Blockchain-Integrated Multi-Modal LSTM-CNN fusion for High-Precision Epileptic Seizure Detection from EEG Signals

Mahmoud O. Mokhiamar [1], Abdelrahman Mahmoud [1], Mohamed I. Eldagla [1], Yassine Aribi [2] and Ahmed M. Anter [3,*]
[1] Egypt-Japan University of Science and Technology (E-JUST), New Borg El-Arab City, 21934 Alexandria, Egypt.
[2] Department of Science and Technology, College of Ranyah, Taif University, Taif, 21944, Saudi Arabia.
[3] Faculty of Computers and Artificial Intelligence, Beni-Suef University, Benisuef 62511, Egypt
[*] Corresponding author Ahmed_Anter@fcis.bsu.edu.eg

***Abstract*—In the field of epileptic seizure detection, integrating advanced technologies is essential for improving accuracy and efficiency. This study introduces a pioneering approach that combines blockchain technology with a multimodal model, integrating Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures, to improve EEG-based seizure detection. The proposed approach addresses the challenge of accurate seizure detection while ensuring secure and private data management through blockchain technology. We generate spectrograms from EEG data to visualize temporal dynamics, enriching the understanding of neural activity patterns. The proposed model effectively integrates the capabilities of LSTM and CNN to capture both temporal dynamics and spatial features in the EEG data. The results show that the proposed model significantly outperforms standard LSTM and CNN models in all performance metrics, including precision, recall, accuracy, and F1-score. Notable improvements were observed, particularly in multi-class seizure detection tasks: binary (ictal vs. non-ictal), ternary (ictal, preictal, normal), and penta-class (ictal, preictal, interictal, postictal, normal). The proposed model achieved a 38.21% increase in test accuracy and a 39% increase in F1-score compared to the baseline models. For binary, ternary, and penta-class classification, the proposed model achieved accuracies of 0.991, 0.979, and 0.907, respectively. Furthermore, the integration of blockchain technology ensures secure and private data management, addressing critical concerns in medical data handling. The proposed hybrid model shows high precision, versatility, security and highlights the potential to revolutionize epileptic seizure detection and contribute to advances in the broader field of EEG analysis.**

Keywords: Epileptic seizure detection, EEG analysis, Multi-modal model, LSTM-CNN fusion, Blockchain, Data security.

I. Introduction

Epilepsy is a chronic neurological condition that causes repeated seizures. It affects millions of people around the world, many of whom have unpredictable seizures that seriously affect their daily lives. Detecting these seizures quickly and accurately is crucial for proper treatment and management. However, even with modern medical technology, it remains difficult to detect seizures due to their varied patterns and the limitations of current methods resulting in a loss of awareness or seizures [1].

Electroencephalogram (EEG) technology has emerged as a pivotal tool in epilepsy diagnosis and monitoring. It provides valuable insights into neural dynamics associated with seizures [2]. Its nonsurgical nature and high temporal resolution make EEG crucial for seizure detection [3]. Recent developments in spectrogram generation from EEG signals further enhance our ability to capture subtle neural activity changes over time, offering deeper insights into seizure dynamics [4]- [5].

Identifying epilepsy from EEG signals is a challenging task because it requires advanced trained neurophysiologists [6]. The abnormal brain activity that occurs during a seizure is captured by the EEG, which monitors brain activity directly. During an epileptic seizure, the typical EEG signal form is altered. Thus, the states of epileptic patients can be classified into five phases: normal, preictal, in-ictal, ictal, and postictal, based on the range of characteristics found in EEG signals. Preictal stage refers to the large number of electrical disturbances that begin in the cerebrum of epileptic patients prior to the actual onset of a seizure. Such electrical disruptions in the patient's brain during the change from the normal to the ictal stage must be recorded in order to identify seizures at this time [7]. Therefore, by allowing patients to take preventative actions to avoid dangerous and potentially fatal mishaps, this early detection of epileptic seizures at the preictal stage may save their lives.

The sheer volume and complexity of EEG data pose challenges for traditional analytical approaches. Manual interpretation by clinicians is time-consuming and subjective, leading to variability in diagnoses. Also, distinguishing these abnormal brain states from normal brain activity can be difficult. Additionally, very few patients with epilepsy respond to anticonvulsant medication, making it difficult to predict when seizures will occur. Therefore, the development of seizure recognition systems can help patients lead normal lives by providing early warning and timely treatment. This technology may save the lives of epileptic patients in emergencies and improve their quality of life [8], [9].

Recognizing these challenges, this study proposed a solution for epileptic seizure recognition based on multi-modal LSTM-CNN fusion model. The proposed approach aims to enhance seizure detection accuracy by integrating Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNN), leveraging their complementary strengths to capture both spatial and temporal features, allowing for in-depth analysis of EEG data. This approach capitalizes on complementary strengths to analyze multi-modal EEG data effectively, leveraging temporal dependencies captured by LSTM and spatial features extracted by CNN. The effectiveness of the proposed model for epileptic seizure recognition is validated using two epileptic datasets. According to the results, the proposed model performs better and more accurately than the competitors in terms of classifying seizure states from EEG, avoiding both over- and under-fitting. Moreover, the proposed model incorporates blockchain technology to ensure data security and privacy in EEG data management, enhancing security and trust in seizure detection systems, providing a comprehensive end-to-end solution for managing and analyzing EEG data in a clinical setting. This integration ensures compliance with healthcare institutions' regulations. In general, the model proposed has the following contributions compared to the study attempts observed in the literature:

- The model combines CNN for spatial features and LSTM for temporal dependencies, ensuring comprehensive analysis of EEG data for improved seizure detection.
- Utilizes the STFT to convert EEG raw signals to images, enhancing the model's ability to analyze time-varying frequency characteristics, by visualizing the frequency content over time, making it easier to identify patterns associated with specific brain activities.
- Unlike most existing methods, the proposed model supports binary, ternary, and penta-class multi-class classification tasks, making it more versatile for real-world application.
- Incorporating blockchain technology ensures secure and private data management, addressing critical concerns in medical data handling.

These advancements highlight the potential of the proposed model to revolutionize epileptic seizure detection and contribute to the broader field of EEG analysis.

The rest of this paper is organized as follows: section II provides related work for seizure classification, ranging from traditional machine learning approaches to modern deep learning architectures. Section III, provides the methods involved in this work and dataset description. Section IV, presents the privacy-preserving epileptic seizure healthcare data using blockchain technology. Section V, provides an implementation of the data confidentiality and access control scheme through blockchain technology. Results and discussion are presented in Section VI. Finally, the conclusion and future works are discussed in section VII.

II. Related Work

Epileptic seizure detection has been extensively studied due to its critical role in improving patient care and outcomes. Various methodologies have been proposed to analyze EEG data for seizure classification, ranging from traditional machine learning approaches to modern deep learning architectures. This section reviews state-of-the-art research, identifies gaps in existing methods, and highlights the novelty of our proposed model in addressing these gaps.

Nkengfack et al. (2021) suggested a method using discrete polynomial transforms, such as Legendre, Chebyshev, and Jacobi transforms, to extract features like beta and gamma rhythms from EEG signals. These features were input into a least-square support vector machine (LS-SVM) classifier with a radial basis function (RBF) kernel, achieving accuracy between 88.75% and 100% for binary classification. However, this method struggled with nonlinear data and lacked scalability for multi-class problems, highlighting the limitations of conventional machine learning methods [21].

Deep learning has significantly advanced seizure detection by leveraging its ability to extract spatial and temporal patterns. Mandhouj et al. (2024) employed Short-Time Fourier Transform (STFT) to convert EEG signals into spectrogram images for CNN classification, achieving effective visual feature extraction. However, this approach failed to capture temporal dependencies in EEG data, limiting its ability to analyze sequential patterns [18].

Islam et al. (2024) proposed an ANN-LSTM architecture that leveraged time-frequency characteristics of EEG signals for binary seizure detection, demonstrating superior performance. However, their method neglected spatial features, focusing primarily on temporal dynamics, making it unsuitable for real-time seizure detection [19].

Wang et al. (2023) introduced a hybrid CNN and LSTM techniques for binary and ternary classification, achieving impressive results. Despite its accuracy, the model lacked provisions for data privacy and scalability for multi-class problems [17].

Anter et al. (2022) proposed the NB-GWOA model for ternary epileptic seizure detection. This hybrid approach combined a genetic algorithm and whale optimization technique with a feature selection methodology. Although effective, the stochastic behavior in the search space posed challenges in finding optimal solutions efficiently, often leading to local minima [20].

Additionally, Khattak et al. (2023) applied deep learning for Alzheimer's disease classification from MRI data, showcasing how temporal and spatial analysis can enhance diagnostic capabilities in medical imaging [40]. Similarly, Li et al. (2020) utilized LSTM-CNN for real-time crash risk prediction, further demonstrating the versatility of this hybrid architecture in handling sequential data across domains [42].

Recent studies have also explored multi-modal architectures for other health applications. Kumar et al. (2023) applied weighted ensemble transfer learning for COVID-19 disease prediction, emphasizing the role of advanced deep learning in handling complex medical datasets [44]. Moreover, Ali et al. (2022) evaluated CNN, SVM, and LSTM algorithms for ECG classification, highlighting the comparative strengths of each algorithm in processing time-series biomedical signals [45].

Chen et al. [41] introduced the concept of medical cyber physical system (MCPS), where they presented a concrete necessity for secure data sharing, real-time monitoring, and privacy in medical applications. The study has also highlighted the merits of integrating secure data-sharing mechanisms within and their transformative influence on healthcare. Similarly, Xu et al. (2020) developed a blockchain-based secure medical data sharing scheme [43], addressing key challenges in MCPS: data security, decentralization, and secure authentication. The contribution of Xu et al. was related to a blockchain-based network model, mitigating reliance on trusted third parties, which guaranteed tamper-proof data sharing through bilinear mapping and intractable problems in the authentication phase. They also integrated a medical consortium blockchain structure to store and manage medical records securely, thus enabling two-way authentication between the hospitals and blockchain nodes. Building on these concepts, our methodology integrates blockchain technology to ensure data security and privacy in EEG data management, enhancing confidentiality, transparency, and tamper resistance of medical data. Other than these frameworks, our proposed model extends their applicability by focusing on a specific medical application: high-precision epileptic seizure detection using a multi-modal LSTM-CNN fusion. Our approach contributes to the development of the principle of secure data sharing while responding to both data security and advanced EEG analysis, thus fostering greater trust and effectiveness in seizure detection systems.

Table I summarizes different approaches for detecting and analyzing neurodegenerative diseases and disorders, this table includes a summary on methodologies, features analyzed, classification types, accuracy, and limitations of these studies.

To address the identified gaps, the proposed model introduces a Blockchain-Integrated Multi-Modal LSTM-CNN fusion model for high-precision epileptic seizure detection.

III. Methodology

In this section, we describe the dataset used and the description of the proposed methodology.

A. Data Description

The dataset consists of five different categories, each containing 100 files. Each file represents a single subject/person and records brain activity for 23.6 seconds. This time-series data is sampled into 4097 data points, each representing the value of the EEG recording at a specific moment in time. With 500 files (subjects/person) and 4097 data points per file, the dataset is substantial. The dataset is divided and shuffled every 4097 data points into 23 chunks, with each chunk containing 178 data points corresponding to 1 second of recording. Consequently, the dataset composed of $23 \times 500 = 11,500$ rows of information [20].

The dataset is categorized as follows: Set A contains EEG recordings from healthy subjects in a relaxed, awake state with eyes open. Set B contains EEG recordings from healthy subjects in a relaxed, awake state with eyes closed. Set C contains EEG recordings from patients during the preictal state, characterized by changes leading up to a seizure. While Set D contains EEG recordings from patients during the interictal state, representing non-seizure brain activity. Finally, Set E contains EEG recordings from patients during the ictal phase, capturing seizure activity. Figure 1 shows the raw EEG signal data for each of the five health states of the patients. While it is difficult to distinguish between the raw EEG signal waveforms of the various normal circumstances, it is easy to see the differences between the epileptic seizure condition and the normal condition [28]. To fully assess the performance of the proposed model, binary-class, three-class, and five-class epileptic seizure recognition tasks are considered in this study.

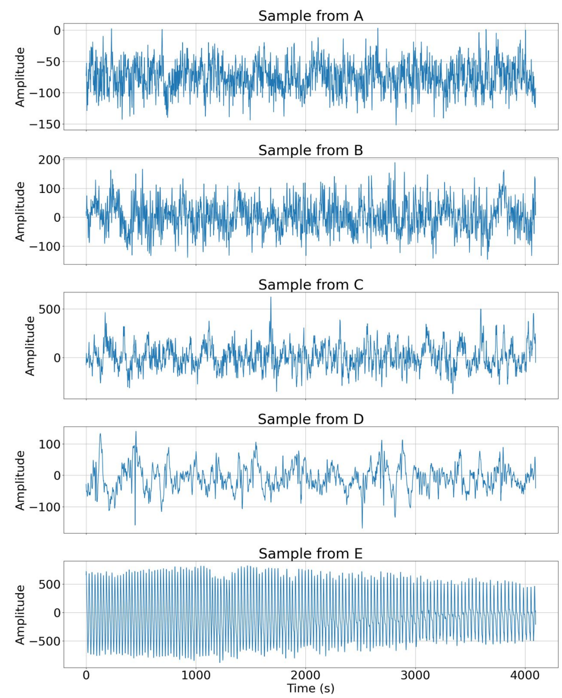

Fig. 1: EEG signals per individual for five different seizure states (A, B, C, D, E).

B. The Proposed Epileptic Seizure Recognition model

In the proposed model (see Figure 2), hybrid learning model based on CNN [5] and LSTM [10] is proposed to incorporate both spatial and temporal features in recognizing epileptic seizures.

Integrating these techniques allow the CNN to extract spatial patterns from EEG images, capturing localized features indicative of seizure activity. The LSTM then models sequential dependencies over time, enabling the recognition of temporal patterns in EEG signals that evolve over time. This hybrid model enhances the model's accuracy by integrating both instantaneous spatial characteristics and evolving temporal dynamics. After that, the CNN model is used to convert signals to images using Short-Time Fourier Transform (STFT) method which is described in the following

TABLE I: Comparison of state-of-the-art approaches for neurodegenerative diseases and disorders.

Reference	Methodology	Features Analyzed	Classification Type	Accuracy (%)	Limitations
Nkengfack et al. (2021)	Polynomial transforms + LS-SVM	Beta and gamma rhythms	Binary	88.75–100	Limited to binary classification, struggles with nonlinear data
Mandhouj et al. (2024)	STFT + CNN	Spectrograms (spatial)	Binary	92	Lacks temporal analysis
Islam et al. (2024)	ANN-LSTM	Time-frequency (temporal)	Binary	94	Neglects spatial features
Wang et al. (2023)	CNN-LSTM	Spatial and temporal	Binary, Ternary	97	Lacks data privacy, limited scalability
Khattak et al. (2023)	Deep Learning	Temporal and spatial features (MRI)	Multi-class	95	The deep learning framework aligns with the methodology proposed; however, it is not applicable due to the distinct characteristics and processing requirements of EEG signals.
Li et al. (2020)	LSTM-CNN	Real-time sequential data	Multi-class	96	Domain-specific application, lacks healthcare-specific considerations
Ali et al. (2022)	CNN, SVM, LSTM	ECG signals	Binary	94	Comparison-focused, lacks hybrid model integration
Kunekar et al. (2024)	LSTM	Temporal EEG data	Binary	97	Limited to binary classification, lacks multi-class capabilities
Khaled e al. (2023)	DWT + PCA + t-SNE	EEG features	Binary	RF:98.09, MLP:98.98	High dimensionality preprocessing complexity, requires feature extraction

sections.

1) Image generation using Short-Time Fourier Transform (STFT): For image generation, this study utilizes the STFT to analyze the time-varying frequency characteristics of a discrete-time signal. The STFT computes the Fourier Transform of a signal over short, overlapping windows of time, enabling the extraction of spectral information across both time and frequency domains [22].

Mathematically, the STFT of a discrete signal $x[n]$ is defined as:

$$X[m,k] = \sum_{n=0}^{N-1} x[n] \cdot w[n-m] \cdot e^{-j2\pi kn/N} \tag{1}$$

where:

- $X[m,k]$ is the STFT of $x[n]$ at time index m and frequency index k.
- $x[n]$ represents the discrete input signal.
- $w[n-m]$ denotes a window function centered at index m, typically with finite support to extract a localized portion of $x[n]$.
- $e^{-j2\pi kn/N}$ represents the complex exponential kernel for frequency k.
- N is the length of the signal $x[n]$.

The STFT decomposes $x[n]$ into its constituent frequency components as they evolve over time, providing a time-frequency representation of the discrete signal. This representation is essential to transform the signals to images to be suitable for CNN training.

2) Convolutional Neural Network (CNN): The CNN component in the proposed hybrid model plays a crucial role in extracting spatial features from EEG data. CNNs have demonstrated exceptional performance in image recognition tasks [10] due to their ability to capture hierarchical patterns through convolutional layers [13]. In the proposed model, we leverage this capability to analyze EEG signals transformed into spectrogram images.

To prepare the EEG data for the CNN method, the Short-Time Fourier Transform (STFT) is employed to convert raw EEG signals into the time-frequency domain, producing spectrograms. This transformation allows us to visualize the frequency content of the EEG signals over time, facilitating the identification of seizure-related patterns that might not be apparent in the raw time-domain data. These spectrograms are then converted to suitable images for CNN model.

The CNN architecture consists of several convolutional layers followed by pooling layers. The convolutional layers apply a series of filters to the input images, detecting various features such as edges, textures, and complex patterns relevant to epileptic seizures.

The mathematical process of convolution involves sliding a filter over the input image and computing the dot product between the filter and the input's overlapping region. The convolution operation can be expressed as follows, the image being processed is denoted as I and the filter as F:

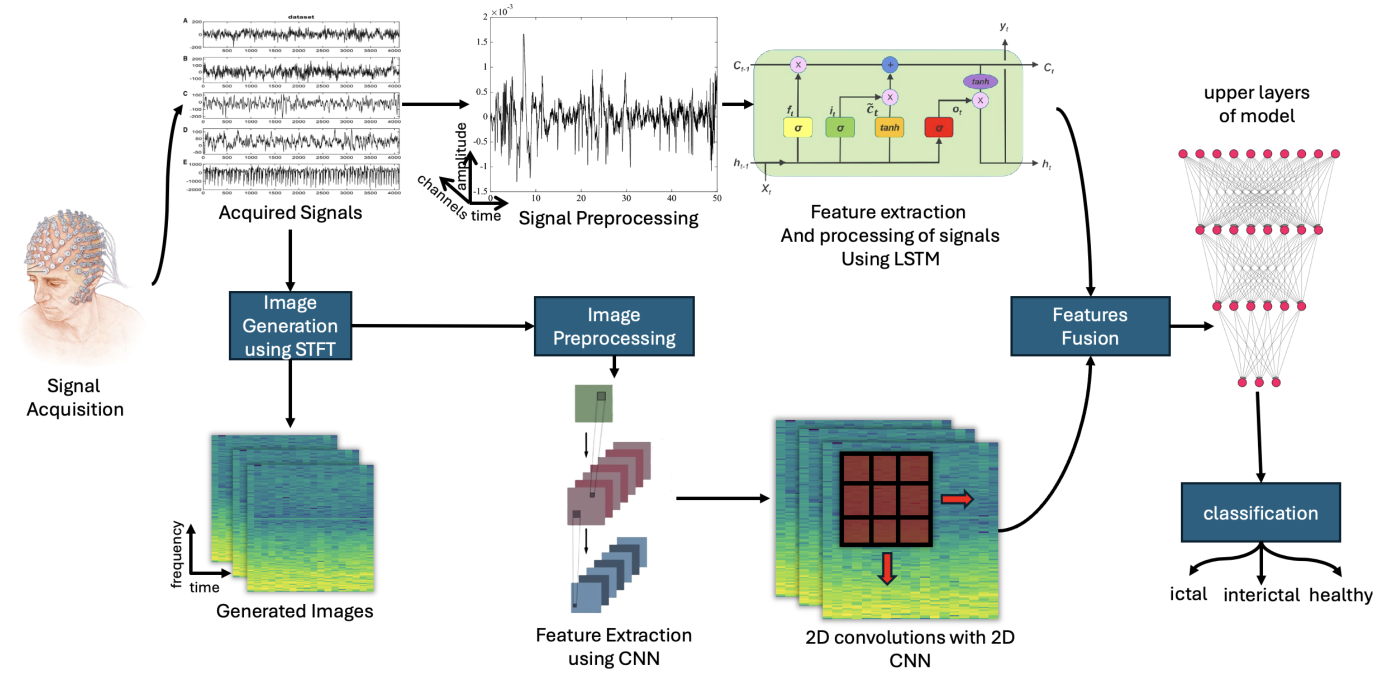

Fig. 2: The pipeline of the proposed model for epileptic seizure detection.

$$S(i,j) = (I * F)(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(i+m, j+n) \cdot F(m,n) \tag{2}$$

where $S(i,j)$ is the output feature map, $I(i+m, j+n)$ is the pixel value at position $(i+m, j+n)$ in the input image, and $F(m,n)$ is the filter value at position (m,n). Here, M and N are the dimensions of the filter. Figure 3 shows how convolving filters with an image can lead to feature extraction, which is used in subsequent layers in the neural network to learn a more abstract version of the input image, leading to a better classification.

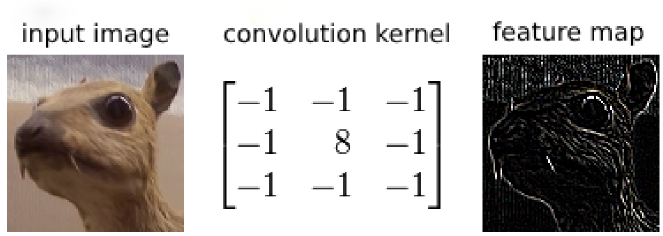

Fig. 3: Convolving filter with images.

Many of these filters are applied to the input image by each convolutional layer, each of which detects a distinct set of features. The output of the convolutional layer is then formed by stacking the feature maps that are produced by each filter. In order to introduce non-linearity, the ReLU activation function is usually used element-wise. This aids in the network's learning of complicated representations, which can be expressed as:

$$R(i,j) = \max(0, S(i,j)) \tag{3}$$

By reducing the spatial dimensions of the feature maps while keeping the most crucial information, pooling layers help to reduce computational complexity and offer some translational invariance. Max pooling is a popular pooling operation that is defined as follows:

$$P(i,j) = \max_{0 \leq m < p} \max_{0 \leq n < q} R(i \cdot p + m, j \cdot q + n) \tag{4}$$

where $P(i,j)$ is the output of the pooling layer, p and q are the pooling window dimensions, and $R(i \cdot p + m, j \cdot q + n)$ is the ReLU-activated feature map value.

From the EEG spectrograms, our CNN is able to learn a rich hierarchy of spatial characteristics by stacking many convolutional and pooling layers. After being flattened, the output of the last convolutional layer is input into fully connected layers, which use the features that were retrieved to classify seizure occurrences.

Overall, the CNN component effectively captures localized spatial patterns in the EEG images, providing a robust feature extraction to be combined with the LSTM component to model the temporal dynamics. This combination allows the proposed model to achieve a high level of accuracy in recognizing epileptic seizures by leveraging both the spatial and temporal characteristics of EEG signals.

3) Long Short-term memory (LSTM): Long Short-term memory, is a type of recurrent neural networks, that are designed to perform sequence modelling and extract temporal features, it also incorporates a set of gates that overcome the vanishing gradients problem that vanilla RNNs encounter [10]. Vanishing gradients is a problem that lead to emphasizing sequential recency in predicting outcomes, rather than making a correct semantic prediction, and hence no rigorous features extraction. Because of the use of gates in LSTM, LSTM networks do very well with time-series data, which makes them ideal for applications using electroencephalograms (EEG) signals [14].

Architecture of LSTM: The memory cells in LSTM networks' architecture are able to retain and update information over lengthy sequences, which helps to overcome the shortcomings of conventional RNNs. The input, forget, and output gates are the three main gates that control the information flow in an LSTM cell [12].

- Forget Gate: The forget gate decides which information from the previous cell state should be discarded. It is formulated as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$

  where σ denotes the sigmoid function, W_f are the weights, h_{t-1} is the previous hidden state, x_t is the current input, and b_f is the bias term.
- **Input Gate**: The input gate updates which new information is added to the cell state. This again consists of two steps: calculation of the gate layer and the candidate values $\tilde{C}_t$ generation:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{7}$$

  The new cell state C_t updates as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{8}$$

- Output Gate: The output gate regulates the information that flows to the next hidden state, computed as:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{9}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{10}$$

  These gates make LSTM networks capable of learning to forget or remember information, thus handling complex temporal dependencies with high accuracy.

4) LSTMs for EEG Signal Processing: EEG signals, being a representation of the brain's electrical activity, are sequential data that in most cases are characterized by complex temporal dependencies. LSTM networks are particularly well adapted to processing such signals given their strong sequence modeling capabilities.

- Input Representation: The preprocessed EEG signals are simply expressed as sequences of vectors. For example, an EEG signal captured over T time steps for N channels can be formulated as a $T \times N$ matrix.
- LSTM Model: The LSTM network can feed in this sequence with every time step being the EEG signal at that moment. The network learns to capture temporal patterns and dependencies relevant to the specific task, for example, mental state classification or seizure detection.
- Output: The LSTM generates a sequence of hidden states which are used to make the final prediction. In classification tasks, the last hidden state can be passed through a fully connected layer followed by a softmax activation to produce class probabilities:

$$\hat{y} = \text{softmax}(W_{\text{out}} \cdot h_T + b_{\text{out}}) \tag{11}$$

  where $\hat{y}$ is the predicted output, W_{out} are the output weights, h_T is the hidden state at the final time step, and b_{out} is the output bias.

C. Multi-Modal LSTM-CNN Model

After building the CNN, and LSTM models, we can build the multi-modal, through making two data channels, sequence of signals go through the LSTM, for capturing temporal dynamics, and the images of signals formed from the STFT, feed into the CNN model to capture spatial features, then the fusion occurs, combining extracted features from the CNN, and the LSTM as apparent in Figure 4, for a better interpretation and precise classification. The proposed framework hence fuses the LSTM and CNN approaches for complementary feature extraction from EEG signals, which effectively represents the challenge in epilepsy detection. EEG signals consist of temporal variations and spectral characteristics that play an important role in the identification of epileptic activity. Accordingly, the LSTM component shows good performance in capturing sequential patterns and long-term dependencies in time-series data. Thus, LSTM is fit for detecting sustained or recurring temporal patterns associated with epileptic events. Meanwhile, the CNN part deals with spectrograms, which are obtained from the STFT, extracting features in the frequency domain that correspond to specific spectral patterns indicative of seizures, such as high-frequency bursts or rhythmic discharges. By concatenating the outputs of these two networks, the model integrates temporal dynamics from LSTM and spectral insights from CNN, creating a synergistic representation. This approach overcomes the shortcomings of each modality when used in isolation, as LSTM captures temporal dependencies that may be absent in CNN, and CNN enhances frequency-specific markers not obvious in raw temporal data. These fused modalities allow more accurate and robust epilepsy detection, with a deeper understanding of how temporal and spectral features interact-a key aspect for clinical applications.

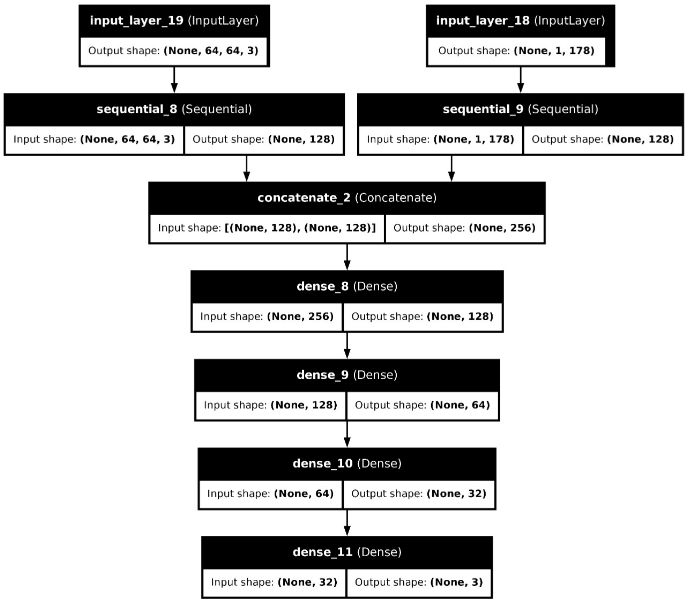

Fig. 4: LSTM-CNN Model Architecture.

IV. Privacy-Preserving epileptic seizure Healthcare Data Using Blockchain Technology

In the digitization era and our extreme dependence on technology in almost every field of our daily lives, one of the major applications is medicine. At the same time, since digitization was unavoidable and AI contributed to many aspects of this field, then certainly, all models would train on data collected from hospitals or medical institutions. In turn, the disclosure of this data would mean a possible threat either to the patients or the institutions themselves. According to National Health Service (NHS) [11], 1156 incidents were due to incorrect recipients or the disclosure of medical data. Hence, an exact scheme for data confidentiality and privacy in emerging applications and research is not an option but a must.

A. Challenges and Risks of Data Disclosure

1) Patient Privacy: Patient privacy is, therefore, the most significant challenge. Identity theft, discrimination, and loss of trust with the patient are some of the severe implications that arise due to unauthorized access to medical data. Patients may be unwilling to share their data if they feel that it could have the potential for misuse or even being inadvertently disclosed without their consent [49].

2) Institutional Risks: Some other risks that are more specific to the institutions related to data disclosure also exist. Breaches can result in financial losses, legal and reputational effects for the institution [50].

3) Data Integrity and Security: Integrity and security of healthcare data go hand in hand. Tampering or loss of data may lead to serious consequences against the patients' care and clinical outcomes. Malicious tampering or loss may lead to incorrect creation of data, diagnosis, and treatment. Usually, the traditional way of storing data in centralized systems can easily be attacked by cyber hackers, who may steal vast amounts of sensitive data [15].

B. Impact of Blockchain on epileptic seizure healthcare data

Blockchain is an emerging technology useful to provide innovative solutions in various sectors, including healthcare. The blockchain network is useful to preserve and exchange patient data and can accurately identify serious mistakes and even dangerous ones in the medical field [46], [47]. The following are the characteristics of blockchain technology.

1) Decentralization: By design, blockchain technology is decentralized—no single entity has control over the whole data set. This lowers the risk of data breaches since there is no central point of failure that attackers can target.

2) Immutability: Once data gets recorded on a blockchain, it cannot be altered or deleted. That property is achieved by storing records in blocks. One block contains a series of transactions, also known as records. These records are hashed, and each block contains a reference or a pointer to the previous block's hash. Thus, changing anything in the block would cause a change in the hash value, which in turn breaks the chain. This immutability property confirms data integrity and makes it tamper-proof. Any alteration of data in a network would require the consent of a majority of the nodes, which is an impossible task to achieve.

3) Transparency and Traceability: Through blockchain, there is an open, transparent, traceable ledger of each transaction. All the accesses done on the data get recorded to form an audit trail, which is always available for scrutiny upon demand in a case of compliance check for data protection rules. This sets in transparency among the patients and various institutions, hence building trust.

4) Smart Contracts: Smart contracts are, to put it simply, self-executing contracts. Lines of code reflect the conditions of the agreement directly. They have the ability to automate access control rules so that, under certain circumstances, only authorized users can access the data. Hence, automation reduces human error and enhances data security. The smart contracts are used in this application to specify the functionality and access control over the medical records for each medical hospitals.

5) Improved Security: Blockchain makes use of the advanced technique of cryptography to protect its data. In a blockchain, every block is connected to the previous block through a cryptographic hash.

6) Access Control: This can be achieved through access control mechanisms that limit the extent to which personal data can be disclosed or modified. Dong et al. proposed using blockchain for access control mechanisms [27], [32], emphasizing its significant advantages. Blockchain addresses issues present in existing access control schemes, such as high computational costs, complex certificate management, and difficult implementation. Considering these challenges, we employed integrated access control mechanisms built on blockchain. These mechanisms are certificate-free, easy to implement via smart contracts, and computationally efficient. They ensure the correct level of authorization before any data read or write operations, making the system distinct from traditional machine learning systems.

C. The Proposed Data Confidentiality and Privacy Scheme

In our data confidentiality scheme for the proposed machine learning model, a key distribution mechanism is implemented for each medical hospital data. Only users with authenticated keys can fetch or upload data. The scheme involves three main entities: the authentication and data collection Server, medical organizations, and the LSTM-CNN Model. Medical organizations, including health centers and hospitals, collect EEG data from patients. These organizations then register with the authentication, data collection server, and a trusted third party. During this registration phase, unique secret keys are generated for each medical organization (see Figure 5). This comprehensive approach leverages a secure key distribution scheme, as proposed by Khalil et al. [16], ensuring a robust data security within the machine learning framework. Once registered, medical organizations send authentication requests to the server, which validates them based on their secret keys. Upon successful authentication, the organizations can upload their EEG data to the server.

The authenticated data is then processed by the proposed hybrid LSTM-CNN model, which extracts visual features and performs sequence learning to predict outcomes. The model ensures data integrity and confidentiality, protecting against both internal and external threats, including "honest-but-curious" insiders who might follow the protocol but are interested in deducing sensitive information.

After key distribution phase, the depicted framework in Figure 6 handles the EEG data securely and efficiently using distributed file systems, blockchain technology, and advanced deep learning models. Initially, medical organization register and receive credentials to securely upload EEG signals to a distributed file server. Upon successful upload, the data is fetched by a model for training. This model employs the CNN to extract visual features from the input EEG data and the LSTM network to learn sequencing, ultimately predicting epileptic seizures.

Sequentially, after the model generates predictions on EEG data, the information is uploaded to a blockchain server, ensuring tamper-proof storage and access restricted to authorized parties. Given the sensitive nature of the medical data, the verification and transmission process involves a series of authenticated steps to maintain data integrity and confidentiality. This framework seamlessly integrates data collection, secure storage, advanced analytics, and robust security measures, providing a comprehensive end-to-end solution for managing and analyzing EEG data in a clinical setting.

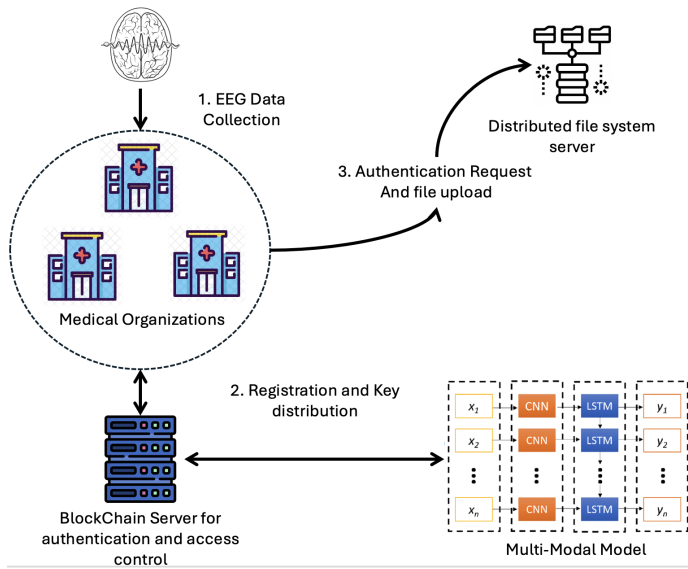

Fig. 5: Authentication scheme for data confidentiality and privacy.

V. Implementation of the Data Confidentiality and Access Control Scheme

The proposed model integrates blockchain technology, smart contracts, and a distributed file system (DFS) to ensure a highly secure, scalable, and efficient framework for handling sensitive medical data. This section provides a detailed walkthrough of the system's implementation, emphasizing the mechanisms of smart contracts, their deployment, and the interaction with the distributed file system for data retrieval.

A. Smart Contract Implementation

Smart contracts are the backbone of the blockchain framework, enabling dynamic, automated, and tamper-proof access control. They are programmed in solidity and deployed on the Ethereum blockchain (or a similar blockchain framework). Key functionalities encoded into the smart contracts include:

- Role-based access control: The smart contract defines roles and assigns specific permissions to each role. For example, only authenticated Medical Organizations can upload patient data, while Researchers can access anonymized datasets for model training.
- Authentication and key management: Upon registration, the smart contract generates a unique private key for each entity. This key is securely stored and used for both authentication and data encryption/decryption. The authentication process ensures that only entities presenting a valid private key can interact with the blockchain and the distributed file system.
- Access logs and traceability: Each access request, including its timestamp, is recorded immutably on the blockchain, enabling full traceability and accountability. Unauthorized attempts to access data are automatically flagged and logged for further investigation.

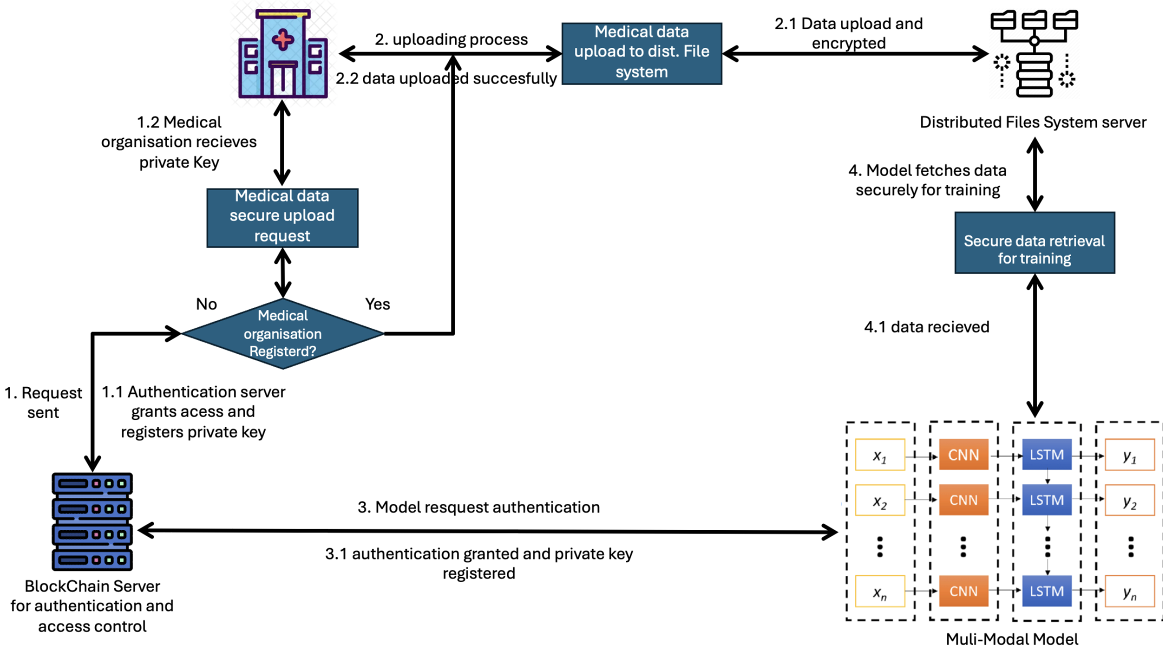

Fig. 6: Storing medical data privately through blockchain technology.

- Dynamic policy updates: Administrators can modify access control policies (e.g., revoking or granting permissions) by updating the smart contract. These changes are propagated across the network without requiring downtime.

To deploy the smart contract on a test network, the following steps are developed.

- Smart contract compilation and testing: The contract is developed and tested in a local environment using Remix and Truffle tools to ensure its correctness and security [23], [24]. Unit tests are conducted to validate each function, including registration, authentication, access requests, and logging.
- Deployment to a test network: The contract is deployed to a blockchain test network using Ropsten and Goerli tools to simulate real-world operations without incurring high costs [25], [26]. Deployment involves publishing the contract to the blockchain, which generates a unique contract address. This address is used to interact with the contract during data uploads and retrievals.
- Verification and optimization: After deployment, the contract is verified on the blockchain explorer to ensure transparency and correctness. Gas optimization techniques are applied to minimize the cost of executing contract functions.

B. Integration with the Distributed File System

Once the smart contract is deployed, it interacts seamlessly with the distributed file system to store and retrieve medical data securely. This process involves the following steps:

- Data upload process: Medical organizations collect EEG data from patients and send a secure upload request to the blockchain server. The smart contract verifies the organization's registration and private key. If authenticated, it generates an encryption key for the data. The data is encrypted using this key and uploaded to the DFS, such as InterPlanetary File System (IPFS), where it is fragmented and stored across multiple nodes for redundancy and security. A hash of the uploaded data, along with metadata (e.g., data owner, timestamp), is stored on the blockchain. This hash ensures the data's immutability and serves as a reference for retrieval.
- Data retrieval process: When the LSTM-CNN model request data for training, they send an authentication request to the blockchain. The smart contract verifies the requests credentials and retrieves the corresponding data hash from the blockchain. The DFS is queried using the hash, fetching the encrypted data. The smart contract then provides the decryption key to the authorized entity, enabling secure data access.

By combining smart contracts, blockchain immutability, and distributed file systems, the proposed scheme delivers a robust, secure, and efficient solution for managing sensitive medical data. Its ability to ensure data confidentiality, integrity, and traceability has the potential to revolutionize the medical field, preventing data-related disasters and fostering trust among stakeholders.

C. Security Evaluations and Quantitative Measures

The blockchain-based data confidentiality and privacy scheme presented in this paper has undergone a comprehensive security evaluation to validate its efficacy. The system was tested against different approaches of penetration, ensuring it meets the highest standards of data protection. Key findings include:

- Unauthorized data modification prevention: All unauthorized changes to data were denied, with a success rate of 100%. This behavior aligns with the tamper-proof property of blockchain, achieved through cryptographic linking of blocks. The blockchain framework ensures that any modification to a single block disrupts the cryptographic hash chain, since each data block is tied to other data blocks through a pointer to previous data block hash, any modification to this data block changes the hash value of the data block, and hence unlinking the linked list of data blocks, rendering the tampered block invalid. This feature is enforced programmatically via smart contracts, which is a software interface that allows developers to control the security system in the blockchain, specifying the desired security properties, access control, as well as additional features such as logging the history of authorized and unauthorized attempts to the blockchain network, assuring full transparency and easier forensics in case of system penetration. Smart contract, which is the software interface developed to specify the blockchain functionalities and its security properties, has security as it's first stage in the software development life cycle, ensuring that the software is built to satisfy the security requirements.
- Data encryption strength: Data stored within the blockchain and distributed file systems were encrypted using the AES-256 (Advanced Encryption Standard with a 256-bit key) algorithm, recognized as a standard for secure encryption by organizations like NIST. The strength of AES-256 lies in its use of a large key size, making brute-force attacks computationally infeasible with current technology. Additionally, the encrypted data, if intercepted, would be entirely unusable due to the absence of the decryption key, as the AES algorithm ensures that even the slightest modification or incorrect key input results in completely unreadable and incoherent output, and even if the attacker was able to intercept the data, he would have to provide the private key for access control, which is ensured programmatically in the smart contract of the application, which makes interception or malicious access to data very unfeasible. However using only AES encryption wouldn't provide a dual key approach (first key for access control, and the second for the decryption), which emphasizes why blockchain is a more secure solution. This guarantees confidentiality and resistance to tampering or unauthorized access during transmission.
- Auditability and traceability: All transactions and data access attempts were logged immutably, with timestamps ensuring real-time traceability. During stress testing, the system recorded a average of 50 transactions per second, without any compromise to logging integrity.
- Performance metrics: The system's max response time for authentication and data retrieval was approximately 900 milliseconds under peak load conditions. This measurement was obtained using a distributed load-testing framework that simulated concurrent user requests across various scenarios. These scenarios included server authentication, file requests (excluding local file transfer time), and other transactions such as blockchain server registration and file decryption. The framework accurately recorded the time taken for each request, from initiation to completion, ensuring precise and consistent measurements. These results demonstrate that the integration of blockchain technology does not significantly impede the system's operational performance.
- Comparison with Traditional Encryption Systems: A comparative analysis was conducted to emphasize blockchain's advantages over traditional encryption methods which are summarized in Table II.

VI. Experimental results and discussion

The efficiency of the proposed LSTM-CNN model based on the Bonn EEG dataset is tested in this section through experiments. The experimental configurations and assessment measures are described in detail below, complying to the best practices of secure software. These measures collectively reinforce the integrity, confidentiality, and availability of sensitive medical data, addressing critical gaps in traditional systems.

A. Experimental Settings

In this paper, we worked on three epileptic seizure detection tasks: binary detection of two categories, ternary detection of three categories, and penta detection of five categories. Among them, binary detection performs between seizure patients and healthy volunteers. Ternary detection divides the seizure condition into three categories: ictal epilepsy, preictal epilepsy, and healthy subjects. The penta-detection divides to five categories that include seizure from four non-onset conditions such as preictal, ictal, postictal, interictal, and normal.

For the evaluation of the proposed model, experiments were conducted using a high-performance workstation equipped with an AMD Ryzen 7 2700x processor with 8 cores at a clock speed of 3.7 GHz, 16 GB of RAM and two NVIDIA GeForce RTX 2060 graphics cards. These specifications provided us with the computational power needed for efficient training and testing, significantly reducing time consuming.

This work used the publicly available EEG dataset from Bonn University, Germany [28], which is an established benchmark for many seizure detection models. This data set was divided into training and testing sets, where 80% of the samples were used for training and 20% for testing.

B. Hyperparameter Configurations

The model was trained and evaluated with predefined hyperparameters to ensure reproducibility, as described in Table III. The batch size was set to 23, while the starting learning rate was set to 0.0001. To ensure better convergence,

TABLE II: Comparison of blockchain-based systems with traditional security methods.

Metric	Blockchain-Based System	Symmetric Encryption (AES)	Public-Key Encryption (RSA)	Traditional Centralized Systems
Tamper-Proof Data	100% tamper-proof (Previous Hash Pointers)	No	No	No
Access Control Automation	Role-Based via Smart Contracts	No	Limited (Via third party software)	Limited (Via third party software)
Auditability	Transparent and Immutable Logs (records every single transaction)	Partial (can only record accesses through third party apps)	Partial (can only record accesses through third party apps)	Limited
Key Management	Dual-Key (Decryption + Access Control Private Key)	Single Key (Decryption Key)	Single Key (Decryption Key)	Single Key (Decryption Key)
Fault Tolerance	Very High (Distributed Network with many nodes running the system)	Single Point of Failure	Single Point of Failure	Single Point of Failure
Response Time	900 milliseconds for max response time (including decryption and access control authentication)	<1 second	2-5 seconds	1-3 seconds

the learning rate was decayed using an exponential schedule during training. The dropout rates were 0.2 for the LSTM architecture and 0.5 for the CNN architecture in an attempt to prevent overfitting of the data.

The Adam optimizer has been used because it is considered extremely efficient when it comes to sparse gradients, and the cross-entropy loss function serves to evaluate classification performance. The CNN model used 50 training epochs, while the LSTM model utilized 20, as a compromise between computational efficiency and model performance. The ReLU activation function introduced non-linearity and, with this, really improved the learning capacity of the models. On the other hand, the softmax activation function is used as the output activation function for multi-class classification. In addition, EEG signals are transformed from 1×178 time-series data into 64×64 pixel images as input to the CNN model.

In addition, data augmentation techniques is used to improve the generalizability of the model and deal with the imbalance of the data set. More precisely, the addition of Gaussian noise was employed to mimic real-world variability, while the oversampling and undersampling techniques were used to reduce class imbalance. The effect of different combinations of these enhancement strategies was systematically evaluated in the search for the most effective approach for each detection task. By focusing the tuning efforts on the data augmentation parameters, it was possible to make the model more robust and reduce overfitting, especially in scenarios with a large class imbalance.

TABLE III: Hyperparameter configurations used in the experiments.

Hyperparameter	**Value**
Batch size	23
Learning rate	0.0001
Dropout rate	0.2, 0.5
Optimizer	Adam
Loss function	Cross-entropy
Number of epochs	50, 20
Activation function	ReLU, Softmax
Input dimensions	1×178, $64 \times 64 \times 3$
Data Augmentation Strategy	Noise, Oversampling, Undersampling

C. Results and Discussion

The proposed spatio-temporal model incorporates LSTM and CNN techniques. Epileptic EEG signals are extracted and classified using this hybrid model. The lower signal-to-noise ratio-related low classification rate in EEG is well addressed by this combination. While the LSTM component more successfully examines the time information within the EEG, the CNN component is superior at extracting features and is also capable of identifying and predicting important spots. In the long-range sequence, the LSTM network learns how information from earlier inputs is forgotten and changes as new inputs become accessible. The hybrid LSTM-CNN model makes up for the drawbacks of employing LSTM and CNN alone. As a result, the hybrid model improves recognition by maximizing the temporal and spatial information of the epileptic EEG signals.

The proposed epileptic recognition model mainly consists of five phases. First phase, the EEG signals are preprocessed to be suitable for classification process by augmenting the data (adding noise), oversampling, and under sampling for training datasets. Second phase, the neuro spatiotemporal features are extracted from CNN and LSTM parts of the model processes. In the CNN, the raw EEG data is prepared and converted to time-frequency domain using STFT, producing spectrograms, then it converted to 2D images to be suitable for CNN model. Third phase, the features are fused to fill gaps between methods and to increase the efficiency of the machine learning performance. Fourth phase, the fused features are fed into fully connected layer for binary, ternary, and Penta classification of epileptic seizure recognition. Fifth phase, seizure detection assessment (SDA) methods are proposed for performance evaluation with different experimental scenarios. There are various benefits and advancements in the joint spatio-temporal LSTM-CNN network automated epilepsy recognition for binary and multi-class epileptic EEG recognition.

Table IV illustrates the performance of the proposed model in detecting epileptic seizures at various seizure states and evaluation parameters. The evaluation process takes a series of metrics into consideration: Training Accuracy (*Tr_Acc*), Testing Accuracy (*Ts_Acc*), Training Loss (*Tr_Loss*), Testing Loss (*Ts_Loss*), *Precision*, *Recall*, and *F1-score*, which provide well-rounded evaluation of the model's performance.

The selection of these metrics ensures a comprehensive model evaluation. Accuracy, *Tr_Acc* and *Ts_Acc*, measures the general correctness of predictions. It helps in understanding how the model is generalizing on unseen data. Quantitatively, loss values of the model are tracked in order to track the optimization process, as it is also helpful for catching any overfitting or underfitting (*Tr_Loss* and *Ts_Loss*). *Precision*, *Recall*, and *F1-score* metrics are included, taking into consideration the class imbalance common to epileptic seizure datasets.

Precision measures the ability of the model to avoid false positives; *Recall* measures its ability to detect true positives. The *F1-score* is the harmonic mean of *Precision* and *Recall*, balancing these metrics for a nuanced understanding of performance. To ensure robustness, the first four columns of Table IV enumerate the parameters—class labels, noise addition, oversampling and undersampling—considered in permutations of parameter values. This systematic analysis reveals configurations that lead to optimal performance when considering dataset attribute differences.

Furthermore, A specific matrix called the confusion matrix (CM) is generated by comparing the predicted labels produced by the trained model against the ground-truth labels from the dataset. It is used to show how well an algorithm performs; each column shows the expected value, and each row shows the actual category. By using CM, we gain valuable insights into the nature of the errors and the classes most frequently misclassified. For example, certain epilepsy states may share similar patterns in EEG signals, potentially causing confusion in the model's predictions, and by examining the CMs for the binary, ternary, and penta states of epileptic seizure as shown in Figure 7 using the proposed LSTM-CNN model, We ensured that the proposed model maintains a high density of counts along the main diagonal. This confirms the model's ability to capture discriminative features that are crucial for correctly identifying seizure states. This comparison shows that the algorithm helps to prevent errors related to false positives and true negatives, which are represented by the off-diagonal line, in addition to ensuring high prediction accuracy for true positives and true negatives for two labels, three labels, and five labels, as shown on the main diagonal line. Figure 8 shows the loss and accuracy performance scores of the multiheaded LSTM-CNN model for training and validation process. From this figure we can see that over-fitten is reduced for all classes and accuracy is increased. Moreover, the cross-entropy loss function decreases during training time.

TABLE IV: Results of the proposed multi-classification model for different epileptic seizure states under different evaluation criteria.

Labels	Noise	Over_S	Under_S.	Tr_Acc	Ts_Acc	Tr_Loss	Ts_loss	Precision	Recall	F1-score
2	X	X	X	1.00	0.982	0.043	0.096	0.98	0.96	0.97
	X	X	✓	0.999	0.987	0.024	0.055	0.98	0.98	0.98
	X	✓	X	1.00	0.977	**0.004**	0.065	0.99	0.95	0.96
	X	✓	✓	1.00	0.981	**0.004**	0.051	0.98	0.95	0.96
	✓	X	X	0.995	0.970	0.036	0.110	0.97	0.93	0.95
	✓	X	✓	0.996	0.986	0.024	0.060	0.99	0.97	0.98
	✓	✓	X	0.997	0.973	0.016	0.124	0.97	0.95	0.96
	✓	✓	✓	**0.998**	**0.991**	0.030	**0.041**	**0.99**	**0.98**	**0.98**
3	X	X	X	0.999	0.958	0.083	0.261	0.96	0.95	0.95
	X	X	✓	0.999	**0.979**	0.029	**0.084**	**0.98**	0.96	**0.97**
	X	✓	X	**1.00**	0.968	0.019	0.173	0.97	**0.97**	**0.97**
	X	✓	✓	**1.00**	0.969	**0.005**	0.106	**0.98**	0.96	0.96
	✓	X	X	0.964	0.959	0.215	0.239	0.97	0.94	0.95
	✓	X	✓	0.982	0.959	0.117	0.199	0.97	0.94	0.95
	✓	✓	X	0.986	0.972	0.090	0.110	**0.98**	0.95	0.96
	✓	✓	✓	0.987	0.977	0.081	0.103	**0.98**	**0.97**	**0.97**
5	X	X	X	0.982	0.836	0.283	0.574	0.84	0.83	0.83
	X	X	✓	0.998	0.891	0.103	0.425	0.89	0.88	0.88
	X	✓	X	**0.999**	**0.907**	**0.078**	**0.411**	**0.90**	**0.91**	**0.91**
	X	✓	✓	0.982	0.841	0.209	0.576	0.85	0.85	0.84
	✓	X	X	0.848	0.814	0.495	0.569	0.82	0.80	0.81

Note:Significant values are in bold.

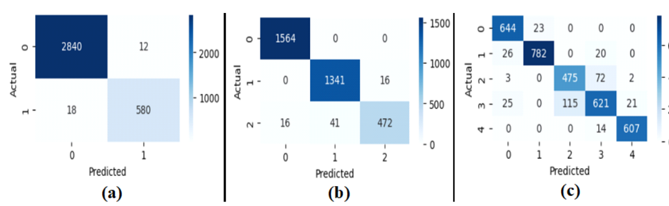

Fig. 7: Confusion matrix of the proposed LSTM-CNN model for the binary (a), ternary (b), and penta (c) states of epileptic seizure.

Table V shows the comparison results and performance of the proposed LSTM-CNN method and the baseline methods LSTM and CNN individually. We included only the best-tuned parameters for each desired number of labels (augmentation with type of noise, oversampling, and under-sampling).

The proposed model outperformed the baseline CNN and LSTM models for each parameter configuration in every metric as seen in Figure 9 and Table V. In the case of binary class labels, the gap is not drastic, showing only a difference of 0.07 and 0.05 in F1_score for LSTM and CNN, respectively, and a difference of 0.04 and 0.02 in test accuracy for LSTM and CNN, respectively. For ternary class labels, the gap is more significant with a difference of 0.27 in F1_score and 0.251 in test accuracy. In the case of 5 labels, the differences in performance metrics are drastic, with a 0.382% difference in test accuracy and a 0.39 difference in F1_score.

Previous researchers have classified the epileptic dataset

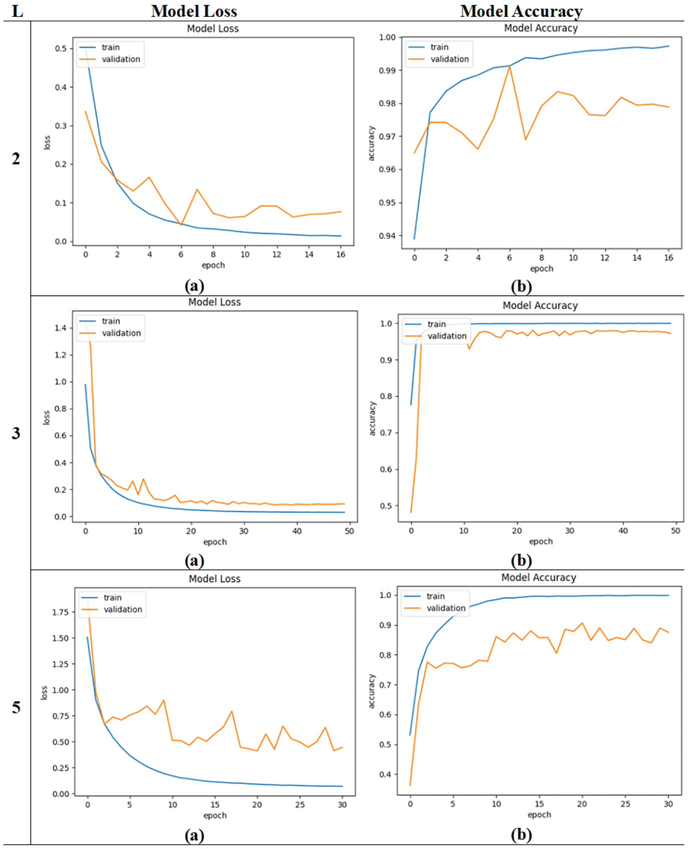

Fig. 8: Performance of the proposed multiheaded LSTM-CNN model for different epileptic seizure classes. (a) shows the LSTM-CNN loss, and (b) shows the LSTM-CNN accuracy.

TABLE V: Comparison results between LSTM, CNN only and multiheaded LSTM-CNN model under different evaluation criteria for different class labels 2, 3, and 5.

Labels	Model	Tr_Acc	Ts_Acc	Tr_Loss	Ts_loss	Precision	Recall	F1-score
2	**LSTM**	0.993	0.951	0.033	0.221	0.960	0.880	0.910
	CNN	0.980	0.971	0.032	0.120	0.942	0.920	0.930
	MultiHeaded	0.998	0.991	0.030	0.041	0.990	0.980	0.980
3	**LSTM**	0.792	0.728	0.528	0.670	0.830	0.740	0.740
	CNN	0.911	0.820	0.215	0.452	0.818	0.817	0.816
	MultiHeaded	0.999	0.979	0.029	0.084	0.980	0.960	0.970
5	**LSTM**	0.681	0.525	0.923	1.199	0.600	0.510	0.510
	CNN	0.782	0.673	0.712	0.740	0.677	0.670	0.670
	MultiHeaded	0.999	0.907	0.078	0.411	0.900	0.910	0.910

into binary classification, such as, Zhao et al. [29], Xu et al. [33], Ramos-Aguilar et al. [35] in 2020 achieved accuracies 0.987, 0.82, and 0.978, respectively. In 2019, Siuly et al. [36] achieved accuracy 0.985. While in (2016-2018) authors, Song et al. [38], Mursalin et al. [30], and Deng et al. [37] achieved accuracies 0.973, 0.974, and 0.970, respectively. However, Wang et al. (2018) [39] conducted ternary classification and achieved accuracy rate of 0.9363. Ilakiyaselvan et al. (2020) [31] obtained accuracy rate of 0.96. Wang et al. (2023) [17],

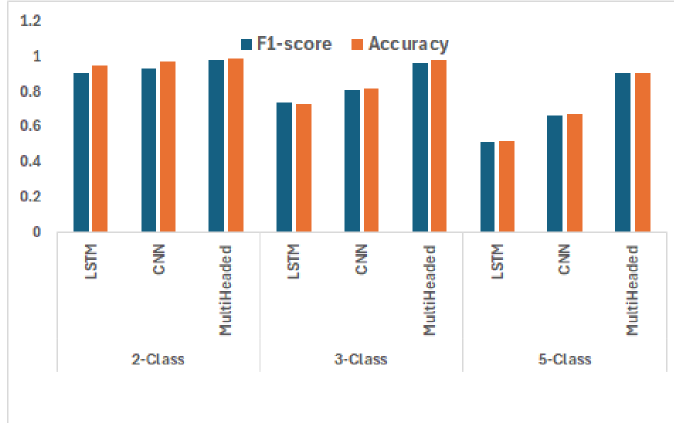

Fig. 9: The Accuracy and F1-score for the proposed model and LSTM and CNN individually.

achieved accuracy 0.98. Moreover, little studies applied multi-classification for five class labels of epileptic seizure. Xu et al. (2023) [34] conducted five classes where achieved accuracy reached to 0.82 using LSTM-CNN and applied deep neural network and CNN with accuracies achieved 0.688, and 0.673, respectively. In contrast, our approach outperformed these methods in the binary, ternary, and penta problems, achieving an accuracy of 0.991, 0.979, 0.907, respectively, using the hybrid LSTM-CNN model. The aforementioned experimental findings indicate the deep learning hybrid model, which combines CNN and LSTM, has the capacity to automatically classify epileptic EEG signals into binary, ternary, and penta categories.

D. Comparisons among different Machine learning methods

Table VI shows the comparison between the performance of the proposed method and different machine learning and deep learning methods (including, extreme learning machine (ELM), differential evolution-based extreme learning machine (DEELM), k-nearest neighbor (KNN), decision tree (DT), artificial neural network (ANN), cascade-forward neural network (CFNN), the recurrent neural network (RNN), feed-forward neural network (FFNN), probabilistic neural network (PNN), naive bayes (NB), convolutional neural network (CNN), long-term short memory (LSTM), and LSTM-CNN with different pretrained models (AlexNet, Vgg16, and ResNet) to find the most effective solution for epileptic seizure detection problem. The proposed method provides the most trustworthy findings, as shown in Table VI, followed by the CNN results, which had an accuracy rate of about 0.97, a recall rate of about 0.94, precision rate of about 0.92, and f1-score rate of about 0.93. Followed by CNN-LSTM based on pretrained ResNet model, which had an accuracy rate of about 0.97, a recall rate of about 0.98, precision rate of about 0.98, and f1-score rate of about 0.975. The results show that the complex parameter adjustments in a supervisory network make it insufficient to handle complex nonlinear data using standard machine learning (ML) methods. EEG signals are high dimensional, complicated nonlinear stochastic timing signals that are challenging to model using standard machine learning. Lower accuracy arises from the classification process's incomplete utilization of important hidden information. Deep learning (DL), on the other hand, has strong learning ability to handle high-dimensional and nonlinear data. From the original data, the DL models are able to automatically learn and extract pertinent information. The original signals can be strengthened, the noise can be decreased, and the signal-to-noise ratio can be raised using convolution procedures.

The proposed method is more practical and allays concerns regarding how model training would alter as the amount of medical data increases. These results show that the proposed strategy performs better and produces good outcomes when it comes to recognizing difficult, intricate, and non-linear epileptic seizures.

TABLE VI: Performance results of the proposed method and different machine learning methods.

Algorithm	Accuracy	Recall	Precision	F1-Score
KNN	0.753	0.971	0.723	0.831
DT	0.701	0.763	0.751	0.754
ANN	0.703	0.783	0.712	0.742
NB	0.612	0.400	0.893	0.553
FFNN	0.741	0.833	0.698	0.764
CFNN	0.730	0.791	0.743	0.768
RNN	0.751	0.832	0.721	0.774
PNN	0.743	0.710	0.953	0.813
ELM	0.944	0.391	0.449	0.418
DEELM	0.958	0.784	0.632	0.698
LSTM	95.07	0.880	0.960	0.910
CNN	0.971	0.942	0.920	0.930
CNN-LSTM-AlexNet	0.962	0.963	0.974	0.968
CNN-LSTM-Vgg16	0.966	0.967	0.977	0.972
CNN-LSTM-ResNet	0.970	0.977	0.980	0.975
Proposed Model	0.991	0.980	0.990	0.980

E. Comparison across different datasets

In order to better assess the effectiveness and generalizability of the proposed model, further experiments were carried out using a publicly available *epilepsy EEG dataset* provided by Nasreddine and Wassim [48]. These data were collected in the Epilepsy Monitoring Unit at the American University of Beirut (AUB) Medical Center and were created specifically for epilepsy detection tasks. AUB Medical center indicated that some channels have been omitted from specific recordings due to artifact constraints. Thus, the quality and focus of this dataset make it an ideal benchmark for testing the performance of models in this specific domain.

Table VII gives a relative assessment of three models used for these data: CNN, LSTM, and the proposed Multi-Headed LSTM-CNN model. The results showed that the proposed model was robust, as it showed consistently better performance than its peers in all metrics considered. This increased performance indicates its ability to respond perfectly to seizure detection even in different and challenging situations, where channel artifacts might present themselves.

TABLE VII: Performance of the proposed multiheaded LSTM-CNN model on AUB dataset under different measurements.

Model	Tr_Acc	Ts_Acc	Tr_Loss	Ts_Loss	Precision	Recall	F1-Score
CNN	79.08	80.49	0.626	0.632	0.81	0.80	0.78
LSTM	97.22	85.75	0.246	0.570	0.86	0.86	0.86
MultiHeaded	**98.06**	**88.58**	**0.191**	**0.450**	**0.89**	**0.89**	**0.88**

The proposed Multi-Headed LSTM-CNN model exhibits the lowest training and testing losses, which indicates better optimization and a greater generalization to new data. Consistent improvement in precision, recall, and F1-score further indicates its ability to accurately and reliably identify epileptic seizures from different data, thus showing its practicability in real-life applications.

F. Statistical Analysis

To validate the findings and ensure the robustness of the proposed model, statistical analysis is conducted on the experimental results. The following tests were applied:

Descriptive statistics were calculated for each of the five groups: A, B, C, D, and E. These groups correspond to different neurological states, ranging from relaxed to seizure phases. The results are summarized in Table VIII.

TABLE VIII: Descriptive statistics for EEG groups.

Group	Mean	Std. Deviation	Min	Max
A	-6.26	48.34	-288.00	294.00
B	-12.51	70.68	-424.00	360.00
C	-8.88	59.39	-412.00	623.00
D	-6.20	90.35	-1147.00	2047.00
E	-4.75	341.16	-1885.00	2047.00

A one-way Analysis of Variance (ANOVA) also was conducted to test significant differences in EEG signal amplitudes across the five groups [51]. The results revealed a significant main effect of the group on EEG amplitudes ($F(4, N) = 142.12$, $p < 0.001$).

In addition, the post-hoc comparisons using Tukey's Honestly Significant Difference (HSD) test identified the following significant pairwise differences [52]:

- Group B exhibited significantly lower mean amplitudes compared to Group A ($p < 0.001$) and Group C ($p < 0.001$).
- Group A had significantly lower amplitudes than Group E ($p < 0.001$) but was not significantly different from Group D ($p = 0.9999$).
- Groups C and E also differed significantly ($p < 0.001$), with Group E showing higher amplitudes.

As we can see, the results of the ANOVA and post-hoc Tukey's HSD test confirm significant differences between several groups, particularly between Group A (relaxed) and Group B (eyes closed), and between the seizure states (Groups C, D, and E).

Cohen's d was used to prove the proposed model, Cohen's d calculated for the pairwise comparisons to assess the magnitude of the differences between groups [53]. The effect sizes ranged from $d = 0.8$ to $d = 1.5$, indicating large to very large effects for the majority of the pairwise comparisons.

Confidence intervals (CIs) were computed for the test accuracy of each classification task [54], as shown in Table IX. As we can see, the narrow confidence intervals for test accuracy further emphasize the reliability of the proposed model.

These statistical analyses validate the superiority of the proposed LSTM-CNN model, reinforcing its potential for practical application in epileptic seizure detection.

TABLE IX: Confidence intervals for test accuracy.

Classification Task	Test Accuracy (95% CI)
Binary Classification	99.1% (98.8%–99.4%)
Ternary Classification	97.9% (97.5%–98.3%)
Five-Class Classification	90.7% (90.1%–91.3%)

VII. Conclusion and Future Work

The proposed model demonstrates robust versatility, successfully processing diverse styles of input data, whether EEG brain signals represented raw or unprocessed signals. The proposed model is able to process data without intensive preprocessing simplifies the overall workflow and reduces computational burden. The neural network model is particularly suitable for both spatial and temporal feature extraction, ensuring accurate and precise epilepsy seizure detection. These capabilities enhance the adaptability of the model and highlight its potential for real-world clinical applications.

The proposed model combines the advantages of CNN-based network and LSTM to extract spatial correlations and temporal dependencies in parallel to employ advanced feature extraction, allowing for in-depth analysis of EEG data. Spatial feature extraction deciphers the brain's electrical activity, identifying important patterns and anomalies, and providing valuable insights into the spatial distribution of seizure episodes. Temporal sequential feature extraction captures the dynamic and temporal aspects of EEG signals, pinpointing the onset and progression of epileptic events with high precision.

Based on the Bonn and AUB EEG datasets, the effectiveness of the proposed CNN-LSTM model for epileptic seizure recognition is verified. The effectiveness of the proposed model is tested across a variety of configurations, individual brain signals, and label variations to achieve optimal detection of brain-signal. This comprehensive testing has shown superior performance compared to other leading approaches for epilepsy seizure detection. Given its high accuracy and reliability, the proposed model can significantly improve patient outcomes and facilitate more effective treatment plans.

Additionally, the proposed model incorporates blockchain technology to ensure data security and privacy in EEG data management, enhancing security and trust in seizure detection systems, providing a comprehensive end-to-end solution for managing and analyzing EEG data in a clinical setting. The proposed model introduces a dual-key blockchain mechanism that integrates access authentication and encryption keys, ensuring tamper-proof, secure, and confidential data sharing. This innovation addresses critical concerns of data manipulation and privacy, providing a reliable platform for sensitive medical information. The proposed model has high performance, evidenced by its high precision and accuracy, outperforms related work in the field, establishing a new benchmark for EEG-based seizure detection. This integration makes the model well-suited for real-world healthcare applications.

In summary, the proposed model represents a significant advancement in epilepsy seizure detection, providing a comprehensive and efficient solution for analyzing EEG data. Its versatility, accuracy, and practical applicability make it a valuable contribution to neuroscience and medical diagnostics, offering rich insights and innovations for the detection of brain signal anomalies in this domain. This work can be extended to improve the model performance using multi-modality data such as (fMRI, EEG, and EMG) from multiple centers, and from different EEG devices.

References

[1] Gupta, V., & Pachori, R. B. (2019). Epileptic seizure identification using entropy of FBSE based EEG rhythms. Biomed. Signal Process. Control, 53, 101569.

[2] Faust, O., Acharya, U. R., Adeli, H., & Adeli, A. (2015). Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis. Seizure, 26, 56–64.

[3] Li, F., Liang, Y., Zhang, L., Yi, C., Liao, Y., Jiang, Y.,& Xu, P. (2019). Transition of brain networks from an interictal to a preictal state preceding a seizure revealed by scalp EEG network analysis. Cognitive neurodynamics, 13, 175-181.

[4] Sairamya, N. J., George, S. T., Ponraj, D. N., & Subathra, M. S. P. (2018). Automated detection of epileptic seizure using histogram of oriented gradients for analysing time frequency images of EEG signals. In Smart and Innovative Trends in Next Generation Computing Technologies: Third International Conference, NGCT 2017, Dehradun, India, October 30-31, 2017, Revised Selected Papers, Part II (pp. 932-943). Springer Singapore.

[5] Alharbi, N. S., Bekiros, S., Jahanshahi, H., Mou, J., & Yao, Q. (2024). Spatiotemporal wavelet-domain neuroimaging of chaotic EEG seizure signals in epilepsy diagnosis and prognosis with the use of graph convolutional LSTM networks. Chaos, Solitons & Fractals, 181, 114675.

[6] Alalayah, K. M., Senan, E. M., Atlam, H. F., Ahmed, I. A., & Shatnawi, H. S. A. (2023). Effective early detection of epileptic seizures through EEG signals using classification algorithms based on t-distributed stochastic neighbor embedding and K-means. Diagnostics, 13(11), p.1957.

[7] Singh, K., & Malhotra, J. (2023). IoT and cloud computing based automatic epileptic seizure detection using HOS features based random forest classification. Journal of Ambient Intelligence and Humanized Computing, 14(11), 15497-15512.

[8] Abualsaud, K., Mohamed, A., Khattab, T., Yaacoub, E., Hasna, M., & Guizani, M. (2018, June). Classification for imperfect EEG epileptic seizure in IoT applications: A comparative study. In 2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC) (pp. 364-369). IEEE.

[9] Garces Correa, A., Orosco, L. L., Diez, P., & Laciar Leber, E. (2019). Adaptive filtering for epileptic event detection in the EEG. Journal of Medical and Biological Engineering, 39, 912-918.

[10] Rawat, W., & Wang, Z. (2017). Deep convolutional neural networks for image classification: A comprehensive review. Neural Computation, 29(9), 2352-2449. https://doi.org/10.1162/NECO_a_00990

[11] Understanding Patient Data. (n.d.). What are the risks around patient data?. Understanding Patient Data. (2024, July), from [https://understandingpatientdata.org.uk/weighing-up-risks, Accessed:05/08/2024]

[12] Mohamed, Y., Anter, A. M., & Zaky, A. B. (2023, July). Recurrent Neural Networks (RNNs) to improve EEG-based person identification. In 2023 Intelligent Methods, Systems, and Applications (IMSA) (pp. 616-621). IEEE.

[13] Anter, A. M., & Abualigah, L. (2023). Deep federated machine learning-based optimization methods for liver tumor diagnosis: A review. Archives of Computational Methods in Engineering, 30(5), 3359-3378.

[14] Mohamed, Y., Mohamed, N., & Anter, A. M. (2023). A Review of Methods Employed for Forensic Human Identification. Nature-Inspired Methods for Smart Healthcare Systems and Medical Data, 1-24.

[15] Rath, B. K., & Kumar, M. (2021). Ensuring data integrity of healthcare information in the era of digital health. Healthcare Technology Letters, 8(3), 66–77. https://doi.org/10.1049/htl2.12008

[16] Khalil, K., et al. (2023). Privacy-Preserving and Hardware Acceleration-Based Authentication Scheme for Data Collection in E-Health Applications. 2023 IEEE 66th International Midwest Symposium on Circuits and Systems (MWSCAS), Tempe, AZ, USA, 2023, pp. 703-707. https://doi.org/10.1109/MWSCAS57524.2023.10405998

[17] Wang, X., Wang, Y., Liu, D., Wang, Y., & Wang, Z. (2023). Automated recognition of epilepsy from EEG signals using a combining space–time algorithm of CNN-LSTM. Scientific Reports, 13(1), 14876.

[18] Mandhouj, B., Cherni, M. A., & Sayadi, M. (2021). An automated classification of EEG signals based on spectrogram and CNN for epilepsy diagnosis. Analog integrated circuits and signal processing, 108(1), 101-110.

[19] Islam, R., Debnath, S., Raen, R., Islam, N., Palash, T. I., & Ali, R. (2022, December). Epileptic Seizure Detection from EEG Signal Using ANN-LSTM Model. In International Conference on Trends in Electronics and Health Informatics (pp. 129-141). Singapore: Springer Nature Singapore.

[20] Anter, A. M., Abd Elaziz, M., & Zhang, Z. (2022). Real-time epileptic seizure recognition using Bayesian genetic whale optimizer and adaptive machine learning. Future Generation Computer Systems, 127, 426-434.

[21] Nkengfack, L. C. D., Tchiotsop, D., Atangana, R., Louis-Door, V., & Wolf, D. (2021). Classification of EEG signals for epileptic seizures detection and eye states identification using Jacobi polynomial transforms-based measures of complexity and least-square support vector machine. Informatics in Medicine Unlocked, 23, 100536.

[22] Chalaki, M., & Omranpour, H. (2023). Epileptic seizure classification using ConvLSTM deep classifier and rotation short-time Fourier Transform. Journal of Ambient Intelligence and Humanized Computing, 14(4), 3809-3825.

[23] Narváez, R. C., Carrión, J., Maldonado, L. B., & del Cisne Ruilova, M. (2022). Smart contracts for user registration on ethereum technology: Systematic literature review. Communication, Smart Technologies and Innovation for Society: Proceedings of CITIS 2021, 699-707.

[24] Mallick, S. R., Sahu, P. K., Bagarti, U., & Lenka, R. K. (2024, September). Blockchain: Tools, Challenges and Benefits. In 2024 IEEE International Conference on Communication, Computing and Signal Processing (IICCCS) (pp. 1-6). IEEE.

[25] Monika, Bhatia, R., Jain, A., & Singh, B. (2022). Hash time locked contract based asset exchange solution for probabilistic public blockchains. Cluster Computing, 25(6), 4189-4201.

[26] Masood, F., & Faridi, A. R. (2024). Developing a novel blockchain-based vaccine tracking and certificate system: An end-to-end approach. Peer-to-Peer Networking and Applications, 17(3), 1358-1376.

[27] Dong, J., Xu, G., Ma, C., Liu, J., & Cliff, U. G. O. (2023). Blockchain-based certificate-free cross-domain authentication mechanism for industrial internet. IEEE Internet of Things Journal, 11(2), 3316-3330.

[28] Bonn-Dataset, (2024), available online [http://epileptologie-bonn.de/cms/upload/workgroup/lehnertz/eegdata.html, Accessed:16/8/2024]

[29] Zhao, W., Zhao, W., Wang, W., Jiang, X., Zhang, X., Peng, Y., & Zhang, G. (2020). A novel deep neural network for robust detection of seizures using EEG signals. Computational and mathematical methods in medicine, 2020(1), 9689821.

[30] Mursalin, M., Zhang, Y., Chen, Y., & Chawla, N. V. (2017). Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier. Neurocomputing, 241, 204-214.

[31] Ilakiyaselvan, N., Khan, A. N., & Shahina, A. (2020). Deep learning approach to detect seizure using reconstructed phase space images. Journal of biomedical research, 34(3), 240.

[32] Dong, J., Xu, G., Ma, C., Liu, J., & Cliff, U. G. O. (2024). Certificate-free cross-domain fine-grained access control mechanism for industrial internet. Human-centric Computing and Information Sciences (HCIS), 14.

[33] Xu, G., Ren, T., Chen, Y., & Che, W. (2020). A one-dimensional CNN-LSTM model for epileptic seizure recognition using EEG signal analysis. Frontiers in neuroscience, 14, 578126.

[34] Xu, X., Zhang, Y., Zhang, R., & Xu, T. (2023). Patient-specific method for predicting epileptic seizures based on DRSN-GRU. Biomedical Signal Processing and Control, 81, 104449.

[35] Ramos-Aguilar, R., Olvera-López, J. A., Olmos-Pineda, I., & Sánchez-Urrieta, S. (2020). Feature extraction from EEG spectrograms for epileptic seizure detection. Pattern Recognition Letters, 133, 202-209.

[36] Siuly, S., Alcin, O. F., Bajaj, V., Sengur, A., & Zhang, Y. (2019). Exploring Hermite transformation in brain signal analysis for the detection of epileptic seizure. IET Science, Measurement & Technology, 13(1), 35-41.

[37] Deng, Z., Xu, P., Xie, L., Choi, K. S., & Wang, S. (2018). Transductive joint-knowledge-transfer TSK FS for recognition of epileptic EEG signals. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 26(8), 1481-1494.

[38] Song, J. L., Hu, W., & Zhang, R. (2016). Automated detection of epileptic EEGs using a novel fusion feature and extreme learning machine. Neurocomputing, 175, 383-391.

[39] Wang, L., Xue, W., Li, Y., Luo, M., Huang, J., Cui, W., & Huang, C. (2018). Automatic epileptic seizure detection in EEG signals using multi-domain feature extraction and nonlinear analysis. Entropy, 19(6), 222.

[40] Khattak, M. I., Shahrestani, S., & ElKhodr, M. (2025). The application of deep learning for classification of Alzheimer's disease stages by magnetic resonance imaging data. IJIMAI, 9(2), 18-25.

[41] Chen, F., Tang, Y., Wang, C., Huang, J., Huang, C., Xie, D., Wang, T., & Zhao, C. (2022). Medical cyber-physical systems: A solution to smart health and the state of the art. IEEE Transactions on Computational Social Systems, 9(5), 1359–1386.

[42] Li, P., Abdel-Aty, M., & Yuan, J. (2020). Real-time crash risk prediction on arterials based on LSTM-CNN. Accident Analysis & Prevention, 135, 105371.

[43] heng, X., Chen, F., Xie, D., Sun, H., & Huang, C. (2020). Design of a secure medical data sharing scheme based on blockchain. Journal of Medical Systems, 44(52).

[44] Kumar, P., & Singh, A. (2023). COVID-19 disease prediction using weighted ensemble transfer learning. IJIMAI, 8(1), 13-22.

[45] Ali, O. M. A., Kareem, S. W., & Mohammed, A. S. (2022, February). Evaluation of electrocardiogram signals classification using CNN, SVM, and LSTM algorithm: A review. In 2022 8th International Engineering Conference on Sustainable Technology and Development (IEC) (pp. 185-191). IEEE.

[46] Onik, M. M. H., Aich, S., Yang, J., Kim, C. S., & Kim, H. C. (2019). Blockchain in healthcare: Challenges and solutions. In Big data analytics for intelligent healthcare management (pp. 197-226). Academic Press.

[47] Alam, M. T., & Raza, K. (2021). Blockchain technology in healthcare: making digital healthcare reliable, more accurate, and revolutionary. In Translational Bioinformatics in Healthcare and Medicine (pp. 81-96). Academic Press.

[48] Nasreddine, Wassim (2021), "Epileptic EEG Dataset", Mendeley Data, V1, doi: 10.17632/5pc2j46cbc.1

[49] Ead, W. M., Mohamed, H., Nasr, M., & Anter, A. M. (2023). Recent Advanced in Healthcare Data Privacy Techniques. In Nature-Inspired Methods for Smart Healthcare Systems and Medical Data (pp. 207-225). Cham: Springer Nature Switzerland.

[50] Kennedys. (2021, October). The dangers of accessing health records without consent. Retrieved from [https://kennedyslaw.com/en/thought-leadership/article/the-dangers-of-accessing-health-records-without-consent/]

[51] Ali, A. R., Couceiro, M. S., Anter, A. M., & Hassanian, A. E. (2014). Evaluating an evolutionary particle swarm optimization for fast fuzzy c-means clustering on liver ct images. In Computer Vision and Image Processing in Intelligent Systems and Multimedia Technologies (pp. 1-21). IGI Global.

[52] Abdi, H., & Williams, L. J. (2010). Tukey's honestly significant difference (HSD) test. Encyclopedia of research design, 3(1), 1-5.
[53] Peng, C. Y. J., & Chen, L. T. (2014). Beyond Cohen's d: Alternative effect size measures for between-subject designs. The Journal of Experimental Education, 82(1), 22-50.
[54] Hazra, A. (2017). Using the confidence interval confidently. Journal of thoracic disease, 9(10), 4125.