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Theme :

Automated Epilepsy Seizure Detection in Pediatric Using Machine Learning

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Abstract

Epilepsy is a prevalent neurological disorder marked by recurrent and unpredictable seizures. In pediatric patients, early and accurate detection is critical to enabling timely medical intervention and improving long-term health outcomes. This thesis presents the development of an automated system for epileptic seizure detection in children using machine learning techniques. The proposed approach leverages a one-dimensional convolutional neural network (1D-CNN) model to analyse and classify CHB-MIT EEG data for the detection of ictal events. The system demonstrates high performance, achieving an accuracy of 97%, sensitivity of 97.03% and specificity of 96.83%. These results indicate the model's strong ability to distinguish between ictal and preictal states, with a low false positive rate (3.17%) and false negative rate (2.97%). The results are promising and highlight the potential of the proposed system in supporting pediatric seizure detection.

Keywords: Epilepsy, Seizure detection, Machine learning, CHB-MIT EEG Dataset, Convolutional Neural Network, Intelligent system.

Résumé

L'épilepsie est un trouble neurologique prévalent caractérisé par des crises récurrentes et imprévisibles. Chez les patients pédiatriques, une détection précoce et précise est cruciale pour permettre une intervention médicale rapide et améliorer les pronostics à long terme. Ce mémoire présente le développement d'un système automatisé de détection des crises d'épilepsie chez l'enfant utilisant des techniques d'apprentissage automatique. L'approche proposée exploite un réseau de neurones convolutif unidimensionnel (1D-CNN) pour analyser et classer les données EEG de la base CHB-MIT en vue d'identifier les états critiques (ictaux). Le système démontre des performances élevées, atteignant 97% de précision, 97,03% de sensibilité et 96,83% de spécificité. Ces résultats indiquent une capacité robuste du modèle à distinguer les états critiques des états pré-critiques (préictaux), avec un taux de faux positifs (TFP) de 3,17% et un taux de faux négatifs (TFN) de 2,97%. Les resultats sont prometteurs et soulignent le potentiel du système proposé pour soutenir la detection des crises d'épilepsie chez les enfants.

Mots-clés: Épilepsie, Détection de crises, Apprentissage automatique, Base de Données EEG CHB-MIT, Réseau de neurones convolutif, Système intelligent.

الملخص

الصرع هو اضطراب عصبي شائع يتميز بحدوث نوبات متكررة وغير متوقعة. لدى المرضى الأطفال، تُعدّ عملية الكشف المبكر والدقيق عن النوبات أمرًا بالغ الأهمية من أجل تمكين التدخل الطبي السريع وتحسين التوقعات طويلة المدى. يقدم هذا العمل تطوير نظام آلي للكشف عن نوبات الصرع لدى الأطفال باستخدام تقنيات التعلم الآلي. تعتمد الطريقة المقترحة على شبكة عصبية التفافية أحادية البُعد (1D-CNN) لتحليل وتصنيف إشارات تخطيط الدماغ الكهربائي (EEG) من قاعدة بيانات CHB-MIT بهدف التعرف على الحالات الحرجة (النوبات). أظهر النظام أداءً عاليًا، حيث بلغ معدل الدقة 97٪، والحساسية 97.03٪، والنوعية 96.83٪. وتُشير هذه النتائج إلى قدرة قوية للنموذج في التمييز بين الحالات الحرجة والحالات السابقة للنوبات (ما قبل النوبة)، مع معدل إيجابيات كاذبة (FPR) يبلغ 3.17٪ ومعدل سلبيات كاذبة (FNR) يبلغ 2.97٪. تُعد هذه النتائج مشجعة وتؤكد على إمكانيات النظام المقترح في دعم عملية كشف نوبات الصرع لدى الأطفال.

الكلمات المفتاحية: الصرع، كشف النوبات، التعلم الآلي، قاعدة بيانات EEG CHB-MIT، الشبكات العصبية الالتفافية، النظام الذكي.

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List of Abbreviations

WHO	World Health Organisation
SUDEP	Sudden Unexpected Death in Epilepsy
EEG	Electroencephalography
Ag/AgCl	Silver/Silver Chloride
HR	Heart Rate
EDA	Electrodermal Activity
EMG	Surface Electromyography
IEDs	Interictal Epileptiform Discharges
ML	Machine Learning
CHB-MIT	Children's Hospital Boston – Massachusetts Institute of Technology
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
FPR	False Positive Rate
FNR	False Negative Rate
AUC-ROC	Area Under the Curve – Receiver Operating Characteristic
FA/h	False Alarm Rate per Hour
DL	Deep Learning
ApEn	Approximate Entropy
FuzzyEn	Fuzzy Entropy
DWT	Discrete Wavelet Transform
SVM	Support Vector Machine
RF	Random Forest

k-NN	k-Nearest Neighbour
DNN	Deep Neural Network
CNN	Convolutional Neural Network
FBCSP	Filter Bank Common Spatial Pattern
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
1D-CNN	One-Dimensional Convolutional Neural Network
STFT	Short-Time Fourier Transform
ReLU	Rectified Linear Unit)
Adam	Adaptive Moment Estimation
AUC	Area Under the Curve
SSD	Solid State Drive
TPU	Tensor Processing Unit
RAM	Random Access Memory
CSV	Comma-Separated Values
NumPy	Numerical Python
pandas	Python Data Analysis Library
ROC	Receiver Operating Characteristic

General Introduction

Epilepsy is a health condition that mainly affects children and can cause seizures at any time. These seizures come without warning and can be dangerous if they last a long time or happen frequently. They affect a child's daily life and may put their health and future at risk. It is very important to find a way to detect seizures quickly and accurately so we can help children in time and avoid complications.

Doctors usually use EEG signals to check the activity of the brain and detect seizures. But looking at all these signals manually is hard and tiring, and it can lead to mistakes. To solve this, many methods have been developed to help doctors find seizures automatically. Some methods rely on classical techniques, while others use more advanced approaches to improve the accuracy of detection.

Machine learning and deep learning methods have become a popular way to solve this problem because they can learn directly from signals. Among these methods, Convolutional Neural Networks (CNNs) are especially useful. They can find patterns in signals that may be hard for a person to see. Instead of relying on manual feature selection, a CNN model can automatically learn relevant features directly from raw signals. This approach increases flexibility and reduces the risk of human bias.

The aim of this project is to develop a 1D Convolutional Neural Network (1D-CNN) model for the automatic classification of seizure and non-seizure signals in children with epilepsy. The approach is designed to be simple, accurate, and reliable. It focuses on 1D signals, which makes it faster and more efficient. The 1D-CNN model is trained and tested on the CHB-MIT pediatric epilepsy database. The results show that this method performs very well in distinguishing ictal (seizure) from preictal(before seizure) signals. This could be a useful tool for doctors and health care providers to make decisions more quickly and with greater confidence.

This document is divided into three main chapters:

- Chapter 1: Gives an overview of epilepsy, its effects on children, and the role of EEG signals in detecting seizures. It also highlights the main problems with manual detection and the need for automated methods.
- Chapter 2: Reviews related methods and techniques that have been used to identify seizures in children. It covers classical methods and more recent techniques based on deep learning, and points out their strong points and weaknesses.
- Chapter 3: Presents the methodology and implementation of the 1D-CNN approach we propose. It describes the CHB-MIT dataset we used, the steps we followed to prepare and split the data, the model architecture, the training process, and the results obtained . Finally, it shows how well the model performs in distinguishing ictal from preictal signals and highlights the main achievements of this approach.

Finally, the conclusion summarises the main results of this master thesis and suggests future directions for improving the system.

Chapter 1

Overview of Epileptic Seizure Detection

1 Introduction

Epilepsy is a common chronic neurological disorder defined by the World Health Organisation (WHO) as the occurrence of two or more unprovoked seizures. It affects an estimated 50 million people worldwide and an estimated 0.5–1% of children [W1][1]. Seizures are paroxysmal manifestations of abnormal, excessive neuronal activity, leading to varying motor, sensory or cognitive manifestations. A child with epilepsy can have problems with cognition and learning above what is accounted for by chance. Early detection of seizures in kids is therefore extremely crucial since ongoing uncontrolled seizures in an immature brain can both impair cognition and normal development[W1][2]. A general overview of epilepsy in children is presented, with a focus on how seizures can be recognised and understood. The goal is to build a basic understanding of the different types of seizures that affect children, how EEG is used in clinical practice to detect them, how electrodes are placed using the 10–20 system, and how seizure phases appear in EEG recordings. The explanation also includes other physiological signals that can support diagnosis, the common methods used by doctors to read EEGs, and some of the challenges faced when relying only on traditional approaches. This background helps prepare for a better understanding of how newer technologies, can support seizure detection more effectively.

2 Pediatric Epilepsy

2.1 Definition

"Pediatric epilepsy" refers broadly to epilepsies with onset in infancy, childhood or adolescence. In practice, it is defined the same way as adult epilepsy: a neurological disorder characterised by recurrent, unprovoked seizures that arise from abnormal, excessive electrical discharges among neurons and manifest as brief episodes of involuntary movements or altered consciousness[W1][3].

2.2 Types of Seizures in Pediatric Patients

Epileptic seizures in children can be broadly classified into focal, generalised, and unknown onset seizures[4], each with distinct features and management considerations(figure 1.1 [4]).

- **Focal seizures:** originates in a specific brain region. It can occur with or without impaired awareness. When awareness is preserved, they are referred to as focal aware seizures, previously known as simple partial seizures, and often present with localised motor or sensory symptoms. If consciousness is altered, they are termed focal impaired awareness seizures, formerly complex partial seizures, and may involve automatisms such as lip-smacking or hand movements[5] [4].
- **Generalized Seizures:** Typically results in immediate loss of awareness. These include generalised tonic–clonic seizures, which are characterised by an initial phase of muscle stiffening followed by rhythmic jerking movements, and absence seizures, which involve brief lapses in awareness often seen as staring spells in children. Other forms include myoclonic seizures, marked by sudden, brief muscle jerks, and atonic seizures, which cause a sudden loss of muscle tone leading to falls or head drops. Tonic seizures involve sustained muscle contractions and are frequently observed during sleep[5] [4].
- **Seizures of Unknown Onset:** These are seizures where the beginning is not observed or cannot be determined—for example, events occurring during sleep or unwitnessed episodes. They may later be reclassified as focal or generalised if more information becomes available[5] [4].

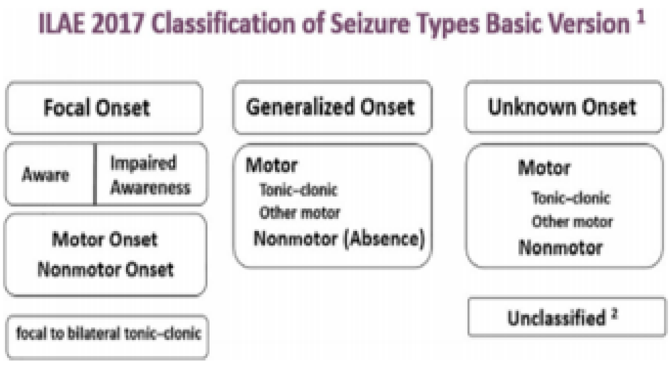

Figure 1.1: The 2017 International League Against Epilepsy classification of seizure types.

3 Seizure Detection: What and Why?

An epileptic seizure is a transient episode of abnormal electrical activity in the brain. Seizure detection refers to identifying such events from patient monitoring data (typically EEG(section 4) signals), including the exact time of seizure onset, where possible, and the type of seizure. In practice, detection means distinguishing the abnormal ictal EEG (section 4) patterns of a seizure from normal activity. Automated detection systems aim to provide reliable, objective records of each seizure's frequency, duration, and type[6]. This automated documentation is critical because patient or caregiver seizure logs are often incomplete; in fact, studies show that many seizures are not reported without such devices [6][7]. In short, seizure detection systems scan EEG (section 4) (and sometimes other physiological signals) to mark when an epileptic seizure begins and classify its characteristics, producing accurate seizure counts that aid clinical care and research[6][8].

Detecting seizures in real time is important for safety and medical management. Timely alerts of seizure onset allow caregivers to intervene immediately (for example, by positioning the patient safely), which can greatly reduce the risk of falls, drowning, or other trauma. Because people with epilepsy – especially children – have a greatly increased risk of sudden unexpected death in epilepsy (SUDEP), seizure alarms may also help by ensuring that convulsive seizures are not left unattended. In addition, automatic seizure detection provides clinicians with precise seizure logs: objective records of seizure frequency and type are essential for accurate diagnosis, treatment planning, and evaluation of therapy effectiveness[6][7].

4 EEG in Pediatric Seizure Detection

Electroencephalography (EEG) is a non-invasive method that records the brain's electrical activity through electrodes on the scalp. Scalp EEG primarily measures the summed postsynaptic potentials of large groups of cortical pyramidal neurons oriented perpendicularly to the surface. The raw EEG trace plots voltage (on the vertical axis) over time (horizontal axis) for each channel[9].

4.1 EEG Placement and Channels (10–20 Electrode System)

In pediatric EEG, the electrodes are placed on the scalp using the International 10-20 system. Typically, 21-256 electrodes made of silver/silver chloride (Ag/AgCl) are used. One electrode serves as the reference, and another as the ground, ensuring that common-mode interference is minimised [10]. These electrodes are placed in specific regions of the scalp to measure electrical activity from different brain lobes. They are labeled by brain region[11]: Fp (frontopolar), F (frontal), C (central), P (parietal), O (occipital), T (temporal). Odd numbers denote left-sided electrodes and even numbers right-sided, with midline positions labelled with "z" (e.g. Fz, Cz). Ear (A1, A2) (figure 1.2[8]). This placement allows clinicians to determine which parts of the brain are involved in seizure activity [11][9].

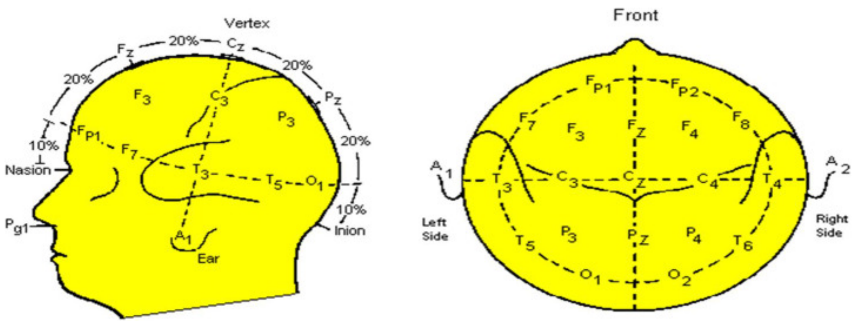

Figure 1.2: 10–20 International system for Electrode Placement

4.2 Seizure Phases on EEG

A seizure is often divided into four phases[12](figure 1.3): the preictal, ictal, postictal, and interictal periods.

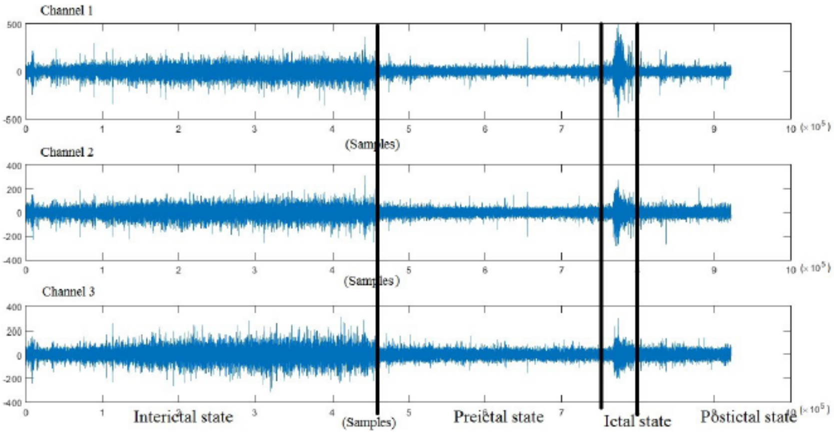

Figure 1.3: Interictal, Preictal, Ictal and Post-ictal States of Seizures from 3 Channels; Each recorded for 1 Hour

- **Preictal Phase:** refers to the period leading up to the seizure(30 to 90 minutes before)(figure 1.4[12]).

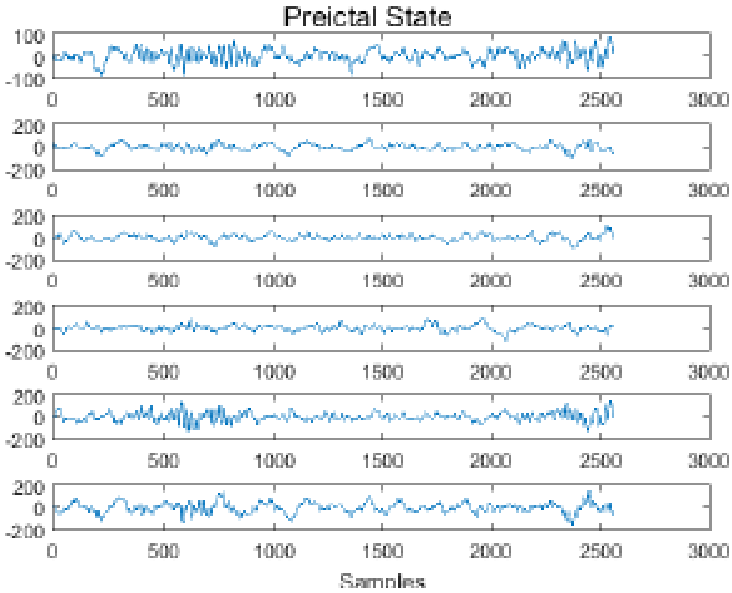

Figure 1.4: Preictal State.

- **Ictal Phase:** The ictal phase represents the period during which the seizure occurs. On EEG, ictal activity is characterised by evolving rhythmic discharges that grow in frequency and amplitude[13](figure 1.4[12]).

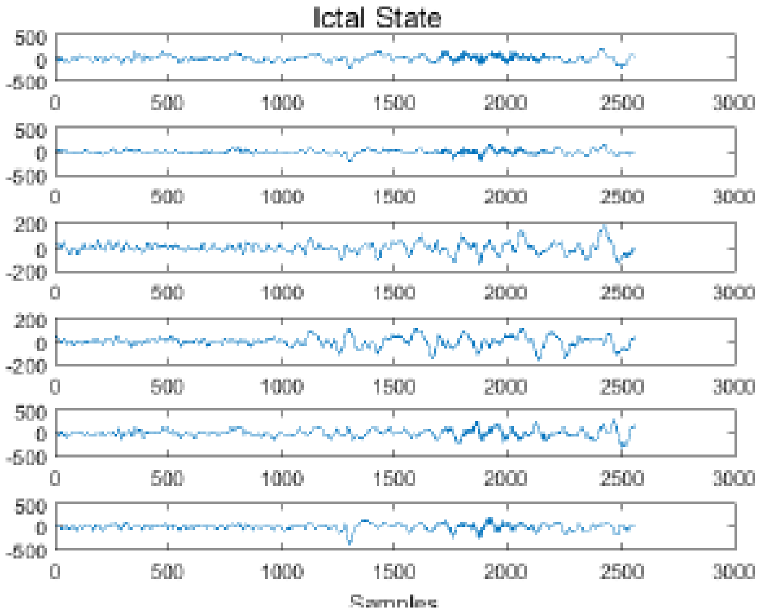

Figure 1.5: Ictal State.

- **Postictal Phase:** the phase that follows the seizure. Marks the end of ictal electrical activity on EEG, lasting between 5 and 30 minutes [14].
- **Interictal Phase:** is the period between seizures, during which the EEG may nevertheless display epileptiform discharges, so the child is seizure-free in this phase[13].

5 Physiological Indicators for Seizure Detection

Beyond EEG, seizures induce characteristic changes in autonomic and motor physiology. These indicators can be exploited by wearables and automated systems.

- **Heart rate (HR)** often increases during seizures; meta-analyses show that over half of seizures cause a change in HR [7][15].
- **Skin conductance (electrodermal activity EDA)** rises when sympathetic arousal increases sweating. Studies of wearable EDA sensors have noted sharp surges in skin conductance at the onset of generalised seizures[15].
- **Surface electromyography (EMG)** detects muscle electrical signals through surface electrodes, which are adhesive patches applied to the skin over the muscles [15].
- **accelerometers/gyroscopes** capture rhythmic shaking movements of convulsions. Respiratory patterns also change during seizures. Many focal seizures can produce central apnea or irregular breathing[16]

6 Limitations of Manual EEG Review for seizure detection

Clinicians traditionally identify seizures by visually inspecting the scalp EEG for characteristic waveforms. In practice, they look for interictal epileptiform discharges (IEDs),brief sharp waves or spike-and-wave complexes that occur between seizures and for ictal EEG patterns, which are evolving rhythmic discharges appearing during a seizure[17][13]. For example, an interictal spike typically has a pointed peak followed by a slower "negative" after-wave, and is often asymmetric compared to the background rhythm. A focal spike will produce a clear phase reversal (polarity inversion) between adjacent electrodes, indicating the underlying source location[17]. In contrast, an ictal rhythm may begin as a sudden build-up of rhythmic waves that change in amplitude or frequency over several seconds, reflecting the spread of the seizure. Clinicians use these EEG features to confirm and classify seizure activity[13].

Despite its clinical value, manual EEG interpretation has serious drawbacks. It is extremely time-consuming and labour-intensive [18]. A single long-term EEG study may last more than a day, and a neurologist must scan through many data channels, often with only one or two seizures in the recording. In addition, visual interpretation remains subjective. Even skilled experts can disagree: subtle normal variants or artefacts are sometimes misread as epileptiform spikes. Such over-interpretation is common enough to cause misdiagnosis; studies report that up to a quarter of patients referred to epilepsy centres were ultimately found not to have epilepsy due to EEG overreading. In short, reading EEGs by eye is an "art rather than a science", and errors can occur. [17]. Consequently, manual detection is not ideal for continuous monitoring outside the lab or for real-time seizure detection.

7 Motivation for Machine Learning–Based Detection

The burdens of manual EEG review motivate for automated methods. Machine learning (ML) offers a way to augment the neurologist by automatically scanning EEG for seizure patterns. ML-based detectors can be trained on examples of interictal spikes and ictal EEG so that they learn the complex features of pediatric seizures without needing explicit programming. In effect, an ML algorithm could serve as a continuous "assistant" to flag suspicious EEG activity. Such automated systems have already emerged as powerful tools in EEG analysis[18] [19]. Overall, machine learning is seen as a way to overcome the constraints of manual review and to support real-time, ambulatory seizure detection in children, potentially alerting interventions or signalling clinicians as events happen.

8 Conclusion

Epilepsy in children is a chronic neurological condition where seizures happen without warning. This chapter gave a general introduction to seizure detection by explaining how seizures are recognised and why this is important in everyday medical care. Detecting seizures properly helps keep children safe by allowing quick responses, and it also gives doctors a clear picture of how often seizures happen and what kind they are. In children, this is especially important, as early and accurate monitoring can support better development and help avoid serious risks. The next chapter looks into how artificial intelligence can be used to improve seizure detection.

Chapter 2

Techniques for the Detection of Epileptic Seizures in Children: A Comprehensive Review

1 Introduction

Seizure disorders constitute a major cause of referral to pediatric neurology clinics, with epilepsy syndromes especially prevalent in younger children [20]. Attacks in this population often occur without warning and can range from brief electrical discharges to full convulsive episodes [21]. EEG serves as a valuable tool, offering supportive evidence for seizure classification [20], but noise and variability make it difficult to differentiate between ictal and preictal EEG patterns. Detecting seizures quickly and accurately can help doctors or caregivers respond in time, reducing the risk of complications or harm, lessening the chances of morbidity or harm. In preparation for backing automated monitoring devices, most studies cast the issue as a two-class classification problem: distinguishing between ictal and preictal (or interictal) EEG states[22]. The sections that follow introduce the main EEG datasets commonly used in seizure detection research, along with the key metrics applied to evaluate model performance. An overview of artificial intelligence techniques used in detecting epileptic seizures is also provided. Lastly, a review of related work highlights existing methods and their outcomes, offering context for the current study.

2 Overview of Key Datasets

Several datasets are commonly utilised in the study of epileptic seizure detection. They differ in data modalities, acquisition protocols, patient populations, and accessibility. These datasets serve as standard benchmarks in the field and are widely used for model development, evaluation, and comparative analysis of detection techniques.

- Bonn: The Bonn EEG dataset, published in 2001 by Andrzejak et al.[23], contains five sets of EEG recordings, each with 100 segments of 23.6 seconds. Sets A and B were recorded from healthy subjects using surface EEG (eyes open and eyes closed). Sets C, D, and E were recorded intracranially from epilepsy patients: set C from non-epileptogenic zones, set D from the epileptogenic zone during seizure-free intervals, and set E during seizures. All segments were selected for weak stationarity and are free of artifacts, providing a balanced and structured dataset for analysing brain activity in different conditions[23].

- Freiburg Epilepsy (Invasive EEG): [W3] An earlier dataset (available via the Freiburg Seizure Prediction project) comprising intracranial EEG from 21 epilepsy surgery candidates . For each patient, there are "ictal" files containing seizures plus 50 min of preictal EEG, and "interictal" files (24h) without seizures . Signals were recorded at 256Hz from 128 intracranial contacts (grids, strips, depths). Unlike scalp EEG, these invasive recordings have high signal quality from seizure foci. However, access is limited (superseded by a purchasable database), and patient count is smaller[W3].

- CHB-MIT Scalp EEG: A widely-used public dataset (PhysioNet). It contains scalp EEG from 23 pediatric patients with medically intractable epilepsy [W2]. Each patient was recorded over several days (anti-seizure drugs withdrawn) using 23 scalp electrodes at 256Hz. The data include 173 seizure events across 916 hours of EEG[24]. This dataset is heavily imbalanced: interictal (normal) EEG vastly outnumbers ictal epochs.

- CHB-MIT Preprocessed EEG DatasetThe dataset is a preprocessed version of the CHB-MIT Scalp EEG Database, made publicly available by Deepa and Ramesh (2022)[25]. It is designed to support epileptic seizure detection and prediction using machine learning and deep learning models. A total of 4096 seconds (approximately 68 minutes) of EEG data were extracted for both ictal (seizure) and preictal (pre-seizure) states for each of the 24 patients. The final dataset is balanced, containing equal durations of preictal and ictal data. It is provided in .csv format, which simplifies data manipulation and model implementation. Several versions of the dataset are available, including raw ictal and preictal files with 96 EEG channels, reduced versions containing only 23 channels, and a consolidated file that includes both classes with a binary outcome column where '0' denotes preictal and '1' denotes ictal data[25].

Table 2.1 summarises commonly utilised datasets in epileptic seizure detection:

Dataset	Year	Description	Components	Subjects	Data Balance
Bonn [23]	2001	Contains EEG segments from both healthy subjects and epilepsy patients in different brain states.	5 datasets (labelled A–E), each with 100 single-channel EEG segments of 23.6 seconds (173.61 Hz sampling)	- Sets A & B: 5 healthy volunteers - Sets C, D & E: 5 epilepsy patients	- Set A: Surface EEG (eyes open) - Set B: Surface EEG (eyes closed) - Set C: Intracranial EEG from non-epileptogenic zone (seizure-free) - Set D: Intracranial EEG from epileptogenic zone (seizure-free) - Set E: Intracranial EEG during ictal (seizure) state. Each set is balanced (100 segments).
Freiburg Epilepsy [W3]	2005 (discontinued)	Invasive intracranial EEG from Freiburg for pre-surgical epilepsy	Intracranial EEG (grid/strip electrodes, 128 channels, 256Hz)	21 adult patients (focal epilepsy)	Ictal and interictal data: ∼50min preictal per ictal file, 24+ hours interictal per patient
CHB-MIT Scalp EEG[W2]	2010	Pediatric long-term EEG from Children's Hospital Boston (CHB)	Scalp EEG (23 channels, 256Hz sampling)	23 children (1.5–22 years old)	Highly imbalanced: few seizure segments vs. much interictal EEG
CHB-MIT Preprocessed [25]	2022	Preprocessed CHB-MIT EEG data for seizure detection and prediction using ML/DL models; provided in .csv format	5 files: ictal/preictal raw (96 ch), ictal/preictal (23 ch), preprocessed balanced (23 ch + label); + metadata sheets and 278 segmented files	24 pediatric patients	Balanced (4096 seconds each of preictal and ictal data)

Table 2.1: Overview of Key Datasets.

The CHB-MIT Scalp EEG dataset is a widely used benchmark for pediatric seizure detection. It is freely available and specifically collected from children with epilepsy, which makes it especially relevant for research in this area. Many machine learning and deep learning methods rely on CHB-MIT to train and evaluate seizure classification models. Although there is a class imbalance since seizure events are rare compared to normal EEGs, the dataset remains one of the largest public pediatric EEG collections, with recordings from 23 cases. Its frequent use in the literature highlights its importance, as seen in many studies that cite it as the main data source [24]. For studies focusing on ictal versus preictal classification, using a preprocessed version of CHB-MIT is especially useful. This version provides balanced data for both classes, simplified in CSV format, and is ready for use in machine learning or deep learning models without the need to manually extract or annotate seizure segments.

3 Evaluation Metrics for Epileptic Seizure Detection

Evaluating the performance of a seizure detection model is an essential step to understand how well the model works and whether it can be used in real-world applications. Several metrics are used to measure how accurately the model can classify seizures and non-seizures. These metrics are based on four main outcomes from the confusion matrix:

- **True Positive (TP)**: The model correctly predicted a seizure (ictal period).
- **True Negative (TN)**: The model correctly predicted a non-seizure (preictal or interictal period).
- **False Positive (FP)**: The model predicted a seizure, but it was actually a non-seizure (false alarm).
- **False Negative (FN)**: The model failed to detect a seizure and predicted a non-seizure instead (missed seizure).

Confusion Matrix

	Predicted: Non-Seizure	**Predicted: Seizure**
Actual: Non-Seizure	True Negative (TN)	False Positive (FP)
Actual: Seizure	False Negative (FN)	True Positive (TP)

Table 2.2: Confusion Matrix.

Accuracy

Accuracy measures the proportion of total correct predictions made by the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2.1}$$

This metric shows how often the model is correct overall. However, accuracy alone is not reliable when the dataset is imbalanced.

Recall (Sensitivity)

Recall, also called sensitivity or true positive rate, measures the model's ability to detect actual seizures.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2.2}$$

High recall means the model is good at detecting most seizures and is less likely to miss them.

Precision

Precision measures how many of the predicted seizures are actual seizures.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2.3}$$

High precision means the model generates fewer false alarms.

F1-Score

The F1-score is the harmonic mean of precision and recall. It balances both values and is especially useful when the dataset is imbalanced.

$$\text{F1\_Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2.4}$$

Specificity

Specificity is the true negative rate. It measures how well the model avoids false seizure predictions.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{2.5}$$

False Positive Rate (FPR)

This shows how often the model raises a false alarm.

$$\text{FPR} = \frac{FP}{FP + TN} \tag{2.6}$$

False Negative Rate (FNR)

This shows how often the model misses a real seizure.

$$\text{FNR} = \frac{FN}{FN + TP} \tag{2.7}$$

AUC-ROC (Area Under the Curve - Receiver Operating Characteristic)

This score represents the model's ability to distinguish between seizure and non-seizure classes. It ranges from 0 to 1. A value close to 1 indicates good classification performance.

False Alarm Rate per Hour (FA/h)

In seizure detection systems that work in real time, the false alarm rate per hour is important. It is calculated as:

$$\text{FA/h} = \frac{\text{Number of False Alarms}}{\text{Total Monitoring Hours}} \tag{2.8}$$

This metric helps evaluate the system's reliability over time, especially for wearable devices or long-term monitoring systems.

4 Overview of AI Techniques in Epileptic Seizure Detection

Epileptic seizure detection has been significantly advanced by intelligent systems powered by artificial intelligence, enabling researchers to extract valuable insights from complex neurological data and accurately anticipate seizure onset. This section presents widely used AI techniques that have demonstrated effectiveness in modeling the dynamic patterns of brain activity, with a specific focus on detecting seizures in pediatric patients.

4.1 Classical EEG-based Seizure Detection Methods

Traditional (non-ML, non-DL) epileptic seizure detection techniques use hand-designed signal features and thresholds rather than learned models. Some examples are amplitude thresholding, spectral (Fourier) analysis, entropy measures (e.g., approximate and fuzzy entropy), and wavelet transforms. All of these methods compute a distinctive statistic on EEG segments that tends to distinguish ictal (seizure) from interictal (non-seizure) states

- **Amplitude thresholding:**is a simple time-domain rule that flags EEG events when the signal amplitude exceeds a set threshold. In practice, the mean or background level of the EEG is first estimated (for example by averaging absolute amplitudes), and any waveform with peak amplitude several times the background is considered a spike or seizure activity. Ardalan et al. famously used a threshold of about four times the baseline amplitude to identify epileptic spikes . In ictal EEG, large synchronous discharges produce high-amplitude deflections, so amplitude thresholding tends to capture those events while rejecting lower-voltage interictal background[26].

- **Spectral analysis (Fourier power):** converts EEG epochs into the frequency domain to examine power at different frequencies . In essence, the Fast Fourier transform (FFT) is applied to compute the power spectral density of each EEG window. Seizures often produce characteristic spectral signatures (e.g. increased power in slow-wave bands or emergence of rhythmic oscillations) that differ from the interictal background. Classical Fourier-based detectors might, for example, compute band-power ratios or identify peak frequencies that rise during seizures. (Because EEG is non-stationary, many approaches use short-window FFT or moving-window spectrograms)[27]. Briefly, spectral features capture the redistribution of EEG power that accompanies ictal onset, enabling discrimination of seizure epochs by their frequency content.

- **Entropy measures:** Quantify the irregularity or complexity of an EEG signal. Approximate entropy (ApEn) measures the predictability of a time series: it computes the likelihood that similar waveform patterns remain similar on the next sample [27]. Lower ApEn values indicate more regular (predictable) signals, whereas higher ApEn reflects greater randomness. Because seizure EEG can be more ordered (e.g. rhythmic spike-wave) or less predictable than interictal EEG, ApEn often changes between states [27]. In practice one computes ApEn on sliding windows of the EEG; ictal segments tend to have systematically different ApEn than background. Fuzzy entropy (FuzzyEn) is a related concept that applies fuzzy set theory to quantify sequence randomness. Like ApEn, FuzzyEn is higher when signal fluctuations are more irregular. Xiang et al [28] showed that FuzzyEn values differ markedly between seizure and non-seizure EEG.

- **Wavelet analysis:** rovides a multi-resolution time–frequency decomposition of EEG signals. A wavelet transform uses basis functions that are localized in both time and frequency [29] [30] . Unlike a fixed-window FFT, the discrete wavelet transform (DWT) adaptively uses long windows at low frequencies and short windows at high frequencies [30] . This allows transient epileptic patterns (which are non-stationary) to be captured effectively. In practice, the EEG is decomposed into several sub-bands by the wavelet filterbank, and features (such as sub-band energy or entropy) are extracted from each band. Several studies have shown that wavelet-based features are effective for seizure detection [29] . For instance, Faust et al. applied DWT-denoising and feature extraction to EEG and reported that the wavelet approach yielded very effective classification [31] . All in all, wavelet analysis yields a rich time-frequency feature set that can distinguish ictal rhythmic activity from background.

Despite their simplicity, these traditional methods can achieve high detection rates on benchmark data.For example, Alotaiby et al. (2017) used a histogram-based threshold method on multichannel scalp EEG and reported 97.1% sensitivity and 98.6% specificity in distinguishing ictal vs non-ictal segments. [32]. Hilbert–Huang transforms and other adaptive spectral methods have likewise been explored: Oweis et al. utilized Hilbert–Huang spectral amplitudes with statistical thresholds, yielding around 94% accuracy and specificity of 96%.[33].An early single-channel statistical algorithm that filtered and rectified the EEG signal and detected seizures via amplitude thresholds was developed by Satirasethawong et al . it achieved about 88.5% sensitivity on CHB-MIT data but still issued 0.18 false alarms per hour [34] . Such threshold-based detectors are computationally cheap and easy to implement, but they have limited sensitivity in noisy EEG and often generate many false positives in long-term recordings. Li et al. (2018) combined fuzzy entropy and distribution entropy on short-term EEG epochs and reported 92.8% accuracy (90.7% sensitivity, 96.0% specificity) for classifying ictal vs interictal segments [35]. This shows that entropy features can be quite effective. However, early entropy-based systems often depend sensitively on window length and can be computationally expensive. Other studies using wavelet or spectral features similarly report sensitivities and specificities typically well above 90% on public EEG databases [30] [28]. These results demonstrate that carefully chosen classical features can be very effective for seizure detection. However, such methods usually require hand-tuning of parameters and may be more sensitive to noise or patient variability than modern approaches.

4.2 Machine learning

Machine learning (ML) is "a branch of computer science that aims to learn patterns from data to improve performance at various tasks"[36]. In the context of EEG-based seizure detection, ML methods ingest numerical features (e.g. summary statistics of EEG segments) and build models to classify inputs into seizure vs. non-seizure states. A typical ML process can be organized as a pipeline of stages transforming raw data into predictions[37]. This pipeline usually includes steps such as data ingestion, preprocessing, model training, and prediction. For example, one common description breaks the pipeline into the following phases [37]:

- **Data Ingestion:**Raw data are collected and loaded into the system. For EEG, this means acquiring and formatting the recorded signals. Any manipulations (e.g. artifact removal) should be documented so that new data can pass through the same process reproducibly .
- **Preparation/Preprocessing:** The collected data are cleaned and transformed to make them suitable for modeling. This can include normalisation (scaling signals to a common range), handling missing values or artifacts, and ensuring the test data are processed in the same way as the training data.
- **Training:** A chosen learning algorithm is applied to the prepared training data to generate a predictive model. This often involves splitting the data further into a training set and a validation set. The model "learns" by adjusting its internal parameters to fit the training data, typically by minimising an error or loss function through optimization. During this phase, one often tries multiple algorithms and tunes hyperparameters (settings not learned by the algorithm itself) to improve performance.
- **Prediction:** Once the model is trained and tuned, it is used to make predictions on new data. A held-out test set (data never used in training or validation) provides an unbiased estimate of the model's true performance .

Briefly stated, a seizure detection machine learning pipeline may involve the collection of EEG data, its cleaning and formatting , splitting into training/validation/test subsets, training and tuning a classifier, and then evaluating its accuracy on held-out EEG recordings .

Key ML techniques, such as Support Vector Machine (SVM),Random Forest (RF) and k-nearest neighbor (k-NN) are the more commonly used techniques in epileptic seizure detection. The sub-sequent sections will provide brief descriptions of these most common machine learning systems[38].

4.2.1 Support Vector Machine (SVM)

Support Vector Machines (SVMs) are supervised learning classifiers used for both classification and regression tasks [39]. In essence, an SVM seeks the hyperplane that maximizes the margin between two classes in the feature space. The support vectors (the training samples closest to the decision boundary) uniquely determine this optimal hyperplane. Formally, given training examples with labels $y_i \in +1, -1$, the SVM solves a quadratic optimization to maximize the margin subject to correct classification (with slack variables for non-separable data). Nonlinear separations are handled via the kernel trick, which implicitly maps inputs into a higher-dimensional space (e.g. using radial-basis-function or polynomial kernels) so that a linear separator exists [39] (Figure 2.1[40]) .

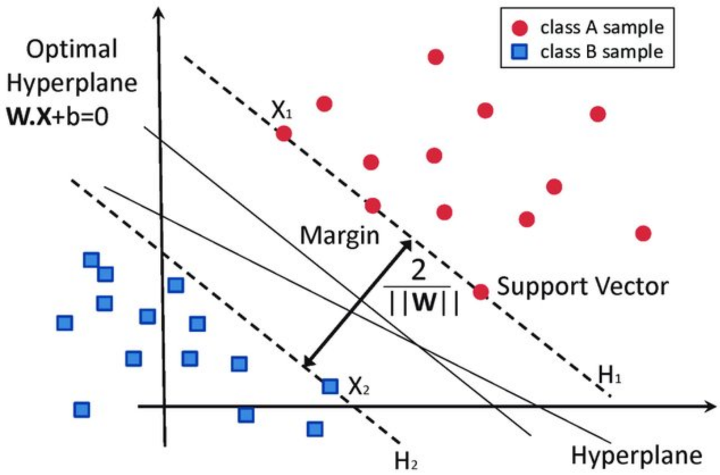

Figure 2.1: Linear SVM model .

In epileptic EEG analysis, SVMs have been widely adopted for seizure detection. After preprocessing and feature extraction (e.g. wavelet or spectral features, statistical measures), each EEG epoch is represented as a feature vector and fed to an SVM classifier. The SVM then labels the segment as "seizure" or "non-seizure" by checking on which side of the learned hyperplane it falls.Overall, the SVM's margin-maximization principle and kernel flexibility make it a powerful tool for automated seizure detection from EEG [39][41]. However, it has the disadvantage of being sensitive to the kernel function used. A good kernel must be chosen since it directly influences the model's capacity to model complicated relationships in the data. An unsuitable kernel will reduce performance and make tuning more difficult.[42]

4.2.2 Random Forest (RF)

Random Forest (RF) is an ensemble learning method that builds a collection ("forest") of decision trees and aggregates their predictions. As Breiman describes [43], *"random forests are a combination of tree predictors such that each tree depends on a random vector sampled independently and with the same distribution"*. In practice, RF training proceeds by bootstrap aggregating (bagging): for each tree, a random sample (with replacement) of the training data is drawn. Each decision tree is then grown by recursively splitting on features, but with an additional randomness: at each split, only a random subset of the feature set is considered(figure 2.2[W4]). This decorrelates the trees. Finally, all trees vote on the class label (majority vote for classification) for a new input. Steps of the application of RF to EEG data are as follows:

- Training (Bootstrap Sampling):Draw a bootstrap sample from the EEG training set.
- Tree Growing: Train a decision tree on that sample. At each node, select the best split only among a random subset of features[44]. Continue splitting until a stopping criterion (e.g. minimum node size) is reached.

- Voting: Repeat for many trees. For a test EEG epoch, each tree outputs a class; the RF outputs the class with the most votes. [44]

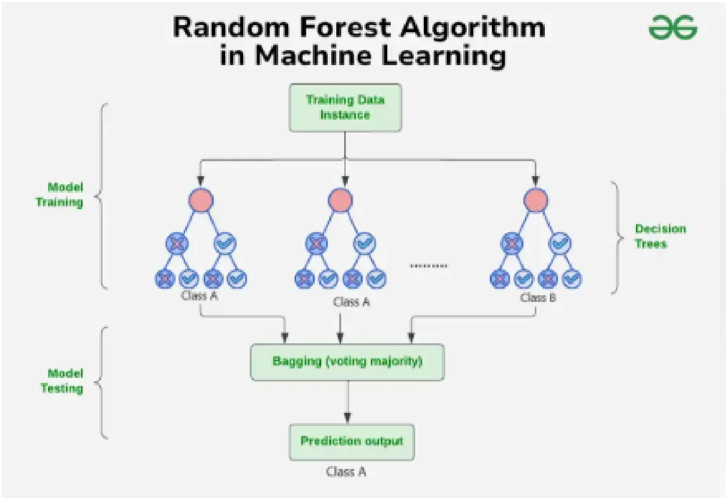

Figure 2.2: Random forest.

RF inherits the low bias of deep trees and reduces variance through averaging. It is well-suited to high-dimensional data [44]. It also implicitly provides estimates of feature importance. Importantly, RF tends to be robust to noise and overfitting; Breiman notes that RF error rates are "more robust with respect to noise" compared to some alternatives[43]. In EEG seizure detection, Random Forest has been applied with success. After extracting features (spectral band powers, entropy measures, etc.), the RF classifier can capture complex, nonlinear patterns across multiple EEG channels. Overall, RF's ensemble mechanism provides high accuracy and generalization in seizure detection tasks, making it a popular choice in recent literature [44],[41].

4.2.3 k-Nearest Neighbor (k-NN)

The k-Nearest Neighbor (k-NN) classifier is a simple, non-parametric method that makes predictions based directly on the training data[45]. It operates under the principle of instance-based learning: to classify a new sample, it finds the k closest training samples (neighbors) in feature space and assigns the most common class label among them. Mathematically, given a test vector x, one computes a distance metric (usually Euclidean) $d(x, x_i)$ to each training point x_i, sorts the distances, and takes the majority vote of the labels of the k nearest points. No explicit model is learned; the "learning" is simply storing the training data[W6](Figure 2.3[46]).

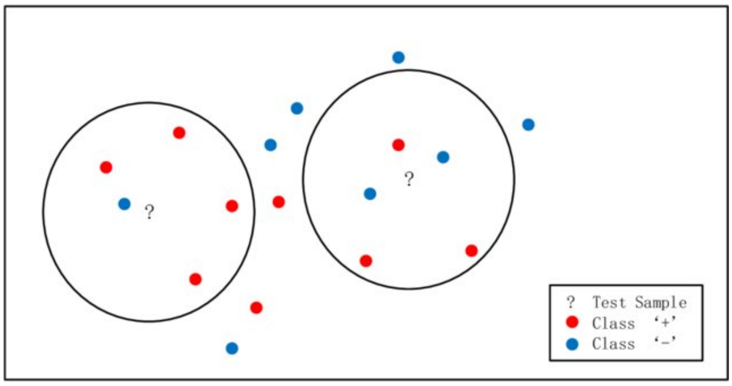

Figure 2.3: An example of kNN classification task with k = 5.

Key properties include: it is lazy (no training phase), and non-parametric (makes no assumptions about data distribution)[45]. Typically, features are normalised beforehand so that all dimensions contribute comparably. The choice of k (often small, e.g. 3 or 5) and distance metric can be tuned via validation. Because k-NN uses local neighbourhoods, it can capture complex decision boundaries but may suffer from high computation at test time and sensitivity to irrelevant features[W5].

In epilepsy detection, k-NN has also been applied to classify EEG epochs. It is valued for its simplicity and often high accuracy with well-chosen features:

- Feature Scaling:All EEG features are normalised (e.g. to unit range) to ensure fair distance calculations[45].
- Distance Computation:For a test EEG segment, compute distance to every training segment in feature space.
- Neighbor Selection:Identify the k closest training segments.
- Majority Vote: Assign the class label (seizure or not) that the majority of the k neighbors possess.

Over the past five years, numerous studies have investigated the use of these techniques for epileptic seizure detection.Ali et al. (2024) designed a Random Forest (RF) pipeline on CHB-MIT dataset, explicitly addressing class imbalance and continuous "event" detection. In realistic testing on CHB-MIT, it achieved only 72.6–75.3% sensitivity(no accuracy reported)[47]. The advantage of RF is interpretability and speed; it handles many features easily. However, the study exposed a major limitation: sensitivity remained low in a realistic setting, indicating many missed seizures despite post-processing – highlighting the difficulty of class imbalance and inter-subject variability[47]. Hazarika et al. (2025)[48] also used an RF classifier to detect seizures. In their patient-independent evaluation, they found RF gave the best performance: "the random forest classifier outperforms other options, with an accuracy of 97% and a sensitivity of 97.20%".Raghu et al. (2020) developed an SVM-based detector using a novel "successive decomposition index" feature and evaluated it on multiple databases including CHB-MIT. Using patient-independent training/test splits, they reported a sensitivity of 97.28% (with about 0.57 false alarms/hour and 1.7s median detection delay) on CHB-MIT [49]. Similarly, Dastgoshadeh and Rabiei, compared several classifiers on public EEG (Bonn) data: a least-squares SVM (LS-SVM) model achieved 98% accuracy, on par with a Naïve Bayes baseline [50] . k-NN classifiers have been used as baselines in several recent works. Dastgoshadeh and Rabiei extracted entropy features from Bonn EEG and evaluated k-NN among other methods . They found k-NN yielded about 94.5% accuracy (with sensitivity 94.5%) [50]. Other CHB-MIT study reported 93% sensitivity and 94% specificity using KNN [51]. These works highlight the strengths of classical machine learning approaches and suggest avenues for future research to refine and extend their performance within established accuracy bounds.

4.3 Deep Learning

Deep learning is a subfield of machine learning that entails the use of multi-layered neural networks in, enabling the automatic learning of hierarchical representations from data. In deep architectures, each successive layer learns increasingly abstract features, building complex concepts out of simpler ones [52],[53]. This hierarchy of concepts allows deep models to "understand the world" in terms of multiple levels of representation, as illustrated by Goodfellow et al.: "computers can learn from experience and understand the world in terms of a hierarchy of concepts" [52]. In practice, deep learning models automatically perform both feature extraction and classification within the same architecture, a capability that distinguishes them from traditional machine learning methods, which usually require manual feature engineering(Figure 2.4[54]) [55], [53].

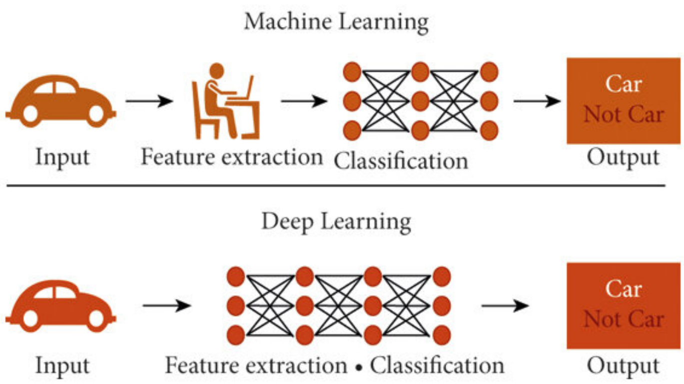

Figure 2.4: Machine Learning vs. Deep Learning.

By using many non-linear layers, deep models can approximate very complex functions: for example, LeCun et al. describe deep networks as models "composed of multiple processing layers to learn representations of data with multiple levels of abstraction" [53]. During training, these layers are adjusted via backpropagation to transform raw inputs into output decisions, effectively learning domain-specific features and decision boundaries without human-crafted filters [55], [56].

In epilepsy detection, for instance, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) (including LSTMs), and related deep architectures have been systematically applied to seizure detection tasks[56].

4.3.1 Deep Neural Networks (DNN)

A deep neural network (DNN) typically refers to a feedforward multilayer perceptron with several hidden layers. Each layer in a DNN consists of fully-connected neurons that compute a weighted sum of inputs, followed by a non-linear activation (commonly ReLU in modern networks) [53]. The architecture can be characterised as: input $\rightarrow$

(affine transform + ReLU) × L layers → softmax output(Figure 2.5[57]). Because every neuron in layer L connects to all neurons in layer $_{L-1}$, DNNs can learn complex nonlinear mappings between inputs and outputs.

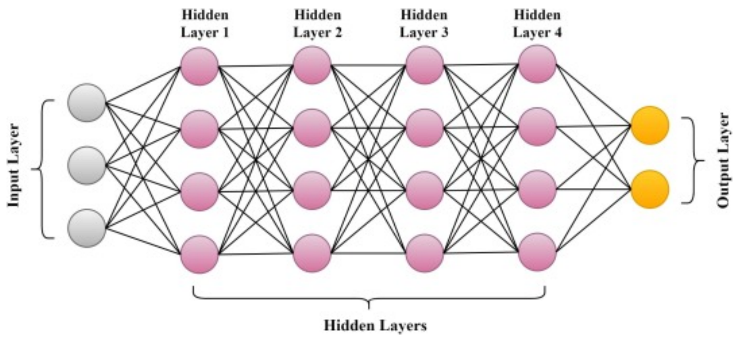

Figure 2.5: A common DNN architecture with three input layers, four hidden layers, and two output layers.

In practice, DNNs are trained by backpropagation and gradient descent, adjusting all weights to minimise a classification loss. The depth of the network (often 5–20 layers) allows for hierarchical feature extraction, enabling the network to represent intricate input patterns[53].

4.3.2 Convolutional Neural Networks (CNN)

A Convolutional Neural Network (CNN) is a deep learning model inspired by the animal visual cortex, primarily used for processing data with a grid-like architecture, such as images. CNNs are designed to automatically and adaptively learn spatial hierarchies of features, from low to high-level patterns [58]. A CNN is composed of convolutional layers, pooling layers, and fully-connected layers [59](Figure 2.6[60]). The main purpose of a CNN is to automatically learn useful features from the input data using convolutional layers made up of learnable filters, which act as feature extractors[58] .

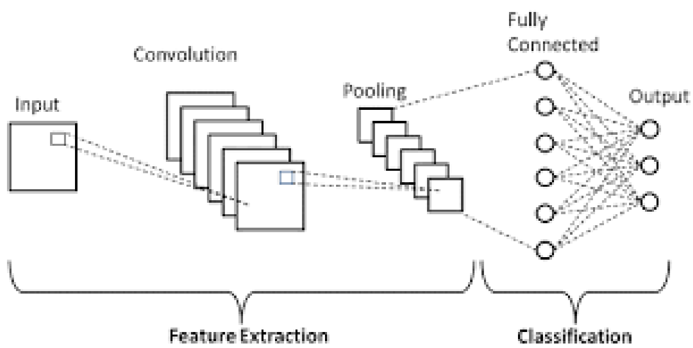

Figure 2.6: Basic CNN Architecture.

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CNNs have demonstrated effectiveness in tasks like face and object identification, traffic sign detection, and self-driving cars. By minimising the number of parameters in an ANN, developers and researchers are motivated to focus on larger models that can be used to solve complicated tasks, which is impossible with traditional ANNs [58]. In EEG, CNNs are used for decoding and visualising brain activity. They can reach accuracies comparable to Filter Bank Common Spatial Patterns (FBCSP) for decoding task-related information from EEG and can learn to use spectral power modulations in alpha, beta, and high gamma frequencies [61].

4.3.3 Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed specifically to handle long-term temporal dependencies within sequential data. In a vanilla RNN, the hidden state is propagated from one step to the next, but basic RNNs suffer from short-term memory issues: they struggle to pass information through long sequences and are susceptible to vanishing or exploding gradients during training [62]. LSTM Cells solve this through an explicit memory cell and gates. Each LSTM unit has three gates – input, forget, and output gates – that regulate the flow of information in and out of the cell state(Figure 2.7[63]). Mathematically, these gates (sigmoid activations) decide which information to retain or discard at each time step [63]. As Khan et al. summarise, these gates "preserve the long sequence of necessary data, and throw away the undesired ones," enabling the network to maintain relevant context over extended intervals [64], [63].

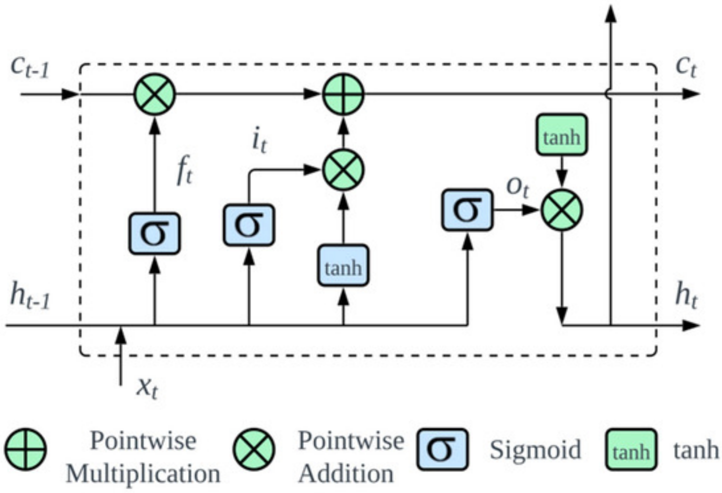

Figure 2.7: Long short-term memory unit architecture.

In effect, LSTM cells can learn to remember salient EEG patterns (e.g. onset of rhythmic discharges) over many seconds or minutes, mitigating the limitations of simple RNNs [64], [63].

Several recent studies have applied end-to-end neural networks to pediatric EEG for seizure detection. For example, Qiu et al.(2023) used 2-second raw EEG windows and a custom 1D-CNN on the CHB-MIT dataset. Using 10-fold cross-validation, the CNN attained 97.09% accuracy[65]. Kaziha and Bonny(2020) applied a 2D CNN with 100 s windows and a 70/30 Train–Test Split, achieving 96.70% acccuracy [66] Shen et al. (2023) applied a 2-second sliding window (overlap 1.35s) on raw CHB-MIT EEG, computed short-time Fourier transforms (STFT), and fed the spectrograms into a pretrained GoogleNet CNN. Their real-time system achieved 97.74% accuracy and 98.90% sensitivity [67]. Similarly, Ravi et al. (2024) proposed a 1D CNN + Bi-LSTM model in parallel paths to capture spatial and temporal EEG features. Using 5-fold cross-validation on CHB-MIT data, the model achieved about 95.9% accuracy, 97.2% sensitivity and 95.95%

F1 [68]. Its advantage is strong feature extraction and temporal memory (via Bi-LSTM), reducing false positives with no manual signal transformations. A limitation is moderate complexity and reliance on large data; performance varies across patients. Lee et al. (2024) developed a ResNet-152 + LSTM pipeline with supervised contrastive learning for patient-adaptive detection. Evaluated on CHB-MIT, it attained 91.90% accuracy and 89.64% sensitivity [69] . This hybrid deep network is robust to variability by fine-tuning on each subject, and the LSTM captures temporal context. However, its sensitivity was lower than accuracy, suggesting missed detections, and the two-stage training is complex. huang al. (2025) introduced a dual-attention ResNet + Bi-LSTM (STFFDA) model. On CHB-MIT, single-patient tests gave 95.18% accuracy [70] and, in 3-class (normal/interictal/ictal) 10-fold cross-validation, 92.42% accuracy [70]. A purely feed-forward DNN was trained on the Bonn dataset (23.6s EEG segments, class 1=seizure vs classes 2–5 non-seizure [71])by khurshid et al(2024). With an 80/20 train/test split, this DNN (several dense layers with ReLU/softmax) reached 97.0% accuracy [71].

Table 2.3 below summarises the main related works reviewed in this section, encompassing classical EEG-based approaches, machine learning algorithms, and deep learning methods for epileptic seizure detection.

Table 2.3: Summary of related works on epileptic seizure detection

Category	Reference	Method	Dataset	Results	Limitation
Classical EEG-based methods	Satirasethawong et al. [34]	Amplitude thresholding	CHB-MIT	Sensitivity 88.5%, FA/h 0.18/h	High false alarms. single-channel only. Performance drops with noise.
	Alotaiby et al. [32]	histogram-based threshold method	CHB-MIT	97.1% sensitivity ,98.6% specificity	Limited Dataset Diversity
	Li et al. [35]	Entropy measures (ApEn, FuzzyEn)	Bonn	Accuracy 92.8%, Sensitivity 90.7%,96.0% specificity	Limited to short windows; not robust to long-term EEG or patient variability.
	Oweis et al. [33]	Hilbert–Huang spectral amplitudes with statistical thresholds	CHB-MIT	Accuracy ∼94%, specificity ∼95.2%	its tendency to cause mode mixing due to the enforced frequency ordering of IMFs.
Machine Learning (ML)	Raghu et al. [49]	SVM (SDI feature)	CHB-MIT	Sensitivity 97.28%, 0.57 FA/h 1.7s delay	Moderate false alarms : Generalisability was not tested on other datasets.
	Hazarika et al.[48]	Random Forest	CHB-MIT	Accuracy 97%, Sensitivity 97.2%	Oversampling may overfit; tested on CHB-MIT only.

Continued on next page

Table 2.3 (continued)

Category	Reference	Method	Dataset	Results	Limitation
	Dastgoshadeh & Rabiei [50]	Least-squares SVM	Bonn	Accuracy 98%	Not tested on broader datasets; possible over-fitting to Bonn EEG.
	Dastgoshadeh & Rabiei [50]	k-NN (entropy features)	Bonn	Accuracy ≈94.5%	no real-time or large dataset validation.
Deep Learning (DL)	shen et al.[67]	GoogLeNet 2D-CNN (STFT)	CHB-MIT	Accuracy 97.74%, Sensitivity 98.90%	High false alarm rate; no generalisation study.
	Qiu et al.[65]	Custom 1D-CNN	CHB-MIT	Accuracy 97.09%	Window length 2s; no tests below 1s.
	khurshid et.[71]	Feedforward DNN	Bonn	Accuracy 97.0%	Long segments (23.6s); no real-time capability.
	Ravi et al.[68]	1D CNN + Bi-LSTM	CHB-MIT	Accuracy 95.9% , sensitivity 97.2% & 95.95% F1	moderate complexity and reliance on large data; performance varies across patients.
	Lee et al.[69]	ResNet-152 + LSTM	CHB-MIT	Accuracy 95.9% & sensitivity 89.64%	sensitivity was lower than accuracy,suggesting missed detection.

Recent advances show that deep learning techniques are among the most effective for detecting epileptic seizures from EEG data. Convolutional neural networks (CNNs), in particular, have proven well suited to this task because they can capture both the time-related patterns in multichannel EEG signals and the spatial relationships between electrode channels. CNNs are able to automatically learn important spatial and temporal features that traditional methods often miss, by building layered representations directly from raw or lightly pre-processed EEG input. Deeper layers in these networks also help reduce the impact of noise and artefacts by focusing on relevant patterns and filtering out distractions. When properly trained, CNN models can adapt well to different patient profiles and recording conditions, due to their ability to scale with larger and more complex datasets. For these reasons, recent studies on seizure detection have consistently shown that CNN-based approaches outperform classical machine learning models.

5 Conclusion

An overview of AI techniques for epileptic seizure detection was given in this chapter, which contrasted deep learning architectures, machine learning techniques, and traditional signal processing methods. While classical and machine learning approaches remain bound by manually constructed features and limited generalisability, deep learning, and particularly CNNs, offer a powerful alternative by learning directly from raw data. CNNs are highlighted in this review as a potentially useful basis for automated seizure detection systems. One method has been selected for the suggested seizure detection system based on these findings, which is explained in the following chapter.

Chapter 3

Methodology and Implementation

1 Introduction

Detecting epileptic seizures from EEG signals is an important task in the field of biomedical signal processing. Deep learning techniques, especially Convolutional Neural Networks (CNNs), have shown great results in this area. This chapter presents the development of a seizure detection model using a one-dimensional Convolutional Neural Network (1D CNN), trained on preprocessed EEG signals from the CHB-MIT scalp EEG dataset. The focus is placed on proper handling of the data, thoughtful design of the CNN architecture, and selection of a suitable training approach tailored to the characteristics of EEG signals. Each step is carefully carried out to ensure the model performs well in detecting epileptic seizures.

2 Proposed Model

2.1 Model selection

Epileptic seizure detection has traditionally relied on hand-crafted EEG features followed by classical classifiers. In such pipelines, features are first extracted in the time or frequency domain, then passed to a classifier for training and prediction. These systems can be highly accurate but depend heavily on expert knowledge in both signal processing and feature design, which may limit their generalisability across patients or recording conditions [72]. Although these methods can achieve high accuracy, they require expert design and may not generalise well to new patients or varying signal conditions. Deep learning offers an end-to-end alternative: a convolutional neural network (CNN) can learn relevant EEG features directly from raw data without manual engineering.CNNs offer a compelling trade-off between accuracy and efficiency. They are particularly well suited to capturing local temporal patterns in multichannel EEG data, while remaining computationally lighter than recurrent models like LSTMs. Some recent work shows that pure 1D CNNs can match or even outperform more complex hybrid CNN-LSTM models for EEG-based tasks [73].Compared to traditional approaches such as Support Vector Machines (SVMs), CNNs avoid the need for fixed-size input formatting and eliminate manual feature computation, making them a better fit for real-time or streaming EEG applications.

Clinically, the model's focus is not just on broad "seizure vs. non-seizure" classification, but on distinguishing preictal (just before seizure) from ictal (during seizure) EEG,.

Seizure detection research has emphasised that an alert just before clinical onset is most useful, while warnings hours in advance often cause anxiety [74]. Therefore, training the CNN model on these specific phases helps it learn features unique to the critical seizure onset window, supporting faster and more meaningful responses.

2.2 Mechanisms of CNNs

Convolutional Neural Networks (CNNs) are composed of layers such as convolutional, activation, pooling, flatten, and dense (fully connected) layers as shown in (Figure 3.1[75]).

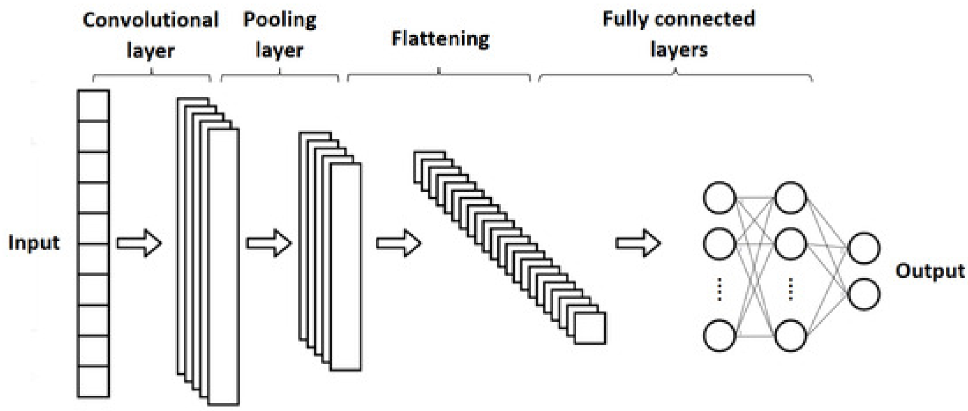

Figure 3.1: CNN layers.

CNNs can be adapted to data in several ways, mainly distinguished by the dimensionality of the input and the convolution operations [52]:

- **1D CNN:**Operates directly on raw 1D signals (such as time-series). It applies 1D kernels along the length of the signals and learns patterns across all channels or components.
- **2D CNN:** Requires a 2D input. This often means converting the data into an image-like format. 2D CNNs can capture spatial patterns but may require additional processing to arrange the data appropriately.
- **3D CNN:** Uses 3D kernels (e.g., time $\times$ height $\times$ width). 3D CNNs are more common in video or medical imaging.

In the proposed model, a 1D CNN is applied, which allows the network to scan each multichannel EEG segment over time [76] and identify patterns specific to preictal and ictal states. In a typical 1D convolutional layer, the output at a given time position $t$is computed as:

$$y(t) = \sum_{i=0}^{k-1} \sum_{j=0}^{c-1} x(t+i, j) \cdot w(i, j),$$

where :

- x is the input signal with c channels,
- w is a kernel of size k

The sums run over the kernel extent and input channels [52]. Including a bias term for each filter, the number of parameters in a convolutional layer is:

$$k \times c \times n_{\text{filters}} + n_{\text{filters}}.$$

Following convolution, activation layers such as ReLU introduce non-linearity, while pooling layers (e.g., max pooling) reduce the temporal resolution, helping the network generalise better and reducing computation. A flatten layer is used to convert the final feature maps into a 1D vector, which is then passed through one or more dense layers to make the final classification [52].

2.3 1D Convolutional Neural Network Architecture

The proposed 1D Convolutional Neural Network (CNN) model is designed to classify EEG signals into ictal and preictal categories. It processes time-series EEG segments through successive layers for feature extraction, downsampling, and classification. Each layer is described below with its mathematical operations, output shapes, and number of parameters [77](Figure 3.2).

2.3.0.1 Input Layer

The input to the model is an EEG segment represented as a tensor $I \in \mathbb{R}^{60\times 23}$, where 60 denotes the number of time steps and 23 refers to EEG channels.

2.3.0.2 Conv1D Layer (32 filters, kernel size = 5, ReLU)

This layer applies 32 convolutional filters with a kernel size of 5 across the input:

$$C_j(i) = \sum_{u=1}^{5} \sum_{k=1}^{23} I(i+u-1, k) \cdot K_{k,j}(u) + b_j$$

where $j = 1, \ldots, 32$ (filters), $i = 1, \ldots, 56$ (valid output positions), and K are the kernel weights. Each activation is passed through the ReLU function:

$$\text{ReLU}(C_j(i)) = \max(0, C_j(i))$$

Output shape: (56×32)
Trainable parameters: Each filter has $5 \times 23 = 115$ weights and 1 bias. Total parameters:

$$(115 \times 32) + 32 = 3{,}712$$

2.3.0.3 MaxPooling1D Layer (pool size = 2)

This layer reduces the temporal resolution by selecting the maximum value over non-overlapping windows of size 2:

$$S_j(i) = \max\{C_j(2i-1), C_j(2i)\}$$

Output shape: (28×32)
Trainable parameters: 0 (non-trainable)

2.3.0.4 Flatten Layer

The pooled feature maps are reshaped into a 1D vector:

$$f(k) = S_j(i), \quad \text{where } k = i + 28(j-1)$$

Output shape: 896 (since $28 \times 32 = 896$)
Trainable parameters: 0

2.3.0.5 Dense Layer (32 units, ReLU)

A fully connected layer maps the flattened input to a 32-dimensional vector:

$$z_l = \sum_{k=1}^{896} W_{lk} \cdot f(k) + c_l, \quad y_l = \max(0, z_l)$$

Output shape: 32
Trainable parameters:

$$896 \times 32 + 32 = 28{,}704$$

2.3.0.6 Output Layer (1 unit, Sigmoid)

This layer produces the final prediction with a sigmoid activation:

$$z_{\text{out}} = \sum_{l=1}^{32} V_l \cdot y_l + d, \quad y_{\text{out}} = \frac{1}{1 + e^{-z_{\text{out}}}}$$

Output shape: 1 (binary classification)
Trainable parameters:

$$32 \times 1 + 1 = 33$$

2.3.0.7 Total Trainable Parameters

$$3{,}712 \text{ (Conv1D)} + 28{,}704 \text{ (Dense)} + 33 \text{ (Output)} = \boxed{32{,}449}$$

This model architecture is designed to efficiently extract both temporal and spatial EEG features, enabling robust seizure detection using a relatively small number of parameters, making it suitable for real-time and embedded systems. Each layer contributes as follows:

- **Conv1D:** Extracts local spatiotemporal EEG patterns.
- **Pooling:** Reduces dimensionality and provides temporal invariance.
- **Dense layers:** Combine learned features and output binary classification.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 56, 32)	3,712
max_pooling1d (MaxPooling1D)	(None, 28, 32)	0
flatten (Flatten)	(None, 896)	0
dense (Dense)	(None, 32)	28,704
dense_1 (Dense)	(None, 1)	33

Total params: 32,449 (126.75 KB)
Trainable params: 32,449 (126.75 KB)
Non-trainable params: 0 (0.00 B)

Figure 3.2: Model summary

3 Dataset Description

3.1 Used Dataset

The dataset utilised in this study is the preprocessed CHB-MIT dataset published by Deepa B. and Ramesh K. [25]. This version (available via IEEE Dataport [W7]) is a balanced dataset (approximately equal total duration of preictal and ictal data), free of redundant channels. By construction, this set no longer contains the overwhelming amount of normal EEG from CHB-MIT; it focuses on the seizure events and their lead-in. This distinction is clinically relevant because it allows the model to learn the subtle changes that occur just before a seizure onset – knowledge that would be obscured if all interictal data were lumped in as "no seizure." In summary, the preprocessed dataset provides clean, balanced, and precisely labelled preictal/ictal EEG with 2 million rows, which suits our detection task as shown in (Figure 3.3).

```
print("Dataset shape:", df.shape)
print(df.head())
```

```
Dataset shape: (2097150, 24)
   # FP1-F7     C3-P3     C4-P4     CZ-PZ     F3-C3     F4-C4     F7-T7  \
0  0.000020  0.000010  0.000022  0.000037  0.000032  0.000035  0.000016
1  0.000022  0.000008  0.000021  0.000039  0.000030  0.000032  0.000015
2  0.000021  0.000012  0.000021  0.000040  0.000025  0.000030  0.000013
3  0.000019  0.000012  0.000021  0.000039  0.000023  0.000028  0.000013
4  0.000019  0.000012  0.000021  0.000036  0.000023  0.000024  0.000012

      F8-T8     FP1-F3     FP2-F4  ...     P3-O1     P4-O2     P7-O1     P7-T7  \
0  0.000046 -0.000007  0.000043  ...  0.000024 -0.000030  0.000010 -0.000011
1  0.000039 -0.000006  0.000042  ...  0.000026 -0.000017  0.000012 -0.000008
2  0.000036 -0.000006  0.000040  ...  0.000027 -0.000018  0.000014 -0.000009
3  0.000035 -0.000008  0.000036  ...  0.000030 -0.000024  0.000015 -0.000009
4  0.000024 -0.000009  0.000032  ...  0.000032 -0.000014  0.000017 -0.000008

      P8-O2     T7-FT9     T7-P7   T8-P8-0   T8-P8-1  Outcome
0 -0.000037  0.000008  0.000012  0.000021  0.000021      0.0
1 -0.000029  0.000010  0.000009  0.000023  0.000023      0.0
2 -0.000034  0.000012  0.000009  0.000027  0.000027      0.0
3 -0.000042  0.000009  0.000010  0.000033  0.000033      0.0
4 -0.000031  0.000009  0.000008  0.000035  0.000035      0.0

[5 rows x 24 columns]
```

Figure 3.3: Data Head

3.2 Data Visualisation

To gain intuition about the data, several visualisations were generated. Figure 3.4 is a correlation heatmap between all channel pairs, computed over several minutes of EEG. High correlations among certain groups of electrodes is observed (e.g. nearby regions), as expected due to volume conduction and common underlying sources. This spatial structure justifies the model's use of filters spanning multiple channels.

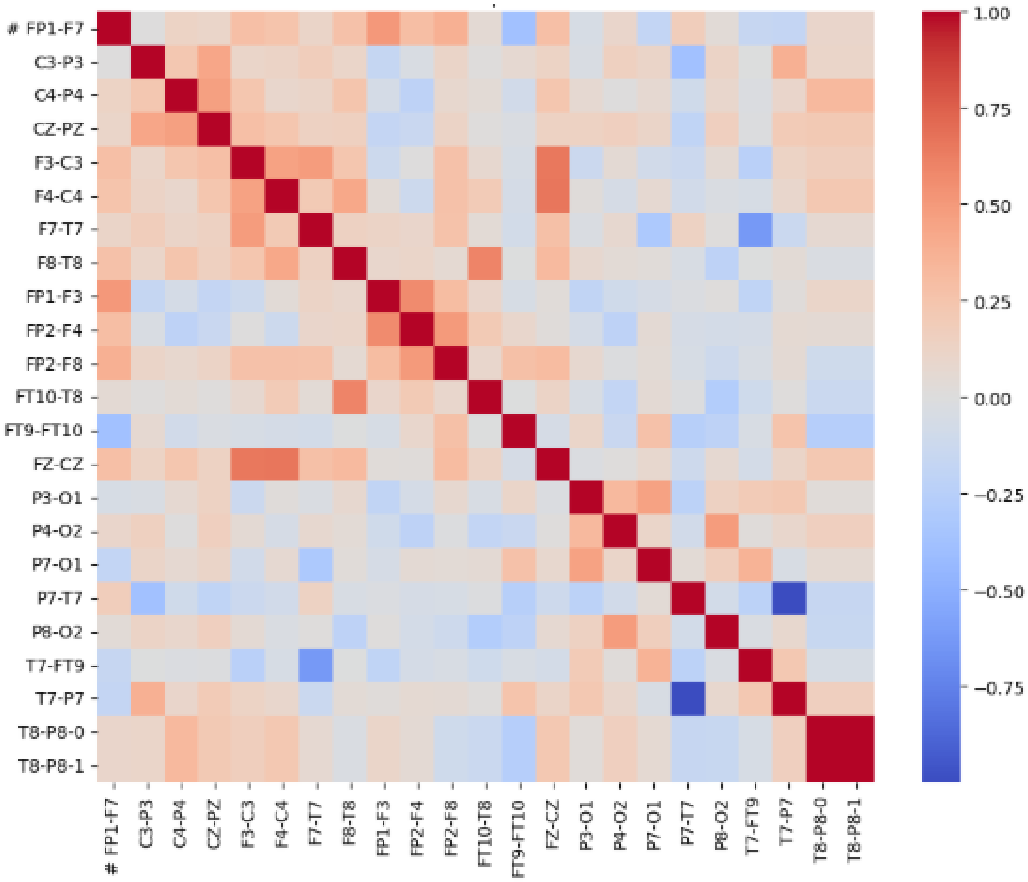

Figure 3.4: Correlation Heatmap of EEG Channels

Figure 3.5 displays the class distribution (count of windows) for preictal vs. ictal in the dataset. Due to the preprocessing, the two classes are roughly balanced. These plots confirm that the data are well-conditioned for training the CNN model and illustrate the typical EEG patterns the network will see.

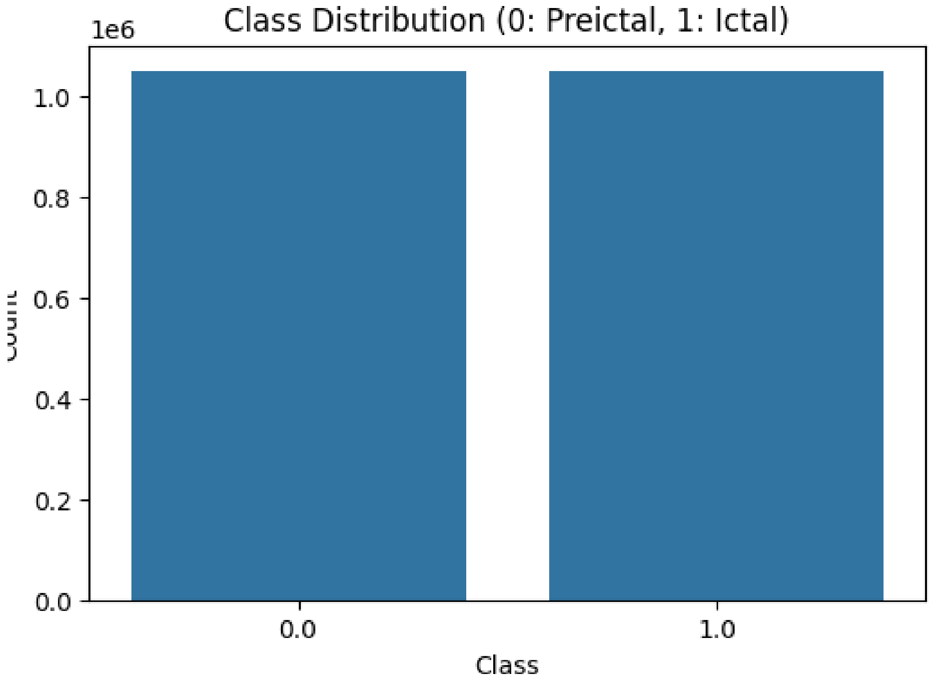

Figure 3.5: Class Distribution

4 Implementation

4.1 Data Preparation

Data standardisation:

Before modelling, each EEG channel was standardised using a z-score (StandardScaler). Z-score normalisation subtracts the mean and divides by the standard deviation of each channel, ensuring zero-mean, unit-variance inputsusing the following equation[78]:

$$X_{\text{std}} = \frac{(X - \mu)}{\sigma} \tag{3.1}$$

where:

- X_{std} is the standardized data value,
- X is the original data value,
- μ is the mean of the data,
- σ is the standard deviation of the data.

This is appropriate for EEG because raw amplitudes can differ substantially between channels and recordings. Without normalisation, large-amplitude channels would dominate the learning. By scaling all channels comparably, the network can focus on patterns rather than absolute voltage[25].

Sequence Creation: To prepare the data for training, overlapping windows were extracted from the continuous EEG recordings that included both preictal and ictal segments. Each window was 60 samples long. Given a sampling rate of 256 Hz, this means each window represents approximately 0.23 seconds of brain activity. A stride of 1 sample was used, so the windows overlapped heavily, each new window shifted by just one sample. This method ensures that very little information is lost between segments, making the most of the available data. The label assigned to each window corresponds to the class of its final sample. By sliding the window this way, a large number of training examples were created, each carrying temporal information from the EEG. This overlap also helps maintain the sequence continuity, which is important when working with time-dependent signals like EEG[79]. The code in Figure 3.6 represents Sequence Creation steps:

```
def create_sequences(features, labels, window_size=60):
    X_seq, y_seq = [], []
    for i in range(len(features) - window_size):
        X_seq.append(features[i:i+window_size])
        y_seq.append(labels[i + window_size])
    return np.array(X_seq), np.array(y_seq)

window_size = 60
X_sequences, y_sequences = create_sequences(X_normalized, y, window_size)
```

Figure 3.6: Sequence Creation steps code

Data Splitting:

Once the EEG windows were prepared, the dataset was divided into training, validation, and test sets using a stratified approach. The split followed a 72%–18%–10% ratio, where 72% of the windows were used for training, 18%for validation, and 10% for testing. This corresponds to a typical 80/20 division between training and validation within the non-test portion. Stratification was important to maintain the same balance of preictal and ictal examples in each set [80], helping to ensure fair training and evaluation(Figure 3.7). To avoid any data leakage, the division was done at the window level in a way that windows from the same seizure were not shared between different sets. This step is crucial because EEG signals taken from the same seizure can have very similar patterns, which might mislead the model during training or testing. By keeping test data completely separate and ensuring no overlap with training windows, the model's final performance could be properly evaluated on genuinely new data[81].

```
Dataset shapes:
Training set: (1509904, 60, 23), (1509904,)
Validation set: (377477, 60, 23), (377477,)
Test set: (209709, 60, 23), (209709,)
```

Figure 3.7: Dataset shapes after splitting and reshaping

4.2 Training Configuration

The CNN was trained with:

- **the Adam optimiser** which adaptively tunes learning rates and often converges faster [82].

- **loss function** which is binary cross-entropy, defined as [83]:

$$L = -\left[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})\right] \tag{3.2}$$

  where:

  - $y \in \{0, 1\}$ is the true label,
  - $\hat{y} \in (0, 1)$ is the predicted probability of the positive (ictal) class.

  Minimising this loss function encourages the predicted probability $\hat{y}$ to closely match the actual class label y.

- **batch size** of 256 was used throughout the experiments. This size was chosen because it is large enough to produce stable gradient estimates during training, but still fits easily on standard modern hardware. Using a larger batch size helps smooth out the noise in the gradient updates, which can make training faster and more consistent. On the other hand, very small batch sizes may introduce too much variability and make learning unstable [84]. The size of the dataset allowed the use of this medium-large batch size without running into memory problems.
  Two callbacks were included to improve generalisation and stability in the 20-epoch training:

  - **EarlyStopping:** If the validation loss fails to improve after a certain patience (3 in this case), training is stopped. This prevents the network from overfitting by continuing to learn from the training data when it's no longer improving on validation. As Hussein and Shareef note, this technique "stops training when the validation loss stops improving", thus preventing the model from learning noise in the training data[85]. In practice, training often finished well before 20 epochs, and early stopping made sure it did not continue unnecessarily, reducing the risk of overfitting.
  - **ModelCheckpoint:** The validation ROC–AUC (area under the ROC curve) was tracked after each training epoch, and model weights were saved whenever this score improved. This helped ensure that the best-performing version of the model was kept, based on its ability to distinguish between seizure and non-seizure cases. AUC is a suitable choice for this kind of binary classification problem because it remains reliable even when the two classes (preictal and ictal) are not perfectly balanced[86]. It gives a clearer picture of how well the model can separate the two classes overall. Accuracy was also monitored during training to give a general idea of how often the model was making the correct prediction, but it was not used to decide which model to save.

The general training configuration is summarised in Table 3.1.

Parameter	Description
Optimizer	Adam (adaptive learning rate optimizer)
Loss Function	Binary Cross-Entropy (for ictal vs. preictal classification)
Batch Size	256 (balances stability and efficiency)
Epochs	Up to 20 (controlled by callbacks)
EarlyStopping	Stops if validation loss doesn't improve (prevents overfitting)
Patient	3 epochs
ModelCheckpoint	Saves best model based on validation AUC

Table 3.1: CNN Training Configuration

5 Environment

5.1 Hardware

The experiments were conducted using both a local machine and a cloud-based environment (Google Colab Pro), with the following specifications:

Local Machine Specifications

- **Operating System:** Windows 10 Professional
- **Processor:** Intel Celeron N4000 CPU @ 1.10GHz (2 cores)
- **Memory:** 16GB DDR4 RAM @ 2400 MHz
- **Storage:** Solid State Drive (SSD),256GB
- **Graphics:** Integrated Intel® UHD Graphics 600

Cloud Environment (Google Colab Pro)

- **Plan:** Google Colab Pro
- **Runtime Type:** Python 3 on Google Compute Engine backend
- **Hardware Accelerator:** v2-8 TPU
- **Colab RAM:** Approximately 35GB (High-RAM session)
- **Colab Disk:** Approximately 107GB

5.2 Used Libraries

- **NumPy:** is a basic Python library used for numerical and scientific computing. It provides the ndarray object, which is an N-dimensional array for storing numbers. NumPy also includes fast functions for doing math on these arrays, like element-wise operations, linear algebra, Fourier transforms, and random number generation.

Since it runs with fast C code in the background, it can handle large datasets efficiently. Many other Python libraries use NumPy arrays as a base, which makes it a core tool in data analysis[W8].

- **pandas:**is a free Python library that makes it easy to work with table-like data. Its main data types are Series (1D) and DataFrame (2D), which help you load, clean, and explore data quickly. You can read files like CSV or Excel, fix missing values, and do basic calculations with just a few lines of code. Pandas is built on top of NumPy and works well with other libraries like Matplotlib. It's mostly used to prepare and understand data before using it in machine learning or analysis[W9].
- **Matplotlib:**Matplotlib is a comprehensive Python library for creating graphs and plots. It supports making a wide range of visualisations (such as line plots, bar charts, scatter plots, histograms, and more), including both static and interactive figures. Matplotlib can produce high-quality figures in multiple formats (PNG, PDF, SVG, etc.) and is commonly used for data visualisation in scripts, Jupyter notebooks, and applications. Its low-level commands and object-oriented interface allow detailed customisation of plots, which is why many higher-level libraries (like pandas and seaborn) use Matplotlib under the hood[W10].
- **TensorFlow:** TensorFlow is an open-source, end-to-end platform for machine learning, developed by Google. It provides a comprehensive set of tools and libraries for building, training, and deploying machine learning models (especially deep neural networks) across different environments (desktop, mobile, web, or cloud). In practice, TensorFlow simplifies workflows by offering high-level APIs (like Keras) and automating many low-level details of model construction and training. TensorFlow is widely used in data science and AI applications for tasks such as image recognition, natural language processing, and large-scale model training[W11].
- **scikit-learn:** A Python library offering tools for machine learning and statistical modeling. It includes algorithms for classification, regression, clustering, and dimensionality reduction, along with utilities for data preprocessing, model validation, and hyperparameter tuning. Built on NumPy and SciPy[87].
- **Seaborn:** is a Python library for making nice-looking and useful graphs, built on top of Matplotlib. It gives you a simple way to create complex charts that help you understand patterns in your data. Seaborn is especially good for showing statistics in a clear and visual way, making it easier to explore and explain your data[88].

6 Results and discussion

To properly evaluate the performance of the proposed 1D Convolutional Neural Network (1D-CNN) for detecting epileptic seizures, we will use common evaluation metrics discussed in Chapter 2. These include accuracy, precision, recall, F1-score, false positive rate, false negative rate, and AUC-ROC. These metrics help measure how well the model can classify and detect seizures correctly.

6.1 Results

The model was tested on unseen data to check how well it performs and how stable it is when making new predictions.
The results are shown in 3.8 as a confusion matrix, which gives a clear picture of how the model did in separating ictal and preictal cases. This helps to understand where the model makes correct predictions and where it may still make mistakes.

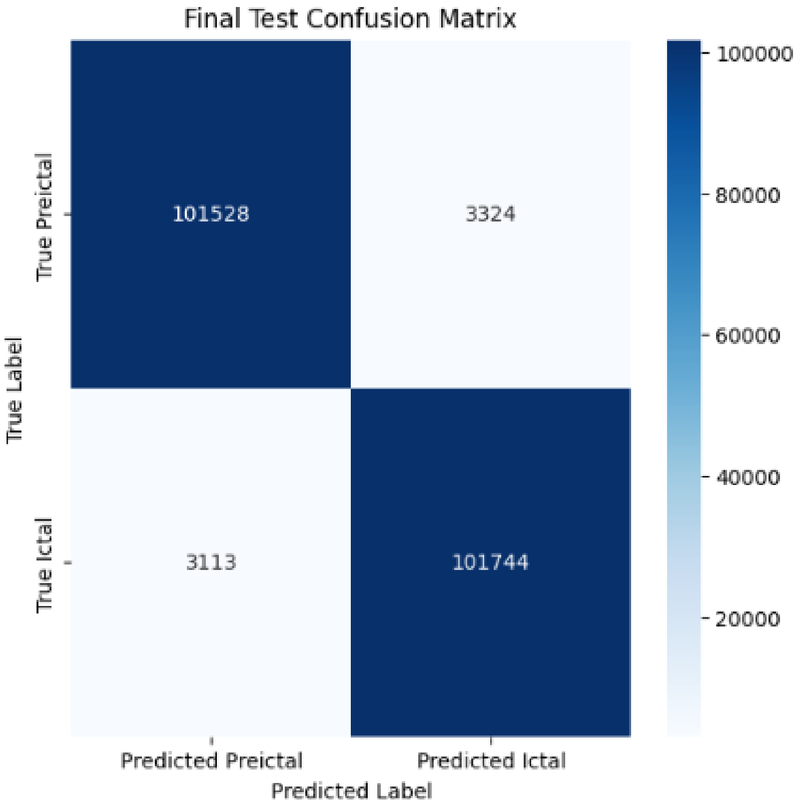

Figure 3.8: Confusion matrix.

The final confusion matrix shows how well the model was able to classify preictal and ictal states. It correctly identified 101,528 preictal examples and 101,744 ictal examples. However, it also made some mistakes, misclassifying 3,324 preictal cases as ictal and 3,113 ictal cases as preictal. Overall, these results show that the model is performing well, with a good balance in recognising both types of signals.

To understand how the model was learning before being tested, Figure 3.9 to Figure 3.11 show the training and validation curves for accuracy, loss, and AUC across all training epochs. The accuracy curves for both training and validation increase steadily and stay close to each other, suggesting that the model was learning well without overfitting. The loss curves go down smoothly, and the validation loss closely follows the training loss, showing good convergence. The AUC curves stay high and stable for both training and validation, which means the model consistently learned to tell the difference between ictal and preictal signals during training.

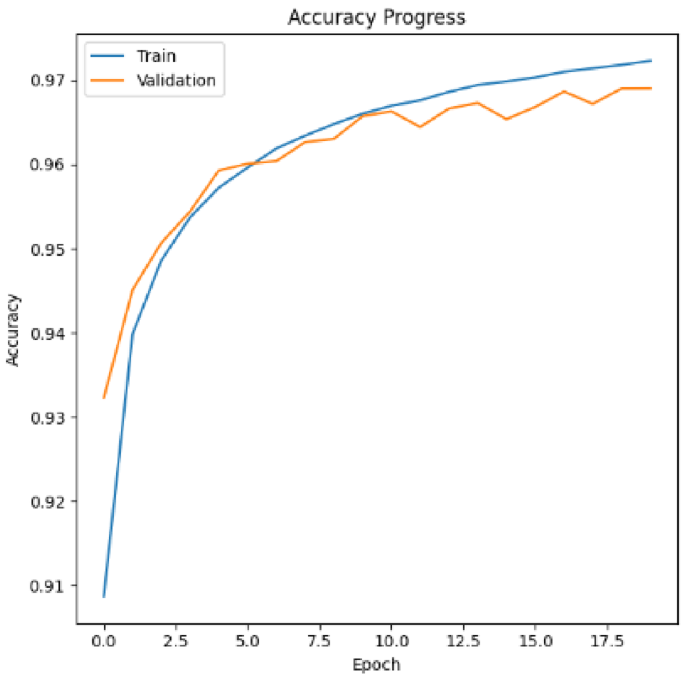

Figure 3.9: The training and validation curves for accuracy over the training epochs.

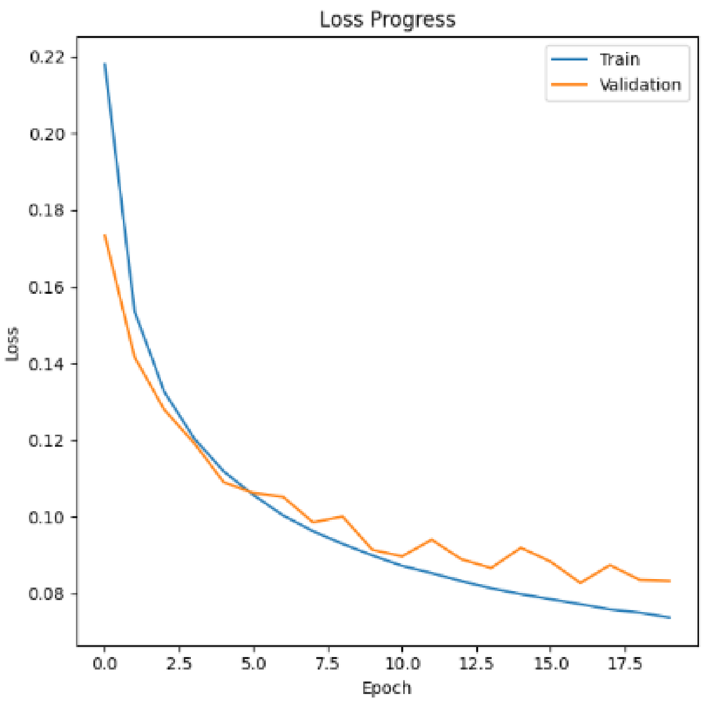

Figure 3.10: The training and validation curves for loss over the training epochs.

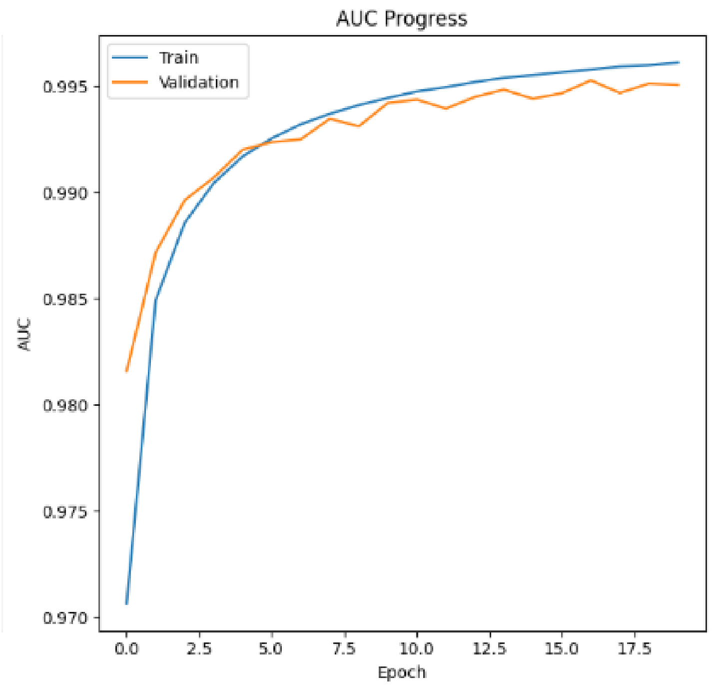

Figure 3.11: The training and validation curves for AUC over the training epochs.

To further evaluate the model's performance, Figure 3.12 presents the classification report, which shows precision, recall, F1-score, and overall accuracy for each class.

Final Test Classification Report:

	precision	recall	f1-score	support
Preictal	0.97	0.97	0.97	104852
Ictal	0.97	0.97	0.97	104857
accuracy			0.97	209709
macro avg	0.97	0.97	0.97	209709
weighted avg	0.97	0.97	0.97	209709

Figure 3.12: Classification report.

The following Table 3.2 summarises the performance metrics of the model.

Metric	**Value**
Accuracy	97%
Sensitivity	97.03%
Specificity	96.83%
Precision	97%
F1-Score	97%
False Positive Rate (FPR)	3.17%
False Negative Rate (FNR)	2.97%

Table 3.2: Summary of Performance Metrics

The results shown in 3.2 and Figure 3.12 show that the proposed model achieves strong performance in distinguishing between ictal and preictal states in pediatric epilepsy cases. It reached an overall accuracy of 97%, showing that it can reliably classify EEG signals linked to seizures. The model's sensitivity was 97.03%, meaning it was able to correctly detect most seizure events, which is important to avoid missing any. Its specificity was 96.83%, showing it also recognised non-seizure periods well and avoided sending too many false alarms. With both precision and F1-score at 97%, the model showed balanced and consistent performance. The low false positive rate (3.17%) and false negative rate (2.97%) also suggest that the model handles challenging EEG data with good stability.

The model's classification performance is also evaluated using the Receiver Operating Characteristic (ROC) curve (Figure 3.13) and Prediction confidence Distribution Plot (Figure 3.14).

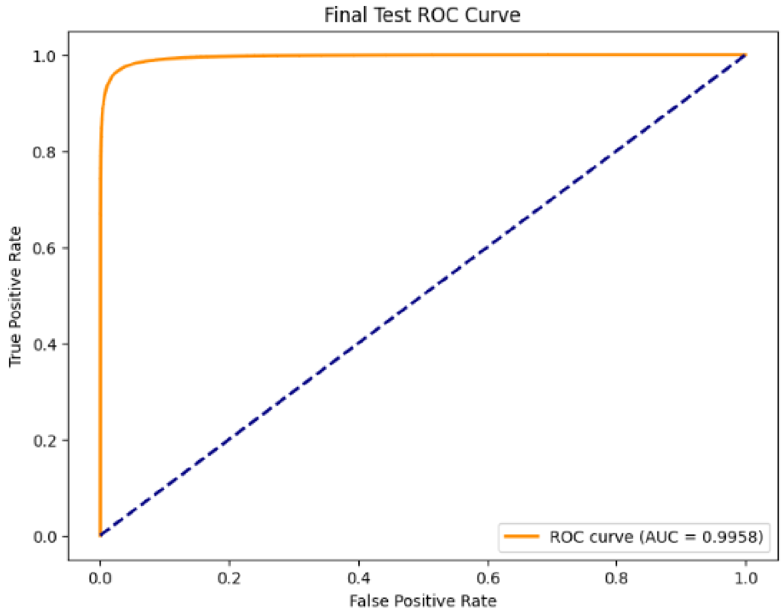

Figure 3.13: The ROC curve.

The curve shows how well the model separates seizure (ictal) and non-seizure (preictal) cases. It compares the true positive rate with the false positive rate at different thresholds. The shape of the curve shows that the model has strong performance, with high sensitivity and low false alarms across various settings.

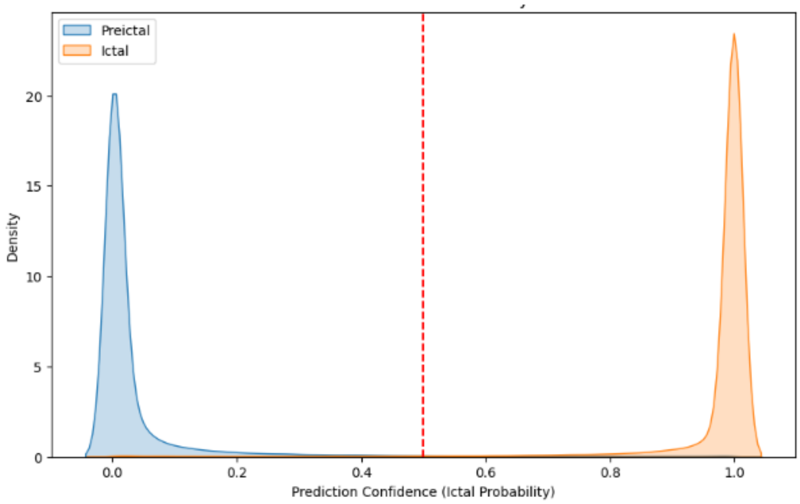

Figure 3.14: Prediction confidence Distribution Plot.

The plot shows how confident the model was when predicting whether a signal belongs to the ictal class. The blue curve shows preictal samples, which mostly have low predicted probabilities (close to 0), while the red curve shows ictal samples, which are mostly predicted with high probabilities (close to 1). The two curves are clearly separated, meaning the model can confidently tell the difference between the two classes. This matches the good results seen in other metrics and confirms that the model makes reliable predictions.

7 Conclusion

This chapter presented the design and evaluation of a deep learning model for detecting epileptic seizures in children using EEG signals. The model was based on a 1D-CNN architecture and used carefully chosen preprocessing steps. It performed well in identifying both preictal and ictal states, achieving high accuracy and strong results on the CHB-MIT dataset. The model showed a good balance between key metrics like sensitivity, precision, and F1-score. When compared to other models, it proved to be both effective and reliable. Overall, the results highlight the value of lightweight deep learning models for building small, real-time seizure monitoring systems, which can help make epilepsy care more accessible and responsive.

General conclusion

This work addressed the problem of automated epilepsy seizure detection in children using 1D Convolutional Neural Networks (1D-CNN). The main aim was to find a way to identify seizures quickly and accurately from EEG signals, in order to help doctors and caregivers respond in time and provide proper care.

This master thesis starts by introducing epilepsy, its effects on children, and the role of EEG signals in detecting seizures. It then reviews related methods and techniques, from classical approaches to more advanced deep learning methods. Finally, it presents the implementation of a 1D-CNN model and demonstrates its effectiveness in distinguishing ictal from preictal signals. Looking forward, future perspectives may include improving the model by adding more data from different children to make it more robust and reliable. Furthermore, trying other deep learning methods or adding additional information from different signals may help to make the detection more accurate. There is also potential for developing a real-time alarm system to help caregivers respond quickly when a seizure starts, and for integrating this approach into a small, lightweight device that children can wear in their daily lives.

In conclusion, this work highlights the ability of deep learning techniques, particularly 1D-CNN, to aid in the automatic detection of seizures in children. By proposing a simple and effective approach and identifying future research directions, this work aims to contribute to improving the health and safety of children with epilepsy.

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