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**BRAIN EPILEPTIC SEIZURE DIAGNOSIS USING
ELECTROENCEPHALOGRAPHIC EEG SIGNALS**

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Master's Thesis

Supervisor

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ABSTRACT

BRAIN SEIZURE DIAGNOSIS USING ELECTROENCEPHALOGRAPHIC EEG SIGNALS

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Monitoring frameworks employing image handling have gained significantly more attention among experts on the moving qualities like minimal costs, dependability, and flexibility toward merging with various innovations. Accordingly, the forest area fire area structure is arranged by creating revelation estimations in view of pictures and picture dealing with methods to segregate fire occasions in light of affirmation from Checking Focuses. In this examination task, the validation of a fire advance notice is supported by the proposed fire check assessment out. The fire check appraisal is proposed for the sales for fire picture and non-fire picture for the reduction of misdirecting cautions using picture managing moves close. A histogram evening out, RGB covering space, and YCbCr model-based structure is envisioned for data extraction from an information picture. The relationship of fire and non-fire symbolism is depicted using rule-based depiction. Histogram change gives the power makeover of fire covering pixels in the data picture, which is moreover overseen for the extraction of RGB parts. The erased RGB parts are sent off the change stage, where the image is exchanged over totally to a YCbCr covering model for secluding luminance from chrominance.

Keywords: Machine Learning, EEG Signal, Chronic Disorder, Seizure Detection.

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ABBREVIATIONS

EEG	:	Electroencephalography
CNN	:	Convolutional Neural Network
IoT	:	Internet of Things
RNN	:	Recurrent Neural Network
SD	:	Standard Deviation
UDWT:		Undecimated Wavelet Transform

1. INTRODUCTION

Epilepsy is a common neurological illness that affects people of all ages and is defined by two or more spontaneous seizures. Epilepsy affects approximately 6 to 7% (50 to 60 million) of the world's population, making it the second most common neuro illness after migraine. Epilepsy is distinguished by two or more spontaneous recurrent seizures that begin abruptly. Seizures can cause anything from a brief loss of awareness to intense convulsions and possibly loss of consciousness. Electroencephalography (EEG) is a test used to analyze electrical activity in the brain, with one of its applications being the detection of epilepsy seizures. Manual EEG examination is performed by experienced neurologist; however, it is a lengthy and time-consuming technique that affects the neurologist's effectiveness. Many examinations have been led to distinguish epilepsy seizures in EEG signals, albeit a large portion of these methodologies depend on transcribed highlights determined in time space, recurrence area (Fourier change), or a blend of time and recurrence (wavelet change). What's more, they all have a few defects, for example, being "prepared on a small dataset," "unfit to work really when relics and repetitive sound present in the sign," and, at long last, they don't function admirably with non-fixed signals (EEG have a place with non-fixed signals). These variables add to the model's lackluster showing.

This proposal centers around the advancement of a Deep Neural Network model to further develop seizure recognition exactness utilizing electroencephalogram (EEG) signals. This initial section lays out the general setting for this review. To start, we will examine the exploration inspiration, trailed by a short portrayal of the issues and the important foundation data about epilepsy to comprehend the extent of the issue that will be tended to in this examination. The examination objective is then introduced. This section finishes up with an outline of the proposition structure.

1.1 MOTIVATION

Manual sickness determination in view of profoundly complex clinical information isn't just tedious, yet in addition mistake inclined. The headway of AI and example acknowledgment permits researchers to give new ways to deal with somewhat robotize and work with a portion of these work serious undertakings. This progression spreads across medical services research regions, yet in addition into multidisciplinary concentrates like mind PC interface.

Brain-computer interface is another area of study that joins a few disciplines, including neuroscience and software engineering. This field of study centers around mind capability and brain electrical action of neurons through electroencephalography investigation (EEG). The EEG signal has turned into a typical strategy for finding out about mind usefulness and neuronal electrical action [12].

The extricated information from the mind can be utilized for different purposes, including halting a driving vehicle when the driver's slowing down expectation is recognized, empowering crippled individuals to control their wheelchair, and diagnosing lies in court, among others. There are various applications that are driven by EEG signals, whether for handicapped or solid individuals, and every one of them allude to cerebrum PC interfaces (BCIs). In the domains of medical care, researchers endeavor to examine and dissect different anomalies inside mind cues to recognize sicknesses and grasp their causes. The present state of the art innovation considers determination utilizing AI (ML) and profound learning strategies to robotize what was recently finished by specialists while consuming most of the day.

Neuroscience specialists inspect EEG signals and cerebrum state attributes. This is achieved through mind cue handling, which means to grasp different complex conditions of the cerebrum when cerebrum reactions vary at a particular time point between two states. The most common way of looking at these different mind states is known as "univariate examination." as a matter of fact, this strategy unravels an individual's mental or perceptual reactions in people [19].

In any case, it is hard to extricate significant data and track down a singular element of interest from high-layered, uproarious EEG information, and signs in EEG information might become excess when they portray various things and characteristically connect to one another. Besides, we approach a predetermined number of tests in neuroimaging at times, including sicknesses, which restricts specialists' capacity to construct an optimal model with numerous boundaries and elements. Electroencephalography (EEG) is a basic part in the conclusion of epilepsy. As per World Health Organization information [12], epilepsy is one of the most widely recognized illnesses on the planet, second just to headache. The EEG gives significant data about foundation EEG and epileptiform releases, and it is expected for the finding of certain electroclinical disorders [4]. This postulation expects to utilize a profound brain network calculation to analyze the normal neurological infection epilepsy utilizing EEG signals.

1.2 RELATED WORK

Since the mid 1970s, specialists have been creating calculations for computerized seizure discovery frameworks. A few AI (ML)- based calculations have been created to tackle this issue. Adeli et al. proposed the wavelet-disorder strategy, a sign handling technique for examining EEG signals with spans of as long as 6 seconds and including sub-groups of EEG signals - alpha, beta, gamma, theta, and delta to recognize seizures in epileptic patients [2]. Ghosh-Dastidar et al. fostered a wavelet-confusion technique in light of brain networks for seizure and non-seizure EEG grouping [12]. They utilized Levenberg-Marquardt back spread NN and got 96% exactness. A classifier in light of head part examination (PCA) was utilized to classify EEG signals, yielding a general precision of close to 100%. Ghosh-Dastidar et al. created Spiking Neural Network (SNN), a sort of ANN, to tackle complex time-subordinate characterization issues. Burg proposed a classifier in view of help vector machines (SVM) that accomplished 93.3% precision [15]. To extricate highlights from EEG sections, hereditary calculations were utilized, where the model learns all alone and performs programmed include choice. The closest neighbor classifier was utilized to accomplish a 93.5% exactness [11]. Bhattacharyya et al. proposed an Empirical mode rot utilizing Random forest area, and their latest work incorporates the execution of Q-wavelet changes with 98.6% accuracy utilizing support vector machines [10]. In NLP applications, RNN-based classifiers are normal. Nonetheless, significant learning-based classifiers have not been entirely researched. In 2017, Acharya et al. made a CNN-based classifier model with an exactness of 88.6% [1].

1.3 PROBLEM STATEMENT

After headache, epilepsy is the second most normal cerebrum problem; programmed recognition of epileptic seizures can essentially work on patients' personal satisfaction. Current electroencephalogram (EEG)- based seizure identification frameworks face various difficulties in genuine circumstances; EEG information are vulnerable to an assortment of clamor types, which lessens the discovery exactness of epileptic seizures. To resolve this issue, we present a profound learning-based strategy for identifying different kinds of patient stories and learning the discriminative EEG highlights of epileptic episodes. More specific, we plan to resolve this issue by utilizing a Long Momentary Memory organization and examining its prospects.

In this study we have tried to classify Epileptic Seizure by training the dataset on two different architectures LSTM and NN . We have done both binary class classification as well as multi class classification and observed the accuracy of the models in each case.

1.4 EPILEPSY AND EPILEPTIC SEIZURES

Epilepsy influences around 50 million individuals around the world, as per the latest World Health Organization (WHO) measurements [12]. It very well may be viewed as a hazardous gamble for epileptic patients in their day to day routines, keeping them from taking part in numerous exercises, for example, getting and utilizing a driver's permit. Patients with epilepsy face social segregation because of negative public insights and confusions about the sickness. As a matter of fact, epilepsy is a neurological condition that can cause at least two unwarranted seizures and the presence of unusual mind movement ways of behaving more than a 24-hour time span.

Epilepsy can be brought about by mind injury, cerebrum growths, diseases, dietary lacks, calcium digestion problems, and different elements. Since neurons create electrochemical driving forces, they meaningfully affect different neurons, which produce considerations, developments, and sentiments. Seizures are brought about by unexpected changes in the electrical working of the cerebrum in the cortex, which upsets the typical example of neuronal way of behaving, bringing about bizarre feelings and ways of behaving, muscle fits, loss of awareness, and different anomalies. On an EEG recording, these irregularities show up as fast spiking waves. Subsequently, electroencephalography (EEG) assumes a significant part in the exact finding and arrangement of different sorts of epilepsy, as well as in distinguishing systems that cause seizures in epileptic issues.

1.5 CONTRIBUTION

EEG information incorporates data about the electrical action of the mind and is in this way generally used to analyze any basic neurological condition like epilepsy. While driving a vehicle or working hardware, epileptic patients are in danger of encountering a hazardous episode. Thus, it is basic to distinguish the times when patients are bound to have seizures. Manual seizure location is exorbitant in light of the fact that it requires a visual assessment of long stretches of EEG information. Underlying seizure discovery and forecast frameworks are expected to consequently order EEG signals into different sorts of signs utilizing AI procedures. In this

review, we depict a seizure location and expectation model in light of repetitive brain organizations (RNN). We propose numerous profound RNN models for seizure expectation. To perform fundamental assessment, the precision of each model is assessed utilizing an openly accessible dataset. The LSTM model accurately orders the EEG information 96% of the time.

1.6 THESIS OUTLINE

This thesis consists of six chapters, the first of which is the basic introduction to this study endeavor, summarizing preliminary findings. The remainder of the thesis is organized as follows:

The accompanying segment gives a definite portrayal of the past composing concentrate on a few timberlands fire acknowledgment systems, showing state of the art work in this field. It likewise talks about the particulars of the prominent survey holes in the flow composing, as well as the examination goals we've laid out for ourselves.

Section 3 researches the execution of a photograph dealing with approach for fire distinguishing proof affirmation. This part centers around the image handling estimation that has been introduced for recognizing fire and non-fire pictures.

Part 4 examines the exploration discoveries and significant commitments of this postulation, as well as the future potential for growing this study work to make it versatile for constant precise discovery of woodland fires.

2. LITERATURE SURVEY

2.1 INTRODUCTION

This section portrays and looks at measurable strategies for fostering a framework that depicts and classifies signs of interest, which is a fundamental part of a total seizure identification framework. We decided to focus on approaches recently utilized for the programmed recognition of seizures in electroencephalography (EEG) information; be that as it may, these handling and order strategies can be applied to an assortment of clinical occasion and expectation location frameworks utilizing different recording modalities.

Most complete sign handling and arrangement frameworks will incorporate pre-handling, include extraction, and order stages. Pre-handling readies the crude sign for include extraction, which evaluates parts of the sign to best depict information credits like biomarkers or relics. To guarantee that there are no repetitive or comparative elements, it very well might be important to lessen the quantity of highlights to those that best address the information or train a model, or to join comparative highlights to make new ones (extraction). In the wake of being "prepared" by AI, the elements picked/made can then be characterized utilizing edge or model-based measures.

To address the issue of automatic recognition of epileptic seizures in long term EEG, as elaborated in the previous chapter, the knowledge about functioning of the brain to analyses EEG signals is a prerequisite. As brain is a complex organ, a brief overview regarding functioning of the brain and capturing of electrical brain signals through EEG will be discussed in this chapter. This chapter will also give an overview of epileptic seizures, its types and the severity and extent of epilepsy in India as well as abroad.

2.2 HUMAN BRAIN

The human body is entirely dependent on the human brain. The brain controls the body through the nervous system. The neurons (nerve cells) are the building blocks of the nervous system which can reach out to most of the body. An estimation shows that 85 billion neurons are there in the human brain [26]. The cerebrum's essential divisions, known as cerebral halves of the globe, are the left and right sides of the equator. Both of these contain four curves of the mind: the cerebrum, worldly curve, occipital curve, and parietal curve. These mind curves have entirely gone against command over the human body [27]. For instance, the left half of the globe of the mind manages

the activities of our right arm or leg, while objects seen on our left side are seen by the curves in the right side of the equator of the cerebrum.

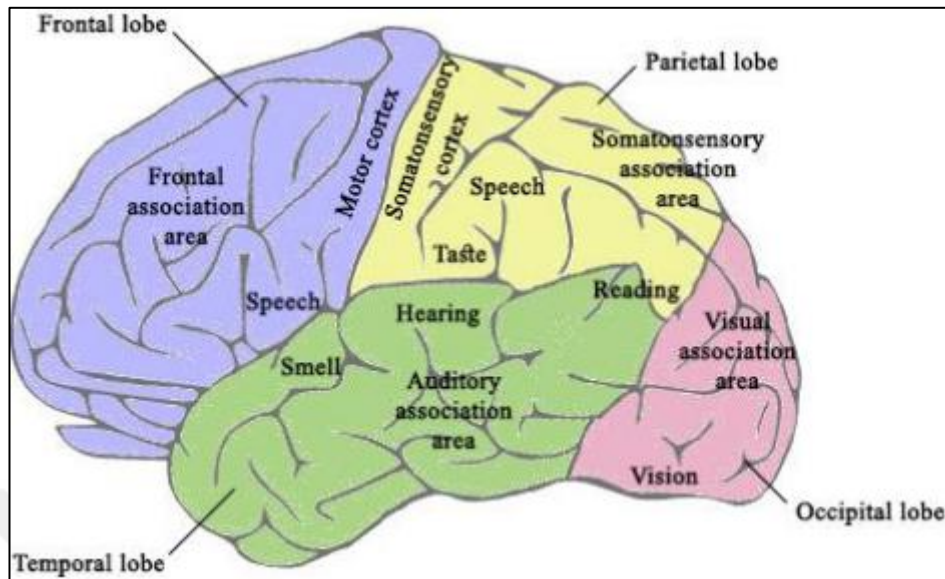


Figure 2.1: The functionality of different areas of the cerebral cortex [28].

Different lobes of the brain

- Frontal Lobe:** The cerebrum is liable for higher mental activities, for example, independent direction, insights, rationale, and thinking. It is situated on the front side of the frontal cortex, underneath the temple.
- Temporal Lobes:** Situated on one or the other side of the head, just underneath the sanctuaries. They help in the impression of sounds and are accountable for memory capacity. It additionally supports close to home articulation.
- Occipital Lobe:** Possesses the rear of the human cerebrum, somewhat higher than the cerebellum (nitty gritty beneath). It manages vision and houses the visual cortex.
- Parietal Lobe:** The uppermost part of the cerebrum where spatial orientation as well as expositions take place. It manages the sensory signals from the body.

2.2.1 Cerebellum and Cerebral Cortex

The cerebellum, which is found just beneath the transient and occipital curves, has an intensely crumpled surface. It helps with the adjustment of our bodies. It likewise supports the control of our viewpoints and the coordination of our body parts. The cerebral cortex is the cerebrum's

outskirts, which remembers every one of the curves for one or the other side of the cerebral halves of the globe, which are associated by the Corpus callosum (nitty gritty beneath). Its thickness regularly goes from 1 to 4.5 millimeters [29]. It is comprised of "dark matter," neurons, and glial cells (helper cells). The neurons help in breaking down and handling data and thusly dispatch these as signs by means of slender nerve filaments known as axons. These axons combine to outline the "white matter" that lies under the cerebral cortex. These strands capability comparatively to telephonic wires, spreading out relationship between various pieces of the psyche and helping with correspondence with the remainder of the body.

2.2.2 Brain Stem and Corpus Callosum

The brain's connection to the spinal cord is established with the help of Brain Stem. It facilitates crucial survival functions. Cerebrum Stem controls significant capabilities, for example, pulse, breathing, processing, and rest. The corpus callosum is an assortment of white filaments that interfaces the left and right halves of the globe of our cerebrum. At the point when seizures start in one piece of the cerebrum and spread to the next, it goes about as an electrical channel.

2.2.3 Thalamus and Hypothalamus

The Thalamus is an enormous mass of dim matter situated in the mind that assists with relating cycles like cognizance and conveys drive messages got through tactile nerves to the cerebral cortex. The Hypothalamus is a very relevant portion of the brain having an authority over the pituitary gland, thereby controlling the hormones secretion. Seizures are often analogous with the emotions and hormonal cycles of the humans. A close check has revealed that the effect of temporal lobes over the hypothalamus is the reason for this. It is located at the base of the brain and is considerably small.

2.2.4 Hippocampus

The Hippocampus is a construction that is tracked down in every fleeting curve and fills in as the focal point of our memory framework. It very well might be harmed because of the etiology of epilepsy, making it harder to follow data.

2.2.5 Gray Matter and White Matter

The cerebral cortex is comprised of gray matter. It is fundamentally comprised of nerve cells known as neurons and glia. Nerve cells capability correspondingly to microchips. White matter is comprised of nerve fiber packs. It is situated underneath the cerebral cortex. These strands' structure correspondence channels, interfacing different pieces of the cerebrum to different pieces of the body like the spinal rope, different organs, and muscles.

2.2.6 Working of Brain

The human mind contains around 85 billion nerve cells known as neurons [26]. They are accountable for communicating signals both inside the cerebrum and to the remainder of the body. Capable of producing electrical signals of very less power, they utilise 'neurotransmitters', a type of chemical, to spread these signals.

As displayed in Figure 2.2, a neuron is comprised of a cell body and an axon. 2. Electrical signs are produced inside the cell body and spread down the axon. The signs meet an unfilled locale referred to as a neurotransmitter as they approach the axon terminals.

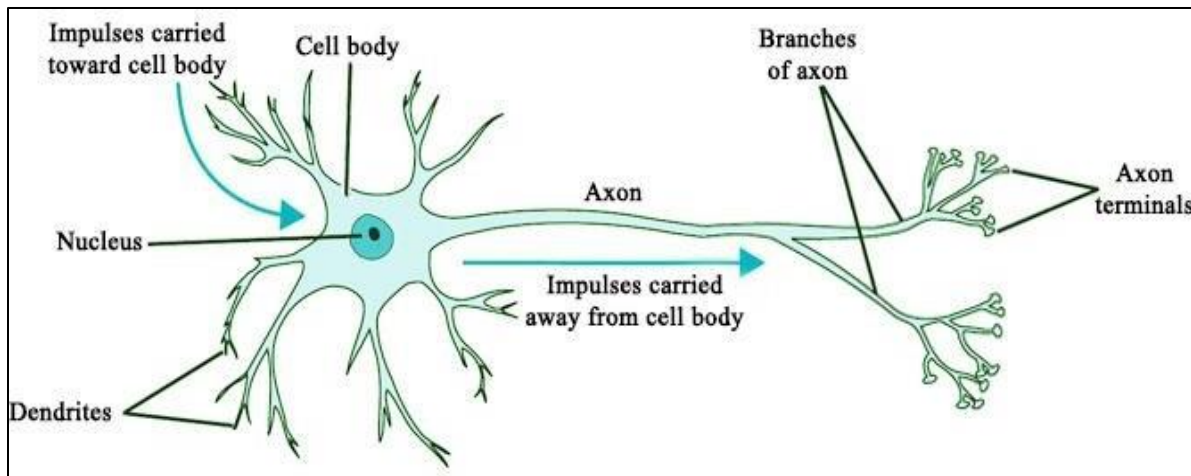


Figure 2.2: The biological structure of a neuron [30].

A substance called a synapse, which is delivered toward the finish of an axon, helps with the association of two neurons. They convey across the neurotransmitter and enact the following neuron. The receptors on the dendrites help in the location of the synapse conveyed by the former neuron. This causes a trigger in the following neuron, which produces electrical signs too. The cycle is rehashed until the sign arrives at its objective.

Synapses don't necessarily in all cases fill a similar need. Excitatory synapses make neurons fire rapidly, expanding mind action. Different synapses, known as inhibitory synapses, repress or obstruct neuronal terminating and in this manner decrease cerebrum movement. One hypothesis recommends that epilepsy is brought about by an awkwardness of excitatory and inhibitory synapses [31].

2.3 EPILEPSY

Epilepsy is a persistent disorder which left the medical ethos clueless about the reason of its occurrence for a long period of time. The patients who suffer from epilepsy have recurrence of unprovoked seizures and are often accompanied by symptoms of other neurological disorders. The term epilepsy gets from the Greek word epilimnion, and that signifies "to seize or assault" [32]. In any case, it is currently perceived that epilepsy is a gathering of neurologic problems portrayed by repetitive ridiculous seizures.

Seizures are events that can go from brief and unnoticeable to delayed episodes of incredible shaking [33]. Epileptic seizures are normal and have no squeezing hidden causes [34]. Seizures that happen for a particular explanation, then again, are not remembered to show epilepsy [10]. "A seizure is a concise event of signs or potentially side effects brought about by strangely high or simultaneous neuronal action in the cerebrum" [10]. The term seizure comes from the Greek word for "to seize." The expression "transient" in the definition alludes to seizures that have a particular beginning and end point. Be that as it may, seizure end is generally more subtle than seizure beginning. A seizure is characterized as a clinical occasion by its signs and side effects. The place of the seizure inside the human mind, the course of spread, the degree of cerebrum development, meds, and different factors, for example, the rest wake cycle all impact seizure organizing. Seizures can create some issues with engine, autonomic, and tactile capabilities. Each seizure doesn't influence all of the previously mentioned factors, however it influences one. Hugh Lings Jackson characterizes seizure as a "side effect, a periodic, over the top, and dislocated release of nerve tissue" in 1970. Maybe Jackson signified "fit for producing brokenness" when he said "jumbled" [35]. In spite of the fact that EEG releases during seizures are all together and relatively generalized, a more normal component of seizures is bizarrely improved neuronal synchrony [10].

Seizures are brought about by strange and unreasonable electrical action in the cerebrum neurons. It's anything but an illness, yet rather a side effect of numerous neurological sicknesses like epilepsy, head injury, mind growth, stroke, metabolic unsettling influence, drug inebriation, etc [36]. Seizures can cause compulsory changes in body capabilities, tactile reactions, etc. It might incorporate muscle quakes, for example, shaking, lip smacking, facial spasms, etc. Seizures can happen in any area of the cerebrum, with fluctuating side effects. It can occur in nerves that control the urinary bladder, for instance, bringing about urinary incontinence. If the seizure occurs in the motor part of the brain, then the symptom might consist of thrashing movements of the body parts. If the seizure occurs in the sensory area of the brain, then it may include unusual feelings like that of pricking of needles [38].

The different parts of an epileptic seizure are delegated follows. Not all seizure types have these parts. The presence and nature of these parts are basic for deciding the kind of seizure [39].

a. Prodromal Phase

This phase sets about few hours or days prior to the actual seizure onset. It is similar to the aura and hence one must be careful to avoid confusion. Headache, restlessness, sleeplessness, bad temper, depression etc. are generally considered as Prodromal symptoms [40].

b. Seizure (ictus)

Most of seizures bring about loss of awareness. In any case, the patient may not remember the seizure accurately. The person will not be able to review any insights regarding the ictus. We should depend on individuals who saw the seizure for this.

c. Post-ictal phase

This phase may either not be present, or may last for a very short period or for several hours, and sometimes may stay even days. Normally, the patient will fall into a profound rest and stir with sleepiness, migraine, disarray, fretfulness, regurgitating, strong torment, or ataxia. This will cause transitory loss of motion of body parts, which might keep going for a couple of hours or days. On the off chance that region of the cerebrum, for example, Broca's region are involved, aphasia or modified discourse will happen. Emotional outbursts and abnormal behaviours will also happen, and if interfered with, patients are likely to go more out of control.

2.3.1 Types of Seizures

The International League Against Epilepsy (ILAE) commission on grouping and wording proposed and supported a characterization of epileptic seizures in view of clinical perceptions and electroencephalographic signs got during or between seizures in 2017 [12]. This grouping is partitioned into three classifications: central (incomplete) beginning seizures, summed up beginning seizures, and obscure beginning seizures. Figure 2.3 portrays a definite grouping of seizures.

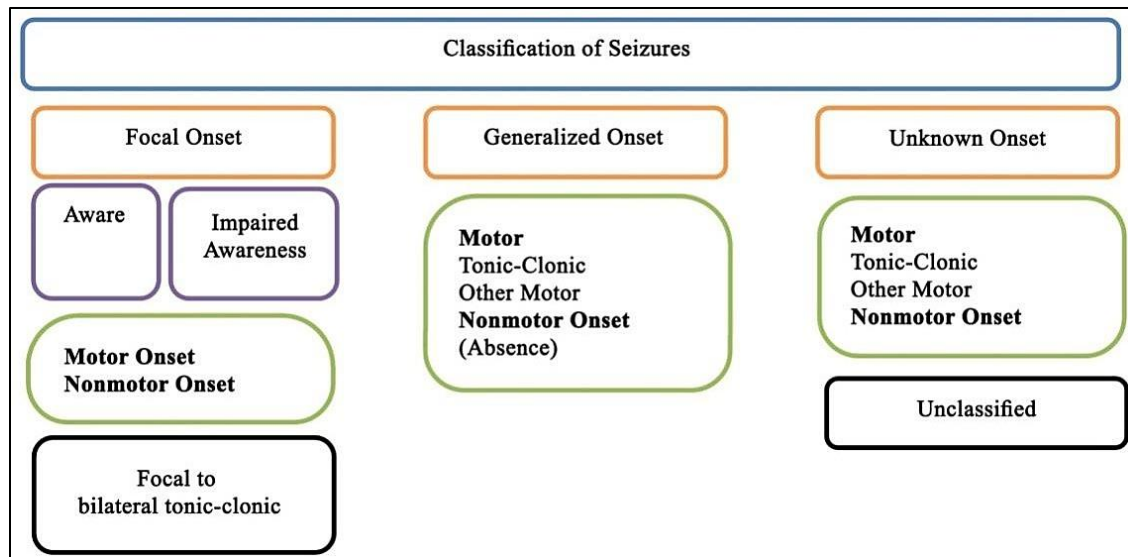


Figure 2.3: Seizure classification proposed by the International League Against Epilepsy in 2017 [12]

Focal Onset Seizures: Seizures that start in one piece of the mind are known as midway or focal starting seizures (connects with prior term partial seizure). Seizures regularly start in one piece of the mind and spread to different parts. Since the impacts of these seizures are much of the time subtle, they slip by everyone's notice or are confounded as intoxication or fantasizing. There are different sorts of focal (inadequate) seizures:

Focal Aware Seizures: During this sort of seizure, the patient doesn't go oblivious. A focal careful seizure is a sort of basic inadequate seizure that influences just a little part of the cerebrum. During such seizures, patients keep up with ordinary consciousness of their environmental elements, yet the impacts of the seizures manifest in the space of the body obliged by the seizure-affected locale of the brain. A straightforward fragmentary seizure influencing the free tactile framework (ANS) may cause changes in circulatory strain, heartbeat, and stomach capacity, in addition to other things.

Focal Impaired Awareness seizure: In this type of seizures, the awareness is altered. Focal impaired awareness seizure corresponds to the prior term complex partial seizures. Although these seizures are confined to a particular region in the brain, it spreads enough that it impairs the patient's level of awareness about their surroundings. These seizures are common, especially when involving the temporal lobe.

Focal Motor Onset seizure: An adjustment of muscle action (spasms) or some likeness thereof will happen in central engine beginning seizures, like jolting (clonic), firmness (tonic), loss of muscle tone (atonic), or automatisms (rehashed or programmed developments).

Focal Motor Onset seizure: Shifts in perspective rate, breathing, or variety (autonomic), clear gaze, failure to talk or move (social capture), disarray, eased back thinking, or/and issues with talking and figuring out (mental changes), unexpected trepidation, fear, tension, or even delight (close to home); or changes in hearing, vision, taste, or deadness, shivering, or agony (tangible) (tactile).

Focal to Bilateral Tonic Clonic: A central seizure can start in one piece of the mind while the individual is cognizant or oblivious. It could then spread to the two sides of the frontal cortex, leaving the individual totally ignorant during the seizure. Different changes happen by and large. For instance, the seizure might spread to cause body solidness (tonic) and snapping advancements (clonic). The old term assistant summarized seizure will be supplanted by vital to two-sided tonic clonic seizure. Basically, the term is utilized to portray the beginning or start of a seizure.

2.3.2 Generalized Onset Seizures

Seizures brought about by far reaching electrical release that show up all around the mind on the double are delegated summed up beginning seizures. These seizures start on the two sides of the mind simultaneously. Most of patients who experience the ill effects of summed up seizures have a hereditary or inherited cause for their epilepsy. There are different kinds of summed up seizures:

Generalized Motor Onset Seizure: A generalized motor onset seizure corresponds to the prior term convulsive seizure which will have muscle activity. Generalized motor tonic-clinic seizures result in the most dramatic convulsions. These seizures start with whole body inflexibility and are trailed by a screech and musical jolting of the body a portion of a moment later. Following the seizure, the patient regularly ends up being mistaken or tired for a few minutes to hours. Tonic seizures are portrayed as whole-body inflexibility, while clinic seizures are characterized as musical jolting of the body without hardening.

Generalized Non-motor Onset Seizure/ Absence seizures: These seizures are commonly short times of obviousness, semi-cognizance, or gazing, with no engine appearances. Petitmal seizures are one more name for them. Despite the fact that patients might seem befuddled or out of it, like

what occurs in complex fractional seizures. For this situation, the patients rapidly get back to business as usual. This sort of seizure is most normal in youngsters.

2.3.3 Unknown Seizures

This is a grouping of seizures that can't be named either central or summed up and are consequently delegated obscure. They include:

- a. Motor onset seizures
- b. Non-motor onset seizures
- c. Unclassified seizures

2.3.4 Changes in Electrical Activity of Brain in Epilepsy

The intricacy of the human cerebrum is a persevering issue. An ordinary individual's mind is fueled by roughly 80 beats of energy each second [41]. Sentiments, considerations, and recollections are created by the volatile development of these heartbeats through the nerve cells. An epileptic seizure is a concise eruption of extraordinary electrical action brought about by an electrical irregularity in the mind. Thus, when the energy vacillations happen, a seizure happens. This extraordinary electrical movement upsets the cerebrum's typical working for a brief timeframe. This impermanent electrical burst can happen in just a little part of the cerebrum, or it can make the whole mind go into an epileptic seizure [41].

2.4 ELECTROENCEPHALOGRAM

The human cerebrum is made out of various nerve cells or neurons that are connected together to frame a mind boggling network structure. Electrochemical signs transport data starting with one neuron then onto the next inside the cerebrum. The brain sign or activity potential is a spike with a length of around 1 millisecond and a plentifulness of 100 V.

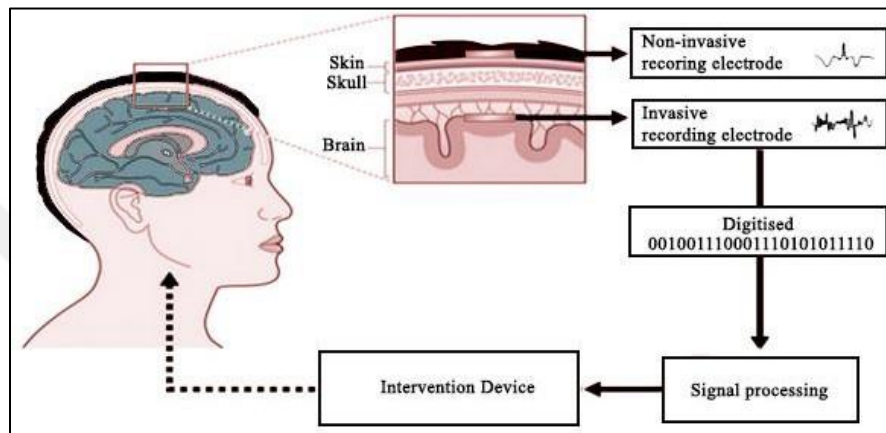


Figure 2.4: Invasive and Non-invasive electrode placements for EEG recording

The electroencephalogram (EEG) is a valuable instrument for perusing the electrical possibilities delivered by the cerebrum during data move between neurons. On EEG accounts, epileptic seizure movement is normally seen as an unexpected change in ghostly substance, frequently as rhythms and spiky waveforms [50]. EEG catches complex examples of brain action that happen in milliseconds and gives a graphical portrayal of spatial voltage dissemination after some time. All EEG recording frameworks are comprised of the accompanying essential units: cathodes, which identify the electrical capability of a given district, intensifiers, which increment the sign greatness, channels, which channel out undesirable segments of the recurrence range, and a recording unit, which gives an extremely durable record. EEG signs can be recorded utilizing both intrusive and painless techniques. The terminals are put inside the scalp and record signals from explicit region of the cerebrum in the obtrusive technique. EEGs are recorded utilizing cathodes put on the scalp in the painless strategy. The standard 10-20 cathode arrangement framework is utilized in the harmless technique [11]. Figure 2.4 portrays intrusive and harmless EEG terminal arrangement.

2.4.1 Method of Scalp EEG Recording

To decrease the impedance brought about by dead skin cells, a region of the scalp is daintily scratched prior to putting the cathodes for customary scalp EEG recording. The terminals, alongside a directing gel or glue, are then applied to the scalp. Numerous frameworks utilize terminals, every one of which is associated with a different wire. Be that as it may, when a high thickness exhibit of terminals is required (on the grounds that cathode installing is required), nets or covers are utilized.

2.4.2 10-20 System of Electrode Placement

In 1924, Hans Berger was quick to effectively record human EEGs by putting a terminal at the rear of the head and one more on the brow [47]. Researchers found that EEG movement fluctuates in various region of the cerebrum in light of the fact that various kinds of occasions happen at the same time inside the mind. This disclosure tempted them to explore the EEG action of the cerebrum at various areas utilizing more anodes simultaneously. As the quantity of cathodes expanded, endeavors were made to situate them in a normalized mode so a patient's record might measure up over the long haul and with records from different patients. At first, recording techniques and standard situation fluctuated enormously from one area to another. A panel of the International Federation of Societies for Electroencephalography and Clinical Neurophysiology proposed the International 10-20 framework for setting terminals in labs under standard circumstances (Figure 2.5) [49].

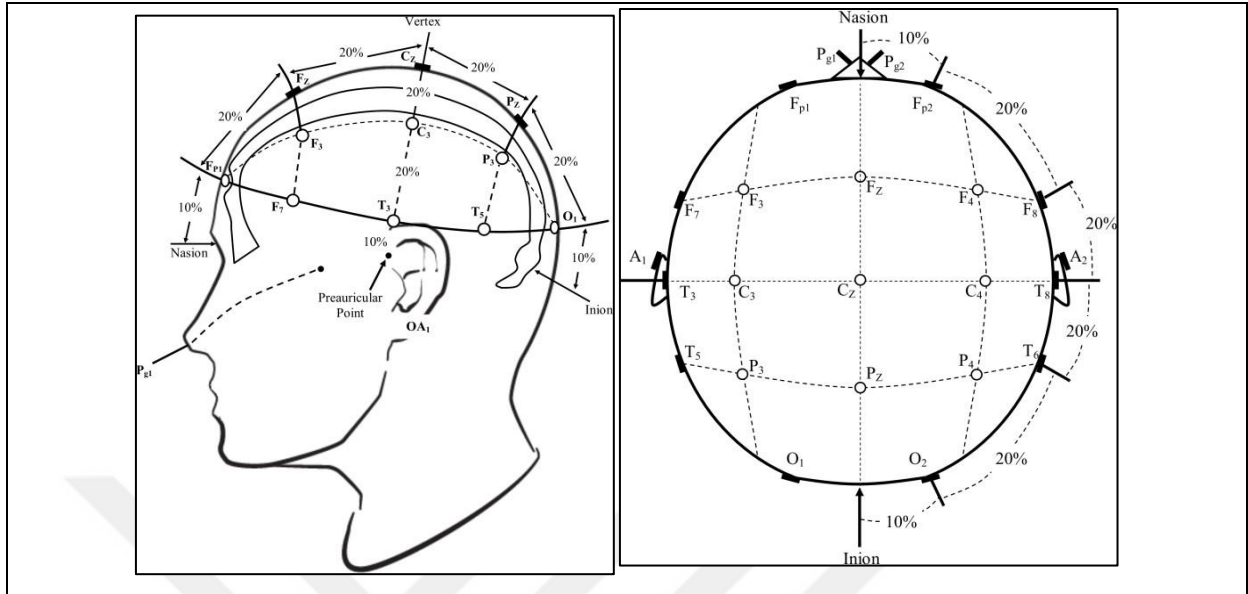


Figure 2.5: The international 10-20 system seen from (a) left and (b) above the head [47].

In the 10-20 framework, 21 cathodes are put on the scalp, as displayed in Figure 2.5 (b). Two reference focuses are picked for the anode situation. To put the terminals, these distances are separated into 10% or 20% stretches. As displayed in Figure 2.5, three more anode focuses are picked on one or the other side of the skull that are proportionately far off from their close by terminal areas (b).

Each site is relegated a letter and an addendum number to distinguish the curve and side of the equator, individually. The principal letter of every curve's name is utilized to address it; for instance, F represents front facing. Additionally, the letters T, P, and O address the worldly, parietal, and occipital curves. Regardless of the shortfall of a focal curve, a few areas are relegated to letter C, and it should be perceived that this is finished for distinguishing proof purposes. Indeed, even numbers (2,4,6,8) are utilized for the right side of the equator of the cerebrum, while odd numbers (1,3,5,7) are utilized for the left half of the globe. Any letter with a "z" (zero) addendum demonstrates a terminal point on the midline. Beside these blends, the letter codes A, Pg, and Fp are utilized to distinguish the ear cartilage, nasopharyngeal destinations, and front facing polar locales, individually.

2.4.3 Brain Rhythms

The example of cerebrum rhythms or waveforms that an individual produces is shown by his age, condition of cognizance, rest or watchfulness, and area on the scalp. These waveforms have explicit amplitudes and frequencies that compare to a particular mental action. In light of their frequencies, mind rhythms are comprehensively characterized into four classes: Delta (δ), Theta (θ), Alpha (α), and Beta (β), a dispersion that guides in the examination of different cerebrum problems. [54]. The above mentioned brain rhythms are shown in Figure 2.6.

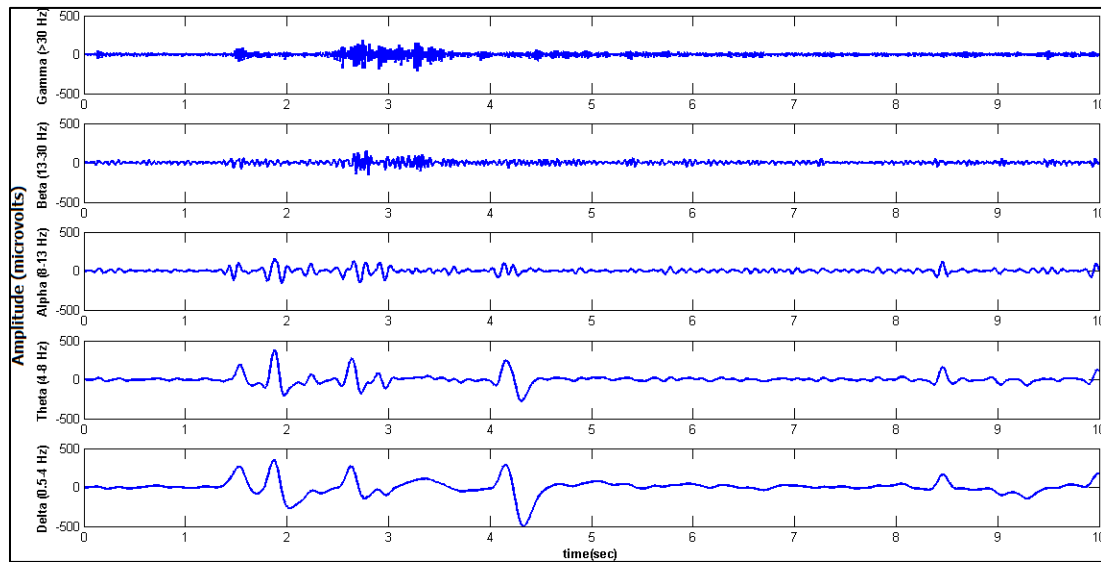


Figure 2.6: Five typical dominant brain rhythms, from high to low frequencies [44]

a. Delta (δ)

Delta waves are tracked down essentially in the parietal curves of the focal frontal cortex. They are in the 0.5-4 Hz range. They have a high plentifulness regardless of having a low recurrence range. They happen during profound rest and during youth. This can likewise be a sign of a serious cerebrum infection.

b. Theta (θ)

Theta waves are tracked down in the mind's parietal and fleeting districts. They have a recurrence scope of 4 to 8 Hz and a plentifulness of something like 100 V. These waves are normal both in early stages and in adolescence. They are most observable when an individual is dozing. It happens in certain grown-ups during close to home eruptions, especially disillusionment and

disappointment. Expanded theta wave movement in a grown-up is viewed as surprising and can be brought about by different neurotic issues.

c. Alpha (α)

Alpha waves are tracked down in the back portion of the head, principally in the occipital curves, and have a recurrence scope of 8-13 Hz. Their appearance demonstrates a condition of quiet mindfulness with no concentration, and they disappear when an individual rests. At the point when an individual's consideration is coordinated to a particular movement that delivers one more class of mind cues, they are typically supplanted by nonconcurrent signs of higher recurrence and lower sufficiency.

d. Beta (β)

The parietal and cerebrums contain beta waves. They have a recurrence scope of 13-30 Hz and a most extreme sufficiency of 30V. They are related with dynamic reasoning, critical thinking, outside center, or exertive spotlight or consideration on something. Beta waves are grouped into two kinds: beta I and beta II.

e. Gamma (γ)

Gamma waves have frequencies over 30 Hz, fundamentally up to 45 Hz, and are now and again alluded to as the quick beta wave. These rhythms have an exceptionally low sufficiency and happen rarely. Thus, recognizing these rhythms can be utilized to affirm the presence of specific cerebrum illnesses.

2.4.4 EEG Artefacts

EEG signals, similar to any remaining signs, are impacted by commotion and the presentation of ancient rarities. These commotions and ancient rarities can have both interior and outside sources. Inside sources incorporate eye squinting, solid movement, electrocardiograms (ECGs), and electrooculograms (EOGs). Figure 2.7 portrays an ordinary part of EEG with curio.

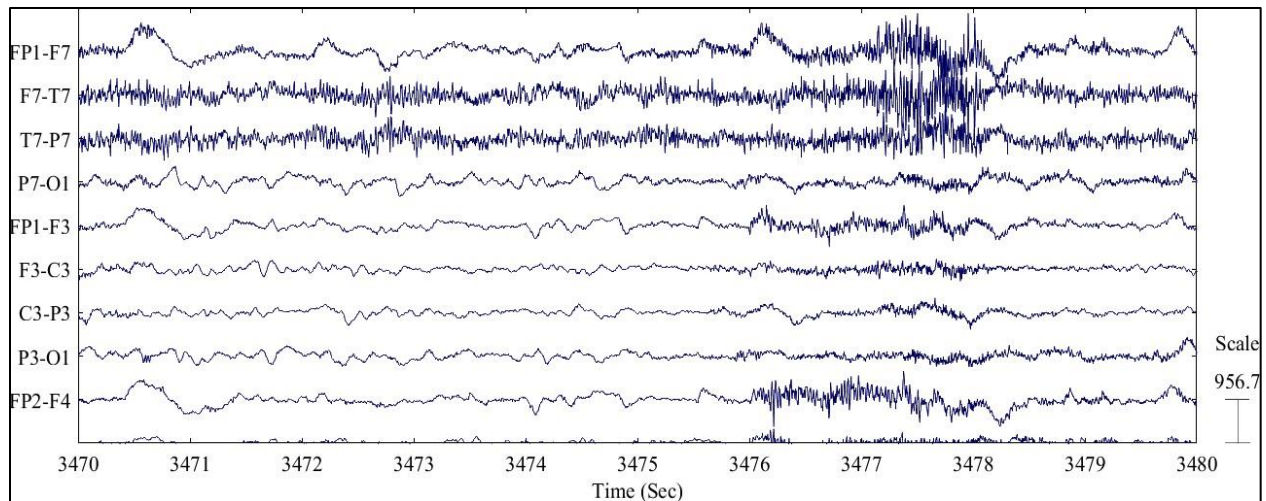


Figure 2.7: Typical segment of normal EEG having artefacts

It is most observable in the foremost polar locale, yet it in the long run spreads to any remaining terminals in the montage and decreases as one maneuvers from the front. Due to its huge plentifulness, it fundamentally affects time examination. Their recurrence content is low and in the alpha band is immaterial. Figure 2.7 shows an eye flicker relic somewhere in the range of 3470 and 3471 seconds. The figure plainly shows that it is available in the mind's prefrontal area (FP1-F7, FP1-F3, and Fp2-F4 channels).

Muscles connected with forehead and jaw development are the most widely recognized supporters of antiques created by strong exercises. Because of mental endeavors, these muscle bunches contract inconsistently. Keeping the tip of the in the middle of between the front teeth or marginally opening the mouth can assist with decreasing the relics created by jaw-related muscles.

Electrooculogram (EOG) antiquities, which are delivered by eye developments, are one more significant inside wellspring of relic. The EOG relics are brought about by a frictional instrument including the retina and cornea of the eye, instead of the eye squint curios, which just include the cornea. They have higher amplitudes and lower recurrence content than eye flicker antiquities. They evenly affect the front worldly and front polar cathodes while moving upward, and an enemy of symmetric impact while moving on a level plane.

The electrical cables cause mains obstruction, which is an outside wellspring of curio. The electrical cables transport electrical signs with a recurrence of 50 hertz and a voltage of 230 volts

(60Hz and 110 Volts in certain nations). This voltage esteem is roughly multiple times more noteworthy than the EEG's 50 to 100 microvolts, and consequently inescapably affects EEG accounts when estimated near them. Protected rooms help in the avoidance of mains obstruction. The EEG recording machine's score channel stifles the signs to a thin band around the mains recurrence. High terminal impedance can every so often cause mains obstruction, which is normally noticeable even after the score channel is enacted.

2.5 SUMMARY

This part portrays how the mind functions, the progressions that happen in the cerebrum during epilepsy, and the different kinds of epileptic seizures. This section additionally gives an outline of EEG signals and recording strategies. EEG estimation utilizing scalp and intracranial EEGs, as well as their utility in recognizing anomalies in cerebrum capabilities, are likewise talked about. This chapter summarises that the major difficulty in detecting epileptic seizure is its randomness and the need of substantial amount of data (due to long duration and number of channels) required to be analysed. This motivates us to use automated methods of detecting epileptic seizures. The next chapter deals with automatic epileptic seizure detection using EEG signals

3. PROPOSED SYSTEM

This section examines the exact dataset utilized in this review. It then, at that point, portrays the proposed approach for identifying the event of seizures.

3.1 COMPUTER-AIDED ANALYSIS SYSTEM

The job of EEG signals in the exact determination of irregularities and neurological problems is turning out to be progressively significant for subject matter experts and doctors. While EEG signals are utilized to analyze numerous psychological and mind neuro-degenerative infections, for example, dementia, Alzheimer's, Parkinson's, headache, rest problems, and awful sensory system problems (e.g., cerebrum injury, mental imbalance, etc), their essential application is for epilepsy. Since EEG information contains a lot of data that differs from one patient to another, breaking down it requires investment. A PC supported examination framework facilitates finding, yet in addition plays out a programmed neurophysiological evaluation for precise discovery of irregularities in EEG signals.

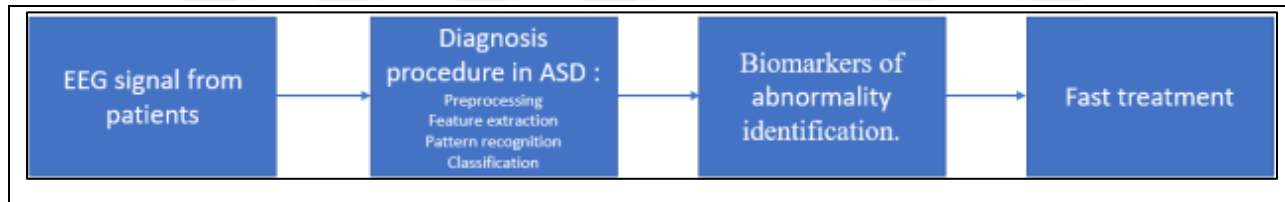


Figure 3.1: The procedure of automated seizure detection (ASD)

As displayed in Figures 3.1, this proposition proposes a PC helped examination framework for robotizing EEG-based seizure finding. It portrays the important phases of finding. The clinician at first gets the EEG signal from the patient. The preprocessing stage is then required. It involves eliminating commotion, which decreases calculation intricacy and calculation time while further developing classifier execution and component extraction effectiveness as biomarkers of infection distinguishing proof. Explicit element extraction is then required, contingent upon the grouping calculation. The framework can perceive the example of happening seizures as seizure biomarkers in the wake of building the model in view of the separated highlights. Subsequently, epileptic patients can profit from a speedy and compelling treatment.

3.2 PROPOSED METHODOLOGY

RNN or Recurrent Neural Networks are basically neural networks that helps in finding the pattern in sequential data like time series data but it has certain shortcomings like vanishing gradient descent and short term memory. LSTM stands for long short-term memory networks, It's basically an extended form of RNN (Recurrent Neural Network) that overcomes the problems posed by RNN and It is capable of learning long-term dependencies, especially in sequence prediction problems. The LSTM has three layers; an input Layer, a single hidden Layer followed by a feedforward output layer.

3.2.1 Dataset

The original dataset from the reference consists of 5 different folders, each with 100 files, with each file representing a single subject/person [5]. We have recorded the brain activity for every 23.5 seconds. We have sampled the corresponding time series into 4097 data points. The value of the EEG recording for each data point is taken at different points in time. So we have a sum of 500 people, each with 4097 data of interest for 23.5 seconds, bringing about an example recurrence of 173.60 Hz. Each lump has 178 data of interest for 1 second, and every information point is the worth of the EEG recording at a particular moment. Following this, we have 11500 data of interest (line) (23 x 500), each line has 178 information focuses caught for 1 second (section), and the last segment addresses the mark $y \{1,2,3,4,5\}$ [5].

Andrzejak et al. at Bonn University gathered the clinical EEG dataset utilized in the task, which is openly accessible [3]. As displayed in Figure 3.2, the EEG signals were recorded utilizing 10-20 standard anode position frameworks. The EEG signal was picked utilizing a low band-pass channel. The fragments come from multichannel electroencephalogram accounts. Interests brought about by squinting or any firm development were taken out from the dataset. The dataset is separated into five instructive sets signified by the letters A through E. Each set has 100 signals, each going on about 23 seconds. Set A reviews surface EEG represents which patients were told to keep up with their eyes open. Set B highlights EEG accounts from five free sound specialists with their eyes shut.

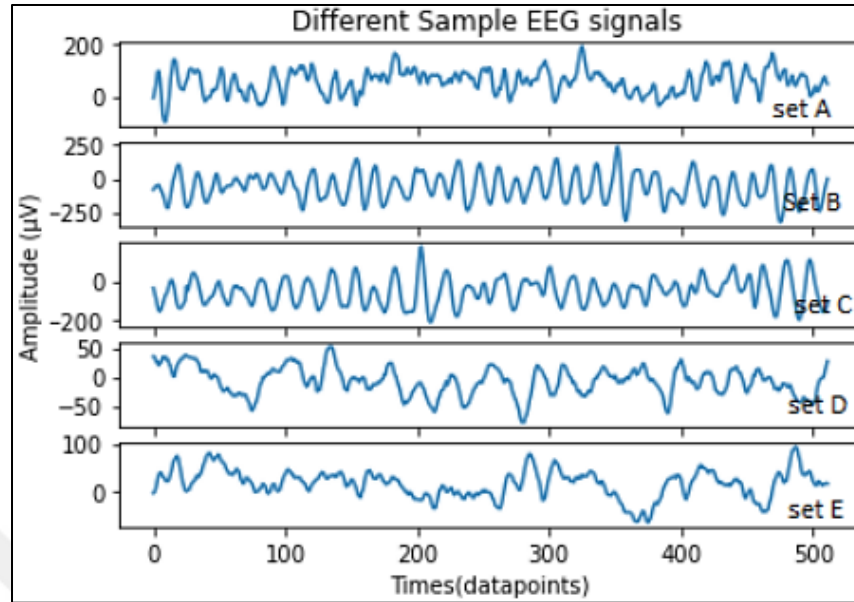


Figure 3.2: Sample EEG signals of five EEG classes

3.2.2 Data Description

The data, published on Bonn University's Epileptology department website, presents Electroencephalogram (EEG) recording of 500 individuals. For each individual, brain activity was recorded for a duration of 23.5 seconds; these recordings are represented by 4096 evenly-spaced, consecutive data points (i.e every 0.0057 seconds). Each row of the dataset, representing an individual's recording, also has a column with the classification of the recording. The five labeled datasets (A, B, C, D, E) are presented below along with their corresponding target classes:

- a. Set A - Class 4: EEG recording of a non-epileptic awake patient with eyes open

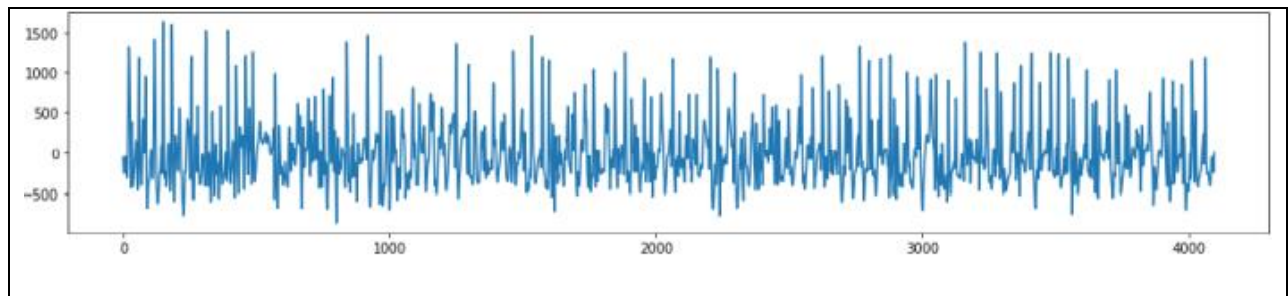


Figure 3.3: Class 4 EEG example

- b. Set B - Class 3: EEG recording of a non-epileptic awake patient with eyes closed

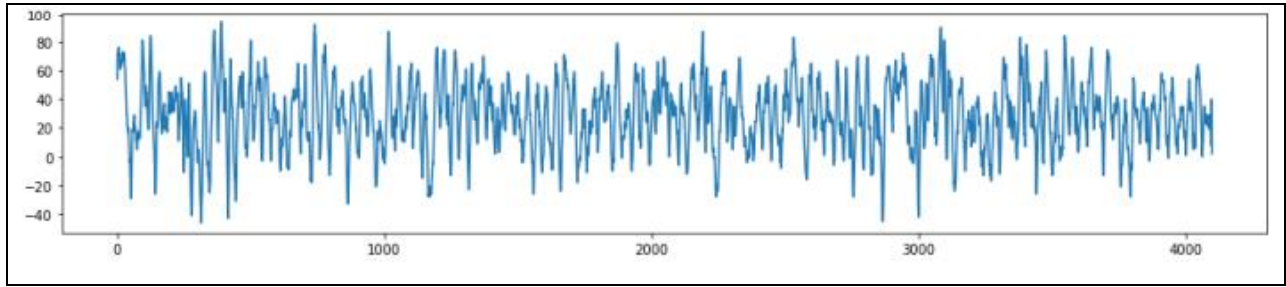


Figure 3.4: Class 3 EEG example

- c. Set C - Class 2: EEG recording of an epileptic patient during seizure free period using electrodes implanted in the brain epileptogenic zone.

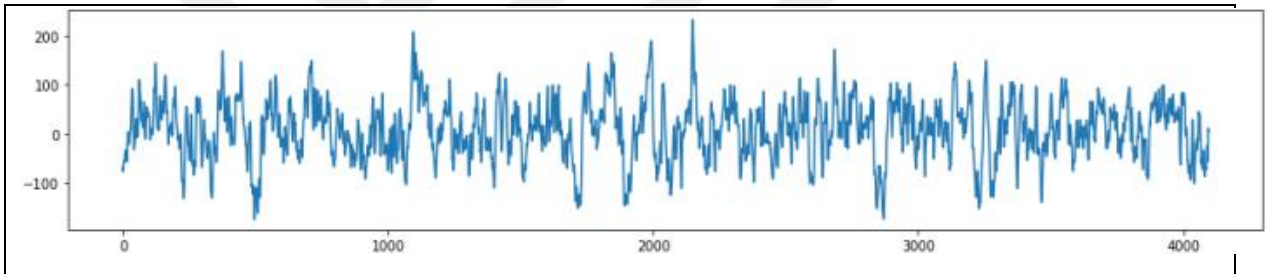


Figure 3.5: Class 2 EEG example

- d. Set D - Class 1: EEG recording of an epileptic patient during seizure free period from the hippocampal formation of the opposite hemisphere of the brain from C.

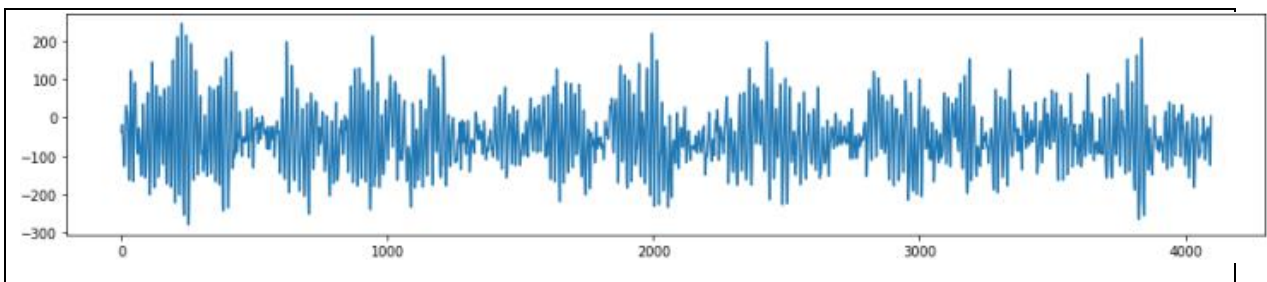


Figure 3.6: Class 1 EEG example

e. Set E - Class 0: EEG recording of a patient experiencing an active epileptic stroke.

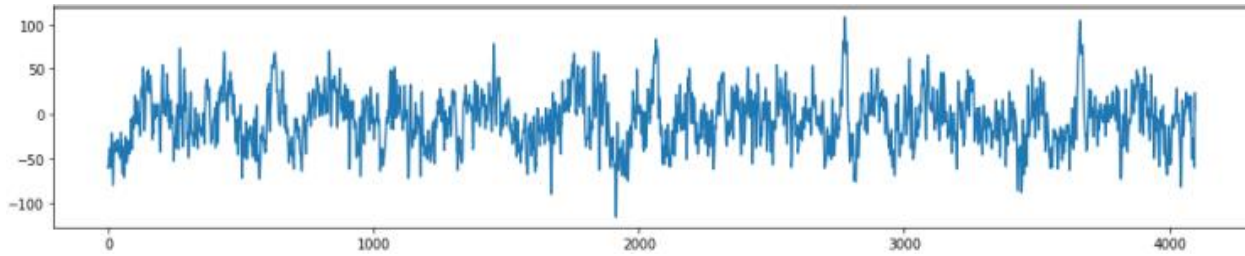


Figure 3.7: Class 0 EEG example

Our objective for this project is to correctly predict these five target classes using an LSTM Neural Network. In order to highlight the capabilities of an LSTM layer, three classification problems will be tackled where the LSTM's performance will be compared to that of a regular deep neural network: i. A two-class problem that classifies whether a patient is having a seizure or not at the time of recording. ii. A three-class problem that requires the classifier to distinguish between a patient that is having a seizure, a patient that is between seizures (inter-ictal), and a healthy patient. iii. A five-class problem that aims to classify all five classes, meaning it should be able to distinguish between a patient that is having a seizure, a patient that is between seizures, and a healthy patient. Additionally, it will be able to determine in which part of the brain the recording is made (Sets C & D) and whether the patient's eyes are open or closed (Sets A & B).

3.2.3 Raw Data Preprocessing

Every EEG signal in the Bonn Dataset was analyzed at 173.6 Hz prior to being digitized utilizing a 12-cycle easy to mechanized converter. To eliminate relics from the EEG information, all EEGs utilized a similar 128-channel speaker structure, which took care of into a band-pass direct with cut-off frequencies of 0.53Hz and 40Hz.

Each recording informational index contains 4096 data of interest, which I partition into portions going long from 1 to 4096 to not just produce many occurrences from a solitary record yet in addition to decide the most effective length of keep to accomplish the most elevated exactness in seizure characterization. These portions act as the establishment for all resulting handling.

In this review, EEG division could dispose of the requirement for an enormous number of marked information tests to construct a substantial model. It is very challenging to acquire an adequate number of all around named information for preparing profound brain networks in true

applications, especially in cases like seizures. Information division permits profound brain organizations to get to additional preparation tests while likewise further developing the profound learning organization's exhibition in tests. Moreover, division makes it simpler to decide the conditions between successive EEG datapoints in every EEG channel signal. Since EEG accounts are non-fixed signals with no steady measurable elements over the long run. EEG division isolates a sign recording into sections with comparable fleeting and ghastly qualities. The different division lengths utilized in this study show which length is the most ideal for proficiently catching elements.

3.3 EEG CLASSIFICATION

A successful order procedure helps with recognizing EEG portions and acquiring a superior comprehension of mental cycles in wellbeing navigation. The essential objective is to sort out some way to address and arrange the explained crude EEG signals for additional investigation. To achieve this, ideal division is expected to separate helpful highlights from crude EEG information and afterward order the information in view of the removed elements. Characterization is regularly used to allude to a calculation strategy for ordering a given piece of info information into one of a given number of classes. The essential objective of characterization is to relegate a class or marks to perceptions in a dataset in view of the found and extricated highlights and in a particular issue.

The characterization calculation (classifier) utilizes preparing sets to plan input information to a classification. The classifier figures out how to distinguish the class accurately. The examination of EEG signal accounts is the focal point of this exploration. Estimating mind cues with EEG recording empowers us to gather important properties of mind cues from a lot of information. There are two kinds of characterization in the grouping domain: administered arrangement and solo order. Perceptions or sets of information are marked to relating class names in regulated grouping. Solo grouping doesn't name or dole out perceptions to a known class.

The most widely recognized approach in biomedical exploration is managed order, and this is the methodology utilized in this review. Managed characterization is performed on a bunch of preparing datasets included a bunch of cases marked with the right result.

3.3.1 Recurrent Neural Networks

People don't start to think and reason without any preparation. It is normally founded on earlier information and experience. The whole thought behind profound learning is to attempt to emulate the human cerebrum and accomplish comparable capabilities as the human mind by using different executions of ANN and CNN. The fundamental benefit of a Neural Network (NN) is that it can gain from related knowledge through ages in a very important and ideal manner.

Albeit the aftereffects of utilizing counterfeit brain strategies to distinguish seizures have been promising, there is still opportunity to get better. CNN-based models look for and gain a similar example in EEG signals from various patients. Nonetheless, the epileptic seizure signature fluctuates among patients and, surprisingly, inside a similar patient over the long haul. To catch these elements, an answer could be proposed. Notwithstanding, conventional brain networks can't meet this prerequisite, particularly with regards to recording EEG signals for seizure discovery. Since we really want to realize what occurred at a past point in the EEG keep to choose and foresee what will occur next by then in the EEG keep to comprehend what is happening now. We would have the option to prepare our model and afterward anticipate whether the seizure would happen in view of the variety of the EEG signal over the long run. The repetitive brain network smoothes this issue and permits data to move through networks by means of circles.

This is the essential justification for why this calculation is proper for consecutive information, like time series. Inward circles can move data starting with one example then onto the next to learn worldly conditions. Vanilla is the first variant of RNN and is addressed by Equations 3.1 and 3.2. This organization utilizes state h at each timestep t and is an element of the ongoing data sources x_t , the past time step's state, h_{t-1} , and weight networks w and U . Conditions 3.1 and 3.2 permit the calculation to register the result at some random time step.

$$h_t = f(wh_{t-1} + U_{xt}) \quad (3.1)$$

$$a_t = f(Vh_t) \quad (3.2)$$

V is the weight matrix associated with the state h when computing the output. As seen in Equation 3.2.

At the end of the day, repetitive brain networks are like conventional brain organizations. It duplicates a similar organization, with each organization making an impression on its replacement. RNNs are cyclic coordinated diagrams, for example, the one displayed in Figure 3-5, that pursue choices in light of both current and past info.

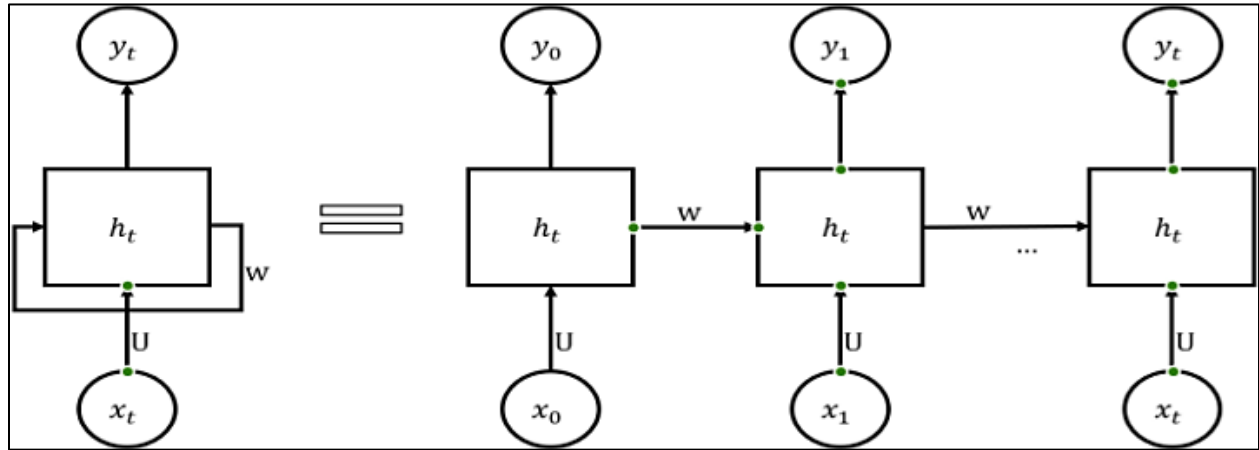


Figure 3.8: A Recurrent Neural Network's architecture demonstrates how a module is repeated and applied to previous outputs and current inputs.

Past information is held in the network's hidden state (h_{t-1}), obtained by Equation 3.3

$$h_t = f(W h_{t-1} + U x_t) \quad (3.3)$$

Thus, h_t is a component of the ongoing information, x_t , and the past secret state, h_{t-1} , increased by weight lattices (w and U). The weight frameworks decide the significance of the current and past states, and they are utilized to limit mistake utilizing a calculation known as Back Propagation Through Time (BPTT). Backpropagation preparing and directed learning calculations are utilized to prepare intermittent brain networks on succession information like time series. Then, at that point, blunders are determined and collected for each time, The organization is moved back up and refresh the loads.

The planning capability, f , can be considered the strategic capability, with BPTT controlling slopes. Since it computes and aggregates the mistakes for each time step. The loads are refreshed toward the end, given w and U all through the organization. This system is rehashed until the

mistake is pretty much as little as could be expected. Because of the secret unit per time step and similar number of updates for each weight update, BPTT turns out to be slow when info arrangements contain great many timesteps. At the point when an enormous number of time steps are expected for longer memory diligence, the organization turns out to be computationally costly, which can make the loads evaporate or detonate, bringing about sluggish learning and wasteful displaying.

3.3.2 Long Short-Term Memory (LSTM)

On account of time series information, the calculation gets a lot of data as a succession of timesteps; nonetheless, not this data might be all basic in working on the calculation's effectiveness in resulting ages. Accordingly, by eliminating a portion of the information from past ages, the neurons would get substantial and adequate data to learn. RRN can't naturally eliminate illogical information from information. It just endeavors to decrease their commitment to the model by changing a little weight for them. Subsequently, neurons can't accurately change their commitment to the result. This technique is computationally costly and may lessen the calculation's learning productivity. The Long Short-Term Memory (LSTM) engineering, then again, gives an answer for this issue.

[40] proposed a novel and unmistakable RNN engineering fit for learning long haul conditions to address the previously mentioned issues. Figure 3.9 portrays the differentiation between customary RNN and LSTM designs. Customary RNNs are portrayed in Figure 3.9. As displayed, the state ht is a component of the past state, $ht1$, and current sources of info like xt .

Figure 3.9 portrays the design of the Long Short-Term Memory (LSTM). To keep away from long haul reliance, the LSTM network is a changed variant of the RNN organization. The LSTM organization, similar to the intermittent brain organization, is worked by rehashing a chain of modules. Through a similar monotonous construction, LSTMs exploit more modern modules.

The principal qualification among LSTM and RNN is that, as opposed to just a single sort of state ht communicating information starting with one timestep then onto the next, there is currently one more kind of state known as the cell state Ct . It is likewise furnished with different entrances that

empower neurons to pick the choice about whether to utilize data from past neurons, as well as the amount of that information ought to be kept up with to chip away at the computation's viability. Thus, information can be eliminated or added to the phone state by means of designs called as doorways.

The LSTMs are numerically addressed by Equations 3.4 to 3.9, which are made sense of further beneath. The administrator represents point-wise duplication. There are two conditions that can be utilized to work out the cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad \% \text{ forget gate} \quad (3.4)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \% \text{ input gate} \quad (3.5)$$

$$\hat{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad \% \text{ output gate} \quad (3.6)$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \hat{C}_t \quad \% \text{ cell} \quad (3.7)$$

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad \% \text{ LSTM output} \quad (3.8)$$

$$h_t = O_t \tanh(C_t) \quad \% \text{ FC layer} \quad (3.9)$$

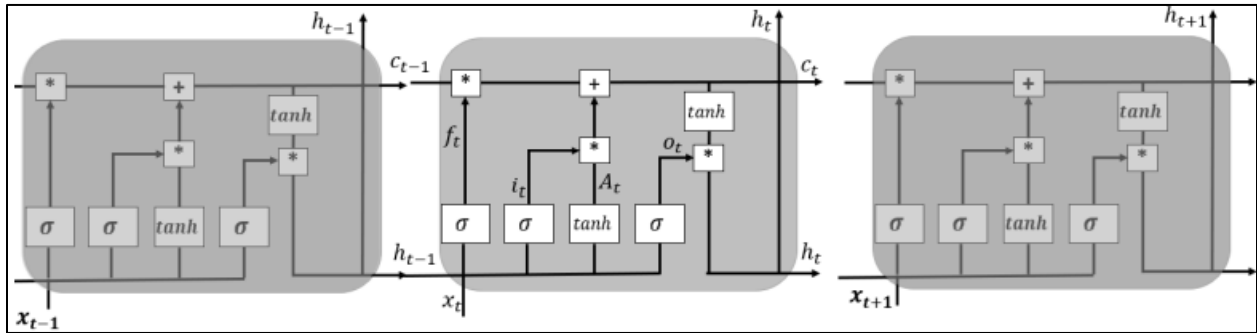


Figure 3.9: Representation of the repeating module in an LSTM

The progression of data through the organization is conveyed by the cell state, which is changed in every unit by its layers. The result of every not entirely settled by duplicating the worth at the result entryway by $O_t = (w_{0ht1}x_t + b_0)$ and the consequence of applying the exaggerated digression to the recently determined cell state. $h_t = O_t \tanh(c_t)$ is the subsequent equation. This

result is workable for each unit. It is workable for the organization to be one to numerous or numerous to many. Nonetheless, contingent upon whether the planning is balanced or numerous to one, yields for some or all units are conceivable. In any case, there are LSTM variations, like peephole LSTMs or different LSTM structures, that utilization several neglect and information doors.

3.3.3 Long Short-Term Memory (LSTM) For Classification

To be prepared, LSTM, similar to some other Deep Neural Network, utilizes the stochastic angle plummet improvement calculation. Stochastic Gradient Descent (SGD) is a technique for iteratively enhancing objective capabilities with reasonable perfection properties (for example differentiable or subdifferentiable). It is normally utilized in high-layered streamlining issues since it lessens computational burden by accomplishing quicker cycles in return for a lower combination rate.

The enhancement calculation over and over gauges the blunder for the present status of the model. This requires the determination of a blunder capability, otherwise called a misfortune capability, that can be utilized to gauge the model's misfortune so the loads can be refreshed to decrease the misfortune on the following assessment or emphasis.

3.3.4 High Level Implementation and Configuration of the Network

Figure 3.10 portrays the obviously noticeable degree of joint effort in the recommended seizure affirmation designing. Each time-series EEG recoding is separated into more modest non-covering parts at first. Following that, the LSTM layers help the fragments. The consequence of the LSTM layers y_i is then observed in the totally related thick layer h , which searches for the most unmistakable EEG attributes related with epileptic episodes. At long last, the Softmax layer finishes the etching estimations by considering the parts found in past layers.

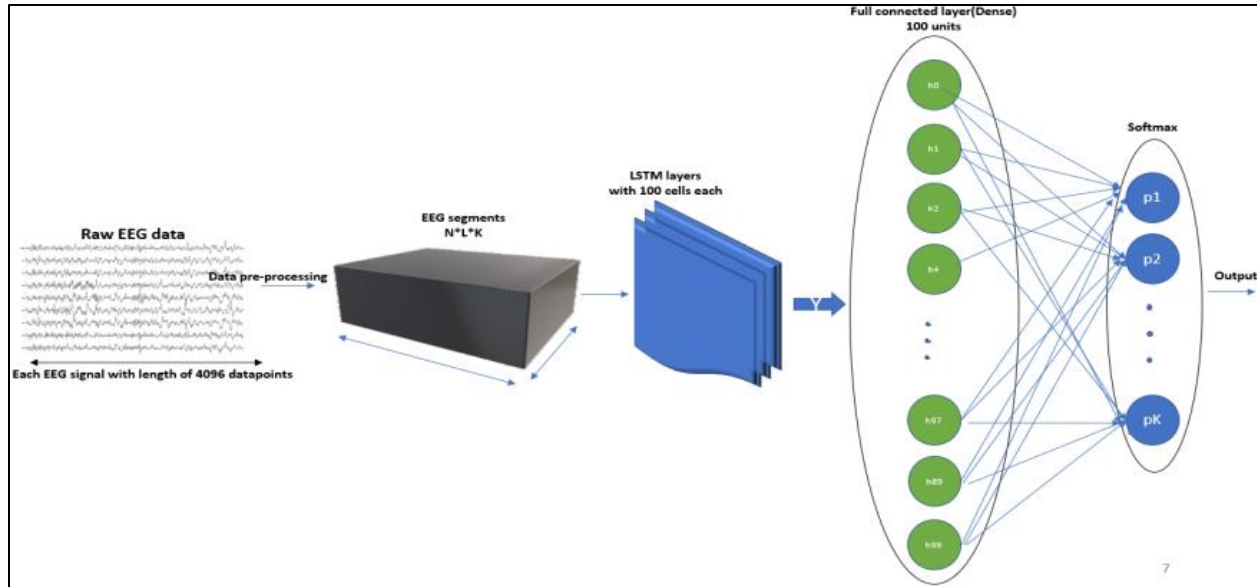


Figure 3.10: High level diagram of the proposed approach for seizure detection system

The open-source library Keras is utilized to lead LSTM investigates EEG highlight learning. Keras is a Python interface for counterfeit brain networks that is open-source programming. The completely associated layer set after the LSTM layers is known as a FC unit. The "bring succession back" boundary was set to "Valid" to guarantee that all EEG portions are considered during the element extraction process. After around 2000 cycles with 40 ages, the organization boundaries met with clump sizes set to 64. While preparing our start to finish brain network model can require as long as four hours, testing it on new information takes under a second. This fast testing execution makes our model ideal for ongoing EEG signal handling in genuine world and clinical applications.

Albeit extremely profound and complex brain network designs might be sufficiently strong to realize all of the valuable data expected for identifying epileptic seizures, growing the organization and adding more boundaries to catch would build the gamble of overfitting. To address the previously mentioned troubles, this paper presents a cunning enormous mind network framework that utilizes LSTM cells from RNN to genuinely exploit transient conditions in time-series EEG inputs, as well as dropout layers to battle overfitting. To get the cleanest and most discriminative EEG information related with epileptic seizures, a completely related layer is utilized on top of the LSTM layer. The computation's pseudocode is shown quickly away.

Table 3.1: Seizure Detection using Deep neural network (Long-Short-Term Memory).

Input: $x \rightarrow$ EEG signals;

Output: Trained LSTM model with optimal accuracy

Initialization: d 4096; M 2048;

Data preprocessing

K number of EEG classes; $K = 2$ and 3 , for two-class, three-class, and detection problems.

EEG segment length change from $L \in \{2^0, 2^1, 2^2, \dots, 2^{12}\}$ and partitioning into segments;

Procedure LSTM($\mathbf{x}$, K , LSTM)

while $t > M$ do
$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad // \text{ forget gate}$$
$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \quad // \text{ input gate}$$
$$\tilde{C}_t = \tanh(Wc \cdot [h_{t-1}, x_t] + b_c) \quad // \text{ output gate}$$
$$C_t = f_{t^0} C_{t-1} + i_t \quad // \text{ cell}$$
$$O_t = \sigma(w_0 \cdot h_{t-1} x_t + b_0) \quad // \text{LSTM output}$$
$$h_t = O_t^0 \tanh(c_t) \quad // \text{FC Layer}$$

End

Compute $P_k = \{P_1, \dots, P_K\} // \text{softmax}(\mathbf{E})$

Find $(\max(P_k))$. class of highest probability

 $\tilde{y}$ = Predicted class label

End

- a. Input weights: $W_c, W_i, W_f, W_o \in \mathbb{R}$

- b. Bias weights: $bc, bi, bf, bo \in \mathbb{R}$

3.4 SUMMARY

EEG or Electroencephalography signals, as recently depicted, record the electrical movement of mind neurons and are generally used to analyze different cerebrum issues. The information gathered from the terminals will be as a period series, and the signs can be characterized into various classes in light of the event of occurrence. In view of the benchmark clinical EEG dataset given by Bonn College, this speculation upheld the improvement of a Long Momentary Memory network model (LSTM) for seizure occasions. The LSTM network model is a kind of sporadic cerebrum network that can learn and review conditions over a lot of information. It is planned for use with information that comprises of long arrangements of information, with time steps going from 200 to 4000 for different issues. This study directed different tests portrayed in Chapter 4 on

various lengths of information successions on variation sets in the dataset to accomplish the most elevated exactness of execution to computerize the seizure location technique.



4. RESULTS AND DISCUSSION

4.1 EVALUATION MEASURE

To measure the degree of success of our classifiers we have to look at the three problems separately. Especially in medical cases correct classification is of high importance (compared to marketing problems for instance), due to the direct impact on people. For the two-class classification problem we have a very unbalanced dataset at hand. A high accuracy could still mean, that we classify those with an active seizure incorrectly, without representing this impact adequate when optimizing for accuracy. Therefore, the correct measure would be precision or recall. As it is an ethical question though, whether it is more important to classify someone having a seizure correctly, or someone not having one incorrectly, we opted to include the confusion matrix that takes both into consideration. But we display the accuracy in the other graphs to keep the results comparable. For the three-class classification problem the data is almost balanced in the sense that we have 300 patients with, and 200 without epilepsy. We consider this an edge case, where there are equal arguments for and against accuracy, but opted for easier interpretability for accuracy. For the five-class classification problem, we have a perfectly balanced dataset, therefore, accuracy is in our perspective the best measure. To reduce the impact of randomness, all results are averaged over five seeds.

4.2 DATA PREPARATION

As the data is considered clean, and the entire dataset has to be used for the question at hand, no modifications were applied to the data. As the dataset is balanced with 100 cases for each category over- or under-sampling techniques were not applied. Enriching the dataset to reduce overfitting in this case is from our perspective not possible, as the patterns in the EEG are of high importance to spot epileptic behavior. Trying to replicate these patterns from the existing samples would be prone to errors as the differences between the samples from the five categories are very hard to spot.

4.3 TWO-CLASS CLASSIFICATION

The most basic classifier for this dataset would be able to distinguish between an individual experiencing a seizure and one who is not. For this model, the target classes have been reduced to patients that are currently experiencing a seizure (label 1: Set E), and patients that are not experiencing a seizure at the time of recording (label 0: Sets A, B, C, D). Our model (LSTM) is tested against a regular deep neural network model (NN) so as to compare the performance of both models on this simplified task. Figures 6 and 7 show the validation accuracies and losses of our LSTM model and the NN model (averaged over 5 seeds). We notice that although the LSTM outperforms the NN model, the results are fairly close. We can conclude from this that on a simplified binary problem, the LSTM doesn't deliver significantly more performance than a regular neural network.

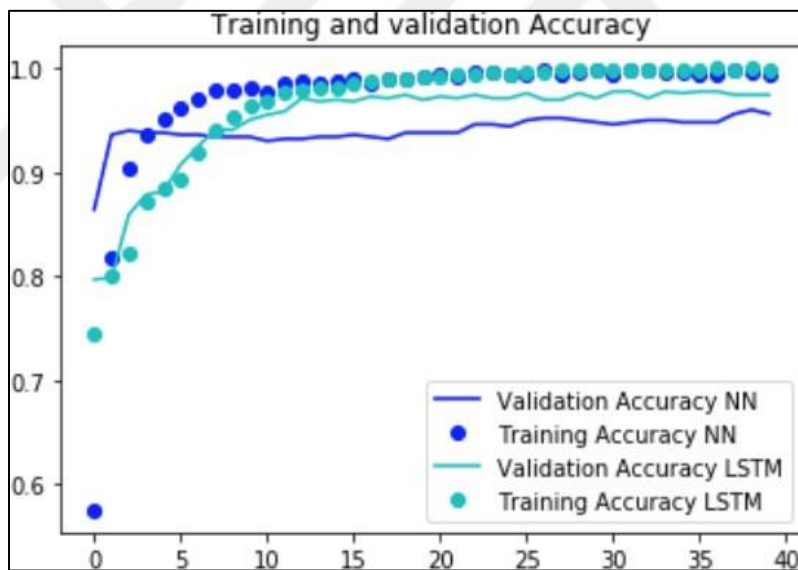


Figure 4.1: Training and validation accuracy

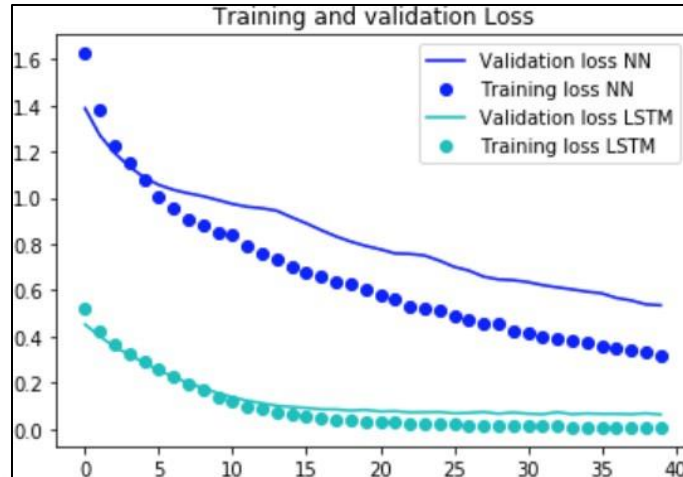


Figure 4.2: Training and validation loss

The confusion matrix shows us that our LSTM model performs well, and that even though our dataset for the two-class classification is unbalanced (400 instances of non-seizure patients (0) and only 100 instances of seizure patients (1)), accuracy is an appropriate measure since it there are no false positives and only 7% false negatives

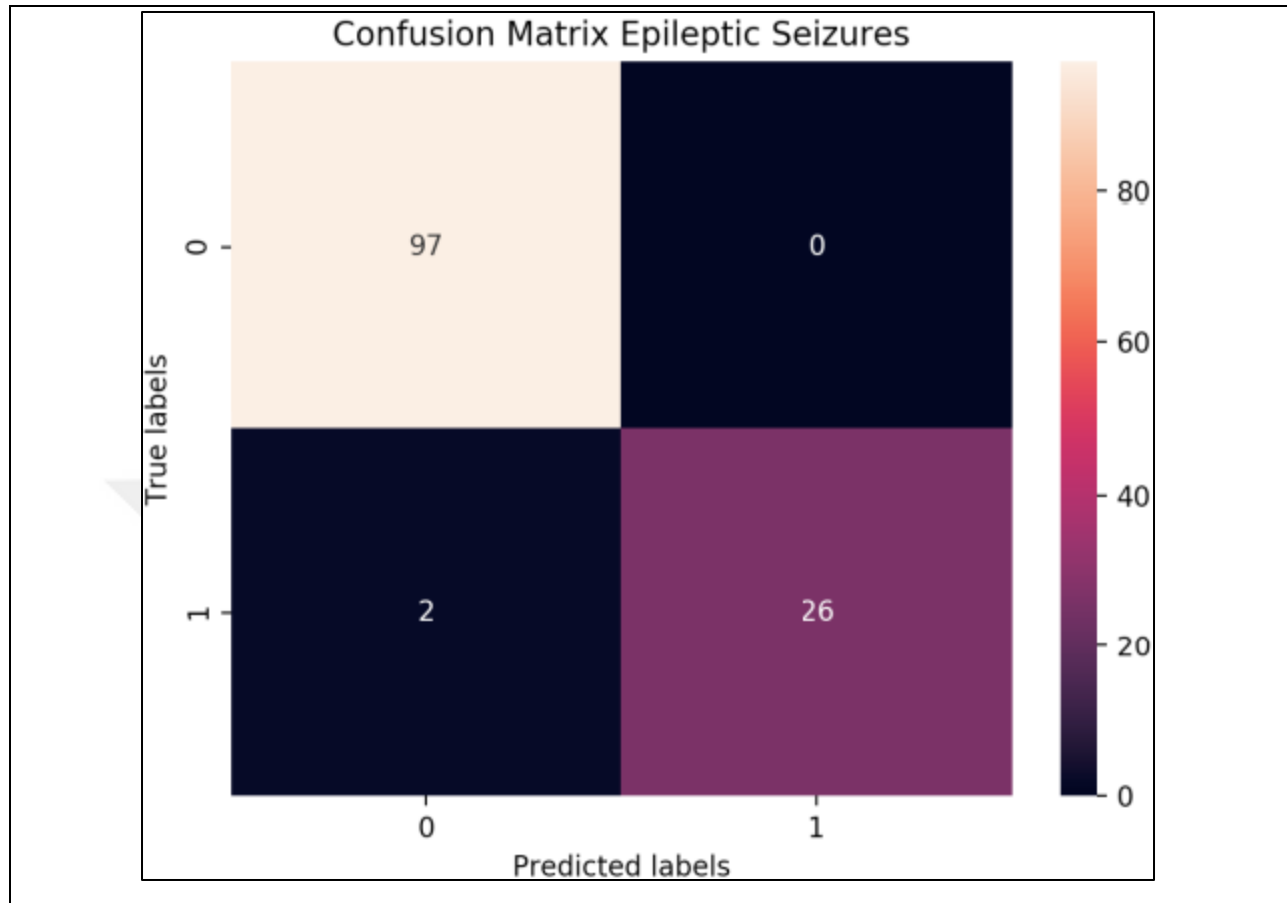


Figure 4.3: Confusion matrix two class classification

4.4 THREE-CLASS CLASSIFICATION

In the three class-problem it becomes clearer that sharing time related information between neurons significantly increases performance and give the LSTM an advantage. Not only does the LSTM perform better, it has much better generalization ability than the regular neural network. We can conclude that the LSTM is appropriate to use for more complex time-series classifications. Figure 4.4 shows us the confusion matrix of our LSTM; we notice that our model can correctly distinguish between non-seizure patients (label 0), inter-ictal patients (label 1), and seizure patients (label 2)

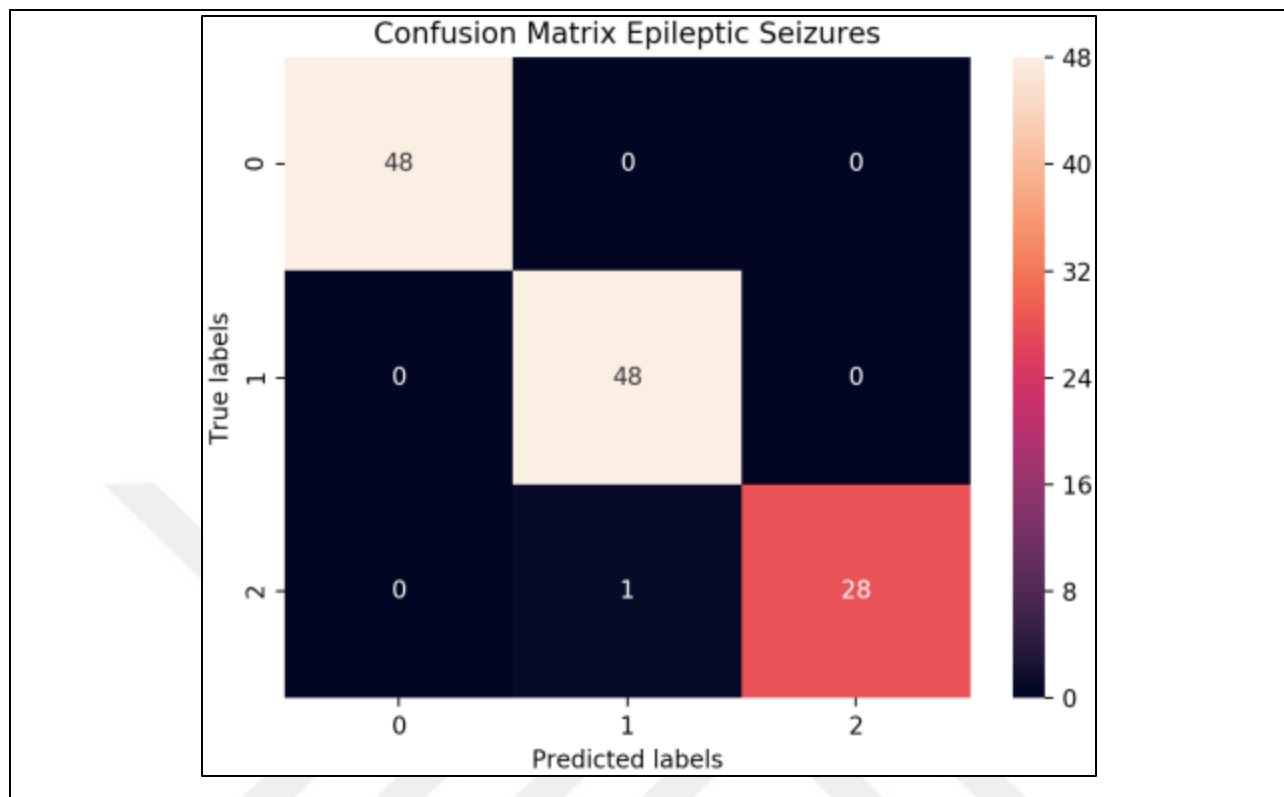


Figure 4.4: Confusion matrix three class classification

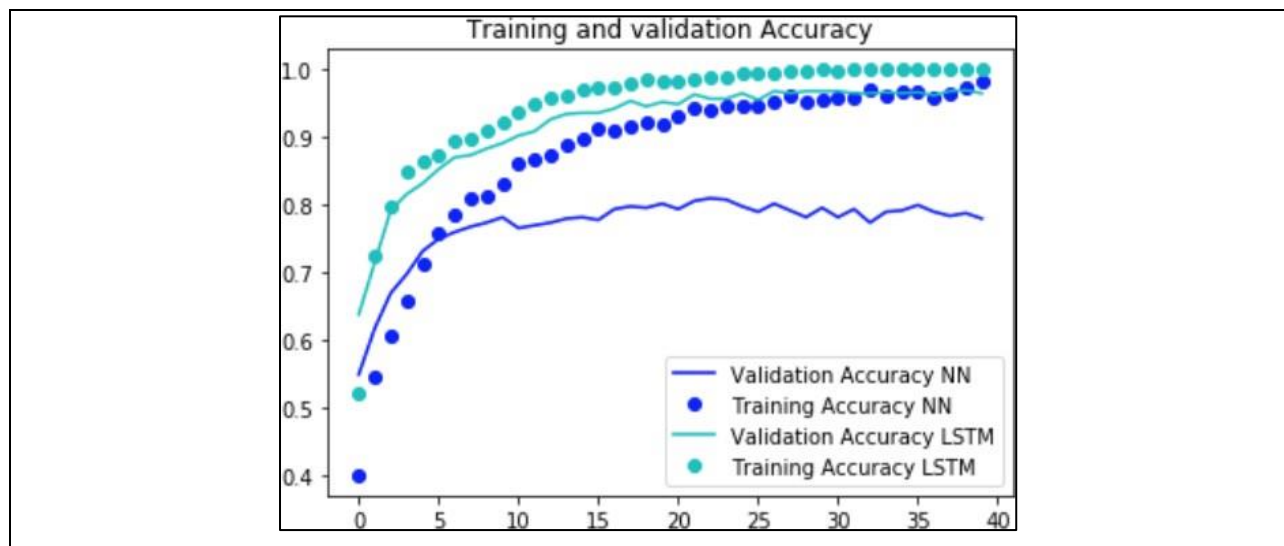


Figure 4.5: Training and validation fitness

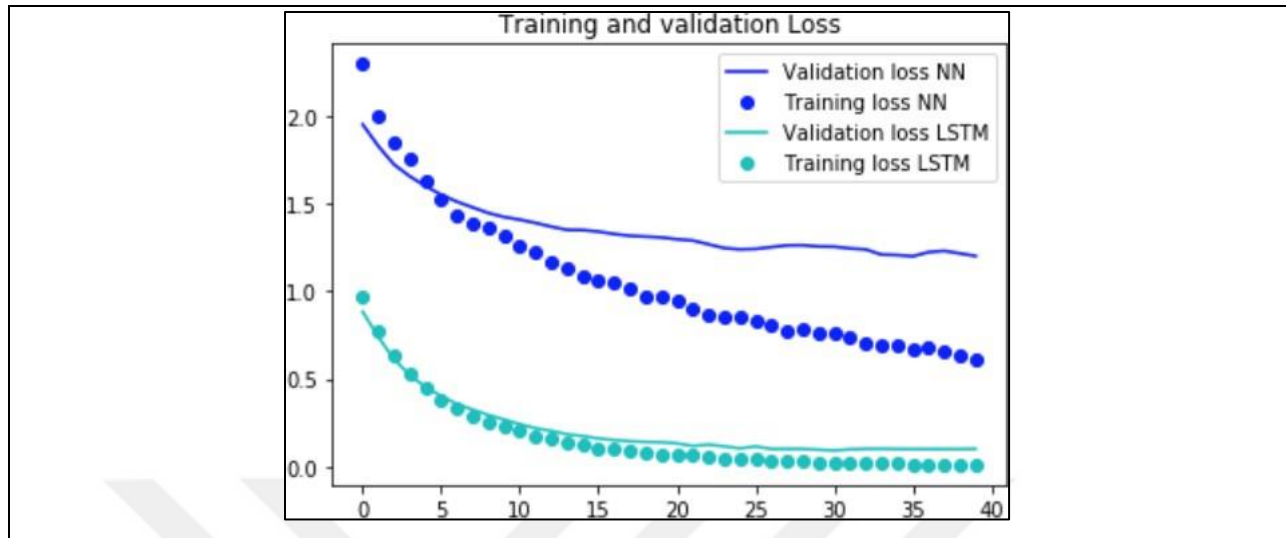


Figure 4.6: Training and validation loss

4.5 FIVE CLASS- CLASSIFICATION

The LSTM performs better than the normal neural network on the five-class problem; this was expected given the results of the three-class problem. However, we noticed that while the LSTM still performs well, there is a significant drop in generalization ability (i.e the LSTM overfits). This holds even more for the generalization ability of the NN. In this section we will further explore the LSTM through a series of optimization techniques, architectural changes, and feature engineering techniques will be implemented and tested in order to further increase its performance and reduce overfitting.

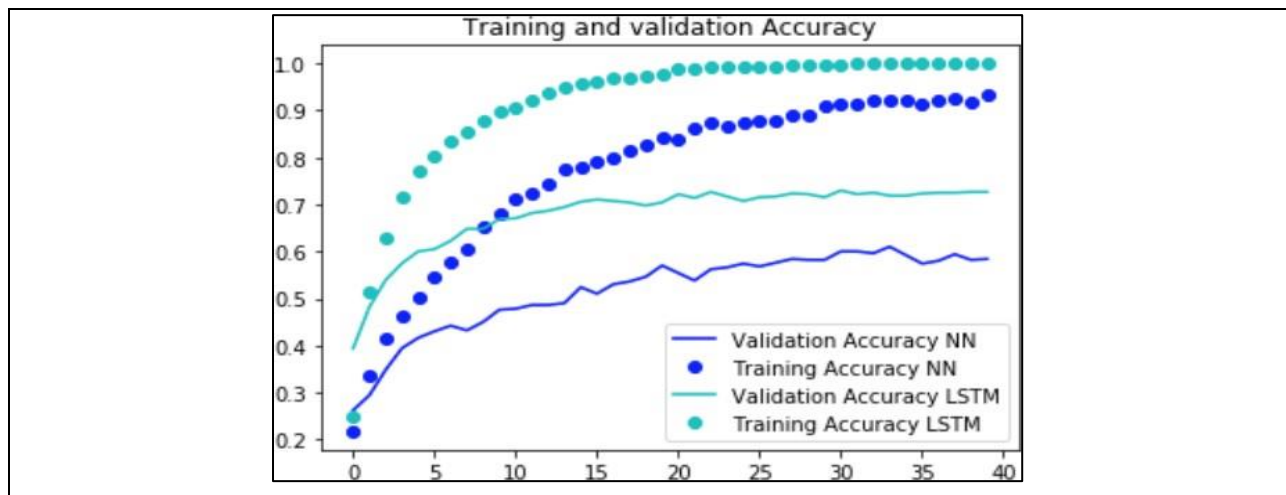


Figure 4.7: Training and validation fitness

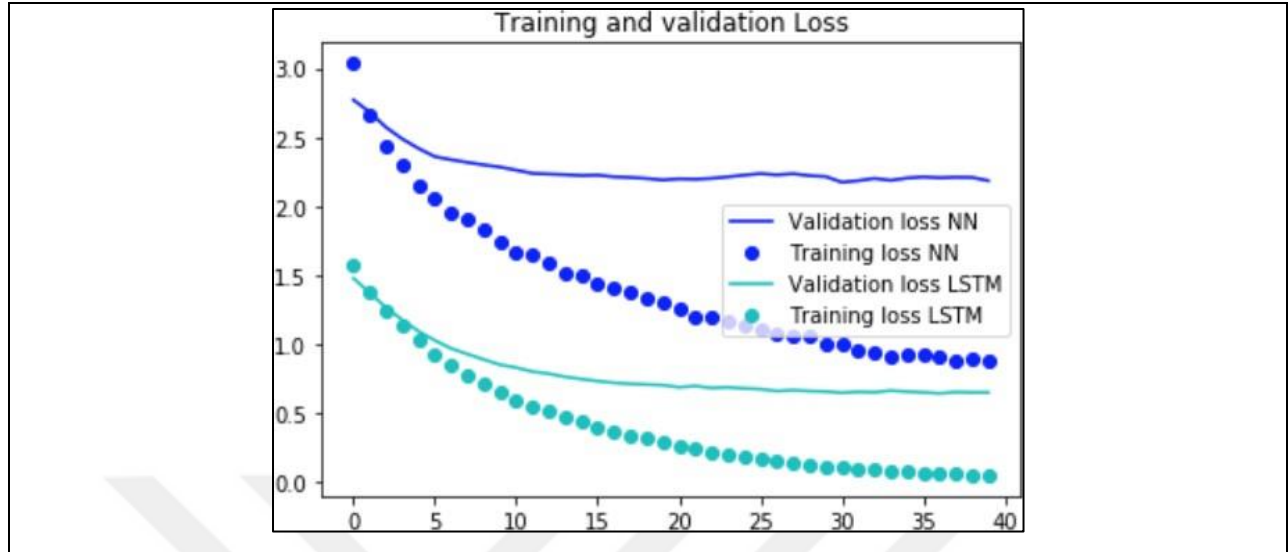


Figure 4.8: Training and validation loss

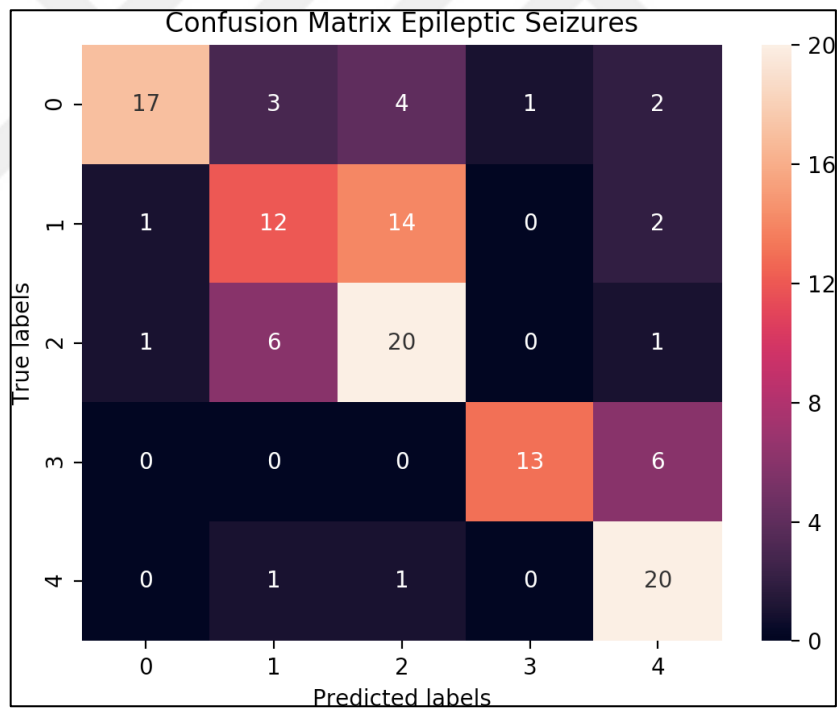


Figure 4.9: Confusion matrix five class classification

We notice from the confusion matrix in figure 4.9 that the model is mainly having trouble distinguishing between classes 1 & 2, these correspond to the ‘recording of an epileptic patient during seizure free period using electrodes implanted in the brain epileptogenic zone’ and the ‘recording of an epileptic patient during seizure free period from the hippocampal formation of the opposite hemisphere of the brain from C’. In other words, while our model can correctly classify

inter-ictal patients, it is having difficulties distinguishing between the different parts of the brain that are being recorded. It seems our model faces two main issues; overfitting and the inability to distinguish between the two types of inter-ictal recordings. In the following sections of this report, we will further explore the architecture and parameters of our model in order to try and improve it.

4.6 METHODOLOGY

In the previous part of the report we used a working configuration of the NN and LSTM model to compare them on each respective problem. We did not finetune the respective model for this part of the report. In the following part we outline elements of the LSTM that we further addressed when finetuning the model. The LSTM consisted of a first LSTM layer with 100 neurons, followed by a 10% dropout, followed by a Time Distributed Dense layer with 50 neurons and a Global average pooling layer. The last layer has the number of neurons fitting to the problem. Further details are in the code.

4.6.1 Epochs

Running our basic LSTM implementation over 100 epochs highlights that the appropriate number of epochs used for our system is at around 40 epochs. In Figure 4.10, we see our validation accuracy stabilizing at around 40 epochs whilst on the right-hand side we observe that beyond 40 epochs, an increasing dispersion between training loss and validation loss arises, suggesting we would be increasingly overfitting.

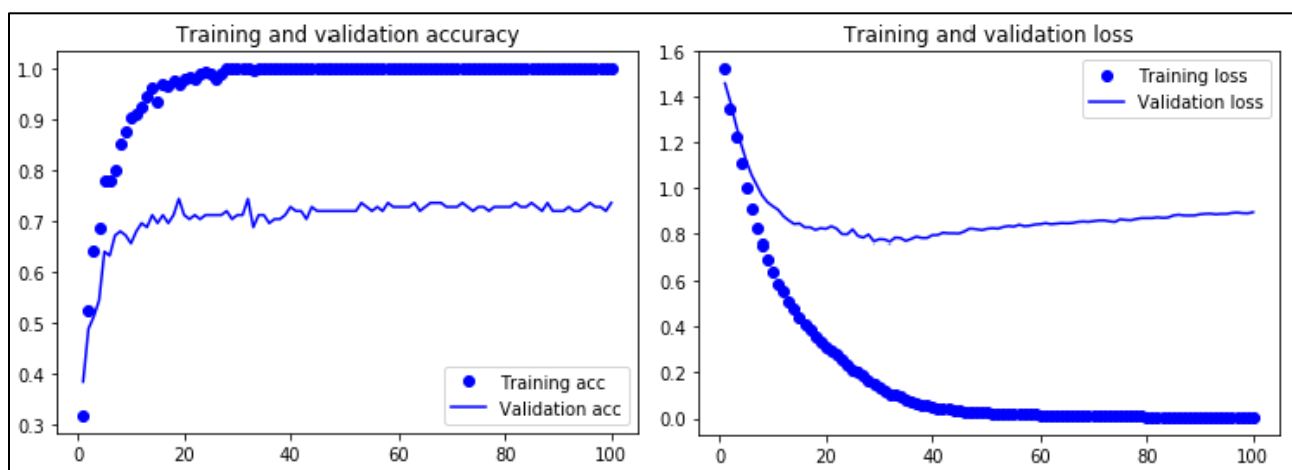


Figure 4.10: Training and validation of fitness and loss

4.6.2 Pooling

Global Pooling layers in convolutional networks play an extremely important role as they reduce the dimension of data from the prior layer through the combination of its neuron clusters into a single neuron in the following layer.

a. Global Max Pooling

Global Max pooling on the other hand extracts the maximum value from a cluster of neurons in the previous layer. Perfect test accuracy is achieved at around 20 epochs and we see our validation accuracy stabilizing at around 55% at 33 epochs and beyond. We observe a final training/validation loss spread of roughly 1.1.

b. Global Average Pooling

Applying the Global Average pooling layer extracts the average value from a cluster of neurons in the previous layer to then in turn create the appropriate output. Our validation accuracy terminates at just above 70% whereas we observe convergence to a perfect test accuracy at around 25 epochs. A final training vs validation loss spread of around 0.8 still provides some evidence of overfitting.

c. Global Average Pooling vs Global Max Pooling

Seeing the two pooling methods in parallel, highlights a clear winner. The lowest observed Validation accuracy for Global Average Pooling is higher than the highest observed for Global Max Pooling. Furthermore, we see significantly more validation loss for Global Max pooling, pointing out such model would likely struggle to generalize as well as our winner, Global Average Pooling.

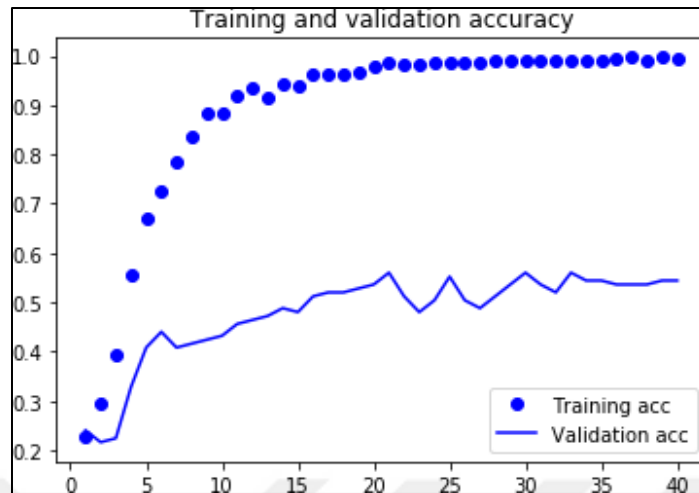


Figure 4.11: Training and validation fitness

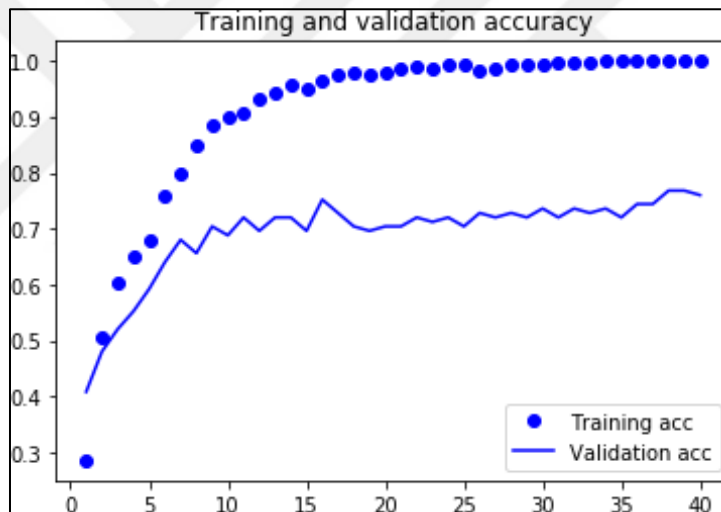


Figure 4.12: Training and validation fitness

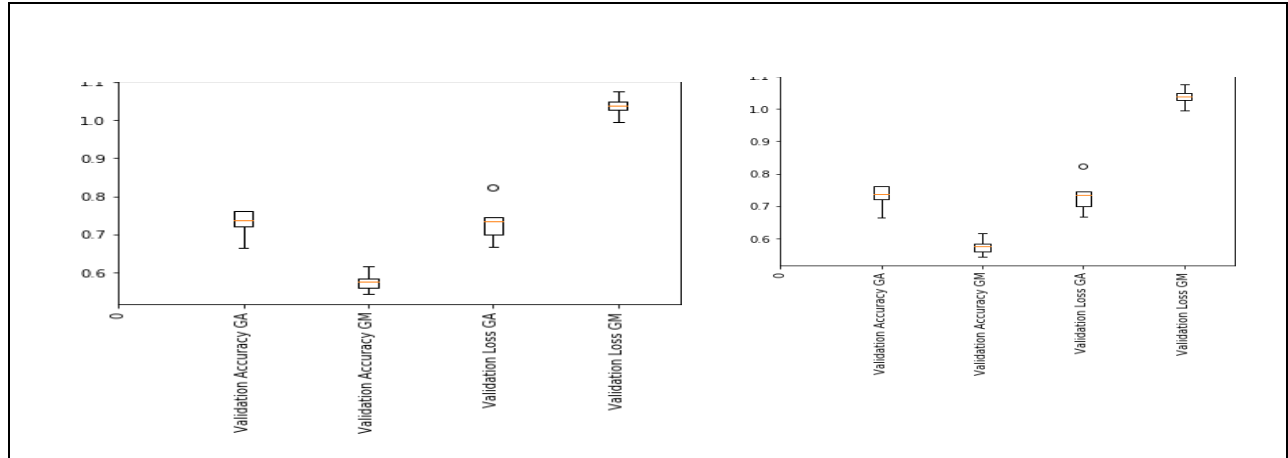


Figure 4.13: Results comparison pooling.

4.6.3 Timesteps & Dimension Sizes

Each row of the epileptic seizure dataset represents a 23.5 sec EEG recording of an individual; this data is represented as 4096 evenly-spaced, consecutive points. Although it is possible to create an LSTM neural network with 4096 input variables, our belief is that this data can be aggregated into a series of shorter time dimensions; aggregating the time information according to smaller timesteps would reduce computational time and create a simpler model. Our parameter timesteps represents the number of times the row data will be divided (i.e the number of input variables our LSTM model will receive). For example, if we choose 128 timesteps, our data will be split into 128 input variables, each containing 32 data points ($4096/128 = 32$).

Our initial model, the one that was tested against a normal neural network for each classification problem, was divided into 64 timesteps; this means the LSTM model received as inputs time blocks corresponding to 64 consecutive recordings. This division was arbitrary; in reality, our time series can be divided into can be divided by any factor pair of 4096 corresponding to the timesteps and data dimension. The times of the data point in an EEG recording are crucial in identifying the type of patient being recorded. In the interest of exploring the time relation between data points, and improving our model's capacity of correctly classifying the two types of inter-ictal patients, different timesteps and data dimensions were tested.

Figure 4.17 shows the validation scores for different data dimensions (i.e number of recordings per timestep), averaged over 5 seeds; we can conclude that 256 timesteps (i.e 16 data dimensions per timestep) yield the best validation scores for our data (Figure 4.14, dim 16). Reducing the data dimension seems to have improved our model’s generalization ability while overfitting less. This leads us to believe that shorter timesteps improves our model; this means our LSTM performs better on this dataset when less information is shared on between the neurons because shorter timesteps account for less variation in the recordings.

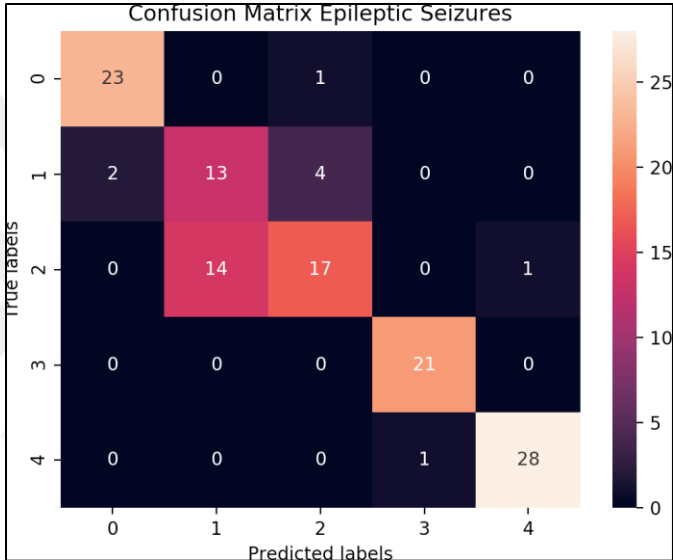


Figure 4.14: Confusion matrix 128 timesteps

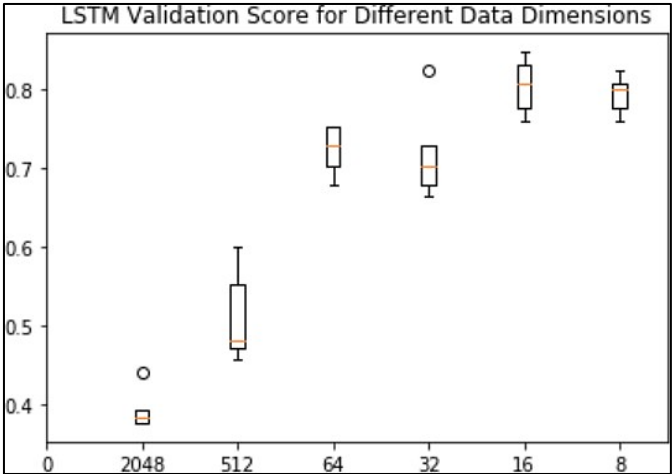


Figure 4.15: Results comparison timesteps

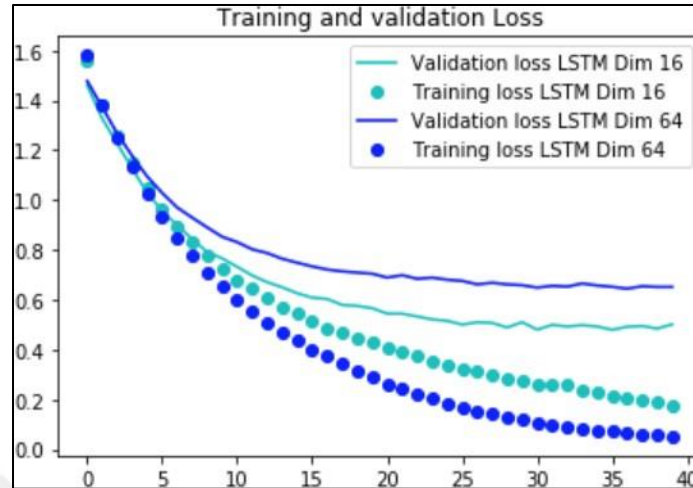


Figure 4.16: Training and validation loss

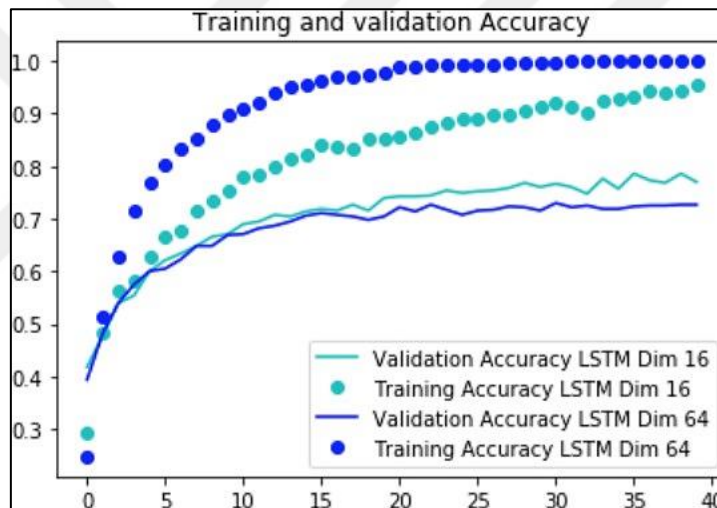


Figure 4.17: Training and validation fitness

4.6.4 Neuron Configurations

To change the configuration of the LSTM model in the dimension of the number of Neurons, two layers can be optimized. Firstly, the number of neurons in the LSTM layer, secondly the number of neurons in the hidden layer. Additionally, further layers can be added to the network, however in theory, this is not necessarily required to solve this problem. When adding neurons to the LSTM layer the accuracy increases. At 400 LSTM neurons the performance on validation accuracy is up around 5% compared to the model with only 100 LSTM neurons. However, the runtime drastically increases more than four-fold compared to 100 neurons in the first layer. Furthermore, an increase in overfitting is observable as the slope of the validation loss curve on the right in Figure 4.18 shows after epoch 25.

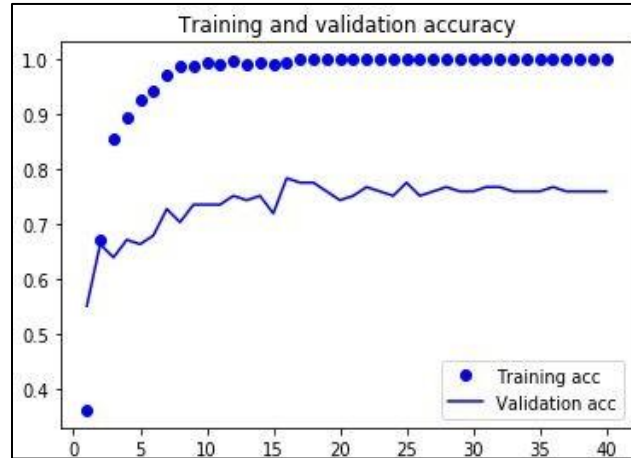


Figure 4.18: Training and validation fitness.

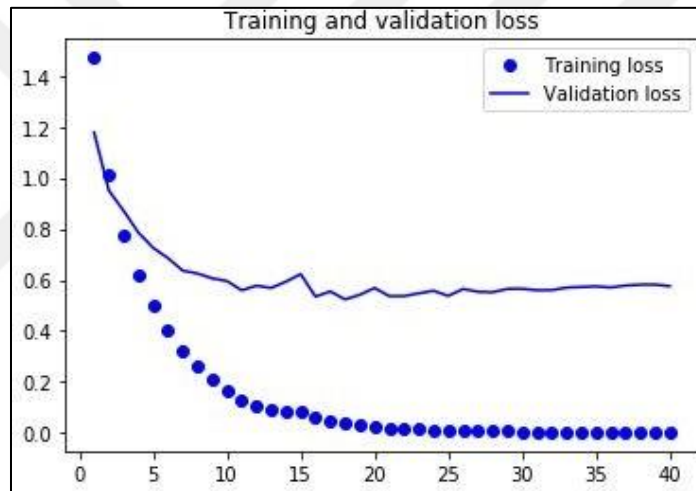


Figure 4.19: Training and validation loss.

In other problems several concurrent LSTM layers, especially for text mining applications, proved useful. However, in our case this did not contribute to better results, probably because of the higher complexity of text analysis.

When changing the number of neurons in the hidden layer, it seems the optimum number of neurons is at 50. Increasing or decreasing only weakens the performance of the classifier. An increase to over 100 neurons seems to have the same overfitting behavior as described above on the instance of the LSTM layer. Adding additional hidden layers with different number of neurons did not contribute to better results, but either the results were worse or rather seed dependent, which we interpreted as another sign of overfitting.

4.6.5 Dropout & Regularization

Introducing Dropout and Regularization to the model are two measures to counter overfitting of the model. The gap between the training and validation data can possibly be reduced by applying these techniques more successfully.

Adding dropout after a layer of neurons of any kind will eliminate the weights at random positions of the model differently at every iteration of the model. Therefore, it will introduce a degree of randomness to the training of the weights.

Without any Dropout in the LSTM model introduced (black in figure 26 on the right), the model performs worst in terms of validation accuracy and validation loss compared to the blue boxes, representing one dropout layer after the LSTM and Dense layer each (dropout probability of 0.1 at optimum configuration), and the orange boxes representing the scores with only dropout after the LSTM layer.

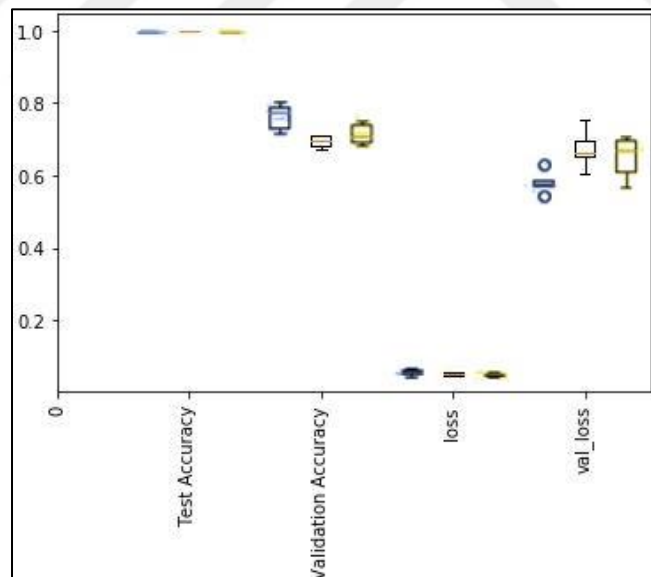


Figure 4.20: Results comparison dropout

For the regularization, three regularizes are commonly used, the L1 (lasso) the L2 (ridge) and L1/L2 (elastic net) regularizes. All these regularizes can be applied to the use of the activation inside the neuron, or to the output of the weights towards the loss function. However, in neither of

the configurations, even with very low boundary values, did not improve the performance of the model or reduced overfitting. What can be observed though, is that the model learns a lot slower, and the initial error is much larger (10 fold) than without regularization as it is shown in figure 4.21 on the right.

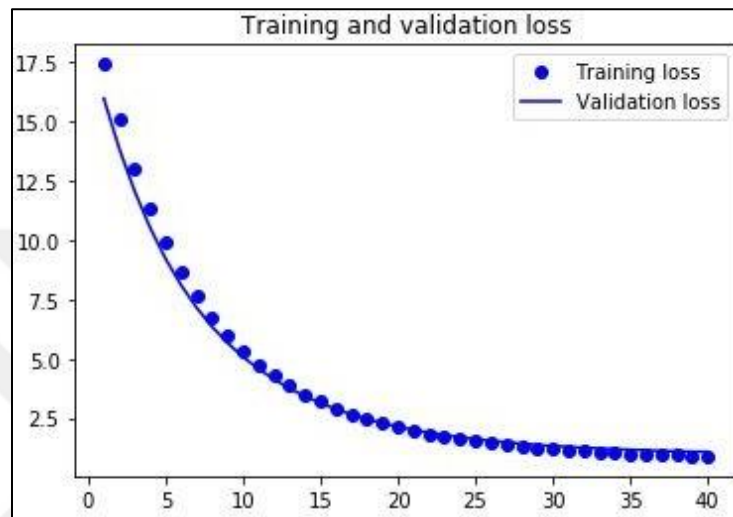


Figure 4.21: Regularized loss development

4.7 DISCUSSION

EEG signals are displayed as time series turbulent information in light of the fact that the cerebrum is a nonlinear unique framework as the actual calculation is unequipped for managing this matter. For the seizure location issue, we utilize different stacked LSTM layers. We report a precision of (98.51.5) % (epileptic versus non-epileptic) and (952)% (typical versus interictal versus ictal), which is higher than most of recently distributed results. This study demonstrates the way that the proposed technique can show the unique idea of EEG signals. The profound LSTM model can precisely catch highlights in EEG flags and perform high-exactness arrangement for 19 different class mixes. The proposed framework utilizing EEG signs could be utilized to help doctors in recognizing epilepsy and could act as a forerunner to helping nervous system specialist in building models and grouping patients' epileptic states with additional exploration.

4.8 CONCLUSION

For the five-class classification, the main objective of this project, we noticed that our model had a tendency to overfit. Furthermore, while it correctly classified the three types of recordings (i.e. seizure, inter-ictal, non-seizure), it had issues identifying the part of the brain being recorded for the inter-ictal patients. While this error is not dramatic in the sense that a wrong classification does not affect the health of a patient, a more accurate classifier would help researchers to better understand and treat patients. In order to tackle the issues of overfitting and wrong inter-ictal classification, different parameters and network architectures were explored. Reducing the dimension of the LSTM output through a Global Average Pooling did not improve our model. However, increasing the number of timesteps (i.e. reducing the data dimensions) improved the model's generalization ability and slightly improved the model's classification ability; shorter timesteps lead to less recording variation being transferred between neurons in the LSTM layer, which leads to a better assessment of the recording at the previous time step. Finally, adding random neuron dropouts to the model, a known technique for combating overfitting, did not improve this particular model. To conclude, this LSTM model is capable of distinguishing seizure patients, inter-seizure patients, and healthy patients with high accuracy, making it a robust model with strong practical applications.

5. CONCLUSIONS AND FUTURE WORKS

5.1 CONCLUSIONS

This exposition is worried about dependable strategies for distinguishing and estimating epileptic seizures. To start with, it examined the significance of this issue to the personal satisfaction of epileptic patients. The impact of various variables, including information division length and arrangement, on forecast execution was then researched utilizing broad tests on genuine EEG information from solid individuals and epileptic seizures patients.

To work on the exhibition of the seizure recognition framework, another intermittent brain organization (RNN) arrangement able to do precisely recognizing epileptic seizure designs was proposed and carried out. To catch both the low-and significant level portrayals of the EEG designs, the created RNN engineering utilized a long momentary memory (LSTM) design. The goals of this review are to respond to the accompanying inquiries: (a) how can it be to further develop identification precision in various mixes of classes viewed as epileptic/non-epileptic, (b) what is the ideal length to consider in the proposed profound learning way to deal with keep up with strong seizure discovery execution, and (c) might the proposed profound brain framework at any point support vigorous seizure recognition execution under evolving length? The exploratory outcomes exhibited that the proposed research calculations accomplish higher characterization and expectation exactness than certain examinations revealed in the writing for the utilized dataset. The proposed calculations could be utilized in demonstrative clinical applications.

5.2 FUTURE WORKS

Bigger EEG datasets, which contain recorded electrical movement from a lot more patients, permit the profound brain network model to gain from additional different examples of epileptic seizures across patients, and subsequently support its communalization, since profound brain network execution improves as preparing information size increments multivariate and other brain organizations, like convolution brain networks for certain changes, can be utilized to take advantage of spatial relationships between's EEG ages from various channels on the scalp.

Despite the fact that EEG and obtrusive EEG signals are the most regularly involved techniques for distinguishing anomalies and seizure event, each enjoys benefits and detriments that should be

thought of, patients should bear the weight of cerebrum medical procedure for terminal situation, including the expense of a medical procedure and the gamble of disease. Expansive, inside and out research is expected to gauge the benefits and weaknesses of the two methodologies for epileptic seizure location and expectation.

Different information assortment advances are accessible to profit from execution upgrade while making less burden the patient. Notwithstanding the EEG scalp, these advances incorporate accelerometer sensors. These advances can give correlative information that works on the recognition and expectation of epileptic seizures.

With the accessibility of enormous datasets that hold longer EEG accounts, useful calculations can be created to empower patients and guardians to know about the requirement for treatment a half hour before the beginning of a seizure. Not really relieving, yet rather further developing the patient's personal satisfaction. There are as yet numerous questions about epilepsy, however the discoveries of ongoing and ensuing exploration reinforce the expectation that one day the secrets encompassing this sickness will be settled, making life simpler for relatives and patients.

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