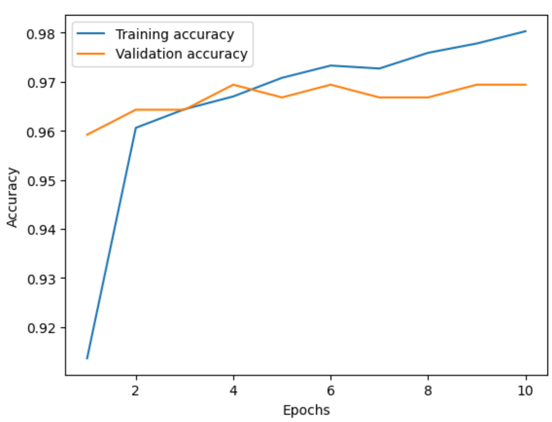

Fig. 4. Testing and training accuracy.

C. Training and Testing Loss

This is seen in Fig. 5 where Testing and Training Loss describes the result of an ML model which incorporates the Hybrid Attention-based CNN-Transformer model for the Training-Testing split with 120 epochs. The blue color is for the training loss while the violet for validation loss at the beginning of epochs it is very huge and then drops hugely this indicate that the model is learning the training data and the samples in general. This steep slope as a characteristic of the model that uses both CNNs and the transformer's attention mechanisms to thoroughly look for the right details hence always homing in a slightly smaller number of mistakes. The orange line, showing the testing loss, is again on a descending path although not as sharp as that of the training loss. This slower reduction in testing loss means that when the Hybrid Attention-based CNN-Transformer model is learning on unseen data it is not able of learning at the optimal level or as efficiently as the CNN in generalization to inputs that were not used during training. The gap between the training and testing loss reveals how much the model depends on the training data set and probably overfitting on that data should they use more complex models such as CNN-Transformer models. These architectures, however, are fairly powerful, but need one or two more steps; for instance, applying regularization methods or adjusting the parameters of the attention layers to improve overfits across datasets. The fact that both loss lines are reducing in the long run also indicate that the model is learning; however, a slightly high testing loss mean that there is still work to be in done in an attempt to make the Hybrid Attention-based CNN-Transformer better especially in easily recognizing unseen data.

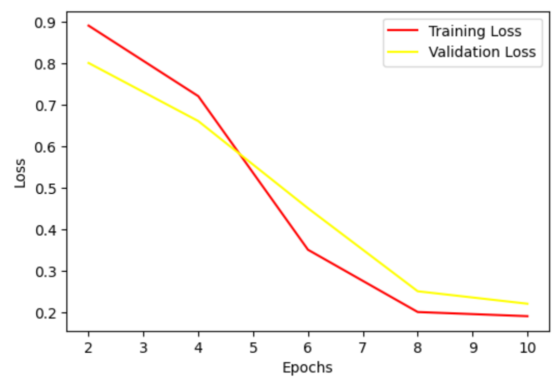

Fig. 5. Testing and training loss.

D. Performance Metrics

To evaluate the efficiency of the suggested approach these following metrics has been used Accuracy, Sensitivity, Specificity, Precision, and F1-measure. The following formula given below in Eq. (2) to Eq. (6).

$$\text{Accuracy} = \frac{True\ Positive\ + True\ Negative}{TP+TN+FP+FN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{4}$$

$$\text{Specificity} = \frac{True\ Negative}{TN+FP} \tag{5}$$

$$\text{F1score} = \frac{2\times TP}{(2\times TP)+FP+FN} \tag{6}$$

Table I shows the effectiveness criteria of the system that has been proposed in this paper. There is 98.3% confidence that the model is correct most of the time, therefore this model comes with a good test accuracy to both positive and negative cases. A given accuracy of 97.9% pays for itself in the ability to recognize true positives. This means that the recognition model's ability to balance between precision and recall is well interpreted based on F1 score of 98.73%. An accuracy of 95.90% demonstrates the model is accurate at determining true positives, positive predictive value of 98.21 defines the same for true negatives in an exceptional manner, thus showing the overall gratifying performance of the model.

TABLE I. PERFORMANCE METRICS OF PROPOSED MODEL

Metrics	Attention CNN-Transformer
Accuracy	98.3
Precision	97.9
F1 score	98.73
Sensitivity	95.90
Specificity	98.21

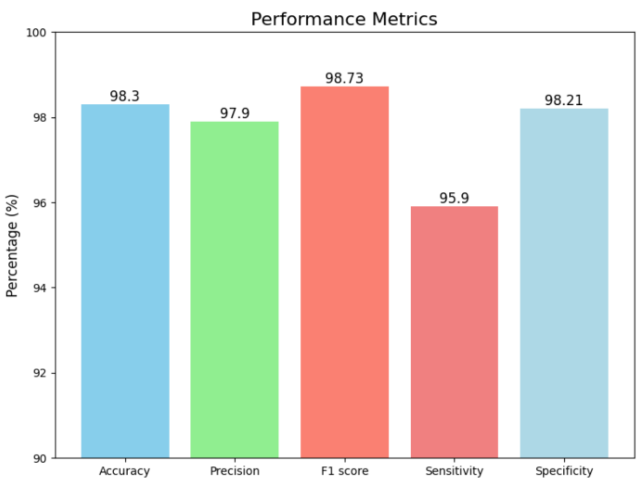

Fig. 6. Performance metrics of proposed model.

It is reflected from the Bar Chart shown in the Fig. 6 based on Performance Metrics of Proposed Model, which has demonstrated the efficiency of the proposed model on Accuracy, Precision, F1 Score, Sensitivity and Specificity. For Accuracy and Specificity, both our model scores at level 1, which tells us as to how well the model has been designed to predict both Positive and Negative cases. Specificity is also high suggesting that there is few misclassifications of true positives. However, F1 Score which is the lowest metric implies that there is a problem with the tradeoff between precision and recall. Again, sensitivity is slightly low compared to precision and this means that there is some room for improvement on true positive. The balance of the model we see is good and some slight modifications are required.

The classification performances of different models based on classification accuracy, precision, F1 score, specificity as well as sensitivity of the classified EEG signals are summarized in the following Table II. An 86.23% accuracy, 82.90% precision, and an F1-score of 84.50 for Sustainable Value Management. The Gaussian model is much more accurate with a total accuracy of 95.49%, total precision of 96.60 % and an F1-Score of 97.50% which makes it among the best models. Random Forest also gives better outputs with 92.06% accuracy rates, and an F1 score of 91.80%, but loses precision and sensitivity when compared with the Gaussian model. Analogue to this, the k-NN shows relatively good performance by achieving 86.89% accuracy, and 85.30% F1 score. Through optimization algorithm $aADGA$ model which is developed for this research yielded an accuracy of 97.49% and F1-score of about 98.2%. However, the proposed method is identified as more accurate than all the other methods having the accuracy of 98.3%, the precision of 0.979, F1-score of 0.9873, specificity of 0.9821 and the sensitivity 0.985. Even though the performances of classifiers were quite similar, it was revealed that the proposed method outperforms all the other methods used in the present study with the best accuracy, sensibility, and efficiency in EEG signal classification as shown in Fig. 7.

TABLE II. COMPARISON OF THE PROPOSED MODEL WITH THE EXISTING APPROACHES

Model	Accuracy (%)	Precision (%)	F1-score (%)	Specificity (%)	Sensitivity (%)
SVM	86.23	82.90	84.50	82.90	87.20
Gaussian	95.49	96.60	97.50	96.60	97.50
Random Forest	92.06	89.70	91.80	89.70	92.20
k-NN	86.89	83.70	85.30	83.70	86.95
$aADGA$	97.49	96.90	98.2	96.90	95.90
Proposed method	98.3	97.9	98.73	98.21	98.5

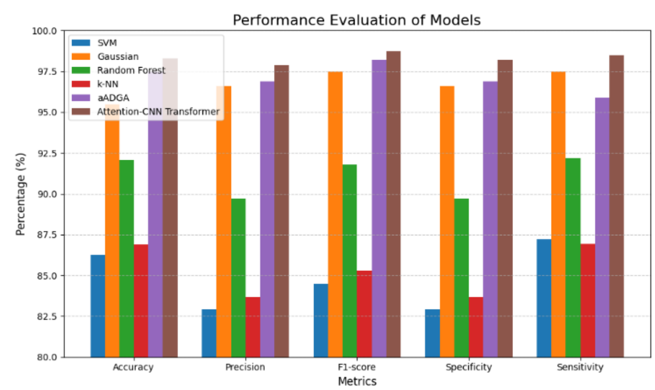

Fig. 7. Performance evaluation of proposed model with existing approaches.

E. Discussion

The suggested CNN-Transformer model exhibits exceptional effectiveness in predicting epileptic seizures from EEG data with high accuracy, precision, and sensitivity. The combination of CNNs for spatial feature extraction and Transformers for long-term temporal dependency capture enables a stronger classification of EEG signals between seizure and normal brain activity. The findings show that the model effectively detects seizure events with 98.3% accuracy, 97.9% precision, an F1-score of 98.73%, specificity of 98.21%, and sensitivity of 98.5% and outperforms classical models like k-NN, Gaussian models, and Random Forest classifiers. Comparison with current approaches indicates that conventional machine learning approaches, i.e., k-NN and Random Forest, are less accurate because they make use of handcrafted features, which may fail to clearly identify the complex spatiotemporal relationships within EEG signals. The Gaussian model was relatively good with an accuracy of 95.49%, but it does not have the flexibility of deep learning-based methods in dealing with big EEG datasets. The hybrid CNN-Transformer solution addresses these limitations by utilizing deep feature extraction and self-attention, enhancing both classification accuracy and false positive minimization. The research underscores the importance of spatial and temporal modeling in the detection of seizures. CNN layers effectively extract local spatial patterns from EEG signals, while the Transformer architecture fine-tunes long-range dependencies to generalize well across varying seizure patterns. The dual-architecture approach reduces misclassification by learning strong signal representations, and this results in a significant reduction in false positives, which is a key issue in seizure prediction.

Another significant contribution is that the model can improve real-time seizure detection and thus is of excellent clinical significance. Reducing the dependency on the preprocessing of huge amounts of data and manual feature design, the approach proposed here offers a scalable, automatic solution to seizure prediction. Its ability to process large datasets makes it promising to be integrated into wearable EEG monitoring devices to facilitate early medical intervention in epilepsy patients [13].

VI. Conclusion and Future Work

This study effectively applies the idea of CNN-Transformer Integration for the epileptic seizure detection from the EEG data. Combining Convolutional Neural Networks for the spatial characteristics and Transformer-based attention for temporal features, the proposed framework improves the seizure prediction's robustness and accuracy. From these findings, it is evident that the hybrid approach enhances the capabilities of prediction with minimized false positive issues, making it a significant step towards solving some of the major challenges that exist in seizure detection. The model achieved impressive performance metrics, including an accuracy of 98.3%, precision of 97.9%, F1-score of 98.73%, specificity of 98.21%, and sensitivity of 98.5%. From these findings, it is evident that the hybrid approach enhances the capabilities of prediction with minimized false positive issues, making it a significant step towards solving some of the major challenges that exist in seizure detection. As depicted above, deep learning techniques can be applied in the enhancement of the area of epilepsy treatment and management not excluded the importance of training models with large-scaled EEG datasets. It opens doors to subsequent research that, perhaps, can enhance and polish such approaches to seizure prediction in order to lead to positive outcomes within clinical practice through timely interventions.

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