



REPUBLIC OF TÜRKİYE

ALTINBAŞ UNIVERSITY

Institute of Graduate Studies

Civil Engineering

**NOVEL APPROACH FOR EARTHQUAKE
PREDICTION AND SEISMIC-QUALITY FACTOR
ESTIMATION USING MACHINE LEARNING
MODELS**

Raad M. Saeed AHMEDTHABIT

Master's Thesis

Supervisor

Assoc.Prof.Dr.Sepanta Naimi

Istanbul, 2023

NOVEL APPROACH FOR EARTHQUAKE PREDICTION AND SEISMIC-QUALITY FACTOR ESTIMATION USING MACHINE LEARNING MODELS

Raad M.Saeed Ahmedthabit

Civil Engineering

Master's Thesis

ALTINBAŞ UNIVERSITY

2023

The thesis titled NOVEL APPROACH FOR EARTHQUAKE PREDICTION AND SEISMIC-QUALITY FACTOR ESTIMATION USING MACHINE LEARNING MODELS prepared BY RAAD M.SAEED AHMEDTHABIT and submitted on 12/04/2023 has been **accepted unanimously** for the degree of Master of Science in Civil Engineering.

Assoc. Prof. Dr. Sepanta NAİMİ

Supervisor

Thesis Defense Jury Members:

Assoc. Prof. Dr. Sepanta NAİMİ

Department of Civil
Engineering,
Altınbaş University

Asst. Prof. Dr. Mohsen SEYEDİ

Department of Civil
Engineering,
Altınbaş University

Assoc. Prof. Dr. Kaveh DEHGHANIAN

Department of Civil
Engineering,
Istanbul Aydın University

I hereby declare that this thesis meets all format and submission requirements of a Master's thesis.

Submission date of the thesis to Institute of Graduate Studies: ____/____/____

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Raad M. SAEED AHMEDTHABIT

Signature

DEDICATION

I dedication my thesis to:

University of Altinbas

My very respected supervisor

All my family members, especially my very dear mother and to my father his soul
hovers around me all the time.



ABSTRACT

NOVEL APPROACH FOR EARTHQUAKE PREDICTION AND SEISMIC- QUALITY FACTOR ESTIMATION USING MACHINE LEARNING MODELS

AHMEDTHABIT, Raad M.Saeed

MSc., Civil Engineering, Altınbaş University,

Supervisor: Assoc.Prof.Dr.Sepanta NAIMI

Date: April / 2023

Pages: 62

In the earth sciences, earthquake prediction is one of the great unsolved problems. Despite decades of research attempting to identify earthquake precursors, there is no proven analytical method to predict earthquakes before they occur. The problem is challenging as there is no discernable signal in the seismic waveform prior to an earthquake. The data are multidimensional, so it is hard for humans to analyze. Moreover, there are a large number of signal processing algorithms that can be applied to the raw data, so choosing the optimum input data is difficult. The application of deep learning is rare in the literature, and therefore may offer a new avenue for research. Our project will attempt to create an earthquake warning system utilizing deep neural networks and the available real time seismic monitoring systems.

Keywords: Earthquakes, Artificial Neural Network (ANN), Seismic Forecasting, Earthquakes Prediction, Seismic Waveform.

TABLE OF CONTENTS

	<u>Pages</u>
DEDICATION	v
ABSTRACT	vi
LIST OF TABELS.....	ix
LIST OF FIGURES.....	x
ABBREVIATIONS.....	xii
1. INTRODUCTION	1
1.1 MOTIVATION AND BACKGROUND	3
1.2 CHALLENGES.....	7
1.3 PROBLEM STATEMENT	10
1.4 THESIS OUTLINE	10
2. BACKGROUND	12
2.1 SEISMOLOGY	12
2.1.1 Measuring Earthquakes	16
2.2 AN OVERVIEW OF THE EARTHQUAKE EFFECTS.....	16
2.3 ARTIFICIAL INTELLIGENCE OVERVIEW.....	17
2.4 EARTHQUAKE PREDICTION USING MACHINE LEARNING	18
2.5 RELATED WORKS	20
2.5.1 Time Series Algorithms	20
2.5.2 STA/LTA	20
2.5.3 Template Matching	22
2.5.4 Autocorrelation.....	23
2.5.5 Deep Learning	23
2.5.6 Clustering and Classification	24
2.6 RESEARCH GAPS.....	27
3. PROPOSED SYSTEM	29
3.1 INTRODUCTION.....	29

3.2	SEISMIC ATTENUATION.....	31
3.3	FREQUENCY DEPENDENCE OF QUALITY FACTOR.....	31
3.4	ESTIMATION OF QUALITY FACTOR.....	32
3.5	MOTIVATION	32
3.6	PROPOSED SYSTEM.....	33
3.6.1	Dataset.....	34
3.6.2	Features Extraction.....	35
3.6.3	Methods.....	37
3.6.4	Performance Evaluation Metrics.....	39
4.	RESULTS AND DISCUSSION	41
4.1	EXPERIMENTAL SETTINGS	41
4.2	SEISMIC WAVEFORM.....	41
4.3	OVER-FITTING & SOLUTION.....	43
4.4	REGULARIZATION.....	43
4.5	CROSS VALIDATION	43
4.6	DATASET AND FEATURES.....	44
4.7	EXPERIMENT RESULTS	44
4.8	CONCLUSION	46
5.	CONCLUSIONS AND FUTURE WORKS.....	47
5.1	CONCLUSIONS.....	47
5.2	FUTURE WORKS.....	47
	REFERENCES	49

LIST OF TABELS

	<u>Pages</u>
Table 2.1: Earthquake Severity	17
Table 4.1: Selected Results of Earthquake Recognition Problem (P1).	45
Table 4.2 : Selected Results of Earthquake Prediction (P2).	45



LIST OF FIGURES

	<u>Pages</u>
Figure 1.1: Diagram Of An Old School, Classic Seismometer [11].	4
Figure 1.2: A Seismometer Recording Of A Tremor Is A Model [12].	4
Figure 1.3: An Illustration Of 24 Hours Of Consistent Waveform Information Recorded At A Station Close To Tanzania's Olduvai Chasm [14].	5
Figure 1.4: An Illustration Of A Three-Part Seismometer Recording Of A Quake [15].	6
Figure 1.5: A Chart Portraying The Development Of Openly Accessible Seismic Information Throughout Recent Many Years [23].	8
Figure 2.1: Earth's Internal Structures [28].	14
Figure 2.2: Primary Wave Motions [25]	15
Figure 2.4: The STA/LTA Calculation Is Shown [4].	21
Figure 3.1: A Schematic Illustration Of The Problems Tackled In This Paper. A Seismometer (Geophone) Records The Displacement Of The Earth As A Function Of Time.	30
Figure 3.2: Two Samples From The Dataset. (Top) A Negative Example In Which There Is Not Earthquake During The Event Period. (Bottom) A Positive Example In Which An Earthquake Occurs During The Event Period.	35
Figure 3.3: Location Of The Study Area (The Geysers) And The Seismic Stations Used To Collect The Dataset.	36
Figure 3.4: Examples of The Raw Data And Spectrogram. A Negative Example In Which There Is Not Earthquake During The Event Period. (Bottom) A Positive Example In Which An Earthquake Occurs During The Event Period.	37
Figure 3.5: Three Neural Network Architectures (A, B, C) And Network Hyperparameters Explored (D).	38
Figure 4.1: Original Seismic Signal For Three Random Earthquakes	42

Figure 4.2: Normalized Seismic Signal For Three Random Earthquakes.....	42
Figure 4.3: Down Sampled Seismic Signal For Three Random Earthquakes.....	42
Figure 4.4: Earthquakes Using A Minimum Magnitude	44
Figure 4.5 : Confusion Matrices With Different Class Weights For The RNN Network Applied on A Dataset With A Minimum Magnitude (M) Of 3.5.....	46



ABBREVIATIONS

FDU	:	Fire Detection Unit
FFD	:	Forest Fire Detection
IoT	:	Internet of Things
RGB	:	Red Green Blue
YCbCr	:	Luminance, Chrominance blue, Chrominance Red
YUV	:	Luma and Chroma Components

1. INTRODUCTION

Seismic constriction is a basic boundary in grasping the viscoelastic genuine way of behaving of the medium. The ability of materials to send and disperse seismic waves is also essential for petrophysical depictions of supply rocks. From a practical standpoint, seismic constriction is caused by three distinct characteristics [1]:

- a. Intrinsic attenuation, which occurs as a result of energy loss due to internal friction and is related to the dissipative behavior of the medium.;
- b. Dispersing lessening, which is the constriction of spreading waves in inhomogeneous earth brought about by diffraction, reflection, and scattering.;
- c. Mathematical spreading, or the abatement in energy thickness as the wavefront's size increments.
- d. Retention and dispersing are in many cases more delicate to dirt substance, pore liquids, gas, or cracking than seismic speeds and densities [1].

The Groundwater, designing, and natural examinations, as well as hydrocarbon investigation and tremor seismology, all have major areas of strength for an in the quality element as a component of profundity [2]. The longing to comprehend the world's constriction properties originates from the perception that the sufficiency of seismic waves diminishes as they spread. The customary technique for assessing lessening is in this manner to gauge irrefutably the spatial rot pace of wave sufficiency in the time space. The translation of the outcomes is generally troublesome, and there is no standard system for constriction estimations in light of the fact that the peculiarity includes numerous perplexing issues, for example, source component, wave dissipating, and mathematical spreading of the wavefront [3]. These issues have held Q back from being tried in proficient practice, regardless of the way that it is a significant boundary to consider for seismic portrayal.

The decrease in plentifulness because of weakening is by and large recurrence ward, and all the more significantly, constriction can give data about lithology, actual state, and level of rock immersion, so it tends to be utilized to portray the material of a land structure involving seismogram examination notwithstanding or rather than seismic speed. The Q -variable of the material is generally used to depict energy dispersal properties. Q , then again, can take on various implications relying upon the unique situation. We should recognize three unique utilizations of the Q -factor: (1) the Q as a proportion of "inward rubbing" utilized in petrophysical translation, (2) various estimated ("clear") Q s emerging from perceptions, and (3) the "proverbial," numerical Q utilized in viscoelastic hypothesis and mathematical displaying [3]. The deliberate or viable Q is a mix of inborn lessening, dispersing, and mathematical spreading; it is otherwise called evident weakening [4]. The exact worth of the Q values is in some cases irrelevant in functional seismic information handling and reversal. Lessening demonstrating is usually used to address information for constriction impacts; an outright Q isn't completely needed for this reason. In seismic demonstrating, then again, it is basic to guarantee that the calculations sufficiently address the actual components of wave lessening, for example, utilizing an exact Q profile for the dirt model, which is connected with petrophysical properties and interior contact [5].

The quality elements are boundaries that should be known to comprehend seismic wave proliferation in the earth completely. High recurrence Rayleigh waves, for instance, contain data about shear (S)- wave speed (Versus) and close surface material quality elements. Flexible wave reenactments are usually utilized in seismic prospecting displaying, and most neighborhood site reaction concentrates on utilize a standard damping element of 0.05% for the whole soil section. In nearby seismic reaction studies, for instance, exact information on the quality component (for example damping) profile can work on the nature of the outcomes. Surface and borehole information can be utilized to appraise weakening. Most of borehole reads up for constriction measures are adjusted for profound profundities, with wide collector dispersing and exhibit length. Others depend on tremor estimations. The idea of creating lessening measures from downhole examinations started with downhole estimations for the 2016 Microzonation crusade [6]. Downhole tests are the most generally involved borehole studies for getting a precise speed profile, and assuming the estimations are performed with the legitimate gear and safeguards, constriction can be dependably assessed even in the close surface reach. Notwithstanding the extensive variety of Q

assessment strategies accessible, a couple of procedures, for example, the ascent time technique or the unearthly proportion strategy, are broadly utilized in borehole studies [8].

1.1 MOTIVATION AND BACKGROUND

Quake discovery is a basic undertaking that includes recognizing seismic occasions in verifiable information or continuously. Finding such occasions is basic for two reasons. To start, quake discovery can report tremor appearance times and separate spans in seismic time series as tremor or commotion, bringing about marked information that can be utilized to foster tremor estimating models. With the headway of profound learning brain organizations, prescient (guaging) models currently require famously a lot of prepared information (marked seismic and commotion information) to deliver the best outcomes. Tremor identification contrasts particularly from the issue of quake estimating, in which a likelihood of a huge and perilous tremor happening soon is stated. [9]. The examination in this proposal centers around quake recognition with the end goal of revelation, which can give a lot of great marked information for the improvement of an exact seismic tremor estimating model (for a foreseeing reason). The subsequent advantage is that seismologists can utilize seismic tomography to examine and remake land structures in the earth, like taking a X-beam of the earth [10]. More recorded seismic occasions consider more exact investigations of a particular district and a more itemized comprehension of the hidden land structures [11].

The recognition of tremors from seismic information is a period series occasion identification issue. Let $[T_1, T_2, \dots, T_n]$ be a period series of tested focuses from a seismometer's recording of the engendering of a seismic wave. The motivation behind seismic tremor recognition is to decide the starting seasons of expected quakes. Enormous greatness tremors are clearly simple to identify on the grounds that they are truly felt. In any case, distinguishing the oftentimes happening miniature seismic occasions is troublesome.

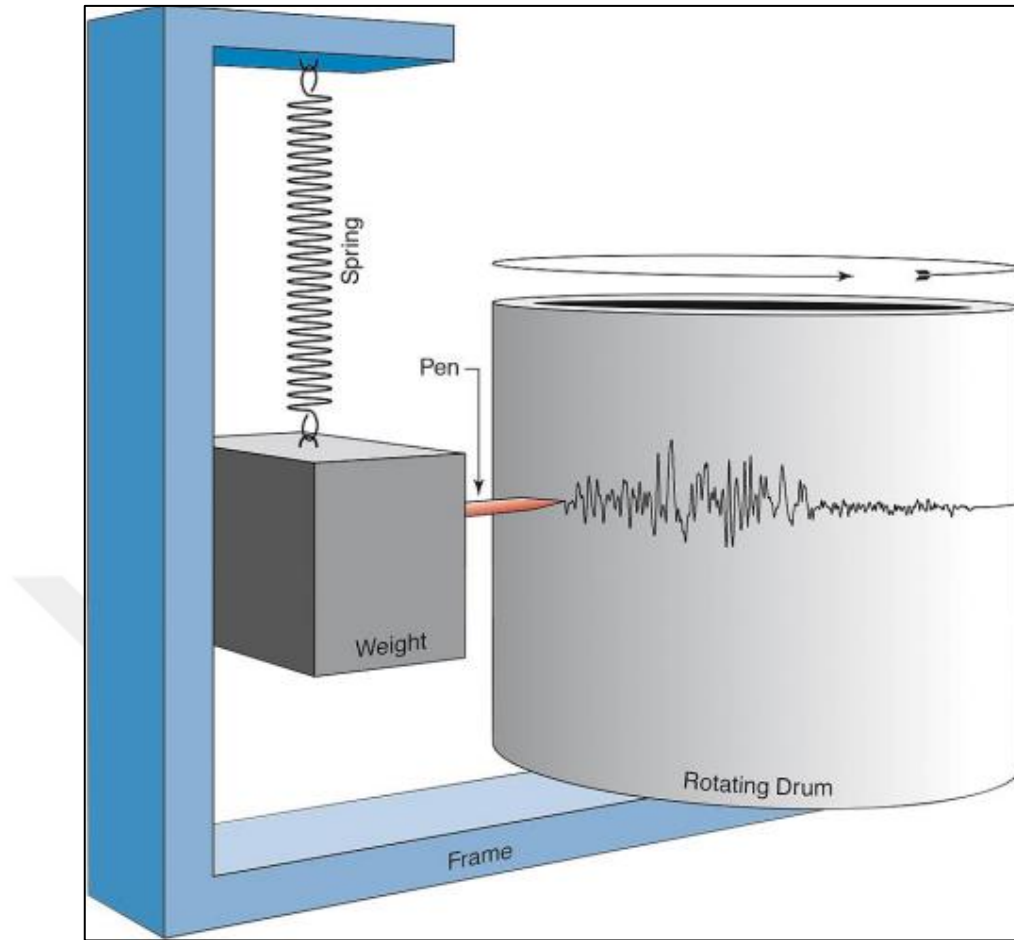


Figure 1.1: Diagram of An Old School, Classic Seismometer [11].

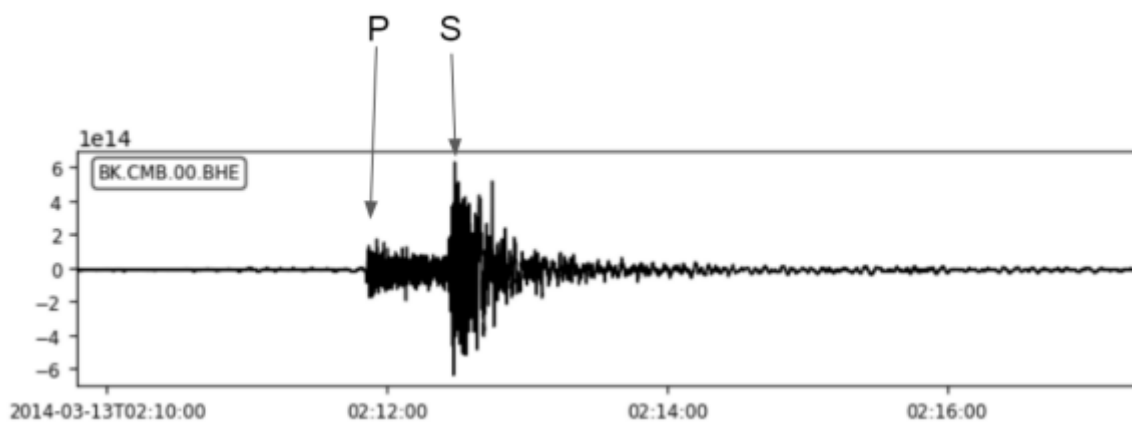


Figure 1.2: A Seismometer Recording of A Tremor Is A Model [12].

The adequacy is addressed by the y hub, and time is addressed by the x pivot. Observe the P wave's trademark first appearance and the S wave's ensuing appearance [13][14].

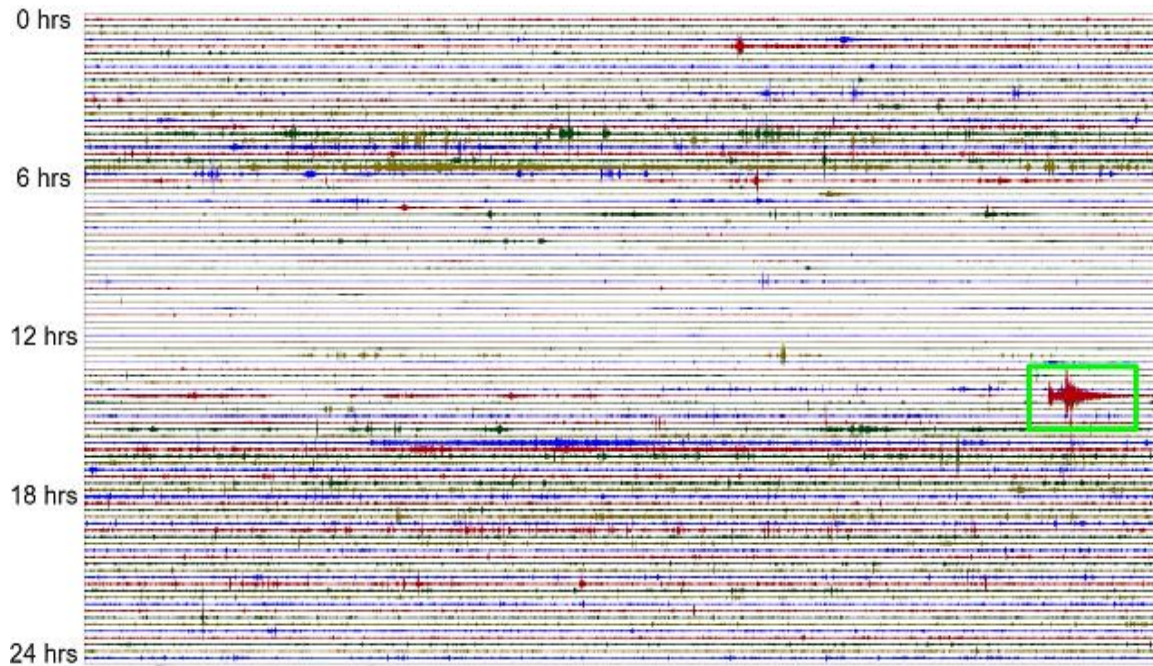


Figure 1.3: An Illustration Of 24 Hours of Consistent Waveform Information Recorded At A Station Close To Tanzania's Olduvai Chasm [14].

Every level dim line addresses 15 minutes of recording, and the whole thing addresses a solitary day. As a result of natural variables, clamor shifts relying upon the hour of day. An ordinary tremor is portrayed in green, with a P wave obviously going before the bigger abundance S wave.

waves (see Figure 1.1). Subsequently, seismic occasions are recorded, as displayed in Figure 1.2. Seismic occasions take many structures, some of which are more challenging to distinguish than others (displayed in Figure 1.4 and Figure 1.3). Computational seismology is a field where information is continually developing, both locally and universally. This is valid both straightly, over the long haul for a particular station, and dramatically, as the quantity of seismic stations overall increments and information turns out to be all the more generally accessible. Information accessibility is becoming pervasive, with administrations like IRIS facilitating enormous data sets of ceaseless waveform information gathered by seismic stations from one side of the planet to the other [15].

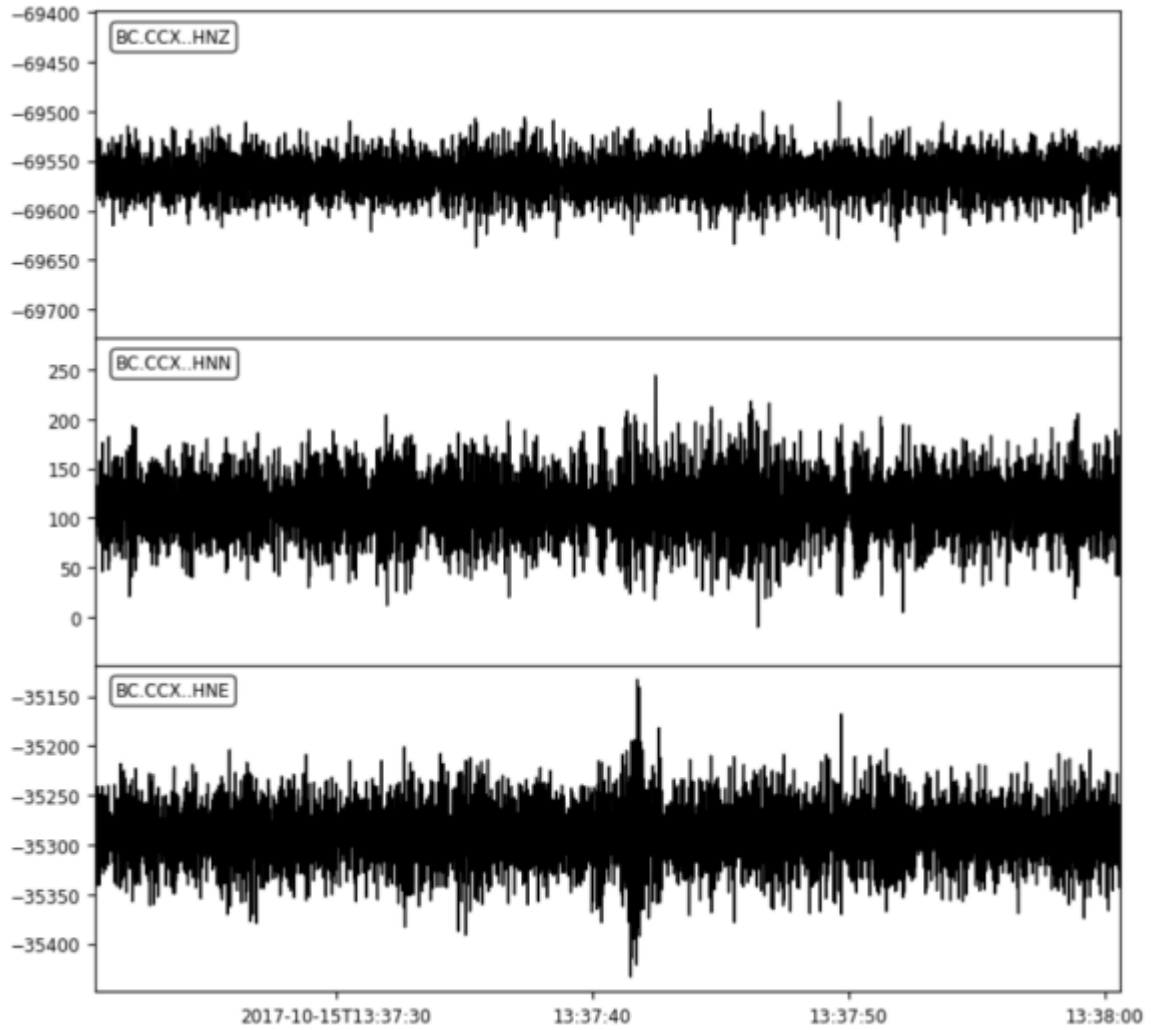


Figure 1.4: An Illustration of A Three-Part Seismometer Recording of A Quake [15].

The abundance is addressed by the y pivot, and time is addressed by the x hub. It is important that seismic tremor is absent in the Z part and is just effectively noticeable in the E part.

Numerous seismological advances have come about because of the variation of calculations usually utilized in the picture and sound areas. PC vision propels have motivated a plenty of uses in different fields, including seismology. Profound learning methods that utilized convolutional brain networks on spectrograms for discourse acknowledgment undertakings [16] roused our exploration. As a matter of fact, seismological information is like sound information in that both are on a very basic level examined by signal handling. In any case, there are a few huge contrasts. The normal recurrence scope of tremors (0.004-35 hz) [18, 19] is a lot of lower than the discernible recurrence scope of people (20-20,000 hz)[20]. Various stations recording a similar occasion are closely resembling different mouthpieces

recording a similar sound source. Nonetheless, for seismological occasions going through actual space on The planet, the time delay between recording gadgets is a lot more noteworthy.

In light of the foundation commotion, distinguishing seismic tremors is a very troublesome undertaking in such uproarious conditions. In spite of the fact that clamor is a worry in both the sound and seismological spaces, its beginnings and qualities can contrast emphatically. Seismograph clamor can be brought about by a close by vehicle or by foundation sea waves, though sound commotion is much of the time brought about by another close by source producing sound [21]. Seismological instruments should likewise manage obstruction from actual peculiarities collaborating with seismic waves as the sign goes through different actual mediums in the earth, though mouthpieces identify sound waves bobbing off neighboring articles [22].

1.2 CHALLENGES

Nonstop waveform information recorded by a seismometer may contain numerous occasions that are undetected by customary procedures like STA/LTA or cross connection [23]. While utilizing conventional strategies, it is hard to distinguish seismic occasions with low sign to clamor proportions (SnR). Autocorrelation, the benchmark method, requires $O(N^2)$ runtime. Applying autocorrelation to even a long time of information throughout longer time spans is unimaginable with a standard PC. AI and profound learning procedures can be utilized to foster more strong and productive seismic recognition calculations, on account of late advances in registering power and far reaching admittance to huge seismic datasets [24].

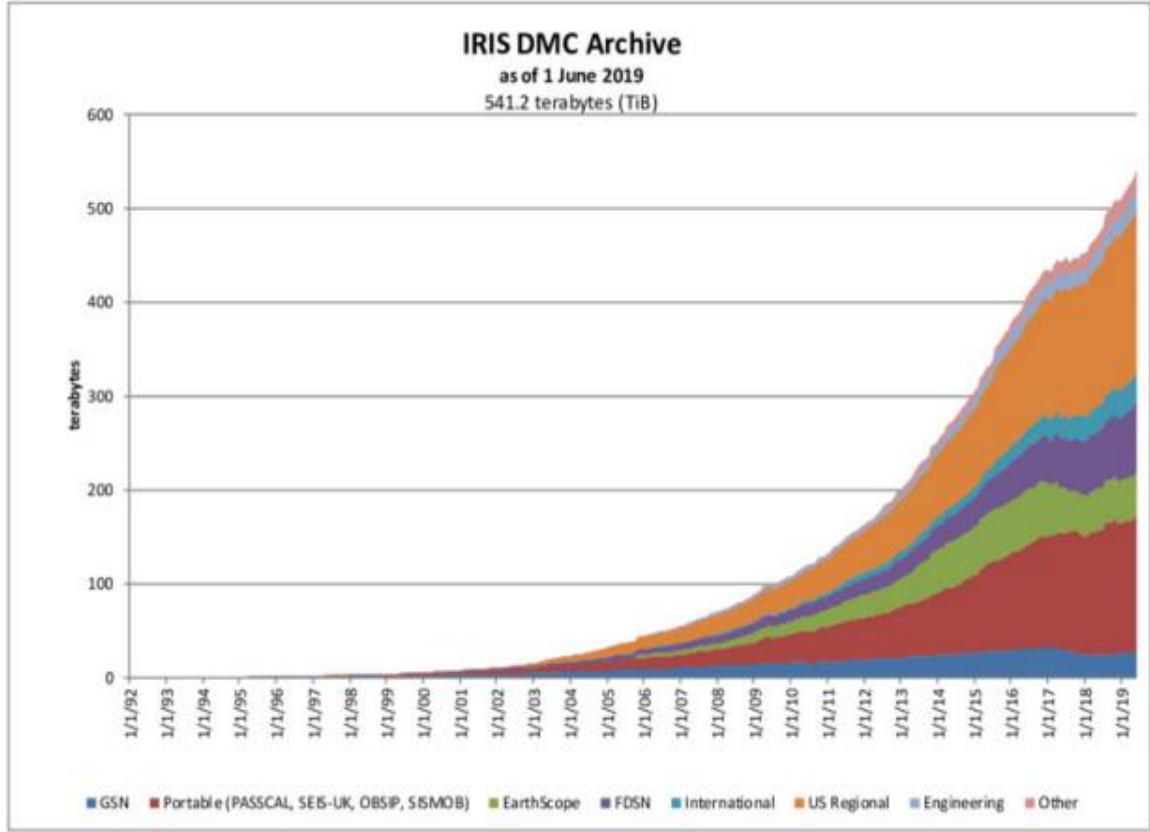


Figure 1.5: A Chart Portraying The Development of Openly Accessible Seismic Information Throughout Recent Many Years [23].

While utilizing conventional strategies, it is challenging to recognize seismic occasions with low sign to commotion proportions (SnR). Autocorrelation, the benchmark procedure, requires $O(N^2)$ runtime. Applying autocorrelation to even a long time of information throughout longer time spans is unthinkable with a standard PC. AI and profound learning methods can be utilized to foster more vigorous and proficient seismic recognition calculations, on account of late advances in registering power and boundless admittance to enormous seismic datasets [24].

Information has been developing at a remarkable rate, and admittance to worldwide seismic data sets, for example, IRIS has empowered enormous information advancement. To accomplish best in class seismic occasion discovery, we use propels in profound learning. Convolutional brain organizations (CNNs) are utilized explicitly to recognize seismic occasions from commotion. A bunch of pre-handling procedures makes changed spectrograms that are utilized as contribution rather than crude waveforms. CNNs have a

strong standing in the picture space, making them ideal for use with spectrograms. A spectrogram is a framework of recurrence power esteems that is regularly addressed as a picture.

Perol et al. created ConvNetQuake, a strategy for distinguishing seismic tremors that involves a convolutional brain organization and beats customary procedures in discovery exactness [25]. To utilize ConvNetQuake, be that as it may, one high priority admittance to a huge pre-marked dataset of occasions and commotion for preparing. ConvNetQuake just works reliably in the Oklahoma district where the brain network was prepared. ConvNetQuake was tried on a Tanzanian organization of stations, however it created a very large number of bogus up-sides [25]. Cross-referring to with up to 7 stations empowered us to sift through more commotion, yet this was restricted to distinguishing high greatness occasions that STA/LTA would have recognized in any case. This is on the grounds that ConvNetQuake was prepared exclusively on information from two Oklahoma stations; discovery capacity won't be quickly summed up to different districts [26].

Our strategy goes for the gold, free seismic tremor location. To achieve this, we really want an exceptionally enormous and different dataset, as well as the speculation of AI models. There are a few significant difficulties to beat to accomplish summed up tremor identification:

- i. Environmental noise can obfuscate events, especially at low magnitudes.
- ii. New occasions won't necessarily relate to a formerly classified layout, particularly assuming the source area setting off the seismic occasions changes.
- iii. Elements learned at one station don't necessarily in every case move to different stations with information reflecting various occasions..
- iv. On the grounds that the size of named preparing information (currently inventoried occasions) will be zero at new stations, fundamental assortment strategies will continuously be required.

P and S wave identification, area discovery, and tremor extent assessment are instances of compatible issues. Beginning with a straightforward errand like summed up parallel order, which recognizes occasions from commotion, is a decent spot to begin. Moreover, when

occasion location windows have been gathered, these different issues can be investigated all the more without any problem. Effective consummation of this twofold order errand will lay the preparation for future development on additional mind boggling issues [27][28].

1.3 PROBLEM STATEMENT

In this specific circumstance, tremor discovery is outlined as a paired grouping issue. There are two kinds of result names: commotion and occasion. The positive class is occasion (a seismic tremor), and the negative class is commotion (no quake). The objective is to track down tremor events in persistent time series waveform information[29][30]. To address constant time series information in discrete pieces, a progression of fixed length windows (with discretionary cross-over) collect. These fixed-length windows either contain or don't contain an occasion, and are named as an occasion or commotion. In additional proper terms, the model results a mark from $y_1, \dots, y_n$ for a window of t seconds, where n is the quantity of result names. There are just $n = 2$ marks for this situation, positive (occasion) and negative (commotion), and t is set to 20 seconds [31].

The previously mentioned issue setting is proper in a solitary situation. The objective, in any case, is to foster an extensively material model for recognizing seismic tremors in a wide range of areas. A definitive objective is to have a model that, subsequent to preparing, requires less preparation information when applied to another area. All the more comprehensively, the objective is to foster a calculation with the most elevated conceivable precision while requiring minimal measure of preparing information at each new area. Besides, utilizing profound learning guarantees the ideal straight run time and steady information utilization.

1.4 THESIS OUTLINE

This thesis includes six chapter inclusive of this chapter comprising the basic introduction of this research work, highlighting preliminaries associated with this research. Rest of the thesis is oriented as follows:

The subsequent part presents a complete outline of the past writing study on different woods fire recognition frameworks, exhibiting cutting edge work in this subject. It additionally talks

about the particulars of the distinguished review holes in the current writing, just as the exploration goals we've set up for ourselves.

Chapter 2 examines the execution of a picture handling strategy for the affirmation of fire identification. This part centers around the picture handling calculation that has been proposed for segregating among fire and non-fire pictures.

Chapter 3 highlights this thesis's research findings as well as key contributions and methodology.

Chapter 4 present the experiment and simulation results and performance analysis

Chapter 5 examines the conclusions and future prospects for expanding this study work to make it resilient for real-time exact detection of forest fires.

2. BACKGROUND

Since 1970 a generous progress in the applications of Intelligence Techniques like, linear programming, nonlinear programming and dynamic programming in natural hazards, geosciences and geotechnical engineering problems like rainfall analysis, ground water level changes, slope stability analysis, satellite image processing, petroleum exploration and estimation, Traffic Engineering, wind power forecasting, etc have been made [32]. Recently evolutionary intelligent techniques like data mining, genetic algorithm, artificial neural networks and fuzzy logic gaining predictable result in various disciplines of sciences and engineering due to their effectiveness in tackling complex problems[33] [35]. Be that as it may, their application in geotechnical designing is new and restricted. The progress of these techniques is intensely dependent on the hypothetical model picked for the framework to be examined, which should match the info yield information. Be that as it may, there are times when the arrangement is information driven as opposed to display based [36].

To resolve such issues, another methodology, Fake Brain Organization (ANN) in light of Computerized reasoning (computer based intelligence), has as of late been created. It immediately acquired broad pertinence across different disciplines. This has brought about an expansion in research exercises in the specialty of applying such techniques to certifiable issues, featuring the innate capacities and downsides of such strategies. The efficiency of all numerical methods is in general problem dependent [37]. As such, none of these techniques can be the universal tool for solving all types of problems; there are several issues which need to be addressed for the successful application of different algorithms. Many papers discussing the possible signals of different phenomena like Climate changes (Humidity, temperature, Rainfall), Ground water level changes, Electrical Current, Magnetic field, ULF- (Ultra Low Frequency) emissions, Animal behaviors, Frequently recorded seismic data base and GPS Method [38].

2.1 SEISMOLOGY

Seismic tremors (EQ) are perhaps of the most disastrous and exorbitant normal peril that a nation faces, as they happen all of a sudden and can bring about serious wounds or the deficiency of living souls because of property harm and the obliteration of numerous structures and other unbending designs [39]. A tremor is characterized as an unexpected

development of the world's surface brought about by the arrival of energy in the world's covering. Inside indicated vulnerability limits, tremor forecast doles out a particular date, area, and size to a quake [40]. The objective of quake expectation is to give early advance notice of possibly harming seismic tremors, permitting individuals to answer suitably to the calamity and limit death toll and property. Many examinations have been led to research the potential signs of different peculiarities like seismicity, power, and radiance that either go with or are trailed by quakes. The possibility that there should be observationally recognizable antecedents to tremors is instinctively engaging, yet concentrates on throughout the course of recent years have neglected to help it, so individual quakes are unusual. The overall agreement on the issue of tremor expectation is that the earth is a complex nonlinear framework, as represented in Figure 2.1 [41]. The hull can be seismically enacted with a somewhat minor bother of the general driving circumstances, and muddled non-direct seismology misses the mark on all around acknowledged actual model; the irregularity in the commencement of an enormous burst blocks the utilization of short expectation windows; tremor event is really stochastic, and endeavors to accomplish deterministic expectation seem unjustifiable; Inhomogeneous blames and shortcoming frameworks; inhomogeneous seismicity at flaws Huge quakes happen extremely rarely for measurable meticulousness to be applied to speculations about how to foresee them. There is still no palatable hypothesis of quake nucleation, and just a simple comprehension of tremor break physical science exists. Understanding the hidden physical science is expected for seismic tremor expectation; dependable antecedents are challenging to recognize, however they are additionally far-fetched to exist on exact actual grounds [42].

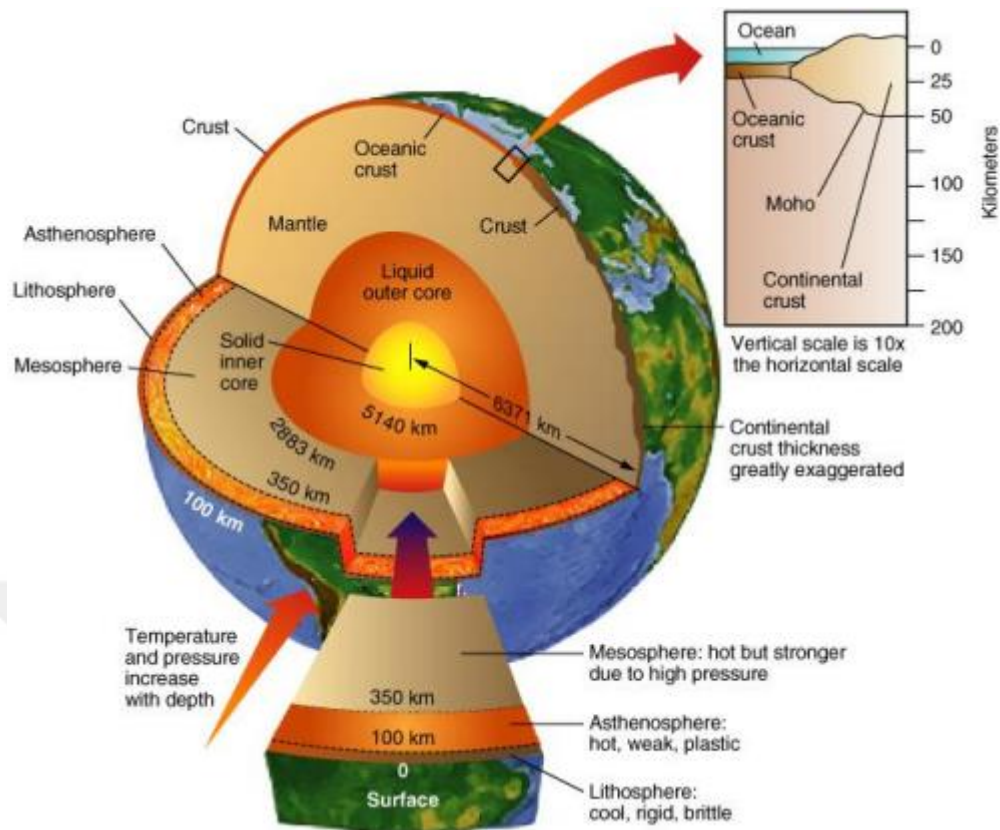


Figure 2.1: Earth's Internal Structures [28]

The introduction of broadband seismometers during the last decade has provided excellent and detailed recordings of ground motion during several large earthquakes and small vibrations also.

Tremor waves will be waves that movement through the Earth or another flexible body. Essential waves, optional waves, and surface waves are the three sorts of tremor waves. P - Wave Essential waves travel at the quickest rate, averaging 4.5 kilometers each second. They can travel through strong stone as well as liquids, for example, water or the world's fluid center layers. After a seismic tremor, P-waves are the main waves to arrive at the World's surface. Essential waves go back and forth in a tough spot they travel through. This causes the World's surface to move to and fro. VP 5-7 km/s in the regular Earth's outside layer; >8 km/s in the World's mantle and center; 1.5 km/s in water; 0.3 km/s in air [31].

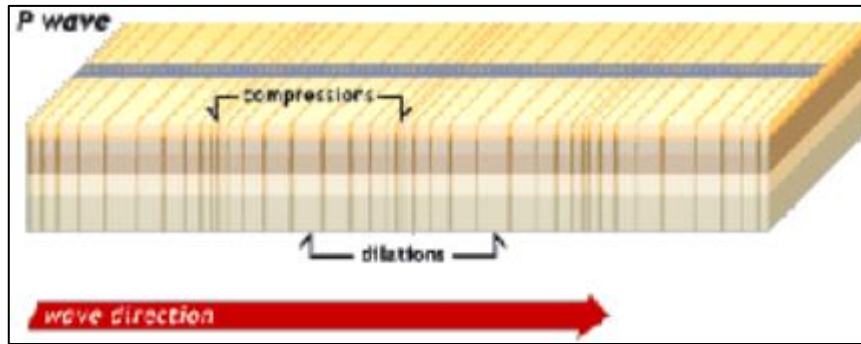


Figure 2.2: Primary Wave Motions [25]

S- Wave Secondary waves travel slower than primary waves. Their average speed is 2.4 kilometers per second. Also called shear waves, S-waves create a side to side motion in the rocks through which they are traveling. S-waves cannot travel through water or the liquid rock of the Earth's core layer. $V_S \sim 3 - 4 \text{ km/s}$ in typical Earth's crust; $> \sim 4.5 \text{ km/s}$ in Earth's mantle; $\sim 2.5\text{-}3.0 \text{ km/s}$ in (solid) inner core.

Fault types: Typical, switch (push), and strike-slip faults are the three principal sorts of shortcomings that can cause a quake. Typical and switch faults are instances of plunge slip, in which the dislodging along the shortcoming is toward the plunge and development on them has an upward part. Typical shortcomings are most normal where the outside layer is being broadened, for example, at a dissimilar limit. Invert faults structure where the outside abbreviates, for example, at a joined limit. Strike-slip shortcomings are steep designs in which the issue's different sides slip on a level plane past one another; change limits are a kind of strike-slip shortcoming. Numerous seismic tremor waves are brought about by development on deficiencies that have both plunge slip and strike-slip parts; this is alluded to as sideways slip. Whenever a quake happens, seismographs near the focal point, out to around 90 km to 1000 km, can record both P and S waves, however those further away can't identify the high frequencies of the main S wave. The distinction in the appearance seasons of the P and S waves can be utilized to work out the distance to the occasion, and the focal point of the tremors can be resolved utilizing known station extents.

2.1.1 Measuring Earthquakes

There are multiple ways of communicating the size of a seismic tremor. There are subjective or no instrumental estimations, as well as quantitative or instrumental estimations, from one side of the planet to the other. Non-instrumental estimations are basic for pre-instrumental occasions and are accordingly expected in the aggregation of authentic seismic tremor lists for risk examination. Subjective scales supplement instrumental information for seismic tremors that have been instrumentally recorded. Seismograms recorded at different epicentral distances are utilized to compute the beginning time, date, scope, longitude, focal point, central profundity, sort of blaming, and event districts, as well as the energy delivered during a tremor. Unmistakable techniques are utilized to depict tremor incited harm and its spatial conveyance. In doing as such, power, greatness, and significant scales are utilized, as definite beneath.

Many examinations have been completed to acquire a superior comprehension of the qualities of seismic constriction as estimated by the quality component Q. P waves (Q waves) and S waves are utilized in these examinations (Q). A concise clarification of the spread and structure of the seismic wave field is expected to depict seismic lessening. At the point when a tremor happens, the energy delivered is somewhat scattered as intensity because of grating brought about by rock masses sliding along the shortcoming surface. The excess energy is somewhat spent as work, bringing about mass uprooting, and mostly proliferates as seismic waves in the ground. Flexible waves proliferate through the ground and on the free surface, with the versatile properties of the medium and the source deciding the speed, recurrence, and adequacy. Seismic waves' energy converts into ground stresses and misshapeness, bringing about relocations (seismic shaking). The kinds of pressure and deformity to which the dirt is oppressed, as well as how the waves engender, recognize body waves (P and S waves) and surface waves (Love and Rayleigh waves)..

2.2 AN OVERVIEW OF THE EARTHQUAKE EFFECTS

An earthquake (also spelled tremor or temblor) is caused by a sudden release of energy in the Earth's crust, which causes seismic waves. Seismometers, also known as seismographs, are used to record earthquakes. The moment magnitude of an earthquake is commonly reported, as is the related and mostly obsolete Richter magnitude, with magnitude 3 or lower earthquakes being mostly imperceptible and magnitude 7 causing widespread damage.

Seismologists use a Magnitude scale to express the seismic energy released by each earthquake. Here are the typical effects of earthquakes in various magnitude ranges:

Table 2.1: Earthquake Severity

Richter Magnitudes	Earthquake Effects
Less than 3.5	Generally not felt, but recorded.
3.5-5.4	Often felt, but rarely causes damage.
Under 6.0	At most slight damage to well-designed buildings. Can cause major damage to poorly constructed buildings over small regions.
6.1-6.9	Can be destructive in areas up to about 100 kilometers across where people live.
7.0-7.9	Major earthquake. Can cause serious damage over larger areas.
>8	Great earthquake. Can cause serious damage in areas several hundred kilometers across.

Quakes manifest themselves at the World's surface by shaking and in some cases uprooting the ground. At the point when an enormous tremor's focal point is found seaward, the seabed can move to the point of causing a tidal wave. Quakes can cause avalanches and, every so often, volcanic movement. Quakes are principally brought about by the break of geographical deficiencies, yet they can likewise be brought about by volcanic action, avalanches, mine impacts, and atomic trials. The concentration or hypocenter of a quake is the place of starting break. The focal point is the point on the ground straight over the hypocenter.

2.3 ARTIFICIAL INTELLIGENCE OVERVIEW

It is something that is a replica of natural intelligence. It has been a goal of science and engineering to develop intelligent machines for many decades. AI is a branch of engineering concerned with the study and creation of computer systems that exhibit some form of intelligence, systems that learn new concepts and tasks, systems that can reason and draw useful conclusions, systems that can understand a natural language or perceive or

comprehend a visual scene, and systems that perform other types of feats that require human type of intelligence.

Precisely, in AI the goal is to develop working computer systems that are truly capable of performing tasks that require high levels of intelligence. A better understanding of AI is gained by looking at the component areas of study that make up the whole. These are:

- i. Robotics
- ii. Memory organization
- iii. Knowledge representation
- iv. Storage and recall
- v. Learning models
- vi. Inference techniques
- vii. Commonsense reasoning
- viii. Understanding natural language
- ix. Pattern recognition
- x. Machine vision methods
- xi. Search and matching
- xii. Speech recognition and synthesis

AI may be one of the most important developments of this century and countries leading in this field will emerge as the dominant economic powers of the world. Most of the applications in AI are Mechanical Engineering, Electrical Engineering, Linguistics, Psychology, Cognitive Sciences, Philosophy, Geosciences and Geotechnical. Also applications of AI have been proven in Civil Engineering, Defense, Chemistry, Biology, Banking, Economics, Manufacturing, Law, Medicine, and Aerospace etc.

2.4 EARTHQUAKE PREDICTION USING MACHINE LEARNING

Seismic tremor is broadly perceived as perhaps of the most pulverizing catastrophic event on earth, causing gigantic misfortune in the human world. Therefore, it is basic to foresee

when and where they will happen, however this is a troublesome undertaking given their intrinsic irregularity [1]. As indicated by [2,] broadly utilized quake expectation approaches can be grouped into four sorts. With a restricted measure of quake information, the initial two methodologies were famous: 1) numerical instruments, for example, FDL [3], and 2) antecedent based strategies that recover topographical highlights, for example, seismic peculiarities [4], cloud pictures [5], and creature conduct[6]. Then, as additional seismic tremors happened, coming about in bigger datasets, AI techniques became the overwhelming focus. [7] utilized one of them, a counterfeit brain organization, to foresee a quake in 2011. The model had a precision of almost 70%, which was not especially great at that point. As per the discoveries, the absence of traits in the dataset, as well as the class unevenness, brought about an unsuitable result.

At last, profound learning approaches have as of late been utilized to anticipate seismic tremors. [8] evaluated a profound brain organization (DNN) model that ordered seismic tremor extents happening in the following seven days utilizing a recently presented boundary Shortcoming Thickness (in light of the idea of spatial impact). DNN beat other AI models with test precision of around 79% on sizes more noteworthy than 8. [9] presented an organization called Chart Convolutional Repetitive Brain Organization (GCRNN) to distinguish the focal points of seismic tremors that happened in two months by joining qualities of convolutional brain organizations (CNN) and intermittent brain organizations. GCRNN utilized a convolutional channel to keep the quantity of prepared boundaries steady no matter what the time successions utilized as information. GCRNN accomplished exactness of around 33% for both 30-second and 60-second waves utilizing essentially less boundaries. Moreover, [2] utilized a repetitive brain network variation called long momentary memory (LSTM) to gain proficiency with the transient spatial conditions of seismic tremor signs and consequently foresee quakes. In spite of the fact that they involved seismic tremor information from the earlier year as info, the exactness was around 75%. Besides, Parisa [10] proposed a CNN-LSTM consolidated organization to gain proficiency with the spatial-fleeting conditions of seismic tremor signals. They evaluated the model's exhibition in nine region of China's central area, utilizing the complete number of quakes that happened in one month somewhere in the range of 1966 and 2021 as information. They additionally viewed as other quake attributes like scope and longitude. They thought about

the exhibition of a few models, including MLP and SVM, and CNN-LSTM proved to be the best.

2.5 RELATED WORKS

By and large, quake discovery was done physically by examining waveforms while comprehension of seismic signs was fundamental and it was restricted to figure power. As innovation has progressed, spectrometers have become significantly more refined and touchy, and there has been an expansion in mindfulness and interest in low greatness seismic signs. Calculations have been created to recognize these low greatness signals, which are frequently challenging to identify even by people because of commotion [25]. There are two sorts of calculations: those that need an inventory of past information and those that don't. The last option utilizes principal signal handling strategies to distinguish seismic tremors without earlier information, though the previous utilizes designs found in a dataset of marked occasions. The two methods enjoy benefits; the previous is generally more affordable to process and has less rigid necessities than the last option [26].

2.5.1 Time Series Algorithms

2.5.2 STA/LTA

Figure 2.1 portrays a typical strategy for seismic tremor identification: Momentary Sufficiency (STA)/Long haul Plentifulness (LTA). This is because of human identification, where a massive change in sufficiency demonstrates a likely tremor and can be outwardly recognized. STA/LTA has two basic boundaries: the momentary window length and the drawn out window length. Standard boundary decisions could incorporate a 3 second momentary window and a 30 second long haul window [18].

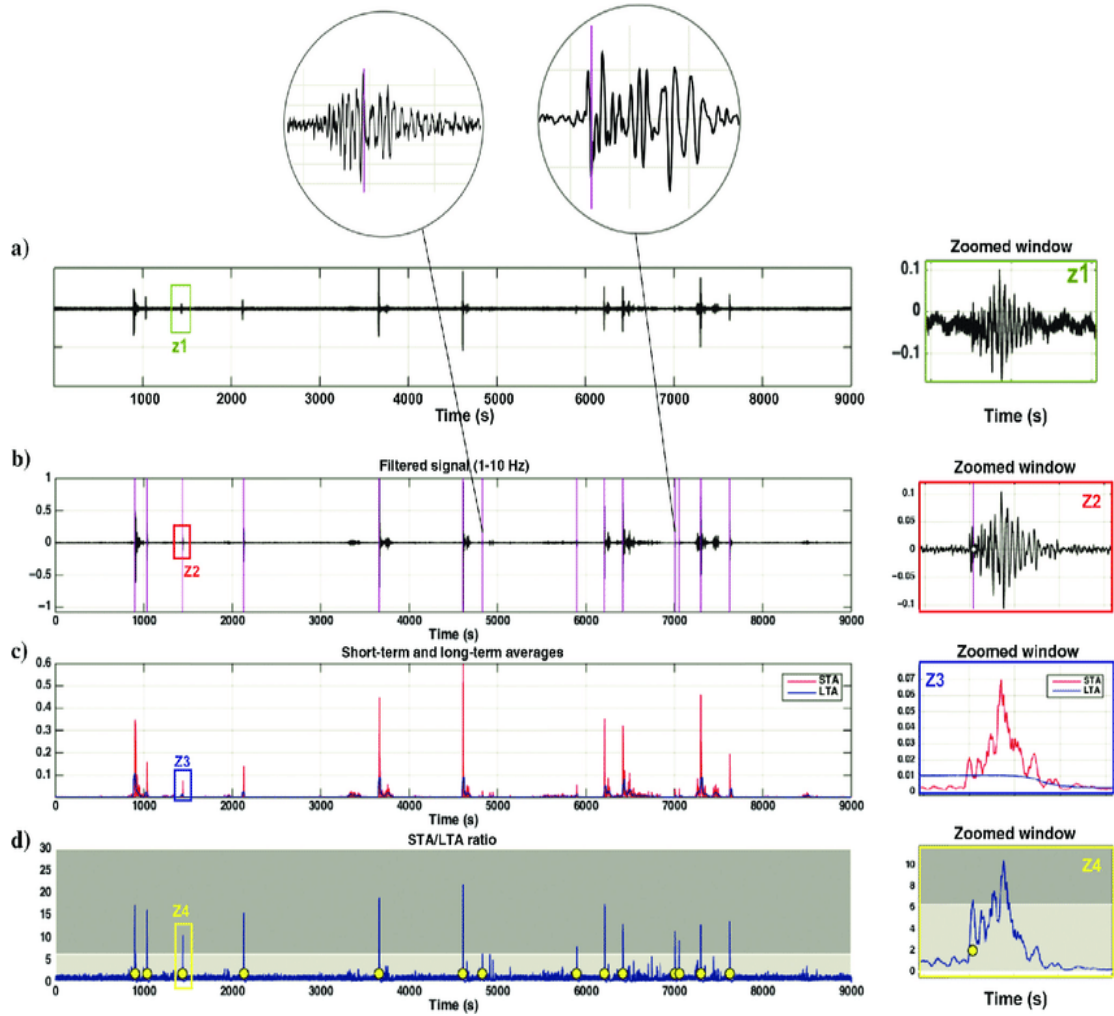


Figure 2.3: The STA/LTA Calculation is Shown [4].

The plentifulness proportion of the more limited blue window is contrasted with the abundancy proportion of the more drawn out green window. The sign proportion in models A, B, and D is low, so no location is set off. Model C is the one in particular that will bring about a set off location.

A third boundary choice can be utilized to change the cross-over between the transient window and the last part of the drawn out window. The accompanying conditions describe exemplary STA/LTA (with right arrangement) [18]:

$$STA_{(xi)} = \frac{1}{ns} \sum_{j=i-ns}^i x_i^2 \quad (2.1)$$

$$LTA_{(xi)} = \frac{1}{nl} \sum_{j=i-nl}^i x_i^2$$

$$r_i = \frac{STA_i}{LTA_i} \quad (2.2)$$

STA/LTA doesn't depend on earlier information, making it valuable in circumstances where stations are recently settled and past information has not yet been recorded. Moreover, in light of the fact that the sliding window calculation is consistent, As per the length of the waveform, STA/LTA will have an $O(n)$ straight run time. STA/LTA is helpful in light of the fact that there are no necessities, it has an immediate run time, and it can distinguish signals with explicit qualities. Its viability, notwithstanding, is reliant upon a high sign to-clamor proportion [31].

2.5.3 Template Matching

Layout matching is a typical cross-connection procedure utilized in many sign handling errands to decide signal comparability. This depends on the actual peculiarity of tremors from a similar source having comparative waveforms as they spread through the earth [19]. An underlying list of occasions, known as formats, is required. The formats are cross-connected with new windows, and a limit is utilized to decide the base similitude expected to be viewed as a match. To become sufficiency invariant, this is habitually characterized as standardized cross relationship. Pearson cross relationship is characterized as the accompanying for two signs [32]:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x}) (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 (y_i - \bar{y})^2}} \quad (2.3)$$

To find coordinates, the full type of format matching circles over every layout and corresponds the picked waveform. Remember that layouts can emerge out of various sources and subsequently have definitely various attributes. This calculation has a period intricacy of $O(kn)$, where k is the quantity of formats and n is the quantity of windows in the signal(s) being handled. This is like different kinds of format matching that have been characterized. In PC vision, for instance, layout matching is characterized as finding events of a format picture in a bigger picture. In this situation, a likeness limit is likewise used to channel matches [33].

STA/LTA are less touchy than layout coordinating and can recognize flags even within the sight of clamor. In any case, in light of the fact that new not set in stone by corresponding with comparable signs in an index, it needs heartiness in distinguishing new signals. It has more tough prerequisites than STA/LTA, and it requires an index of layouts for identifications. The bigger the index, the more exact the layout coordinating, however to the detriment of computational intricacy [34].

2.5.4 Autocorrelation

Autocorrelation is an identification technique that includes contrasting a sign with itself (known as autocovariance in certain disciplines). Autocorrelation is utilized in signal handling to track down designs that recurrent all through a sign. Rather than regarding the whole waveform as a nonstop sign, it is partitioned into fixed-length discrete windows. Every window in the sign is corresponded with each and every window in the sign, recreating a sign shift as for itself (known as slack). To wipe out possible clamor, numerous overt repetitiveness strategies can be utilized (relationship least limit, least number of matches, and so on.). To be impervious to changes in sufficiency, it is often executed as standardized autocorrelation. It is characterized as follows [35]:

$$\frac{\sum_{t=k+1}^n (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^n (y_t - \bar{y})^2} \quad (2.4)$$

Autocorrelation is powerful for distinguishing quake signals since it recognizes rehashing signals with high accuracy and precision. It likewise doesn't require the utilization of an index, as layout matching does. The time intricacy, then again, is $O(n^2)$, where n is the length of the waveform. Autocorrelation is accordingly unsatisfactory for long time spans of months or years. Nonetheless, in more limited time spans, it is viewed as a best quality level method for tremor discovery [36].

2.5.5 Deep Learning

ConvNetQuake is a convolutional brain network-based profound learning model. In a consistent time window, the information is three parts of a handled waveform (sifting, tightening, and so on), and the result is one of seven marks. Six of the names allude to various regions from which the occurrence might have started, while the last class is upheaval. This can be considered a probabilistic occasion region map. This can likewise be seen as a

matched portrayal task, with the initial six classes tending to source regions as a positive disclosure and the last upheaval class as a negative revelation [37].

The profound learning model's engineering is clear. There are eight convolutional layers and one completely associated layer altogether. The convolutional layers test the information while recognizing the main elements, which are leveled and taken care of to a feed-forward layer. The model was prepared utilizing a l2 punishment and an ADAM enhancer. The model was prepared on a huge number of occasions recorded at an Oklahoma radio broadcast, with the underlying list accumulated by [38] utilizing an alternate technique known as subspace location. 32,000 emphases were utilized to prepare the model. For this dataset, the outcomes show unbelievably high exactness and accuracy, far surpassing that of autocorrelation or Quick. ConvNetQuake has severe information essentials and needs speculation. To prepare the brain organization, a huge index of named occasions should be available, which is habitually not the situation in genuine situations. Moreover, preparing in one area doesn't ensure high exactness in another. Involving the pre-prepared ConvNetQuake at stations in Tanzania, Africa, didn't create significant outcomes in our tests.

ConvNetQuake just requires the brain network boundaries to be kept in memory, so information utilization is steady. It is additionally very effective at distinguishing new occasions (forward passes in the organization are speedy) and has state of the art precision at the station where it is prepared. The clearest improvement is further develop speculation so the brain network model needn't bother with to be retrained at each new station. In any case, computer based intelligence calculations seem, by all accounts, to be the most proficient and exact regarding registering effectiveness. For correlation, the run times for the three top calculations on multi week of nonstop waveform information are as per the following.,

2.5.6 Clustering and Classification

Grouping, which is characterized as perceiving designs in unaided situations [32], is pertinent to seismic location. While setting up another seismic station, there will be no named information from the outset, so an inventory should be procured utilizing unaided strategies. Information focuses that are near one another structure bunches, inferring that they have comparable qualities. This is vigorously dependent on information preprocessing, which is connected with the recently talked about inserting, pressure, and component determination.

A basic inquiry is the way to evaluate object comparability. The issue is portrayed in [33] as Nonlinear Dimensionality Decrease by Locally Straight Implanting: "The prerequisite to dissect a lot of multivariate information raises the crucial dimensionality decrease issue: how to find conservative portrayals of high-layered information.." K-implies [34], mean-shift [35], DBSCAN [36], various leveled grouping [37, 38], and K-closest Neighbors [39] are famous bunching procedures. Grouping can be applied in various ways, contingent upon the dissemination and qualities of the dataset [40]. Comparative seismic occasions ought to frame groups with each other, while commotion might be in isolated bunches or not by any stretch. This idea is applied by Quick's area delicate hashing, which proficiently hashes comparative waveforms into a similar hash cans [41].

In the wake of obtaining an inventory of pre-marked information, grouping calculations can be utilized to learn models that partition the classes into expectation spaces. Customary managed characterization calculations incorporate credulous bayes [42], strategic relapse [43], support vector networks [44], administered k-closest neighbors [39], choice trees [45], and irregular backwoods [46]. In benchmark tests, for example, ImageNet [47], varieties of Feed Forward Brain Organizations (Convolutional, Repetitive, and so on) are the cutting edge characterization calculations, with well known structures, for example, AlexNet [48], ResNet [49], and VGG [50] taking the top exhibitions yearly. The paper [51], aims to study the seismic protection of structures subjected to earthquakes utilizing seismic base isolation and multiple tuned mass damper systems. The authors explore the use of these systems for the protection of structures against seismic forces and analyze their effectiveness through various simulations. The paper provides insights into the application of these systems in the context of earthquake engineering and contributes to the broader field of structural engineering. Recently, [52], aims to explore the use of a feed-forward BP neural network model for earthquake prediction. The authors perform a thorough analysis of seismic data and assess the effectiveness of the neural network model in predicting earthquakes. The paper provides valuable insights into the use of artificial neural networks for earthquake prediction, which could have significant implications for disaster response and management. It is a promising contribution to the field of earthquake engineering and data analysis. The paper [53] published in the Periodicals of Engineering and Natural Sciences, aims to investigate the potential liquefaction issues that Turkish dams may face during earthquakes. The authors use a combination of analytical and numerical techniques to assess the seismic

performance of the dams. The paper provides insights into the potential vulnerability of Turkish dams to earthquakes and discusses the importance of effective risk reduction strategies. This paper provides valuable information to engineers, policymakers, and stakeholders involved in dam safety planning and management. Overall, it is a significant contribution to the field of geotechnical engineering and earthquake engineering. Further, [54] presents a numerical investigation of the use of replaceable dampers in precast reinforced concrete beam-to-column joints. The authors use advanced numerical techniques to assess the performance of the dampers in reducing the seismic response of the joints. The paper discusses the importance of seismic protection in the design of precast concrete structures and examines the effectiveness of using replaceable dampers for this purpose [55]. This research is a significant contribution to the field of earthquake engineering and highlights the potential of innovative solutions for seismic protection in precast concrete structures. Overall, this paper provides valuable insights for structural engineers and researchers interested in the development of sustainable and resilient construction materials and technologies. In addition the study [56] examines the effect of near-fault earthquakes on buildings and the need for retrofitting them. The paper discusses the importance of seismic safety and the potential risks associated with earthquakes that occur near faults. The authors analyze the seismic response of buildings using nonlinear static and dynamic analysis methods and propose retrofitting strategies to enhance their seismic performance. This paper provides valuable insights for researchers and structural engineers involved in the design and retrofitting of buildings in seismic zones. Overall, it is a significant contribution to the field of earthquake engineering and highlights the importance of proactive measures to ensure the safety and resilience of structures against seismic hazards. In the same context [57] investigates the use of nonlinear analysis methods for assessing the seismic retrofitting of two five-story buildings that underwent urban transformation projects. The authors conduct nonlinear static and dynamic analyses using experimental data obtained from shake table tests on scaled models of the buildings. The paper evaluates the effectiveness of various seismic retrofitting techniques, such as adding steel braces and shear walls, based on the analysis results. This research is a significant contribution to the field of earthquake engineering and highlights the importance of using advanced analysis techniques for the assessment of retrofitting strategies in urban transformation projects. Overall, this paper provides valuable insights for researchers and practitioners involved in the design and

retrofitting of buildings in seismic prone regions. More recently, [58] investigates a novel method for enhancing the ductility of post-Northridge connections in steel beam structures. The authors propose the use of multilongitudinal voids in the beam web to increase the plastic rotation capacity of the connections and improve their seismic performance. The paper presents the results of experimental studies conducted on full-scale specimens and investigates the effect of various parameters, such as void geometry and width, on the ductility enhancement. This paper provides important insights for researchers and structural engineers involved in the design and retrofitting of steel structures to improve their seismic performance. Overall, it is a significant contribution to the field of earthquake engineering and highlights the potential of innovative design approaches in enhancing the resilience of structures against seismic hazards. In the same context [59] investigates the use of the Fourier pseudospectra method (FPM) for simulating wave propagation in unbounded domains under a Dirac delta function. The authors propose a numerical scheme based on FPM to simulate the propagation of elastic waves in a homogeneous half-space medium. The paper presents the theoretical background of FPM and verifies the accuracy and efficiency of the proposed scheme through numerical experiments. The results show that the proposed method can accurately model wave propagation and capture the effects of the Dirac delta function on wave behavior in unbounded domains. This paper provides valuable insights for researchers involved in the field of wave mechanics and numerical methods for simulating wave propagation in complex domains. Overall, it is a significant contribution to the field of mathematical engineering and highlights the potential of FPM as an effective tool for simulating wave propagation in unbounded domains under a Dirac delta function.

2.6 RESEARCH GAPS

Tremors are the most hazardous catastrophic events for people. They happen as often as possible and all of a sudden. Despite the fact that tremors are inescapable, an exhaustive evaluation of seismic peril and gamble with decrease can assist with lessening social and financial misfortunes during a quake. During the 20th hundred years, huge quakes killed roughly 17,000 individuals each year by and large. Most of these tremors happened along plate edge structural belts all over the planet, including the circum-Pacific ring of fire and the Himalayan mountain range. Due to the seriousness of huge quakes and the gigantic harm they cause, there is consistently a dire requirement for seismic tremor to the measurement

and monitoring studies, construction laws, and safe designs, especially in non-industrial nations like India. The progressions in tremor risk appraisal and peril the board that outcome will bring about critical reserve funds in human existence and property.

Continuous seismology, which manages the issue of assessing the greatness and area of a tremor from the very outset of the break cycle, gives the logical establishment to the idea of early-advance notice transfers. Accordingly, quake forecast is broadly viewed as perhaps of the most troublesome logical issue, both regarding cultural pertinence and intrinsic intricacy. Quake expectation can assist with reorienting current procedures toward expanded tremor readiness by giving essential information on expected seismic tremor overall setting.



3. PROPOSED SYSTEM

3.1 INTRODUCTION

Seismic tremors are perhaps of the most costly regular risk that the nation faces since they happen all of a sudden and can cause serious wounds or demise because of harm to structures or other inflexible designs. The weakness of humankind to catastrophes brought about by the development and convergence of populaces, economies, radioactive, harmful, and other perilous materials and enterprises has expanded emphatically in late many years and keeps on rising; many serious quakes have brought about billion-dollar property misfortunes [50]. While seismic tremors are by all accounts not the only wellspring of risk, six of them rank among the world's main 20 cataclysmic events somewhat recently of the 20th 100 years. These tremors were not the biggest, yet they represented 35% of all out monetary misfortunes from catastrophic events, outperforming floods (30%), windstorms (28%), and others (7%), as per Feline I administration information (2000). Seismic tremors are additionally the most deadly of every cataclysmic event [51]. To actually relieve seismic tremor harm, endeavors should move away from exceptionally costly post-fiasco salvage tasks and toward information based peril versatile public resources. Consistently, roughly 80,000 individuals kick the bucket, with 220 passing on each day. The table underneath shows the typical number of tremors recorded each day and year [52].

The ground motions observed at the surface due to artificial source (exploration seismology) or natural source (earthquake seismology) are affected by source characteristics, medium properties and site conditions. The medium properties are related to the attenuation of seismic waves propagating between source and receiver [53]. The attenuation properties of a medium affect the amplitudes of ground motions at various distances from the source. Subsurface factors attributing to the seismic wave attenuation are geometrical spreading, absorption, inter-bed multiples generated by thin layering, diffractions and the focusing or defocusing effects of the reflector curvature or velocity [54]. Among these subsurface factors, absorption reveals geological information, which includes attenuation of both intrinsic and scattering effects. Seismic wave attenuation plays a pivotal role in exploration seismology as well as in earthquake seismology. In exploration, it helps in improving the seismic resolution for reliable interpretation of hydrocarbon prospects and can be used as an attribute for delineation of the reservoirs [55]. In earthquake seismology, it correlates with

regional heterogeneities such as major folds, faults or near-surface complexities and helps in categorizing the scale of tectonic activity in the region [56].

Earthquake seismology is a major topic relevant to understanding hazards due to natural and induced earthquakes as well as understanding physical properties of the earth's crust. In the past decade, the number of seismic monitoring stations has increased dramatically, leading the field of research to transition from an observation-based science to a data-driven science [57]. In general, earthquake seismology problems fall into three categories: earthquake recognition for data mining and early-earthquake detection [58] [59], earthquake prediction for a warning system [60] [61]. In this paper, we address the earthquake recognition (P1) and earthquake prediction problems (P2) illustrated in Figure 1. We test the performance of 1D CNN, 2D CNN, and RNN neural networks on both problems using a dataset of seismic waveforms from 46 stations near the Geysers geothermal area, California [62][63]. In the P1 problem, the goal is to predict whether an earthquake has occurred given a seismic waveform. State-of-the-art performance is generally high on this problem, largely depending on the magnitude of earthquakes considered. In the P2 problem, the goal is to predict whether an earthquake will occur given a seismic waveform [64][65][66]. In contrast to the P1 problem, there is no proven analytical method to predict an imminent earthquake [67], and therefore state-of-the-art performance is non-existent.

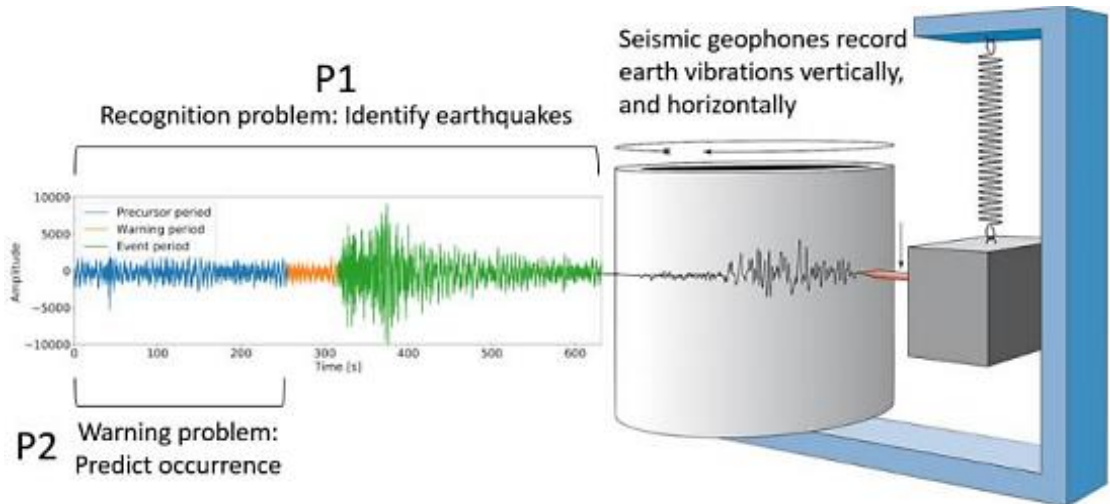


Figure 3.1: A Schematic Illustration of The Problems Tackled in This Paper. A Seismometer (Geophone) Records The Displacement of The Earth As A Function of Time.

3.2 SEISMIC ATTENUATION

Seismic waves undergo attenuation and dispersion attributing to the frictional losses or the scattering while passing through the dissipative earth. The frictional losses are often termed as intrinsic attenuation, which occurs due to the relative movement of grains or fluids in the rock matrix. The intrinsic properties of the medium such as grain type, architecture, porosity, fluid type, viscosity, permeability, saturation and pressure are usually accountable for these losses in sedimentary rocks. Scattering attenuation is because of random heterogeneities in the near surface or weathered basalts and by the layering effects such as stratigraphic filtering. Both intrinsic and scattering losses eventually lead to phase distortion, degradation of seismic resolution and poor imaging below absorptive zones.

3.3 FREQUENCY DEPENDENCE OF QUALITY FACTOR

The quality factor is often considered as independent of frequency in seismic exploration bandwidth (10 to 100 Hz) as recommended by many researchers [68] observed the frequency dependence of Q across different bandwidths ranging from seismic (100 Hz) to the sonic and the core-testing band (1M Hz). The frequency dependence is generally noted for the physical phenomena like viscous relaxation [69], patchy saturation [70], squirt flow [71]. If the medium is frequency-dependent, the assumption of constant Q may lead to large systematic errors [72][73] in estimation.

However, many researchers (Johnston et al., 1979) have observed that the frequency dependence of Quality factor in seismic is negligible. We have also assumed a frequency-independent Q as adopted in various studies [74] for datasets across the seismic bandwidth. In earthquake seismology, the dependence of Q with frequency is often investigated to study the crustal and upper mantle seismic attenuation using earthquake data. It is generally expressed as a power law [12].

$$Q = Q_0 \left(\frac{f}{f_0} \right)^\eta \quad (3.1)$$

Where Q_0 represents the quality factor at the reference frequency f_0 (usually 1Hz). The parameter ' η ' describes the frequency-dependency whose value ranges from 0.1 to 2.0 ($\sim$ close to 1) depending on the heterogeneity (Aki 1981) in the study area. A strong variation of Q with frequency is generally observed in a tectonically active region as compared to a

stable region. The quality factor obtained from seismograms of exploration seismology is termed as Seismic-Q and that of obtained from tail of earthquake seismograms (coda waves) is termed as Coda-Q.

3.4 ESTIMATION OF QUALITY FACTOR

In oil and gas exploration, the measurement of Quality factor has been carried out from core samples, Well logs, VSP and surface seismic data. The measurement of Q from core data is not reliable[9] as it is performed at very high (kilohertz-range) frequencies at limited pressure and temperature conditions in the laboratory compared to in-situ conditions. VSP or check-shot survey datasets[10] are considered as ideal for Q estimation because of the simple source-receiver geometry and isolation of the target zone. The main drawback of this dataset is that it provides a single vertical Q profile without any areal coverage. On the other hand, the surface seismic reflection survey provides better areal coverage, but data at each receiver has suffered attenuation loss characteristic to its ray path in the earth. The discrete ray paths of each record lead to variations in the reflectivity-transmissivity effects. Further, the source directivity (aggravates the problem of Q estimation, particularly at shallow targets.

Spectral ratios, peak/centroid frequencies which are the input to the spectral ratio method and the frequency shift method represents large zone near the target reflector when spectra are calculated by standard Fourier transform. To obtain high resolution time-frequency spectra for estimation of accurate equality factor [13] several time-frequency transforms like Gabor transform, continuous wavelet transform (CWT) and Stockwell transform (ST) has been incorporated in various studies. Blias (2012) have also demonstrated improved accuracy in Q estimation through an optimization approach to the spectral ratio method.

Generally used methods for estimation of seismic-Q (e.g. spectral ratio method) and coda-Q involves the linearizing of the equation by taking logarithm and then apply least square criteria. This procedure may lead to biased results (e.g. Menke, 1984). The present thesis presents a non-linear approach for the estimation of seismic-Q and coda-Q.

3.5 MOTIVATION

Earthquakes are the results of the Earth's crust movement. At the surface, they appear by shaking. They might lead to loss of life and destruction of property. So, they have

sociological and economical costs. The World's costliest earthquake is recorded as the 2011 Tōhoku Earthquake and Tsunami in Japan. According to the Japanese National Police Agency the earthquake caused over 15,000 deaths, and the property damage valued at about \$235 billion making it not only the costliest earthquake ever but also the most costly natural disaster ever [1]. Because the climate data did not seem correlated, it did not prove itself as a good candidate to be a second dimension for earthquake prediction. Hence, a prediction for earthquakes was made by using only earthquake data. Linear regression is used to observe the trend. The plot suggested that we will have more earthquakes. Polynomial regression is used to make the prediction. Because of lack of the second dimensional data, prediction was not successful. But it was a good step to start with. This paper can encourage further studies to work relational analysis on earthquakes.

3.6 PROPOSED SYSTEM

In the earth sciences, earthquake prediction is one of the great unsolved problems. Despite decades of research attempting to identify earthquake precursors, there is no proven analytical method to predict earthquakes before they occur. The problem is challenging for several reasons: (1) any precursor signal that may exist is likely dwarfed by the background seismic noise; (2) seismic data is multidimensional recording different directions of motion, and is therefore difficult to analyze; (3) different seismic stations will record the same event differently due to heterogeneity in the earth and attenuation of propagating waves; and (4) earthquakes occur infrequently, resulting in an unbalanced prediction problem. Nevertheless, the application of deep learning is rare in this field of research, and therefore may offer a new avenue forward (e.g., Wang et al., 2017; Lipski et al., 2017). In this project, we aim to create an earthquake warning system utilizing deep neural networks that are capable of predicting an earthquake 60 seconds prior to the event occurring. There are several different approaches to building a prediction model from seismic waveform data. In one approach, the seismic waveform is pre-processed to extract features from the time-series data such as various summary statistics, autocorrelation at different lag values, and fft wavelet coefficients (Chu and Maurer, 2016; Addair, 2012). A related approach condenses information in the waveform into a binary “fingerprint” for a fast data mining algorithm by thresholding a spectrogram of the waveform (Yoon et al., 2015). In our initial testing, we found that the feature extraction approach is too slow for an earthquake warning system.

Therefore, we analyze the raw seismic waveform and the spectrogram of the waveform. In the following sections we describe our dataset, deep learning approach to earthquake prediction, and preliminary results.

3.6.1 Dataset

Seismic waveform data is available through publicly funded seismic station networks that monitor and catalog seismic events. Accessing the data is relatively simple using the Obspy python library (Krischer et al., 2015), which allows seismic waveform data to be queried based on location, time, magnitude of events, seismic station, and waveform component. In order to create an earthquake early warning system, we define our data variable to be some nominal “precursor period” prior to a 60 second “warning period” before the earthquake event (Figure 1). The prediction variable is a binary variable (0 - no earthquake; 1 - earthquake). Because there is no proven method for identifying earthquakes precursors, we have no information about the characteristics of a potential earthquake precursor signal. For example, the precursor signal may only exist prior to large magnitude earthquakes, it may ramp up slowly over a long period of time, or exist as discrete bursts of high-frequency signal. Therefore, in order to find an optimal dataset, we created several datasets with different properties such as magnitude of earthquake events, time period, and number of stations.

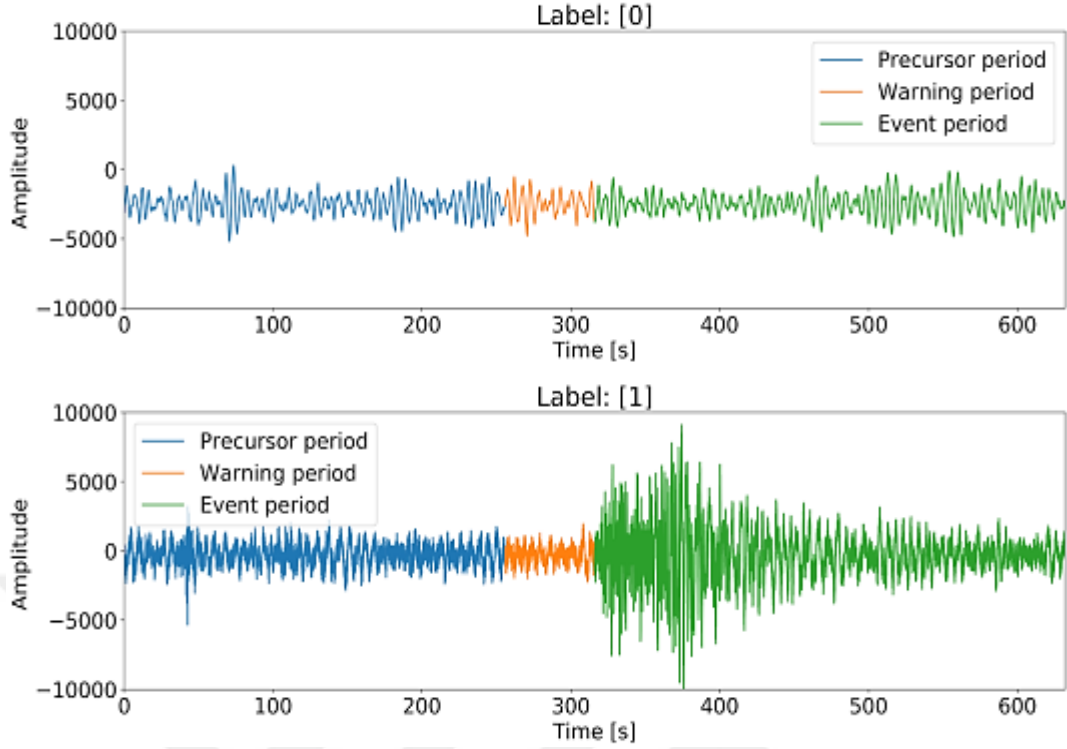


Figure 3.2: Two Samples From The Dataset. (Top) A Negative Example In Which There Is Not Earthquake During The Event Period. (Bottom) A Positive Example In Which An Earthquake Occurs During The Event Period.

3.6.2 Features Extraction

Continuous seismic waveform data is available through many publicly funded seismic station networks that monitor and catalog seismic events. Because there is no proven method for identifying earthquake precursors, there is little information about how to create an optimal dataset for the earthquake prediction problem. Therefore, we wrote a python script that generates multiple datasets for specified

- i. Seismic stations across different regions,
- ii. Minimum earthquake magnitude, and
- iii. Single (vertical displacement measurements) or multi-channel waveforms.

After some initial experimentation, we determined that using many stations clustered in a geologically similar environment offered the best balance of containing a large number of

samples drawn from the same distribution. We also decided to use a balanced dataset of positive and negative samples based on the conclusions of Buda et al. (2017) who found that training a convolutional neural network on under sampled negative samples yielded the best result.

The procedure used in the python script is as follows: 1) for each seismic station, we query the catalog for all earthquakes above a minimum magnitude and within ~ 10 kilometers of the station; 2) for each earthquake, we estimate the time of arrival of the seismic wave using the “iasp91” earth model; 3) we then download the seismic waveform for a specified period of time around the arrival time of the earthquake; and 4) we download a random seismic waveform from the same station to create a balanced dataset of positive and negative samples. The final datasets used in this paper included 1671, 614, and 176 positive samples (single-channel, vertical displacement) for minimum earthquake magnitudes of 3, 3.5, and 4 respectively. These samples are retrieved from 46 stations from the Berkeley Geysers Network, located ~ 110 kilometers north of the Bay Area, California (Figure 3). The region is seismically active and with a relatively dense array of monitoring stations.

Figure 3 shows an example seismic waveform for the 1D CNN model. For the earthquake prediction problem, the “precursor period” is used as input, whereas for the recognition problem a small window centered around the earthquake event is used as input. For the 2D CNN and RNN models, the spectrogram of the time-series data is used as input (spectrogram is a representation of the signal energy at different frequencies). Both input types - the raw time series and the spectrogram - are normalized using the z-score transformation.

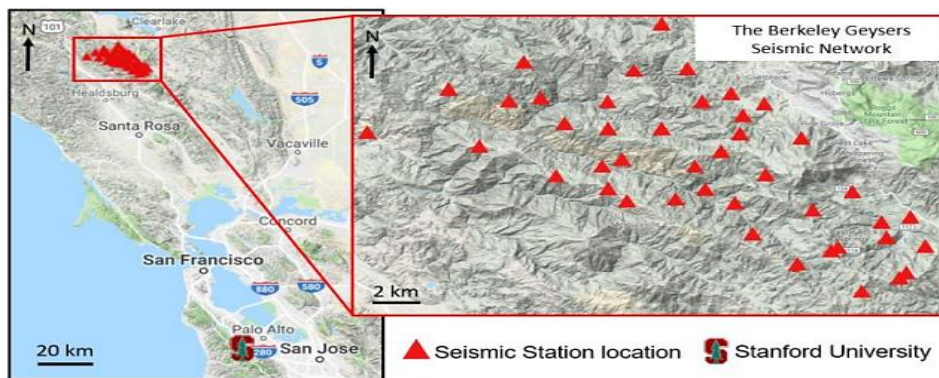


Figure 3.3: Location of The Study Area (The Geysers) And The Seismic Stations Used To Collect The Dataset.

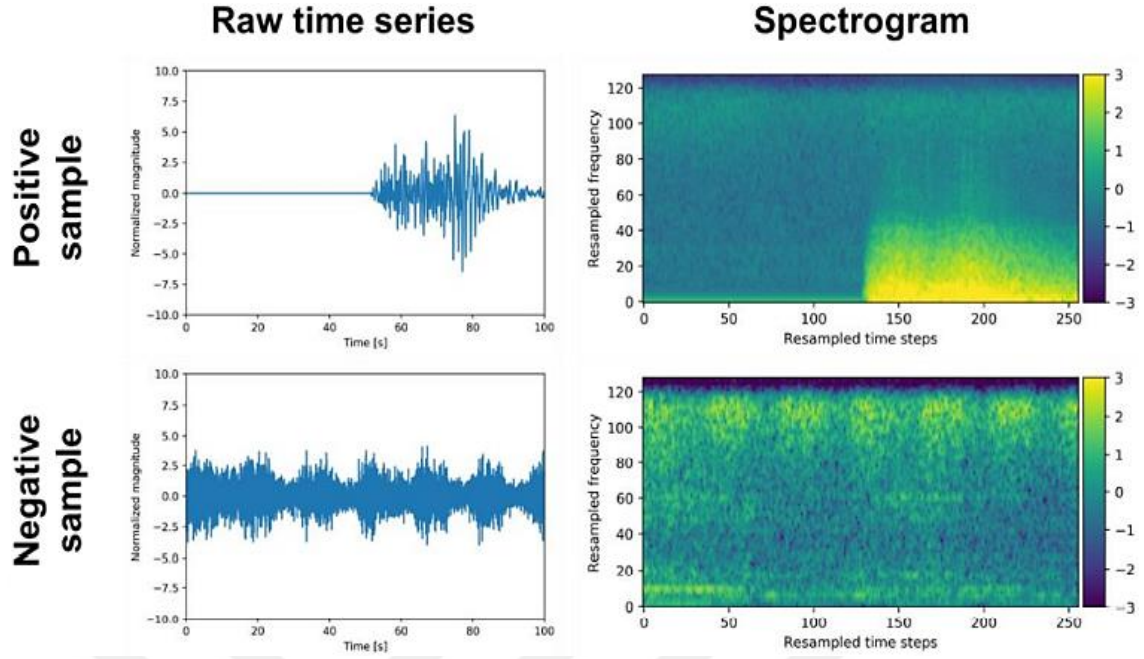


Figure 3.4: Examples Of The Raw Data And Spectrogram. A Negative Example In Which There Is Not Earthquake During The Event Period. (Bottom) A Positive Example In Which An Earthquake Occurs During The Event Period.

3.6.3 Methods

Three neural network architectures – 1D CNN, 2D CNN, and RNN – were developed using the Keras library for both earthquake recognition and prediction problems. Figure 4.5 illustrates architecture configurations and the hyperparameters explored during training. The 1D CNN model consists of a series of 1D convolution and pooling layers, and uses the time-series of the seismic waveform as the input variable. The 2D CNN model is similar but uses the spectrogram of the seismic waveform as the input variable. Finally, the RNN model consists of a 1D convolution layer followed by two LSTM layers, and also uses the spectrogram of the seismic waveform as the input variable. In all models, binary cross entropy is used for the loss.

Models were tuned by exploring several hyperparameters using a training/validation/test set approach. The dataset is first split into training/test sets using a 9/1 ratio, and then 10% of the training set is used as a validation set. Hyperparameters are tuned by computing accuracy on the validation set. For example, the optimum values of dropout rate and number of epochs were determined such that the model does not overfit the training data. We used dilation rate

in the 2D CNN model to explore a larger area of the spectrogram without increasing the filter size. We used class weights in the RNN model to force increasing accuracy in a specific class.

Several different datasets and window sizes for the seismic waveform were explored to increase performance of the models. For example, using a smaller window (~1 minute before and after the earthquake) was found to increase the accuracy of the recognition model, suggesting that selection of the window size is an important pre-processing step. In the case of the prediction problem, selecting the window size is more complex because of the computation cost of using a larger spectrogram. Generally, increasing the size of the time interval while fixing the resolution of the spectrogram results in decreasing accuracy of the model.

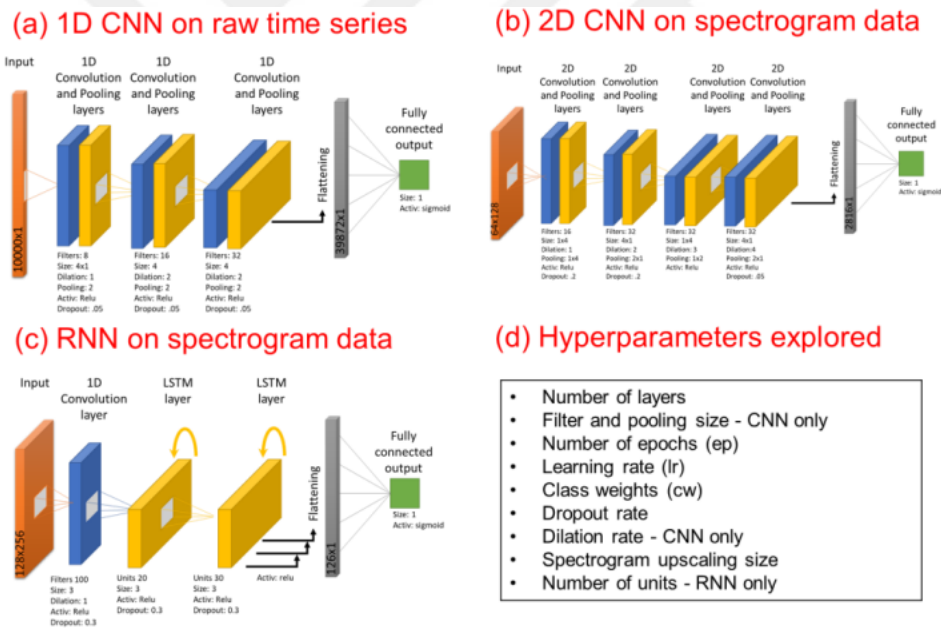


Figure 3.5: Three Neural Network Architectures (A, B, C) and Network Hyperparameters Explored (D).

We will attempt to obtain a probability of the a chance of an earthquake occurring in the next few minutes near the monitoring station using data from the previous few minutes. Because this is a classification problem (earthquake will occur, or not occur), a simple confusion matrix can be used to evaluate the results.

3.6.4 Performance Evaluation Metrics

The previously mentioned networks have just two potential results: 0 for foreseeing that a tremor won't happen and 1 for foreseeing that a quake will happen. One of the assessment measurements for such paired classifiers is the disarray grid [21]. Every lattice part in the tremor forecast task is entirely made sense of.

- i. Genuine Up-sides (TP): The times the model accurately estimates a tremor in the following 30 seconds.
- ii. Genuine Negatives (TN): The times the model accurately predicts that there will be no quake in the following 30 seconds.
- iii. Misleading Up-sides (FP): The times the model mistakenly predicts a tremor in the following 30 seconds.
- iv. Misleading Negatives (FN): The times the model predicts inaccurately that a tremor won't happen inside the following 30 seconds.

We battle that FN raises the most serious worries in light of the fact that a quake will cause enormous misfortune on the off chance that it isn't anticipated to happen. In the interim, we are watching out for FP. In the event that the quake doesn't happen however is anticipated to happen, the general public might be troubled by a clearing drill. Thus, among the significant assessment measurements got from the disarray lattice, positive prescient worth (PPV, otherwise called accuracy) and genuine positive rate (TPR, otherwise called awareness or review) connected with FP are utilized for our situation. They are defined as follows:

$$Precision = \frac{TP}{TP+FP} \quad (3.2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3.3)$$

Accuracy, as characterized by the equations, is the quantity of quakes that happen among every one of those anticipated to happen. The quantity of tremors anticipated to happen among everything quakes that happen is alluded to as review. At the point when a FN shows up, the review rate endures. Also, at whatever point a FP shows up, the accuracy rate is punished. Thus, review and accuracy are supposed to be all around as high as conceivable

to diminish the punishment brought about by FN and FP. One more measurement known as f1-score is utilized to adjust the impacts of accuracy and review on the assessment. It's the symphonious mean [22] of the accuracy and review:

$$F1\ Score = \frac{2TP}{2TP+FP+FN} \quad (3.4)$$

At long last, considering that the dataset is generally adjusted, test precision is remembered for the measurements to show the general presentation of the model on inconspicuous information straightforwardly. It is characterized as the level of accurately anticipated test information:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3.5)$$

4. RESULTS AND DISCUSSION

In this section, we first give details on the procedures taken to process the raw earthquake data that happened using a dataset of seismic waveforms from 46 stations near the Geysers geothermal area, California. In the P1 problem, the goal is to predict whether an earthquake has occurred given a seismic waveform. The information can be all found on the Worldwide Organization of Advanced Seismograph Organizations (FDSN) site [24]. Following that, the engineering plans of the three profound brain networks referenced in Segment 2.1 are portrayed exhaustively. At last, we examine the over-fitting issue that emerged during execution and the way things were settled.

4.1 EXPERIMENTAL SETTINGS

We start by relegating every tremor and typical sign to the nearest station utilizing incredible circle distance [27]. The models are prepared station-by-station, with each organization input addressing one example. The organization's result is the probability that the info succession is named a seismic tremor. The probabilities under 0.5 are shortened to 0, demonstrating typical way of behaving, while those more noteworthy than or equivalent to 0.5 are viewed as 1, showing tremor conduct. To utilize cross approval (talked about in Segment 3.4.3), 10% of the dataset is utilized as the testing set. The excess 90% is separated into five subsets, one for approval and the other four for preparing the model during every emphasis. The quantity of still up in the air by the Early Stop procedure [28], which is one more technique for abstaining from over-fitting (will be referenced in Area 3.4). In the event that the approval misfortune doesn't diminish for 7 back to back ages, we force the preparation cycle to stop. We normal the outcomes north of 5 emphases to diminish the impact of over-fitting. The accompanying segment contains data on every boundary setting.

4.2 SEISMIC WAVEFORM

The seismic waveform [25] of the tremors is then researched. We recover the waveform time series of 30 seconds before the quake, estimated along the upward pivot and recorded at 100 HZ, for example 100 examples each second, for every one of them. Figure 4.1 portrays the sign distinguished by three arbitrarily chosen stations. The signs are then standardized to guarantee that they are in similar reach for all stations, as displayed in Figure 4.2. Moreover, information with a high recurrence normally contains commotion that can be sent to the

organization, which can adversely affect the result [26], while information with a low recurrence might need helpful information highlights. Given the requirements of time and gadget quality, as well as model execution, we decided to downsample⁴ the waveform to 50 HZ, as displayed in Figure 4.3.

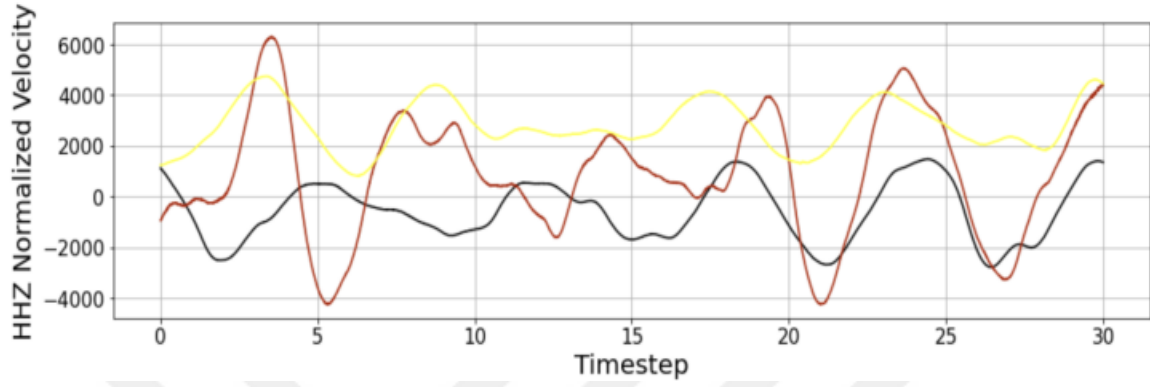


Figure 4.1: Original Seismic Signal For Three Random Earthquakes.

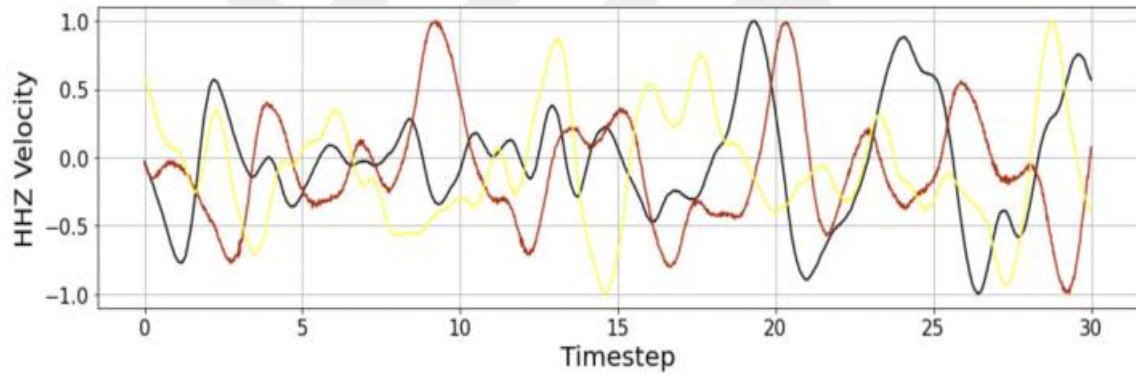


Figure 4.2: Normalized Seismic Signal For Three Random Earthquakes.

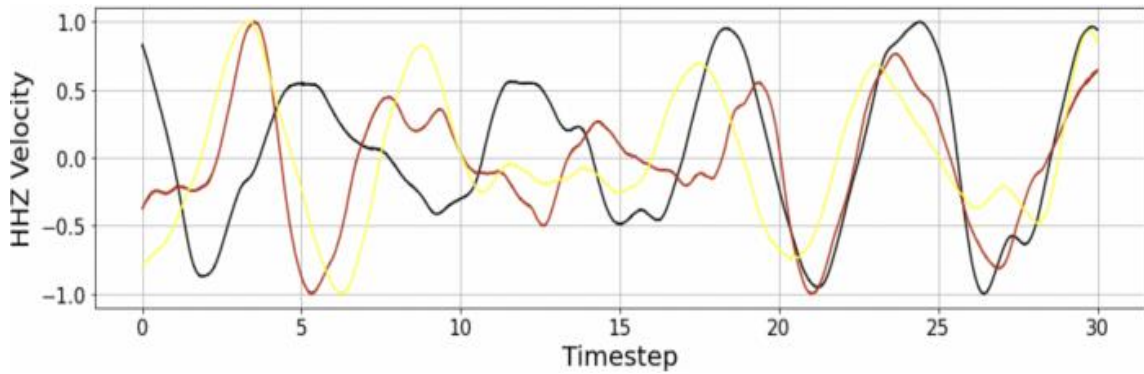


Figure 4.3: Down Sampled Seismic Signal For Three Random Earthquakes.

A calculation is intended to track down the greatest stretch between the timestamps of two seismic tremors to get typical waveform information. Spans are arranged in slipping request, and a waveform range in the center is picked beginning with the biggest stretch (we think about them as quiet minutes). In the event that the waveform's timestamp isn't found in the tremor information list, the waveform is delegated a typical waveform signal. This method creates roughly 160k ordinary signs.

4.3 OVER-FITTING & SOLUTION

Over-fitting is an issue in computer based intelligence wherein the model fits eagerly or even flawlessly to a specific dataset, which is regularly the readiness set, but fails to perform well on hid data, which is for the most part the test set [29]. Even more exhaustively, the model may be wounded by trivial information in the arrangement set, making it fight to learn data features. To determine the issue, we propose regularization (counting dropout), cross endorsement, and grid search on hyperparameters.

4.4 REGULARIZATION

Regularization is a well known strategy for forestalling over-fitting by adding a punishment term to the misfortune capability on the preparation set [30]. At the point when the information contains countless helpful elements that are not supposed to be disposed of, regularization is utilized to diminish the heaviness of those highlights, and in this way the intricacy of the learned model. Our models are exposed to L2 regularization (otherwise called weight rot), and preliminary reaches are incorporated.

[31] proposed a dropout way to deal with take care of the over-fitting issue in 2014. As per the paper, dropout is a method wherein irregular neurons are briefly disposed of from the organization during the model's preparation interaction (the result of the enactment capability of such neurons is set to 0), which is identical to tracking down a more slender organization from the first organization.

4.5 CROSS VALIDATION

Cross approval was acquainted with permit the model to advance however many information designs as would be prudent while lessening commotion, which is probably going to bring about high predisposition and change [32, 33]. For our situation, we utilize a variation known

as k-fold cross approval. K-fold cross approval, as the name infers, uniformly isolates the dataset into k subsets, each addressing one fold. The model will then, at that point, be prepared for k cycles. During every epoch, one of the k subsets is utilized for approval, while the leftover k - 1 subsets are utilized as preparing set. At last, the test blunder is regularly shown up at the midpoint of over k primer outcomes to decide the model's general show [34]. Because of the time imperative, we set $k = 5$ for the quake expectation task. 10% of the dataset was utilized for the test set, while the excess 90% was equally isolated into five folds.

4.6 DATASET AND FEATURES

We used the Obspy library [3] to assemble the dataset through the procedure outlined. We experimented with different datasets, determining that tightly clustered stations is preferred. Three datasets are assembled with 1671, 614, and 176 earthquakes using a minimum magnitude (M) of 3, 3.5, and 4 respectively

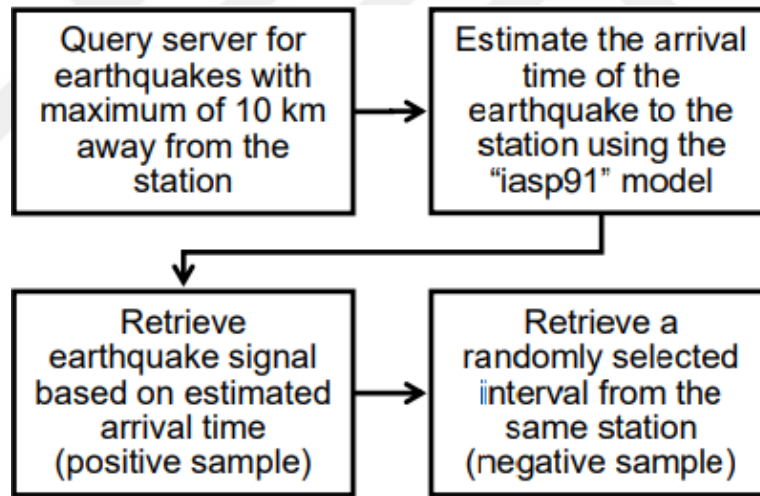


Figure 4.4: Earthquakes Using A Minimum Magnitude.

4.7 EXPERIMENT RESULTS

Table 1 shows selected results for the earthquake recognition problem (P1 in Figure 1). Overall, all the architectures performed well (>90% accuracy), and 2D CNN and RNN obtained 100% test accuracy. This indicates that neural networks can be reliably trained to identify earthquakes in seismic waveform data. Table 2 shows selected results for the earthquake prediction problem (P2 in Figure 1). The results obtained are higher than 50%

(i.e. the expectation of random guessing). This suggests that there is some pattern in the precursor signal that is indicative of earthquake occurrence in the next minute. The reported results are typical and not merely the best obtained results in our model training. In some runs, the test accuracy obtained reached 62% (using the dataset with higher magnitude earthquakes). However, because higher-magnitude earthquake occurrence is sparse, the dataset is small, and therefore the test accuracy may not reflect the true accuracy of the model.

Table 4.1: Selected Results Of Earthquake Recognition Problem (P1).

Model	Parameters	Training Accuracy	Test Accuracy
1D CNN	M = 3.5, lr = 0.001, ep = 10	97.5%	94.4%
2D CNN	M = 3.5, lr = 0.001, ep = 10	100%	100%
RNN	M = 3.5, lr = 0.001, ep = 50	100%	100%

Table 4.2 : Selected results of earthquake prediction (P2).

Model	Parameters	Training Accuracy	Test Accuracy
1D CNN	M = 3, lr = 0.002, ep = 40	56.0%	54.2%
2D CNN	M = 3, lr = 0.001, ep = 12	60.0%	52.6%
RNN	M = 3, lr = 0.001, ep = 100, cw = [0.5, 0.5]	82.5%	54.5%
	M = 3, lr = 0.001, ep = 100, cw = [0.4, 0.6]	83.8%	56.4%
	M = 3, lr = 0.001, ep = 100, cw = [0.25, 0.75]	74.7%	53.9%

In the RNN model, modifying the class weights was found to increase the overall test accuracy. As illustrated in the confusion matrices (Figure 6), penalizing the network to prefer true-positive accuracy to 0.6 resulted in an overall increase in accuracy. However, further increasing the true-positive accuracy to 0.75 then decreased the overall accuracy.

Although our results indicate improvement over random guessing, the test accuracy of the models is quite low. Possible issues include: 1) there is simply no physical mechanism prior to an earthquake that generates a seismic signal; 2) the precursor signal cannot be isolated in our dataset; or 3) the network architectures are not suitable for the setup of our problem. If there is no signal that is generated before the earthquake (issue 1), then the problem is unsolvable in its current formulation. If the precursor signal cannot be isolated in our dataset

(issue 2), then assembling a better dataset might yield a better accuracy. If the network architectures are unsuitable (issue 3), then a more complex architecture might be useful.

After considering the different issues, we think that issue 2, the dataset, is likely the most important issue. A possible next step is to manually pick the arrival times of each earthquake rather than relying on the “iasp91” earth model, which might result in a more precise dataset. Then, we could experiment with using shorter “warning periods” (Figure 1) to test whether accuracy improves with shorter warning times. This would suggest that we can isolate when the precursor signal exists, and then explore the characteristics of the precursor signal.

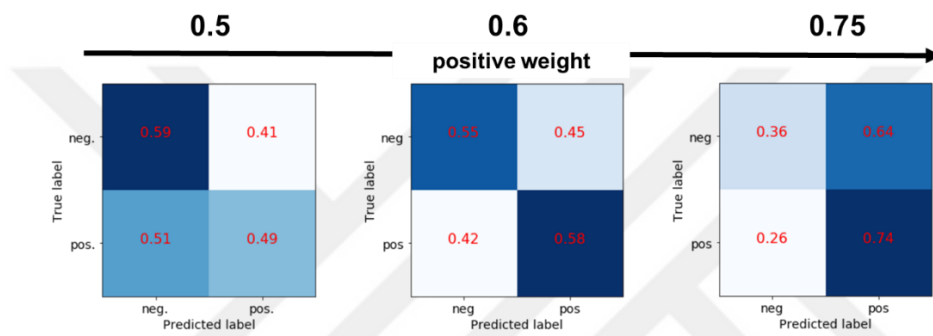


Figure 4.5 : Confusion Matrices With Different Class Weights For The RNN Network Applied On A Dataset With A Minimum Magnitude (M) Of 3.5

4.8 CONCLUSION

In this thesis, we conducted an extensive earthquake analysis using deep learning techniques. The regional analysis of earthquakes was also made. In this paper, we address the earthquake recognition (P1) and earthquake prediction problems (P2) illustrated in Figure 1. We test the performance of 1D CNN, 2D CNN, and RNN neural networks on both problems using a dataset of seismic waveforms from 46 stations near the Geysers geothermal area, California. In the P1 problem, the goal is to predict whether an earthquake has occurred given a seismic waveform.

5. CONCLUSIONS AND FUTURE WORKS

5.1 CONCLUSIONS

This paper suggested the conversation starter of how individual time series models, explicitly vanilla RNN, LSTM, and CNN, look at regarding transient quake expectation (30 seconds before tremor). To respond to the inquiry, 30 second waveform signs of quakes happening were gotten from a dataset of seismic waveforms gathered from 46 stations close to the Fountains geothermal region in California. The objective of the P1 issue is to foresee whether a quake has happened in view of a seismic waveform. We picked the nearest station to get distinguished quakes and typical signs. The organizations were planned and prepared station by station utilizing information from 30 seconds. Over-fitting was found in certain stations during the preparation and approval process. A few methodologies, including regularization and framework search, were utilized to attempt to take care of the issue. In spite of the way that the issue stays because of the examination time limit, the models' exhibitions have gotten to the next level. The eventual outcomes showed that each of the three models perform better compared to quake signals at accurately arranging ordinary conduct signals. LSTM has the best exhibition of the three models, with a found the middle value of exactness of around 66.5% on foreseeing with concealed information, while CNN is adversely impacted by information with commotion. More methodologies, for example, network extending and preparing with information of fluctuating frequencies, can be utilized in the future to further develop exactness.

5.2 FUTURE WORKS

A few thoughts and preliminaries are hampered by time requirements and gadget quality limitations. In the first place, no matter what the over-fitting showed by a couple of stations, the other few stations show that preparation and approval exactness vacillated inside a reach during the preparation and approval process. We accept this is because of the basic organization engineering plan. Accordingly, we can build the quantity of layers in each organization with the goal that it can advance additional successive attributes from the information [36]. Different ways to deal with managing over-fitting can be attempted, for example, cluster standardization [37]. Beside exploring different avenues regarding different methodologies, the scope of hyperparameters can be extended. Weight rot, specifically, may

have more choices to browse. A secret organization size reach can likewise be incorporated. Moreover, network search can be utilized on every one of the 27 stations to track down normal hyperparameters. All the while, information with various frequencies ought to be tried different things with to find an offset point between information with numerous qualities and information with few qualities. At long last, the discoveries of this study showed that tremor expectation stays a troublesome issue. Accordingly, various kinds of profound learning strategies can be utilized, either alone or in mix [38], to train individuals what the best answer for such time series to the measurement and monitoring assignments is.

Seismology requires distinct benchmark datasets, like what is accessible in picture acknowledgment fields like ImageNet. For better profound learning model preparation, better measurements for deciding quality datasets and techniques for accumulating enormous information are required. Joining numerous stations to take care of the convolutional brain net could be a technique for consolidating more data and accomplishing a higher identification rate. A summed up model that does exclude move learning would bring about a more limited expectation to learn and adapt for clients and "off the rack" use. One of the main benefits of a genuine summed up identification model is that it doesn't need earlier preparation information to be applied to new areas. As the default strategy for recognizing quakes, a very high performing summed up model could be utilized.

Iterative preparation to produce extra preparation information is a neglected thought. Iterative preparation (otherwise called deep rooted learning) includes utilizing a current model that has been prepared on a set number of information focuses to find extra information focuses that can be utilized to prepare the model further . This is effectively relevant to seismic datasets with little beginning inventories. With an enormous number of commotion windows to test from, the organization can be prepared to diminish the probability of misleading up-sides while finding new occasions to retrain on.

REFERENCES

- [1] T. Bhandarkar et al. "Earthquake trend prediction using long short-term memory RNN". In: International Journal of Electrical and Computer Engineering 9.2 (2019), p. 1304, 2019.
- [2] Q. Wang et al. "Earthquake prediction based on spatio-temporal data mining: an LSTM network approach". In: IEEE Transactions on Emerging Topics in Computing, 2017.
- [3] A.Boucouvalas, M.Gkasios, N.Tselikas, and G.Drakatos. "Modified fibonacci-dual-lucas method for earthquake prediction". In Third International Conference on Remote Sensing and Geoinformation of the Environment, pages 95351A-95351A. International Society for Optics and Photonics, 2015.
- [4] Chouliaras, G. "Seismicity anomalies prior to 8 June 2008 earthquake in Western Greece". Nat. Hazards Earth Syst. Sci., 9 (2): 327-335, doi:10.5194/nhess-9-327-2009, 2009.
- [5] J. Fan, Z. Chen, L. Yan, J. Gong, and D. Wang. "Research on earthquake prediction from infrared cloud images". In Ninth International Symposium on Multispectral Image Processing and Pattern Recognition (MIPPR2015), pages 98150E-98150E. International Society for Optics and Photonics, 2015.
- [6] M. Hayakawa, H. Yamauchi, N. Ohtani, M. Ohta, S. Tosa, T. Asano, A. Schekotov, J. Izutsu, S. M. Potirakis, and K. Eftaxias. "On the precursory abnormal animal behavior and electromagnetic effects for the kobe earthquake (m 6) on april 12, 2013". Open Journal of Earthquake Research, 5(03):165, 2016.
- [7] M. Moustra, M. Avraamides, and C. Christodoulou. "Artificial neural networks for earthquake prediction using time series magnitude data or seismic electric signals". Expert systems with applications, 38(12):15032-15039, 2011.
- [8] Mohsen Yousefzadeh, Seyyed Ahmad Hosseini, Mahdi Farnaghi. "Spatiotemporally explicit earthquake prediction using deep neural network". Soil Dynamics and

- [9] Luana Ruiz, Fernando Gama and Alejandro Ribeiro. "Gated Graph Convolutional Recurrent Neural Networks". arXiv:1903.01888, 2019.
- [10] Parisa Kavianpour, Mohammadreza Kavianpour, Ehsan Jahani, Amin Ramezani. "A CNN-BiLSTM Model with Attention Mechanism for Earthquake Prediction". arXiv:2112.13444, 2021.
- [11] G. Mazzola. "Graph-Time Convolutional Neural Networks". MSc thesis, TU Delft, 2020.
- [12] Williams, Ronald J.; Hinton, Geoffrey E.; Rumelhart, David E. . "Learning representations by back-propagating errors". *Nature*. 323(6088):533-536, October 1986.
- [13] Petneházi, Gábor. "Recurrent neural networks for time series forecasting". arXiv:1901.00069, 2019-01-01.
- [14] <https://blog.floydhub.com/a-beginners-guide-on-recurrent-neural-networks-withpytorch/>. Accessed: 2022-01-19.
- [15] Graves, A., Schmidhuber, J.. "Offline handwriting recognition with multidimensional recurrent neural networks. *Advances in neural information processing systems*", 21, 545- 552, 2008.
- [16] Graves, Alex; Mohamed, Abdel-rahman; Hinton, Geoffrey E.. "Speech Recognition with Deep Recurrent Neural Networks". *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*: 6645-6649, 2013.
- [17] Manaswi N.K. "RNN and LSTM". In: *Deep Learning with Applications Using Python*. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4842-3516-4_9, 2018.

- [18] Schmidhuber, Jürgen; Gers, Felix A.; Eck, Douglas. "Learning nonregular languages: A comparison of simple recurrent networks and LSTM". *Neural Computation*. 14 (9):2039- 2041, 2002.
- [19] <https://blog.floydhub.com/long-short-term-memory-from-zero-to-hero-with-pytorch/>. Accessed: 2022-01-19.
- [20] Sundermeyer, Martin, et al. "Translation modeling with bidirectional recurrent neural networks.". *Proceedings of the Conference on Empirical Methods on Natural Language Processing*, October 2014.
- [21] Shaikh, S.A.. "Measures Derived from a 2 x 2 Table for an Accuracy of a Diagnostic Test". *Journal of biometrics biostatistics*, 2, pp. 1-4, 2011.
- [22] Wirth F. Ferger. "The Nature and Use of the Harmonic Mean". *Journal of the American Statistical Association*, 26:173, 36-40, 1931.
- [23] Kulevome, D. K., Wang, H., Wang, X.. "A Bidirectional LSTM-Based Prognostication of Electrolytic Capacitor". *Progress In Electromagnetics Research C*, 109, 139-152, 2021.
- [24] FDSN webservice for New Zealand. <https://www.geonet.org.nz/data/tools/FDSN>. Accessed: 2021-11-15.
- [25] Weik M.H.. "seismic wave". In: *Computer Science and Communications Dictionary*. Springer, Boston, MA. https://doi.org/10.1007/1-4020-0613-6_16842, 2000.
- [26] Shivani Gupta et al. "Dealing with Noise Problem in Machine Learning Data-sets: A Systematic Review". *Procedia Computer Science* 161 (2019) 466-474, 2019.
- [27] R. Bullock. "Great circle distances and bearings between two locations". In: *MDT*, June 5, 2007.
- [28] Yao, Yuan, Lorenzo Rosasco, Andrea Caponnetto. "On Early Stopping in Gradient Descent Learning". *Constructive Approximation*. 26 (2): 289â315, 1st August, 2007.

- [29] Chicco, D. "Ten quick tips for machine learning in computational biology". *BioData Mining* 10, 35. <https://doi.org/10.1186/s13040-017-0155-3>, 2017.
- [30] Stephen Merity, Nitish Shirish Keskar, and Richard Socher. "Regularizing and optimizing lstm language models". *arXiv:1708.02182*, 2017.
- [31] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, Ruslan Salakhutdinov. "Dropout: A Simple Way to Prevent Neural Networks from Overfitting", 15(56):1929-1958, 2014.
- [32] K. Taunk. "A Brief Review of Nearest Neighbor Algorithm for Learning and Classification". 2019 *Int. Conf.Intell. Comput. Control Syst.*, no. *Iciccs*, pp. 1255â1260, 2019.
- [33] G. Guo, H. Wang, D. A. Bell, and Y. Bi. "KNN Model-Based Approach in Classification KNN Model-Based Approach in Classification". *On the move to meaningful Internet Systems Intl conference*, 2003.
- [34] Hussin Ragb, Redha Ali, Elforjani Jera, Nagi Buaossa. "Convolutional neural network based on transfer learning for breast cancer screening". *arXiv:2112.11629*, pp. 3-4, 2021.
- [35] Shashank Shekhar, Adesh Bansode, Asif Salim. "A Comparative study of HyperParameter Optimization Tools". *arXiv:2201.06433*, p. 2, 2022.
- [36] Yoav Levine, Or Sharir, Amnon Shashua. "Benefits of Depth for Long-Term Memory of Recurrent Networks". <https://openreview.net/forum?id=HJ3d2Ax0->, 2018.
- [37] Ioffe, Sergey; Szegedy, Christian. "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift". *arXiv:1502.03167*, 2015.
- [38] Indu Kant Deo, Rajeev Jaiman. "Learning Wave Propagation with Attention-Based Convolutional Recurrent Autoencoder Net". *arXiv:2201.06628*, 2022.

- [39] Bora, N., Biswas, R., and Dobrynina A. A., 2017. Regional variation of coda Q in Kopili fault zone of northeast India and its implications. *Tectonophysics*. 722 (2018) 235–248,
- [40] Chapman, S., Tisato, N., Quintal, B., and Holliger K., 2016. Seismic attenuation in partially saturated Berea sandstone submitted to a range of confining pressures. *J Geophys. Res Solid Earth* 121(3):1664–1676.
- [41] Cooper, J., and Poole, G., 2017. Structurally consistent amplitude Q compensation using tau-pxpy inversion. 79th Annual International Conference and Exhibition, EAGE, Extended Abstracts,
- [42] Dinh, H. N., Van der Baan, M., and Landro, M., 2015. Time-lapse Processing Strategies for Detecting 4D Attenuation Changes and Shallow Gas Movement. Pages 1–4 of: 77th EAGE Conference and Exhibition. Madrid.
- [43] Dutta, G., and Schuster, G. T., 2014. Attenuation compensation for least-squares reverse time migration using the viscoacoustic-wave equation. *Geophysics*, 79, no. 6, S251–S262,
- [44] Dutta, G., 2016. Skeletonized wave-equation inversion for Q. 86th Annual International Meeting, SEG, Expanded Abstracts, 3618–3623.
- [45] brahim Z., and Porsani, M. J., 2015. A combined Wigner-Ville and maximum entropy method for high-resolution time-frequency analysis of seismic data. *Geophysics*, 80(6), O1-O11.
- [46] Kumar, A., and Mitra, S., 2015. Coda Q and its frequency dependence in the eastern Himalayan and Indo-Burman plate boundary systems. in *Eos Trans. Fall Meet. Suppl.*, Abstract, pp. T21C– 2829, AGU
- [47] Li, F., Verma, S., Zhou, H., Zhao, T., and Marfurt, K. J., 2016. Seismic attenuation attributes with applications on conventional and unconventional reservoirs. *Interpretation: SEG* 4 (1): SB63-SB77.

- [48] Liu X., Gao, F., Zhang, Y., Rao, Y., and Wang, Y., 2018. Seismic resolution enhancement in shale-oil reservoirs. *Geophysics* 83: B281-B287.
- [49] Lupinacci, W. M., and Oliveira, S. A. M., 2015. Q factor estimation from the amplitude spectrum of the time–frequency transform of stacked reflection seismic data. *Journal of Applied Geophysics*. Elsevier BV, 114, pp. 202–209.
- [50] Lupinacci, W. M., Franco, A. P., Oliveira, S. A. M., and Moraes, F. S., 2017. A combined time-frequency filtering strategy for Q-factor compensation of poststack seismic data. *Geophysics*, 82, V1-V6
- [51] Naimi, S., and Waheb, M.H., (2019). “Deprem Etkisindeki Yapıların Sismik Taban İzolasyonu Ve Çoklu Ayarlı Kütle Sönümleyici Sistemleri İle Karma Korunması,”, *Erzincan Üniversitesi Fen Bilimleri Enstitüsü Dergisi*, 12 (1), 499- 516.
- [52] Abdulelah, O., and Naimi, S., (2023). Seismic data analysis using feed forward BP neural network model for earthquake prediction. *International Journal of Nonlinear Analysis and Applications*, 14(1), 2079-2090. doi: 10.22075/ijnaa.2022.7161
- [53] Mahmood, L., and Naimi, S., (2022). “Investigating the potential of liquefaction issue of some Turkish dams during earthquakes.”, *Periodicals of Engineering and Natural Sciences*, Vol. 10(6), pp. 57–66, doi: <http://dx.doi.org/10.21533/pen.v10i6.3345>
- [54] Dehqan Nezhad, Y., and Naimi, S., (2022). “Numerical investigation of precast reinforced concrete beam–to– column joints by replaceable damper.”, *Journal of Sustainable Construction Materials and Technologies*, 7(2): 81-87. <https://doi.org/10.47481/jscmt.1117101>
- [55] Naimi, S., and Peker, Ö., (2022). “Deprem Etkileri Altındaki Farklı Tiplerde Çelik Yapıların StaSTEEL ve SAP2000 Kullanılarak Karşılaştırılması.”, *Journal of the Institute of Science and Technology* , 12 (3) , 1577-1591 . DOI: 10.21597/jist.1121614

- [56] Kaniarfar, M., and Naimi, S.. (2016). “Faya Yakın Depremlerin Etkisi ve Yapıların Güçlendirme Amacı ile İncelenmesi.”, İstanbul Aydın Üniversitesi Dergisi , 8 (32) , 127-136 . Retrieved from <https://dergipark.org.tr/en/pub/iaud/issue/40593/487917>
- [57] Olbak, M., and Naimi, S., (2016). “Kentsel Dönüşüm Uygulanmış 5 Katlı İki Yapı Örneğinin DeneySEL Verileri Kullanılarak Doğrusal Olmayan Analiz Yöntemleri İle Güçlendirme Sonuçlarının İrdelenmesi.”, İstanbul Aydın Üniversitesi Dergisi , 8 (31) , 145-166 . Retrieved from <https://dergipark.org.tr/en/pub/iaud/issue/40585/487826>
- [58] Naimi, S., Celikag, M., and Hedayat, A. A., (2013). “Ductility enhancement of post-Northridge connections by multilongitudinal voids in the beam web.”, The Scientific World Journal, 2013, 1–14. <https://doi.org/10.1155/2013/515936>
- [59] Moazam, S., Boroomand, B., Naimi, S., and Celikag, M., (2014). “Wave propagation in unbounded domains under a dirac delta function with FPM.”, Mathematical Problems in Engineering, vol. 2014, Article ID 470346, 8 pages, 2014.