# Study on Advance AI Methods Used in Seismology – Machine Learning System and Deep Learning System

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**Abstract: In this current world predicting earthquake is critical for seismic risk assessment, prevention and safe design of major structures. Due to the complex nature of seismic events, it is challengeable to efficiently identify the earthquake response and extract indicative features from the continuously detected seismic data. These challenges severely impact the performance of traditional seismic prediction models and obstacle the development of seismology in general. Taking their advantages in data analysis, artificial intelligence (AI) techniques have been utilized as powerful statistical tools to tackle these issues. This typically involves processing massive detected data with severe noise and also the vibration on earth's surface to enhance the seismic performance of structures. From extracting meaningful sensing data to unveiling seismic events that are below the detection level, AI in ML, Deep Learning system, etc. assists in identifying unknown features to more accurately predicting the earthquake activities. In this focus paper, the history of seismology is analysed and I provide an overview of the recent methods like AI studies in seismology and evaluate the performance of the major AI techniques including machine learning and deep learning in seismic data analysis.**

**Keywords: Seismology, Artificial Intelligence, Machine Learning System, Deep Learning System.**

## INTRODUCTION

Seismology, the study of earthquakes and seismic activity, is a critical field of research that plays a pivotal role in saving lives and reducing the impact of natural disasters. Over the years, scientists have strived to improve earthquake prediction techniques, and the integration of Artificial Intelligence (AI) has emerged as a game- changer.

AI for Seismology refers to the application of Artificial Intelligence (AI) techniques and technologies to the field of seismology, which is the study of earthquakes and seismic activity. AI for Seismology leverages machine learning, deep learning, data analysis, and other AI methodologies to enhance our understanding of seismic events, improve earthquake prediction, and mitigate their potential impact. AI for Seismology takes significant strides toward a safer, more resilient future, where the devastating impact of earthquakes is minimized, and lives are preserved through timely warnings and informed action.

In sectors crucial to human well-being, such as healthcare, finance, and criminal justice, the intricate nature of AI algorithms has generated a pervasive sense of mistrust among users. The decisions made by AI systems in these domains carry significant consequences, amplifying the need for transparency.

AI Clarity serves as a remedy to these concerns by dismantling the opacity that often shrouds the decision-making process. By offering a transparent lens into the intricate workings of AI algorithms, users gain a comprehensive understanding of the rationale behind specific choices.

This newfound clarity not only demystifies the technology but also fosters confidence, laying the foundation for users to trust and embrace AI applications. In healthcare, it ensures patients comprehend diagnostic or treatment decisions, in finance, it elucidates investment strategies, and in criminal justice.

It clarifies sentencing or profiling choices, thereby transforming complex algorithms into comprehensible tools that augment human decision-making.

## LITERATURE REVIEW

MAJDI FLAH, ITZEL NUNEZ, WASSIM BEN CHAABENE & MONCEF Applications of Machine Learning (ML) algorithms in Structural Health Monitoring (SHM) have become of great interest in recent years owing to their superior ability to detect damage and deficiencies in civil engineering structures. With the advent of the Internet of Things, big data and the colossal and complex backlog of aging civil infrastructure assets, such applications will increase very rapidly. ML can efficiently perform several analyses of clustering, regression and classification of damage in diverse structures, including bridges, buildings, dams, tunnels, wind turbines, etc. In this systematic review, the diverse ML algorithms used in this domain have been classified into two major subfields: vibration-based SHM and image-based SHM. The efficacy of deploying ML algorithms in SHM has been discussed and detailed critical analysis of ML applications in SHM has been provided. Accordingly, practical recommendations have been made and current knowledge gaps and future research needs have been outlined.

MOSTAFA MOUSAVI AND GREGORY C. Machine learning (ML) is a collection of methods used to develop understanding and predictive capability by learning relationships embedded in data. ML methods are becoming the dominant approaches for many tasks in seismology. ML and data mining techniques can significantly improve our capability for seismic data processing. In this review we provide a comprehensive overview of ML applications in earthquake seismology, discuss progress and challenges, and offer suggestions for future work. Conceptual, algorithmic, and computational advances have enabled rapid progress in the development of machine learning approaches to earthquake seismology. The impact of that progress is most clearly evident in earthquake monitoring and is leading to a new generation of much more comprehensive earthquake catalogues. Application of unsupervised approaches for exploratory analysis of these high-dimensional catalogues may reveal new understanding of seismicity. Machine learning methods are proving to be effective across a broad range of other seismological tasks, but systematic benchmarking through open-source frameworks and benchmark data sets are important to ensure continuing progress.

HARENDRA KUMAR DADHICH Undoubtedly one of the most destructive natural catastrophes is an earthquake. Aroundthe world, they frequently result in significant losses in terms of people, structures, economies, and societies. It is still impossible to accurately anticipate the location and timing of catastrophic occurrences, despite the fact that analytical and measuring techniques have advanced steadily over the previous few decades. The chapter provides an overview of applications of machine learning (ML) and Artificial Intelligence (AI) in seismology so that above mentioned problems in this field can be resolved. The MLModel helps to identify unseen signals and patterns to extract features that might improve our physical understanding of earthquakes. The modelling capabilities of the

ML-based methods have resulted in their extensive applications in science and engineering. Herein, the role of ML as an effective approach for solving some problems in geosciences will be highlighted. ML algorithms in seismology address various problems like earthquake detection, phase picking, EEW, ground-motion prediction, seismic tomography, and earthquake geodesy. AI-based algorithms are used for earthquake analysis and prediction, deciphering complex stress development patterns, and developing fully automatic seismic event detection using SVM. ML techniques, such as ANN and GA, estimate earthquake source parameters, while classification algorithms like Artificial Neural Network (ANN) and Support Vector Machine (SVM)have been used to study to identify shallow focus (depth < 70 km) tsunami genic earthquakes at a regional distance. Also, a lot of ML and AI models can be used in seismology to resolve various key problems of seismology from detection to prediction tasks.

G. WADGE Seismology has dominated the study of earthquakes. In recent years, however, the ability to measure the surface ground motion field associated with fault rupture by InSAR has brought a new dimension to the study of shallow earthquakes. By invertingthe co-seismic motion field of InSAR with numerical models of the fault plane motionin a 3D space, knowledge of the earthquake fault mechanism can be improved. Specifically, InSAR can greatly improve knowledge of exactly where the fault plane rupture was and estimates of its dip, whilst seismology is better at resolving the moment released. Immediately following a large earthquake, the ground surface can move moreslowly over the following months. This can be measured by InSAR to help constrain the physical processes potentially involved: after slip on the fault plane, poroelastic pressure changes or viscoelastic relaxation in the lower crust/mantle. The other component of the earthquake cycle, the interseismic strain, can also be detected by InSAR, for example, on the San Andreas and North Anatolian Faults. This requires pushing the technique to its limits of sensitivity in measuring very slow strain buildup over several years across widths of about 100 km.

Not all Earth strain involves seismicity and sudden displacements. InSAR is starting toreveal a wealth of surface strain events in the continental plate boundary zones that whilst linked to fault systems, do not themselves display significant seismicity. Aseismic displacement events triggered by nearby seismic events has been measured and shallow folding deformation may be revealed in low competence rocks. This raisesthe exciting prospect of being able to relate the current day surface deformation to neotectonics processes and geomorphological features of the past few hundred to thousands of years.

## ARTIFICIAL INTELLIGENCE IN SEISMOLOGY

AI methods have shown its great potential in automation tasks, such as seismic detection and phase arrival picking, and are thus being widely adopted.

## MACHINE LEARNING SYSTEM

DEFINITION:
As a branch of AI, ML involves systems capable of automatically learning from data, identifying patterns and making decisions. The salient beauty of ML is that it enables computers to learn without being explicitly programmed. Most of the ML-based methods are essentially inspired by biological learning. In seismology, ML uses series of techniques to find the inherent rules and dependences between data and then classify or regress them. Also, ML is commonly used to categorize and analyse unseen patterns or features in detected data since it, unlike seismologists that analyse data using intuition and logics, discovers unconsidered features beyond human capability displays the main components of ML, which can be grouped into supervised and unsupervised. The former typically consists of regression and classification methods, and the latter includes reduction and clustering techniques. There is also another category called semi-supervised learning algorithms that can organize the data as well as make predictions.

However, characterizing into supervised learning and unsupervised learning, ML in seismology is developed using probability theory in five steps, including:
(1) collecting and partitioning seismic data for training and testing,
(2) preprocessing to clean, format and remove/recover seismic data,
(3) training model uses numerical optimization algorithms to tune the seismic variables,
(4) evaluating model with respect to the prediction accuracy using the test data, and
(5) generating new data for prediction using an ML algorithm.
Machine learning is a subfield of artificial intelligence (AI) that uses algorithms trained on data sets to create self-learning models that are capable of predicting outcomes and classifying information without human intervention. Machine learning is used today for a wide range of commercial purposes, including suggesting products to consumers based on their past purchases, predicting stock market fluctuations, and translating text from one language to another.
In common usage, the terms “machine learning” and “artificial intelligence” are often used interchangeably with one another due to the prevalence of machine learning for AI purposes in the world today. But, the two terms are meaningfully distinct. While AI refers to the general attempt to create machines capable of human-like cognitive abilities, machine learning specifically refers to the use of algorithms and data sets to do so.

## HOW DOES ML WORKS?

Machine learning is both simple and complex.
At its core, the method simply uses algorithms, essentially lists of rules, adjusted and refined using past data sets to make predictions and categorizations when confronted with new data. For example, a machine learning algorithm may be “trained” on a data set consisting of thousands of images of flowers that are labelled with each of their different flower types so that it can then correctly identify a flower in a new photograph based on the differentiating characteristics it learned from other pictures.
To ensure such algorithms work effectively, however, they must typically be refined many times until they accumulate a comprehensive list of instructions that allow them to function correctly. Algorithms that have been trained sufficiently eventually become “machine learning models,” which are essentially algorithms that have been

trained to perform specific tasks like sorting images, predicting housing prices, or making chess moves. In some cases, algorithms are layered on top of each other to create complex networks that allow them to do increasingly complex, nuanced tasks like generating text and powering chatbots via a method known as "deep learning."

## TYPES OF ML

To help you get a better idea of how these types differ from one another, here's an overview of the four different types of machine learning primarily in use today.

### SUPERVISED MACHINE LEARNING:

In supervised machine learning, algorithms are trained on labelled data sets that include tags describing each piece of data. In other words, the algorithms are fed data that includes an "answer key" describing how the data should be interpreted. For example, an algorithm may be fed images of flowers that include tags for each flower type so that it will be able to identify the flower better again when fed a new photograph.

Supervised machine learning is often used to create machine learning models used for prediction and classification purposes.

### UNSUPERVISED MACHINE LEARNING:

Unsupervised machine learning uses unlabelled data sets to train algorithms. In this process, the algorithm is fed data that doesn't include tags, which requires it to uncover patterns on its own without any outside guidance. For instance, an algorithm may be fed a large amount of unlabelled user data culled from a social media site in order to identify behavioural trends on the platform.

Unsupervised machine learning is often used by researchers and data scientists to identify patterns within large, unlabelled data sets quickly and efficiently.

### SEMI-SUPERVISED MACHINE LEARNING:

Semi-supervised machine learning uses both unlabelled and labelled data sets to train algorithms. Generally, during semi-supervised machine learning, algorithms are first fed a small amount of labelled data to help direct their development and then fed much larger quantities of unlabelled data to complete the model. For example, an algorithm may be fed a smaller quantity of labelled speech data and then trained on a much larger set of unlabelled speech data in order to create a machine learning model capable of speech recognition.

Semi-supervised machine learning is often employed to train algorithms for classification and prediction purposes in the event that large volumes of labelled data is unavailable.

### REINFORCEMENT LEARNING:

Reinforcement learning uses trial and error to train algorithms and create models. During the training process, algorithms operate in specific environments and then are provided with feedback following each outcome. Much like how a child learns, the algorithm slowly begins to acquire an understanding of its environment and begins to optimize actions to achieve particular outcomes. For instance, an algorithm may be optimized by playing successive games of chess, which allows it to learn from its past successes and failures playing each game.

Reinforcement learning is often used to create algorithms that must effectively make sequences of decisions or actions to achieve their aims, such as playing a game or summarizing an entire text.

## MACHINE LEARNING IN SEISMOLOGY

In seismology, we are currently undergoing rapid changes in the "3V's" often discussed by the big data community volume, variety, and velocity. For example, the archive of seismic waveform publicly available from Incorporated Research Institutions for Seismology (IRIS) is increasing in size exponentially This dramatically increased volume of data (and the secondary products derived from the raw data) makes manual processing difficult. Many ML algorithms are designed with large datasets in mind: typically, more data gives better results. Dataset variety has increased too.

Besides seismic data, other types of relevant geophysical datasets (e.g., Global Positioning System [GPS] time series and Interferometric Synthetic Aperture Radar [InSAR] images) are readily available from UNAVCO and other resource centres. The use of joint geophysical datasets might provide better resolution in certain problems, and carefully designed ML techniques can help analyse these datasets without introducing unnecessary complexity. Finally, velocity refers to the speed of data processing and distribution. This is important for real-time earthquake detection and earthquake early warning (EEW), which rely on rapid analyses of high-velocity data streams.

## APPLICATION OF ML IN SEISMOLOGY

In the following, we present a detailed survey of five specific applications of ML to earthquake seismology, while acknowledging that there are many other worthy applications that merit discussion.

Earthquake Detection and Phase Picking:

Here, we outline some of the most promising examples of ML applied to the earthquake detection problem.

Over the last decade, there has been an explosion of interest in using the similarity of waveforms between nearby sources to detect previously unidentified earthquakes. This originally began with matched filtering (template) which uses waveforms of known events as templates to scan through continuous waveforms for new event detection Recently, there has been an interest in applying ML and data mining algorithms for similarity based event detection. In a convolutional neural network (CNN) was trained too simultaneously detect and locate earthquakes based on single-station waveform classification.

Ground-Motion Prediction Using Supervised Learning:

Ground-motion prediction is a crucial aspect of earthquake hazard assessment, and although simple in concept it is challenging to perform in practice. classical approach to ground-motion prediction uses linear regression to model the first-order aspects of these effects. In a linear ground-motion prediction equation (GMPE), the predicted ground-motion Y (in logarithmic units) is a normal distributed random variable that is a linear function of the input variables, which include the earthquake magnitude Mand source–site distance R.

Tomography and Illuminating Geophysical Structure with ML:

ML in seismic tomography has shown great promise for improving our understanding of subsurface geophysical structure. Seismic tomography methods obtain subsurface models or images from sensor array observations of seismic waves, which are generated by anthropogenic sources, earthquakes, or ambient noise processing. Seismic tomography is critical for deducing geophysical structure and characterizing seismic hazard. However, the demands placed on these methods are great, as tomography models are often estimated from limited and noise corrupted observations with nonlinear forward models. Such ill-posed inverse problems require regularization or assimilation of hypothesized geophysical structure to obtain physically plausible solutions. ML represents a modern paradigm for signal processing, with more sophisticated model priors and latent representations than classic inverse methods like Tikhonov or total variation regularization. ML priors include sparsity constraints and latent dictionaries. The nonlinear general function approximation capability of NNs permits replacement of seismic data simulation and inversion procedures with NNs.

Earthquake Geodesy and Noninertial Deformation:

Although classical seismology has focused on high-frequency inertial deformation of the earth, the full spectrum of earthquake cycle behaviours also includes prolonged noninertial deformation. These motions include post seismic deformation (durations of years) and interseismic deformation (durations of decades), as well as slow or silent earthquakes (durations of weeks). Because these motions are noninertial, they are typically measured using geodetic techniques such as GPS and InSAR to estimate time-dependent displacements at Earth's surface.

## DEEP LEARNING SYSTEM

DEFINITION:

Deep learning is just a type of machine learning, inspired by the structure of the human brain. Deep learning algorithms attempt to draw similar conclusions as humans would by continually analysing data with a given logical structure. To achieve this, deep learning uses multi-layered structures of algorithms called neural networks.

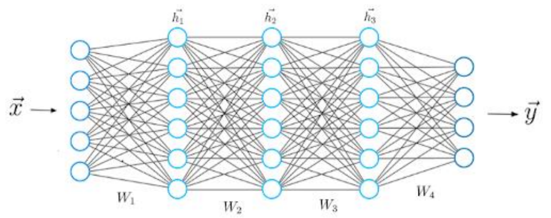
Deep-learning architectures such as deep neural networks, deep belief networks, recurrent neural networks, convolutional neural networks and transformers have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

## DEEP LEARNING IN SEISMOLOGY

Deep-learning system was usually an updated version of ML that approaches have entered almost every subfield of seismology, for which they have shown the ability to outperform classical approaches, often dramatically, for seismological tasks such as denoising, earthquake detection, phase picking, seismic image processing and interpretation, and inverse and forward modelling. Some properties of DNNs—such as their universal approximation capability, automatic feature extraction, and dimensionality reduction—have been shown to be particularly advantageous in processing high-dimensional seismic recordings, which often are noisy and incomplete. Seismological deep learning can process massive amounts of multifidelity seismic observations with unprecedented spatiotemporal coverage and lead to new insights and discoveries. Deep learning may be particularly effective for seismological problems for which the underlying physical processes are incompletely understood but for which the data are abundant and of high quality.

## HOW DOES DL WORKS?

Deep learning algorithms attempt to draw similar conclusions as humans would by constantly analysing data with a given logical structure. To achieve this, deep learning uses a multi-layered structure of algorithms called neural networks.



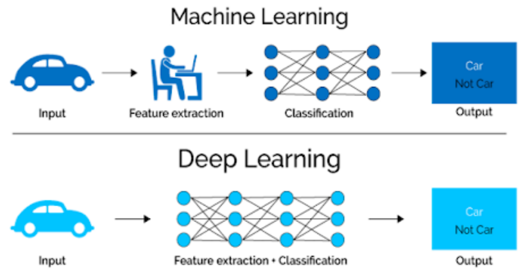
The design of the neural network is based on the structure of the human brain. Just as we use our brains to identify patterns and classify different types of information, we can teach neural networks to perform the same tasks on data.

The individual layers of neural networks can also be thought of as a sort of filter that works from gross to subtle, which increases the likelihood of detecting and outputting a correct result. The human brain works similarly. Whenever we receive new information, the brain tries to compare it with known objects. The same concept is also used by deep neural networks.

Neural networks enable us to perform many tasks, such as clustering, classification or regression.

With neural networks, we can group or sort unlabelled data according to similarities among samples in the data. Or, in the case of classification, we can train the network on a labelled data set in order to classify the samples in the data set into different categories.

A more and more abstract and compressed representation of the raw data is produced over several layers of an artificial neural net. We then use this compressed representation of the input data to produce the result. The result can be, for example, the classification of the input data into different classes.




## APPLICATION IN DL IN SEISMOLOGY

### DATA PROCESSING AUTOMATION:

Seismic data are recorded (often irregularly or heterogeneously) as time series of ground motion by sensors that are deployed either sparsely (in a network) or densely (in an array) and that register acceleration, velocity, or displacement as output. Typically, these quantities are recorded in three perpendicular directions, so that we work with three-component vector ground motion. Important extensions to conventional seismic recording include rotational motion and tensorial strain.

In both passive and active-source seismology, usually a sequence of processing and analysing steps exists that needs to be performed. Despite decades of earlier efforts to develop algorithms to automate such data-processing and analysing tasks, many cases remain for which manual processing by skilled analysts is the most reliable option (such as phase picking or seismic interpretation). The accelerating expansion of seismic data volumes poses new challenges and brings with it the need to develop a new generation of robust processing tools by using data-driven approaches such as deep learning.

### SEISMIC IMAGE PROCESSING:

Reflected and refracted seismic waves recorded by an array of seismic sensors are used to image subsurface geology and structure. Deep learning has proven an effective tool in the processing steps used to improve the quality of seismic images and to transform them into an interpretable image of the subsurface by removing data acquisition artifacts and wave propagation effects to highlight events that more accurately portray the true geology and structure.

FORWARD PROBLEMS:

The impressive predictive power of DNNs makes them popular tools for forward modelling problems in seismology. We outline three categories—seismic wave simulation, ground motion characterization, and earthquake forecasting—as instructive examples of forward-modelling tasks in seismology for which DNNs have been used.

SEISMIC WAVE SIMULATION:

To date, applications of deep learning for seismic wave simulation have been limited. Nevertheless, deep learning appears to provide an effective alternative for standard numerical methods and can address issues such as discretization errors and high computational complexity. The use of physics-informed neural networks (PINNs) and GANs are two current trends. In PINNs, a DNN is trained to learn the solution of the wave equation for a medium by implicitly defining the boundary conditions and the wave equation in the loss function used in training of the neural network. These deep- learning models can learn to solve the wave equation in 2D or 3D media, even for complex faulted structure or topography, and generalize well beyond the time stamps of their training dataset. They are much more efficient in computing arbitrary space- time points in the wavefield than are traditional numerical simulations and reduce computation time by at least an order of magnitude.

GAN simulators use the universal function approximation ability of DNNs to learn the probability distributions of attributes of training data by optimizing a generator network. This generator model can be used as reparameterization of such distributionsto generate new samples drawn from the learned distributions during inference. GANs have been used to generate synthetic earthquake and no earthquake seismograms as a data augmentation tool for training deep-learning earthquake detectors; to generate broadband seismic signals by blending the low-frequency output of numerical physics-based simulations with sparsely sampled broadband observations; and to generate 3C strong motion time series for different magnitude, distance, and site conditions. They provide an efficient framework for generating large-scale synthetic training data to improve the performance of deep-learning classifiers and detectors.

UNDERSTANDING IN MACHINE LEARNING

When neural networks were first applied to seismology in the late 1980s, the focus was on classification tasks in automatic data processing with supervised methods. Although data processing tasks still comprise a major part of the latest surge of ML applications in seismology, inverse problems are gaining rapid an apparent downturn in the total number of publications in the two most recent years. The tally for 2022 is for only part of the year. Also, the figure includes publications on seismological ML model development, rather than ML applications. The decrease in the number of ML models published in seismology in 2021 appears to be real and can also be observed in the number of conference presentations. Some caveats are that conference presentations might be influenced by the pandemic and that while we have tried to be comprehensive in our coverage of ML publications in seismology, our database may be incomplete. Time will tell whether this trend persists.

Supervised learning has dominated ML approaches in seismology to date; however, ML offers data-driven discovery, imaging, and interpretation of patterns in seismic data in a high-dimensional space as well. Seismologists are increasingly finding important applications for alternative approaches such as unsupervised learning and GANs, but exploratory analysis of high-dimensional seismic data has been only thinly investigated. We expect applications of unsupervised approaches in seismology will be a growth area

The limitations on training data and generalization are the main challenges in solving inverse and forward problems using supervised DNNs. A common approach to mitigate this is to train a network on synthetic data and fine-tune it, or to perform transfer learning with field data.

Moving toward semi supervised approaches, where both labelled and unlabelled data are used for the training, is another likely growth area. PINNs, where the governing physical theories are imposed as constraints into data-driven ML models, are a promising direction for improved generalization. Real seismic data are often poorly sampled, noisy, incomplete, and unbalanced, all of which pose challenges for ML techniques. Combining data-driven ML methods with physical models could be transformative.

Neural networks are the main ML method used in seismological applications. Among the variety of neural network types, fully connected and CNNs are used the most. U-net and autoencoders form the most commonly used neural network architectures. Both of these have butterfly forms and are composed of an encoder that transfers the input data into a high-level but lower-dimensional representation and a decoder that generates the output (often with the same dimension as the input) from this low-dimensional representation. Encoder-decoder networks are clearly a highly suitable architecture for many seismological applications.

Event discrimination, detection, and phase picking are fairly mature applications. The emphasis now is shifting to earthquake characterization and exploratory data analyses. Even in well-studied applications, however, important issues are unresolved. For example, it is difficult to determine the relative performance, strengths, and weaknesses of each method due to a lack of standard benchmarking.

Labelled data sets are required for building supervised models or testing unsupervised models. Even for seismological tasks (e.g., earthquake detection and phase picking) where ample labelled data exist, the reliability of those labels is variable and uncertain. Two analysts will differ in their measurement of the arrival time of a seismic phase in an earthquake signal, which introduces bias. A challenging task in building training data sets is quality control of the labels. There are only a few seismic data sets that can serve as benchmarks. however, these data sets are suitable for only some of the tasks we have outlined. Standard benchmark data sets can serve as ground truth and accelerate progress in application of ML methods. Efficient simulation methods for fast generation of synthetic data at a large scale could also play an important role.

## UNDERSTANDING IN DEEP LEARNING

Deep learning and more complex ML techniques have successfully improved the performance of some tasks; however, this does not guarantee their suitability for other problems and data types. That simpler ML and traditional methods can match the performance of deep-learning models for aftershock forecasting and infrasound classification, respectively. Simpler and more transparent methods that can be tied to the physical properties of the waveforms, yet provide a similar performance, are preferable to less interpretable.

Even though DL was the advanced technique than ML, in current world ML was the friendliest techniques which the world is using. But in our study, I insist to use the DL, because DL has an automatic intelligence system compared to ML. The Application software was literally same compared to human intelligence. How the human can feel the negative vibrations which can cause by natural hazardous or any other accidental activities? In that case the DL can be compared to human intelligence. In conclusion, in ML method we need to manually insist the intelligence to predict the vibration. Whereas, in DL the with the help of past activities it can analysis and can differentiate the Vibrations itself. So, In Future, I believe that DL can be play a big and necessary role in seismology.

## FUTURE SCOPE

1. To Develop an Application Based on this study and to do practical research on it.
2. Here I have given some examples as a solution:

- Alerting System: Firstly, it will consist of two components like Base, transmitter and a receiver. Here the base will place in a surface of the earth and by vibration activities it will analysis the different kind of vibrations, As the software were developed by AI it will Filter the various kind of motion. And secondly, the transmitter helps to transits the data from base to receiver. Finally, the receiver will be the alerting system (i.e.) our application which portably has by everyone within 7 to 8 seconds. The analysis of vibration and the validation of data was done and will finalize by the base system itself it will play a vital role here.
- Earthquake prediction application: Firstly, as the theories we discussed about ML and DL in Seismology so far and developing as portable application in order to give an easy analysis to Engineers, Architectures and also for every human being. It will use to help in designing an earthquake design building in consideration of the past natural hazardous activities done in the particular area. And also, the application will predict the future actives so that we can design a building accordingly.

## CONCLUSION

In conclusion, Machine learning has made significant progress in P-wave FMP identification and has initially demonstrated its application potential in the automatic inversion of focal mechanisms. Of course, in practical applications, in addition to FMPs, many other factors would also affect the inversion results, for example, the azimuth distribution of stations, the signal-to-noise ratio of data, or the choice of velocity models that we have not discussed in this article. Since no matter how well-trained the machine learning model is, it will make a small number of mistakes and has a certain degree of randomness, it is very important to establish an effective tolerance mechanism for mistakes. One of the better strategies is to use ML FMPs together with manual FMPs, especially in those regions with relatively dense station coverage. ML is a great complement to human recognition results. In areas with low signal-to-noise ratios or sparse stations, automatic identification methods should be used more cautiously. This situation will improve with more data sets with high-quality and multi-category labels like Diting has continuously been proposed, and the generalization ability of machine learning models will improve over time.

The successful outcomes of This thesis underscore the potential of utilizing A1 tools like Machine Learning and Deep learning system as sustainable alternatives in the test result for upcoming seismology techniques, offering not only structurally advantages but also contributing to environmental conservation by technological software's.

Where the study says that Machine Learning System and Deep learning in Seismology were used for Predicting the future actives of earthquake and also can be used by every Individual human being in all over the world. Here I wish to insist My ideology here by this study. As engineer everybody Should know about or should have an awareness about the earthquake. Some may have the awareness but don't know how to get a knowledge of it. Here when we develop an earthquake prediction application the precautions steps like stepping to safe place etc. In this application we also have the options like the structural health monitoring by its early stage before constructing a building. Many may Raise a Questions Like how you can analysis an earthquake for structural health monitoring? But yes, we can. By Choosing the respected location and by the tectonic plates it can analysis the past earthquake activities which we before feed to the software using AI technologies which we discussed so far.

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