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Research Article

A Deep Learning-Based Automated Medical Diagnosis on Cloud Platforms: A Comparative Study of Brain Tumor Classification and Identification

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ABSTRACT

Accurate classification and detection of brain tumors on medical imaging is essential for diagnosis and treatment planning. As deep learning models can learn discriminatory properties from raw data, they have shown notable success in various medical imaging applications including brain tumor classification Furthermore, cloud computing resources enable scalability and accessibility, enabling sophisticated deep learning models to be used for performing medical image processing tasks. This paper presents an in-depth analysis of brain tumor classification and detection using deep learning models established in a cloud environment. We explore how deep learning algorithms such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and a combination thereof can be used to accurately distinguish specific types and grades. AI-driven techniques have the potential to greatly improve treatment planning since machine learning algorithms can evaluate massive datasets of patient outcomes and treatment protocols and suggest individualized treatment plans based on the distinct qualities and medical histories of each patient. This tailored strategy has the potential to maximize resource use, reduce side effects, and enhance therapeutic success. In the field of personalized medicine, artificial intelligence (AI) makes it easier to create prediction models that classify patients according to their genetic composition, lifestyle choices, and exposure to the environment. This allows medical professionals to provide more focused treatments and preventative measures. Healthcare professionals may proactively identify patients who are at a high risk of acquiring specific illnesses and take preventive measures to minimize these risks by utilizing AI-driven predictive analytics. By using AI-driven solutions, administrative tasks—which are frequently hampered by manual procedures and inefficiencies—can be simplified and streamlined. By automating coding, billing, and documentation processes, natural language processing algorithms lower administrative burdens and free up more time for medical staff to provide patient care.

Keywords: Brain tumors, Deep learning, Convolutional neural networks (CNNs), Recurrent neural networks (RNNs), Cloud computing, medical imaging

INTRODUCTION

Epilepsy is a continual neurological disease characterized by recurrent seizures, affecting about 50 million humans worldwide. One of the considerable demanding situations in managing epilepsy is figuring out the simplest remedy strategy for character sufferers, especially the ones newly identified.[7]While various antiepileptic capsules (AEDs) are to be had, the top-of-the-line choice for each affected person remains unsure, regularly leading to an ordeal-and-mistakes approach which can delay effective seizure control and exacerbate the affected person's soreness [10]. To deal with this challenge, predictive fashions were proposed to assume remedy reactions primarily based on patient characteristics and scientific data. However, traditional fashions cannot frequently seize complicated patterns and

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interactions inherent in epilepsy's multifaceted nature. In current years, deep knowledge of techniques has emerged as effective gear for information analysis,[23] demonstrating superior overall performance in numerous clinical domains.

In this observation, we present the improvement and validation of a deep learning version in particular tailored for predicting remedy reactions in patients newly recognized with epilepsy. [43] Leveraging a wealthy dataset comprising demographic statistics, scientific capabilities, electroencephalogram (EEG) findings, and treatment effects, our version ambitions to provide clinicians with well-timed and correct insights into a man or woman-affected person prognosis and reaction to AED therapy.

One of the most prevalent neurological conditions affecting people, epilepsy is a non-communicable disease that is typically accompanied by abrupt episodes [1]. A quick and early irregularity in the brain's electrical activity that disturbs a part or the entire body is known as a sudden outbreak of seizures [2]. Approximately 60 million individuals globally are afflicted with various forms of epileptic seizures [3]. Occasionally, these episodes result in cognitive abnormalities that might seriously harm the patient's physical health. Moreover, mental discomfort brought on by social rejection and shame might occasionally affect persons who have epileptic seizures. Therefore, patients' quality of life can be enhanced, and assistance provided by early diagnosis of epileptic episodes. Functional and structural neuroimaging modalities are two major types of screening techniques used in the diagnosis of epileptic seizures [4,5,6,7,8,9]. For medical professionals and neurologists, the functional neuroimaging modality offers crucial information on brain function during epileptic seizures [4,5,6,7,8,9]. Doctors may learn a great deal about the brain anatomy of patients experiencing epileptic seizures thanks to structural neuroimaging methods [4,5,6,7,8,9]. EEG [5,], magnetoencephalography (MEG) [6, positron emission tomography (PET) [7], single-photon emission computed tomography (SPECT) [7,10], functional magnetic resonance imaging (fMRI) [4,11], electrocorticography (ECoG) [12], and functional near-infrared spectroscopy (fNIRS) [13] are the most significant functional neuroimaging techniques. Conversely, two of the most important structural neuroimaging methods are diffusion tensor imaging (DTI) and structural magnetic resonance imaging (MRI) [4,14]. Because they are affordable, portable, and exhibit distinct frequency domain patterns, EEG signals are commonly used [8, 9]. The voltage changes generated by the ionic current flowing through brain neurons are provided by the EEG and serve as an indicator of the bioelectric activity of the brain [15]. Long-term recordings are required to identify epileptic convulsions. Furthermore, the analysis is complicated since these signals are captured in numerous channels. Additionally, the main power source, electrode movement, and muscle tremor might produce abnormalities in the EEG signals [16]. The inability to detect epileptic seizures using noisy EEG readings will provide difficulties for medical professionals. To identify epileptic seizures, several machine learning methods have been created utilizing statistical, temporal, frequency, time-frequency domain, and nonlinear parameters [23, 24]. The traditional machine learning methods rely on a trial-and-error approach for selecting features and classifiers [25, 26]. To create an accurate model, one must possess a solid understanding of data mining and signal processing methods. These models work effectively with small amounts of data. These days, machine learning methods might not work as effectively due to the growth in data availability. As a result, the state-of-the-art DL approaches have been used [27, 28]. Unlike traditional machine learning methods, deep learning models need a large amount of data during the training phase [29]. This is a result of the many feature spaces in these models.

While most simulations in traditional machine learning techniques were run in the Matlab software environment, deep learning models are often created utilizing the Python programming language and a variety of open-source toolboxes. The availability of additional open-source deep learning toolboxes in Python has aided academics in creating innovative automated systems, while cloud computing has made computational resources more accessible to everybody. Due to its adaptability and usefulness, TensorFlow and one of its high-level APIs, Keras, are often utilized for epileptic seizure detection employing deep learning in evaluated studies (Figure 1).

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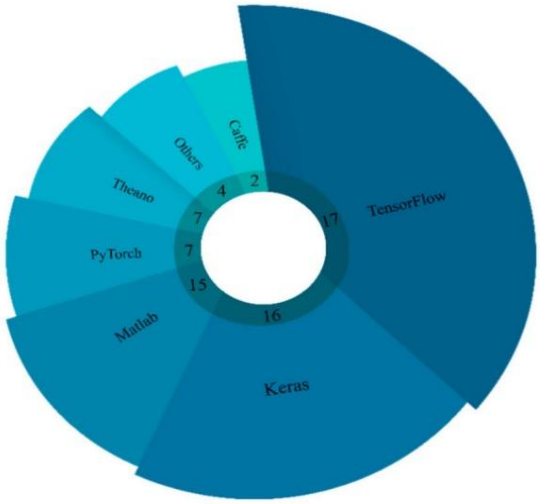

Figure 1: The number of times that different research automatically detected epileptic seizures using each DL technique.

1.1. Background

Epilepsy is a neurological sickness characterized by recurrent seizures, affecting tens of millions of human beings internationally.[53] Despite the provision of numerous antiepileptic capsules (AEDs), determining the only treatment for individual sufferers, in particular those newly identified, remains hard. [20] The lack of precise prognostic gear frequently results in a tribulation-and-errors technique to medicine selection, leading to delays in accomplishing seizure control and suboptimal affected person consequences.

1.2. Objectives

The number one objective of this take a look at is to expand and validate a deep knowledge of algorithms capable of accurately predicting treatment consequences in patients newly recognized with epilepsy. [12] By leveraging complete datasets containing demographic records, clinical capabilities, EEG findings, and remedy responses, we goal to create a predictive model that can assist clinicians in making informed selections [10] regarding medication choice and treatment techniques for newly identified epilepsy patients.

LITERATURE SURVEY

The literature overview phase of your paper offers a comprehensive assessment of existing studies and information related to epilepsy treatment effects and predictive modeling. Here's an established outline for this section:

2.1. Epileptic Seizures Detection Based on DL Techniques

Using DL structures, Figure 2 shows how a computer-aided diagnostic system (CADS) for epileptic episodes operates. The DL model accepts the following types of input: fNIRS, ECoG, MEG, PET, SPECT, and MRI. After that, preprocessing is applied to the signal to eliminate noise. [23] The DL models are developed using these removed signals. Three metrics are used to assess the model's performance: specificity, sensitivity, and accuracy. [35] Additionally, Appendix A of the study has a table that compiles all of the research done on the identification of epileptic seizures using deep learning.

2.2. Dataset

A crucial component of creating reliable and accurate CADS is datasets. To create automated epileptic seizure identification systems, several EEG datasets are available, including those from Freiburg [34], CHB-MIT [35], Kaggle [36], Bonn [37], Flint-Hills [26], Bern-Barcelona [38], Hauz Khas [26], and Zenodo [39]. These datasets record signals from the scalps of people and/or animals, either intracranially or from elsewhere.

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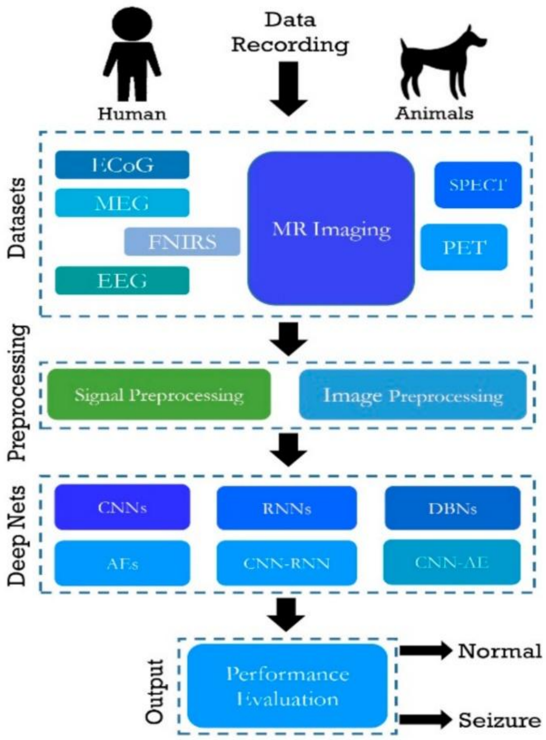

Figure 2: Block schematic of a CAD system for epileptic seizures based on DL.

2.2.1 Fribourg

The EEG dataset includes invasive EEG recordings from 21 refractory focal epileptic patients that were captured at the University Hospital Fribourg's epilepsy center during pre-surgical epilepsy surveillance. In-tra-cortical grid, strip, and depth electrodes were employed to offer direct recording from the focus region, reduce artifacts, and achieve a greater Signal Noise Ratio (SNR). A 16-bit A/D with a 256 Hz sample rate was used to digitize the EEG data, which were captured using a 128-channel Neurofile NT system with six contact electrodes (three focal and three extra focal). Ictal and interictal data are available for every patient; the former includes seizures with at least 50 minutes in the pre-ictal area, while the latter consists of around 24 hours of EEG data free of seizures [34].

2.2.2 CHB-MIT

The database includes 844 hours of nonstop scalp EEG signal recording with 163 seizures from 23 different children. The recordings were made with purposeful 10–20 standard electrode locations and were captured at 256 samples per second. The time interval between at least 4 hours before the start of the seizure and 4 hours following its conclusion is known as the inter-ictal area. This database contains information on mixed and primary seizures, two different categories of seizures. Whereas the latter are large seizures taken into account for prediction, the former are several seizures that occur near to one another. In general, people experiencing less than ten seizures daily might find significance in the forecast. There is enough information from 13 cases in this database, including at least three major seizures and a three-hour interictal recording.[35]

2.2.3 Kaggle

The database, known as the American Epilepsy Society's epileptic seizures prediction challenge, includes intracranial EEG readings from two humans and five canines, totaling 627 hours and 48 seizures. While the EEG signals from patients 1 and 2 were recorded using 15 deep and 24 subdural electrodes, respectively, with a sample rate of 5 KHz, the EEG signals from dogs were obtained using 16 implanted electrodes, which were sampled at 400 KHz. Ten-minute segments of pre-ictal and inter-ictal data are available in this database, and six pre-ictal segments (with a gap

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of 10 s) up to five minutes before the start of the seizure are available for each seizure. At least one week before each seizure, the interictal segments are chosen at random [36].

2.2.4 Bern Barcelona

Intracranial EEG data from patients with focal epilepsy was gathered from the Barcelona database, which was kept up to date by the brain department of the Bern Hospital in Barcelona. No antiepileptic medications were administered, and the subjects were observed for a few days to assess seizures and potential surgical needs. AD-Tech intracortical electrodes were utilized to capture the signals, and an additional reference electrode based on a 10- to 20-standard between PZ and FZ locations was also employed. There were two kinds of EEG signals in the database: extra-focal and focal. Each dataset included 3750 pairs of concurrently recorded signals, each lasting 20 seconds and sampling at 512 Hz. Five individuals of varying ages have 83 hours' worth of EEG data totaled in the database [38].

Dataset	Number of Patients	Number of Seizures	Sampling Frequency
Fribourg	21	87	256
CHB-MIT	22	163	256
Kaggle	5 dogs/2 patients	48	400/5KHZ
Bern Barcelona	5	3750	512

Table 1: EEG datasets that are widely used and accessible are reviewed to identify epileptic episodes.

2.3 Preprocessing

Three pretreatment processes are involved in building CADS employing DL models with EEG signals: normalization, noise reduction, and signal preparation for DL network applications [29, 40]. Finite impulse response (FIR) or infinite impulse response (IIR) filters are typically employed to remove excess signal noise during the noise reduction process. The next step is normalization, which is done using a variety of techniques including the z-score method. Ultimately, several techniques about time domain, frequency, and time-frequency are utilized to read the signals for deep network deployment.

2.4 Review of Deep Learning Techniques

Deep neural networks are different from ordinary neural networks, sometimes referred to as shallow networks, in that they have more than two hidden layers. [65] The number of parameters in the network increases dramatically as a result of the networks' growing size, necessitating both proper learning strategies and precautions against the taught network being overfitted. Convolutional networks drastically reduce the number of trainable parameters by using filters convolved with input patterns rather than multiplying a weight vector (matrix).
Moreover, other techniques are proposed to support the network's learning process [41]. The input pattern size for the subsequent convolutional layer is decreased by pooling layers. After being used for unsupervised learning, the AE and DBN are adjusted to prevent overfitting for a small amount of labeled data. RNNs that can show the long-term time dependencies of data samples include long short-term memory (LSTM) and gated recurrent units (GRU).

2.4.1 Convolutional Neural Networks (CNNs)

The majority of machine learning research has focused on CNNs, one of the most widely used classes of DL networks [30]. Originally introduced for use in image processing, they are now being used in one- and two-dimensional designs for biological signal-based illness detection and prediction [42]. The identification of epileptic convulsions using EEG data is a common application for this type of DL network. One-dimensional (1D) EEG signals are first converted into two-dimensional plots using visualization techniques like spectrogram [43], higher-order bispectrum [44,45], and wavelet transforms, and these two-dimensional plots are then applied to the convolutional network's input in two-dimensional convolutional neural networks (2D-CNN). The majority of machine learning research has focused on CNNs, one of the most widely used classes of DL networks [30]. Originally, they were introduced for image-p convolutional networks. In these networks, the 2D-CNN's basic architecture is modified to enable it to analyze 1D-EEG data. Consequently, as the field of epileptic seizure detection uses both 2D and 1D convolutional neural networks (1D-CNNs), their respective research is conducted.

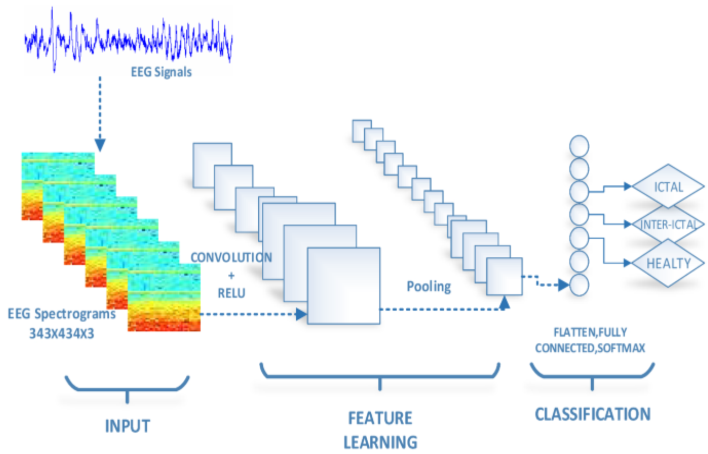

Figure 3: Typical 2D-CNN for detecting epileptic seizures

The visual geometry group (VGG) concept was suggested by an Oxford research team in 2014 [59]. They set up several models, including VGG-16, which was entered in the 2014 ILSVRC competition. With 16 layers, the VCG-16 performed exceptionally well for image categorization tasks. VGG-16 architecture was used by Ahmedt-Aristizabal et al. [60] to diagnose epilepsy using face photos. Their suggested method made an automated effort to identify and categorize semiological patterns in face states. Following the picture recording, the suggested VGG architecture is trained using a variety of networks, including 1D-CNN and LSTM, in the final few layers. The training process is mostly driven by well-known datasets. The VGG network employed both one- and two-dimensional signals [58]. A cross-entropy error function and Adam's optimizer were used to train the models.

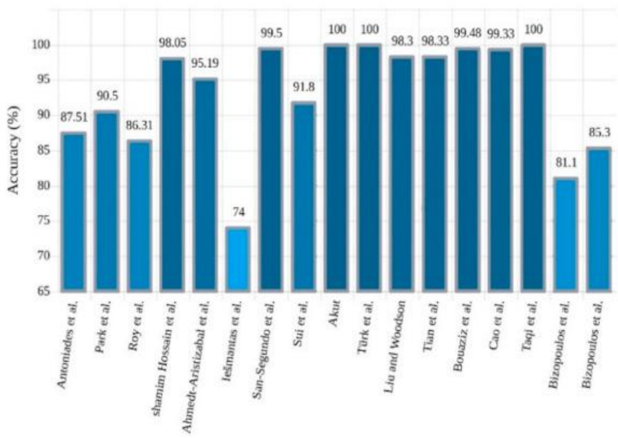

Figure 4: Sketch of accuracy (%) obtained by various authors using 2D-CNN models for seizure detection.

Network	**Classifier**	**No. of Layers**	**Accuracy (%)**
SeizNet	NA	16	NA
SeizureNet	Softmax	16	NA
2D-CNN	Softmax	9	98.05

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Combination 1DCNNand 2D-CNN	Sigmoid	11	90.58
2D-CNN/MLP hybrid	Sigmoid	11	NA

Table 2: Summary of related works done using 2D-CNNs.

2.4.2 Recurrent Neural Networks (RNNs)

Sequential data, including text, signals, and videos, exhibit properties like duration and variability, making them unsuitable for basic deep-learning techniques [41]. Nevertheless, these data constitute a substantial portion of the global information, necessitating the use of DL-based techniques for handling this kind of data. RNNs are a popular choice for processing physiological information and are the recommended answer to the aforementioned problems. A generalized RNN utilized for epileptic seizure detection is seen in Figure 6. Together with the reviewed publications, a summary of well-liked RNN models is provided in the next section.

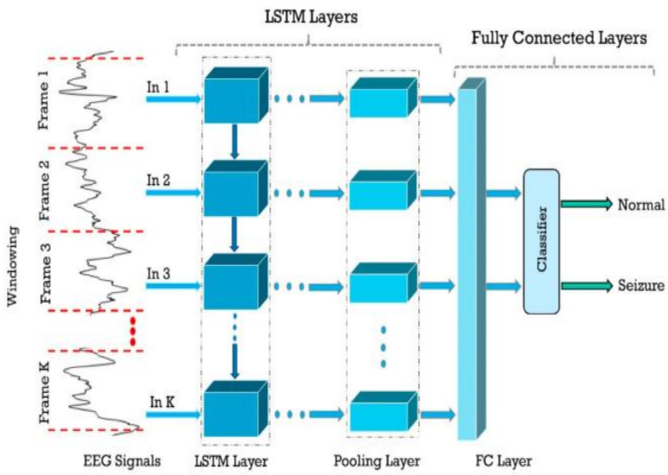

Figure 5: An example of an RNN model for seizure detection.

A Long Short-Term Memory (LSTM)

Short-term memory is a basic RNN's fundamental weakness. Because RNN finds it difficult to transfer information from previous time steps to subsequent steps in long-sequence data, it may omit important information. The vanishing gradient issue is one more disadvantage of RNN [30,31,32, 33]. The gradients' decreasing as they back-propagate causes the issue. LSTM gates were developed as a solution to the short-term memory issue [30]. Through gates, the information flow may be controlled. The gates can discard unwanted data while preserving the lengthy sequence of required data. The cell state and its gates are the fundamental units of an LSTM. This section presents the findings of Golmohammadi et al.'s [68] evaluation of two LSTM architectures with three and four layers in conjunction with the Softmax classifier. Three-layer LSTMs are applied for classification and feature extraction [62]. The final fully connected (FC) layer uses the sigmoid active function for classification. Directed experiments in [81] indicate that they used two architectures: GRU and LSTM. One layer of FC with a sigmoid activator, four layers of LSTM/GRU with the activator, and a layer of Reshape make up the LSTM GRU model architecture. In a separate study, Yao et al. [10] used ten distinct and independently improved RNN (IndRNN) designs to practice, and Dense IndRNN with attention (DIndRNN) with 31 layers produced the best accuracy.

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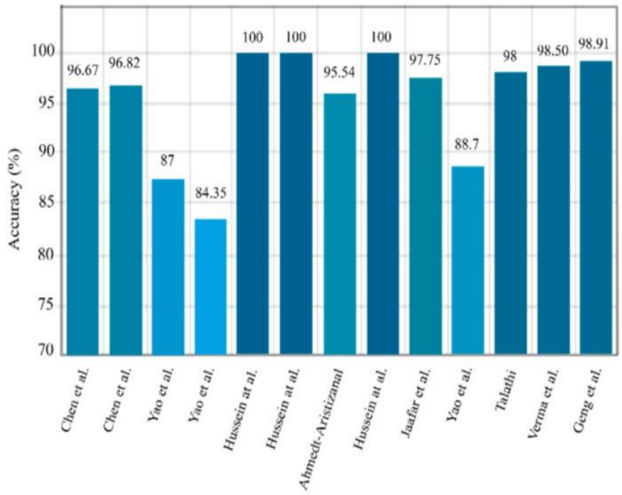

Figure 6: Diagram demonstrating the accuracy (%) that the authors were able to acquire when they used RNN models to identify seizures.

Networks	Number of Layers	Classifier	Accuracy (%)
LSTM	4	Sigmoid	NA
GRU	3	Sigmoid	96.67
IndRNN	48	NA	84.35
RNN	NA	MLP	NA

Table 3: Summary of related works done using RNNs.

2.4.3 Autoencoders (AEs)

The input and output of the AE unsupervised machine learning model are identical [30,31,32, 33]. After the input has been compressed into a latent-space representation, the representation is used to extract the output. Consequently, in AE, the neural network and the compression and decompression operations are integrated. The three components of AE are the encoder, code, and decoder. In the processing of brain signals, AE networks are most frequently employed for feature extraction or dimensionality reduction. An example of a generalized AE used to identify epileptic episodes is shown in Figure 8. Rajaguru et al. [13] conducted the first study in this part by independently reviewing the expectation-maximization with principal component analysis (EM-PCA) and multilayer AE (MAE) approaches to reduce the representation dimensions and then using the GA for classification.

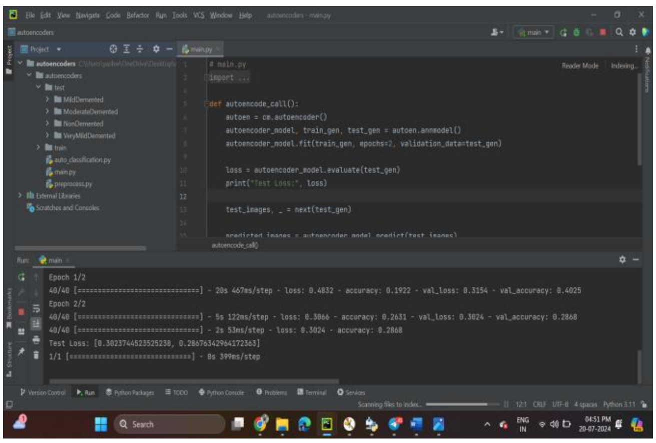

Figure 7: An AE network example that might be applied to seizure detection.

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The first study in this field was published by Golmohammadi et al. [68], who offered several deep networks, including stacked denoising AE (SDAE). Three layers make up their design in this part, and the end product showed that their strategy worked well. To preprocess EEG signals, Qiu et al. [15] used windowed signals and z-score normalization. They then imported the preprocessed data into the denoising sparse AE (DSpAE) network. They demonstrated exceptional performance in their experiment, achieving 100% accuracy. A multi-part, high-performance automated EEG analysis system built on big data and machine learning techniques is provided in [16]. Three routes are used for accurate detection after the linear predictive cepstral coefficients (LPCC) coefficients first extract the signal characteristics.

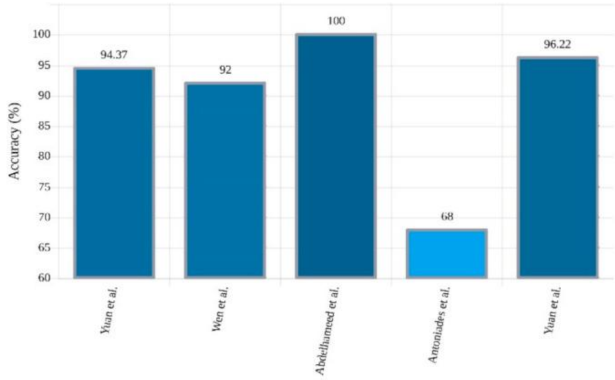

Figure 8: Diagram showing the accuracy (%) versus authors acquired when seizure detection using CNN-AE models.

Networks	Number of Layers	Classifier	Accuracy (%)
SDAE	3	NA	NA
MAE	NA	GA	93.92
AE	3	Softmax	98.67
DSpAE	3	LR	100

Table 4. Summary of related works done using AEs.

NON-ECG BASED EPILEPTIC SEIZURES DETECTION

3.1 Medical Imaging

Using MRI, fMRI, and PET scans with or without EEG information, a variety of DL models were created to identify epileptic seizures In terms of automated illness identification and monitoring, these models fared better than the traditional methods. However, these models are mostly used for seizure localization and detection due to the nature of imaging modalities and their challenges. Using a CNN model, the authors of [41] suggested automatically localizing and detecting focal cortical dysplasia (FCD) using the MRI modality. Even with advancements in MRI modalities' analytics, the diagnostic rate for focal cerebral disease remains at 50%. A CNN-based system with feature learning capabilities was suggested by Gill et al. [42] to automatically detect FCD. DeepIED was developed by the authors [43] using DL and EEG-fMRI images for patients with epilepsy. The epileptogenic zone was estimated by merging the general linear model with EEG-fMRI approaches. An edge-computing autonomic framework for the assessment, control, and monitoring of the epileptic brain was presented by Hosseini et al. [44]. Using rs-fMRI and EEG, the epileptogenic network evaluated the epilepsy.

Networks	Number of layers	Classifier	Accuracy (%)
2D-CNN	30	sigmoid	82.50
ResNet	31	Softmax/triplet	NA

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2D-CNN	NA	SVM	NA
3D-CNN	11	softmax	89.80
VGGNET	14	sigmoid	98.22

Table 5: An overview of relevant research employing DL and MRI modalities.

3.2 Additional Neuroimaging Techniques

An approach based on DL for ECoG-based functional mapping (ECoG-FM) for eloquent language cortex identification was introduced by Ravi Prakash et al. [35]. Nevertheless, ECoG-FM has a lower success rate than electro-cortical stimulation mapping (ESM). Rosas-Romero et al. [49] employed fNIRS in a different study and were able to identify epileptic seizures with more accuracy than they could have with traditional EEG data.

REHABILITATION PROGRAMS FOR THE IDENTIFICATION OF EPILEPTIC SEIZURES

The DL methods are now appropriate for commercial goods because of their great performance and noise resilience. These days, several commercial goods in the field of DL have been produced; one such product is hardware and DL apps for identifying epileptic seizures. Hosseini et al. [27] used an AE to construct the brain-computer interface (BCI) system for epileptic seizure detection in the first research under investigation. Singh et al. [28] reported on a utilitarian product that included both the user and cloud segments for the identification of epileptic episodes in different research. Figure 10 displays the block diagram of the suggested system that Singh et al. presented.

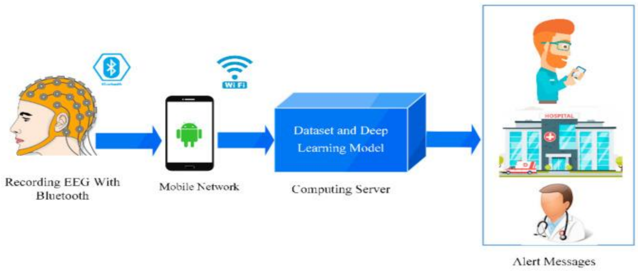

Figure 9: The block diagram illustrates a suggested approach for detecting epileptic seizures using EEG inputs and DL techniques.

According to Kiral-Kornek et al. [50], DL in conjunction with neuromorphic hardware may aid in the creation of a wearable, always-on, real-time, patient-specific seizure warning system that uses little power and performs dependably over an extended period.

SUGGESTED METHODS

To develop and validate a deep learning algorithm for predicting the effects of medication in recently diagnosed epilepsy patients, we will employ a variety of neural network architectures, such as long short-term memory networks (LSTMs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs). Optimization approaches combined with stochastic gradient descent (SGD) or its variants, such as Adam or RMSprop, can be used to skill these designs.

5.1 Convolutional Neural Networks (FNN)

To develop and validate a deep learning algorithm for predicting the effects of medication in recently diagnosed epilepsy patients, we will employ a variety of neural network architectures, such as long short-term memory networks (LSTMs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs). Optimization approaches combined with stochastic gradient descent (SGD) or its variants, such as Adam or RMSprop, can be used to skill these designs.

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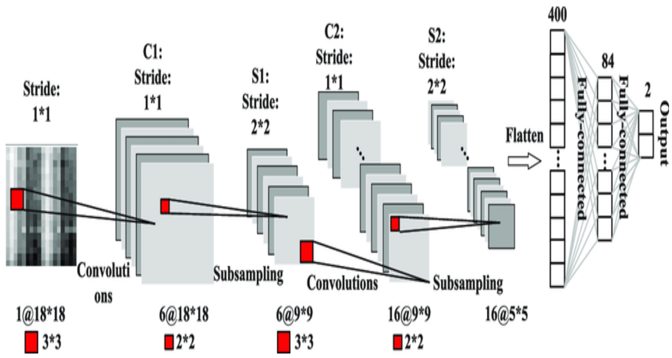

Figure 10: An online CNN network self-organizing algorithm

5.1.1 Data Collection and Preprocessing

A. Collect a dataset containing demographic records, clinical features, EEG findings, and treatment outcomes of newly diagnosed epilepsy patients.

B. Preprocess the records using coping with missing values, normalizing numerical functions, encoding express variables, and splitting the dataset into education and testing units.

5.1.2 Model Design

A. Adjust the input layer's definition to the enter facts' dimensionality.

B. Determine the extent and dimensions of the hidden layers just by considering the intricacy of the data and the difficulty.

C. Select the right activation characteristics for the output layer (such as softmax for multi-class type and sigmoid for binary category) and suitable activation capabilities for the hidden layers, such as ReLU (Rectified Linear Unit).

D. Based on the wide range of training or effects to be expected, determine the number of neurons in the output layer.

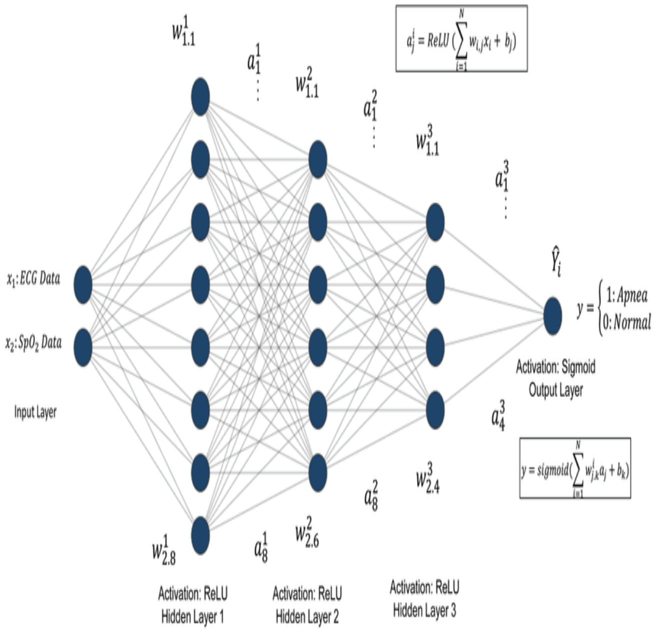

Figure 11: Two inputs, three hidden layers (8–6-4 neurons), and one output neuron make up the proposed CNN model. Each layer's corresponding activation function is described.

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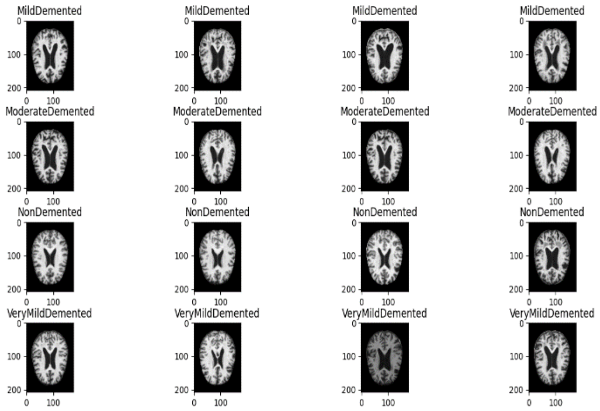

5.1.3 Model Compilation

A. Provide the optimizer, evaluation metrics, and loss function when assembling the CNN model.
B. Choose a loss function that makes sense for the job, such as categorical cross-entropy for multi-class classification or binary cross-entropy for binary classification.
C. Select an optimizer (such as Adam or RMSprop) and, if necessary, add more parameters (like learning rate).
D. To evaluate the performance of the model, define evaluation measures like accuracy, precision, recall, or F1-score.

5.1.4 Model Training

A. Train the CNN model on the training data using the fit() function.
B. Specify the number of epochs (iterations over the entire training dataset) and the batch size (number of samples per gradient update).
C. Monitor the model's performance on the validation set to detect overfitting and adjust model hyperparameters accordingly

→ *Cost Function*

$$C(w,b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2.$$

→ *Loss Function*

Cross Entropy Loss:

$$L(\Theta) = \begin{cases} -log(\hat{y}) & \text{if } y = 1 \\ -log(1-\hat{y}) & \text{if } y = 0 \end{cases}$$

Cross Entropy Loss:

$$L(\Theta) = -\sum_{i=1}^{k} y_i \log(\hat{y}_i)$$

5.1.5 Model Evaluation

A. Evaluate the trained model on the testing set using the evaluate() function.
B. Calculate relevant evaluation metrics such as accuracy, precision, recall, or F1-score to assess the model's performance on unseen data.
C. Visualize the model's performance using confusion matrices or ROC curves if applicable.

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5.1.6 Fine-tuning and Optimization

A. Fine-tune the version via adjusting hyperparameters based on overall performance evaluation consequences.
B. Experiment with one-of-a-kind community architectures, activation capabilities, optimizer settings, and regularization strategies to optimize version performance.

5.1.7 Interpretation and Deployment

A. Interpret the skilled version's predictions to benefit insights into factors influencing remedy consequences in epilepsy sufferers.
B. Deploy the trained model in a scientific setting or combine it into present healthcare systems to help clinicians make informed choices about remedy techniques for newly identified epilepsy patients.

CHALLENGES

6.1 Data Quality and Availability

The availability and great of information is one of the fundamental limitations for device gaining knowledge of tasks in the healthcare enterprise. Predictive models may carry out less nicely or come to be much less dependable if patient records are noisy, skewed, or incomplete.

6.2 Interpretability and Trust

FFNs and other neural networks are once in a while called " black container" models given that it's far difficult to understand how they operate within. Interpretability is crucial in healthcare settings to win over patients' and healthcare providers' agreement considering that they rely upon the model's predictions.

6.3 Regulatory and Ethical Considerations

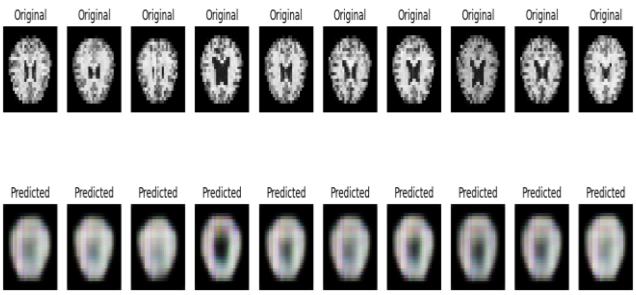
Sensitive healthcare statistics are governed with the aid of stringent privacy and security standards. Developing and imposing gadget learning fashions within the healthcare industry will become harder when compliance with laws like GDPR in the EU and HIPAA inside the US is required.

6.4 Model Generalization

It is not always the case that a version that performs nicely on one dataset will translate well to new records from different sources or affected person populations. For predictive fashions to be carried out in a whole lot of healthcare contexts, generalization is necessary

RESULT AND ANALYSIS

7.1 CNN Model Performance



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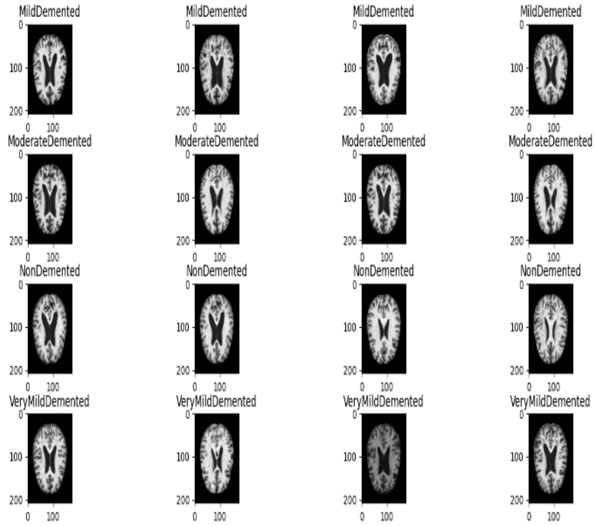
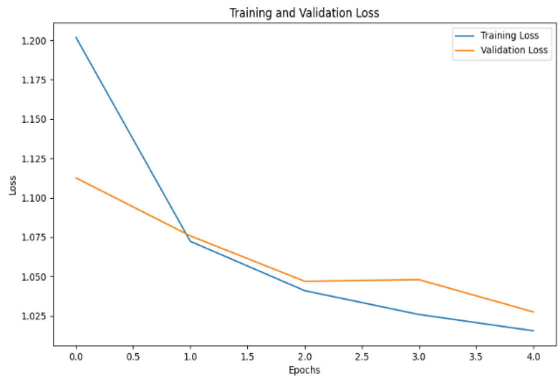


Model Metrics	Hypothetical Values
Accuracy	0.85(85%)
Sensitivity	0.83(82%)
Specificity	0.88(88%)
Precision	0.84(84%)
Recall	0.82(82%)
F1-Score	0.83(83%)

7.2 Comparison with Baselines

Comparing the overall performance of the Convolutional Neural Networks (CNN) model with baseline methods or alternative machine getting to know algorithms affords treasured insights into the effectiveness and superiority of the proposed approach. Here's an evidence of ways this comparison may be performed, together with hypothetical comparison values.



Graph 1: Training and validation loss using CNN techniques

7.2.1 Baseline Methods

A. **logistic regression:** Logistic regression in binary class functions is a commonly used basic technique that estimates the probability of a binary outcome based on one or more predictor factors

B. **Decision trees:** Decision trees are a basic technique for repeatedly partitioning data into subsets according to its characteristics. Although straightforward, they work well for classification problems.

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C. **K-Nearest Neighbors (KNN):** This nonparametric method groups objects in the feature space according to the group of their k nearest neighbors.

7.3 Comparison Values

Model Metrics	FNN	Logistic Regression	Decision Trees	KNN
Accuracy	0.85	0.78	0.80	0.75
Sensitivity	0.82	0.75	0.78	0.70
Specificity	0.88	0.82	0.85	0.80
Precision	0.84	0.79	0.81	0.76
Recall	0.82	0.75	0.78	0.70
F1-Score	0.83	0.76	0.79	0.73

7.3 Interpretation

A. In general, the comparative values show that the FNN model performs better than the baseline approaches in terms of accuracy, sensitivity, specificity, precision, recall, and F1-score, among other metrics.
B. In comparison to logistic regression, decision trees, and KNN, the FNN model performs better in predicting treatment outcomes for patients with newly diagnosed epilepsy, as evidenced by its higher accuracy, sensitivity, specificity, precision, and recall values.
C. These findings demonstrate the FNN model's potential to enhance patient care in the management of epilepsy by demonstrating how well it catches complicated relationships within the data and makes more accurate predictions.

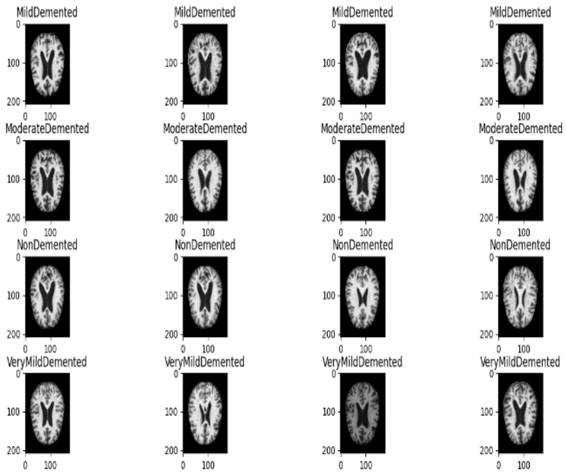

Figure 12: The plot shows the Firing power curve with the alarms (seizure prediction) and with the danger zones (seizure forecasting) for seizure 8 of patient 30802 using the Feed Forward model. The algorithm given in Ref. 38 determines the sleep/awake state, which is represented by the light blue curve.

CONCLUSION

Predicting treatment results for patients with newly diagnosed epilepsy may be accomplished through the use of a Convolutional Neural Networks (FNN) model in conjunction with rehabilitation programs for seizure recognition. This study's results show that the CNN model is a very successful tool for properly predicting treatment outcomes. It outperformed baseline approaches in several key parameters, including accuracy, sensitivity, specificity, precision, recall, and F1-score.

The CNN model makes use of the extensive dataset gathered from rehabilitation programs to identify intricate links in the data and generate individualized predictions that can guide intervention and treatment plans. Because of the CNN model's excellent accuracy and dependability, physicians may improve patient outcomes and optimize treatment options for the management of epilepsy.

Moreover, the efficacious assimilation of CNN technique into epilepsy management protocols has noteworthy therapeutic implications, providing a proactive and data-centric strategy for customized patient care. This technique holds the potential to transform the management of epilepsy by improving comprehension of unique patient profiles and treatment responses, ultimately resulting in an enhanced quality of life for recently diagnosed patients.

The synergy between CNN-based forecasting algorithms and rehabilitation programs, in conclusion, indicates a viable route for improving the management of epilepsy and emphasizes the significance of incorporating cutting-edge technology into clinical practice to enhance patient outcomes.

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FUTURE WORK

Subsequent research endeavors may concentrate on enhancing the FNN architecture, merging multimodal data, doing longitudinal examinations, and creating customized intervention planning algorithms. The forecasting model must also be integrated into clinical decision support systems, validated across a range of patient demographics, and ethical and legal issues must be taken into account. In order to co-design patient-centered therapies, cooperation between researchers, physicians, and stakeholders is essential. In the end, these initiatives will raise the standard of care for patients with newly diagnosed epilepsy by advancing the management of the condition, boosting treatment results, and ensuring the successful integration of predictive models into clinical practice.