EARTHQUAKE PREDICTION USING DEEP LEARNING WITH SPATIOTEMPORAL PRIORS

A Project Report submitted in the partial fulfillment
of the Requirements for the award of the degree

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted by

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CERTIFICATE

This is to certify that the project entitled "EARTHQUAKE PREDICTION USING DEEP LEARNING WITH SPATIOTEMPORAL PRIORS" is a bona fide work done by Ammisetty Chamundeswari (22471A05L1), Chaganti Rethika Reddy (23475A0509), Tadi Anusha (22471A0504) in partial fulfillment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in the Department of COMPUTER SCIENCE AND ENGINEERING during 2025-2026.

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I declare that this project work titled "**EARTHQUAKE PREDICTION USING DEEP LEARNING WITH SPATIOTEMPORAL PRIORS**" is composed by me, that the work contained here is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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- **PEO2:** Utilize various software tools and technologies to address challenges related to academia, industry, and society.
- **PEO3:** Work with ethical and moral values in multidisciplinary teams, while communicating effectively and embracing continuous learning.
- **PEO4:** Pursue higher studies and build successful careers in the software industry.

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PROGRAM OUTCOMES

PO1: Engineering Knowledge

Apply mathematics, science, and engineering fundamentals to analyse and solve complex problems such as earthquake prediction.

PO2: Problem Analysis

Analyse challenges in earthquake early warning systems using research literature, with consideration for sustainability and risk mitigation.

PO3: Design / Development of Solutions

Design and develop deep learning–based solutions to estimate earthquake parameters, emphasizing safety and societal impact.

PO4: Conduct Investigations of Complex Problems

Investigate complex engineering problems through systematic research methods, data analysis, and seismic modelling.

PO5: Engineering Tool Usage

Utilize modern engineering and IT tools for modelling, prediction, evaluation, and deployment of earthquake warning systems.

PO6: The Engineer and the World

Assess the societal, environmental, and safety impacts of engineering solutions applied to disaster management.

PO7: Ethics

Adhere to professional ethics and ensure responsible and secure use of seismic data in engineering practice.

PO8: Individual and Collaborative Team Work

Work effectively as an individual and as a member of multidisciplinary teams.

PO9: Communication

Communicate technical concepts effectively through reports, presentations, and visualizations.

PO10: Project Management and Finance

Apply project management principles and economic considerations for efficient system planning and development.

PO11: Life-Long Learning

Engage in continuous learning to adapt to emerging technologies and evolving engineering challenges.

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Project Course Outcomes (COs)

- **CO421.1:** Analyse seismic waveform data and identify key problems in Earthquake Early Warning (EEW).
- **CO421.2:** Identify and classify requirements for preprocessing, feature extraction, and model building.
- **CO421.3:** Review related literature on deep learning, spatiotemporal priors, and hybrid models for seismic prediction.
- **CO421.4:** Design and modularize a hybrid Transformer–BiLSTM model with feature-level fusion.
- **CO421.5:** Construct, integrate, train, test, and implement the proposed earthquake prediction model.
- **CO421.6:** Prepare project documentation and effectively present results using explainability techniques (attention maps, SHAP).

Course Outcomes – Program Outcomes Mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1	✓	✓			✓	✓						✓		
C421.2	✓	✓	✓		✓							✓	✓	
C421.3			✓	✓	✓	✓						✓		✓
C421.4		✓	✓		✓	✓			✓			✓	✓	
C421.5	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
C421.6					✓					✓	✓		✓	

(✓ indicates mapping; detailed correlation levels can be filled as in your earlier table if required.)

Course Outcomes – Program Outcome correlation

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1	2	3										3		2
C421.2		2	2		3							3	2	
C421.3			2	2	2	3	3					3		2
C421.4		2	2		2	1	1		2			3	3	2
C421.5	3		3	3	3	3	2	2	3	2	2	3	2	3
C421.6					3				2	3	2		2	3

Note: The values in the above table represent the level of correlation between COs and POs:

1. Low level **2.** Medium level **3.** High level

Project mapping with various courses of the Curriculum with attained POs:

Name of the Course from which principles are applied	Description of the Activity	Attained PO
C2204.2, C22L3.2	Requirement gathering and problem definition; planning a hybrid Transformer–BiLSTM model for earthquake parameter prediction	PO1, PO3
CC421.1,C2204.3, C22L3.2	Critical analysis of requirements; identification of preprocessing, feature engineering, and model design	PO2, PO3
CC421.2, C2204.2, C22L3.3	Logical model design using a multi-branch architecture with team collaboration	PO3, PO5, PO9
CC421.3, C2204.3, C22L3.2	Model training, testing, and validation using seismic datasets (K-NET / KiK-net)	PO1, PO5
CC421.4, C2204.4, C22L3.2	Preparation of technical documentation and result analysis	PO10
CC421.5, C2204.2, C22L3.3	Periodic presentation of work progress and research outcomes	PO10, PO11
C2202.2, C2203.3, C1206.3, C3204.3, C4110.2	Implementation for real-time earthquake early warning and societal applications	PO4, PO7
C32SC4.3	Development of a user interface for the visualization of predictions and system outputs	PO5, PO6

ABSTRACT

Earthquake early warning (EEW) systems require fast and reliable estimation of earthquake parameters to mitigate the impact of seismic events on human life and infrastructure. Traditional staged models with shallow regressors often face high latency and limited generalization, reducing their effectiveness in real-time applications. To address these challenges, this work proposes a unified **deep learning framework** that jointly predicts **magnitude, epicentral distance, azimuth, and focal depth** using only the first three seconds of seismic waveform data along with geospatial metadata. The proposed model integrates **Convolutional Neural Networks (CNNs)** for local feature extraction, **Bidirectional LSTMs (BiLSTM)** for sequential learning, and **Transformer encoders** for capturing long-range dependencies. Additionally, handcrafted statistical features, including peak displacement (Pd), amplitude statistics, skewness, and kurtosis, are combined with deep features to enhance robustness. Uncertainty estimation is incorporated through **Monte Carlo dropout**, while **SHAP values and Transformer attention maps** provide interpretability by highlighting critical waveform regions and metadata contributions. The model is trained and validated on high-resolution seismic datasets from **K-NET and KiK-net networks**, with results showing significant improvements over baseline models. Experimental evaluation demonstrates low prediction errors across all tasks, with magnitudes (MAE = 0.18), epicentral distances (MAE = 5.21 km), azimuths (MAE = 13.6°), and focal depths (MAE = 2.7 km). By combining accuracy, real-time readiness, and explainability, the proposed system provides a reliable solution for earthquake early warning and can be deployed in safety-critical seismic monitoring environments.

Index Terms—Earthquake early warning, Rapid parameter estimation, Deep learning, Transformer, LSTM, Spatiotemporal priors, Uncertainty quantification, Explainable AI

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CHAPTER 1

1. INTRODUCTION

1.1 Background

Earthquakes represent some of the most devastating natural hazards, capable of causing widespread destruction to human lives, infrastructure, and economies. Their sudden onset and unpredictable nature, combined with their large-scale impact, make them incredibly challenging to manage and mitigate. Historically, seismic events have resulted in millions of casualties and inflicted economic damages amounting to billions of dollars across the globe. Although preventing earthquakes remains unattainable with current scientific understanding, rapid detection and timely response can significantly minimize damage. Even a brief early warning, ranging from a few seconds to several tens of seconds, can save lives by enabling actions such as halting trains, shutting down power grids, ceasing industrial activities, and initiating evacuation procedures.

To address this critical need, Earthquake Early Warning (EEW) systems have been developed worldwide. These systems focus on rapidly detecting the initial P-waves—the earliest seismic signals generated by an earthquake—and utilize these to estimate key characteristics including the earthquake's magnitude, epicentral distance, azimuth, and focal depth, all before the arrival of more destructive S-waves and surface waves. Traditionally, EEW methods rely heavily on dense networks of seismic sensors and empirical correlations based on features extracted from P-wave signals, like peak ground displacement (Pd), characteristic period (τc), and signal duration.

While these conventional approaches have demonstrated success in certain geographic regions, they suffer from notable limitations. They often require in-depth seismological expertise to design and tune feature extraction methods, posing challenges for scalability. Their performance is typically sensitive to noisy environmental conditions, which hinders robustness in practical scenarios. Furthermore, they struggle to generalize effectively across varying tectonic and geological settings, as seismic wave characteristics differ significantly by location. Additionally, traditional systems usually employ multi-stage processing pipelines that separate feature extraction, regression, and prediction modules, inherently introducing latency that conflicts with the low-latency demands of real-time EEW applications.

The emergence of Deep Learning (DL) has brought transformative capabilities to numerous scientific fields, including seismology. DL models excel at learning relevant features directly from raw data, reducing reliance on handcrafted inputs. Advanced architectures like Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM) networks, and Transformer models with attention mechanisms offer powerful tools for analyzing complex seismic waveforms. These models are capable of automatically identifying hierarchical spatial and temporal patterns.

Moreover, integrating deep learning with statistical and contextual metadata enables the development of EEW systems capable of delivering accurate, fast, and geographically generalizable earthquake predictions.

Building upon such technological advances, this thesis introduces a unified hybrid deep learning framework that combines CNN, BiLSTM, and Transformer components. The model jointly predicts multiple earthquake parameters—magnitude, epicentral distance, azimuth, and focal depth—using only the first three seconds of seismic waveform data. The framework also incorporates uncertainty estimation alongside interpretability mechanisms to enhance trustworthiness and usability, meeting the rigorous demands of operational EEW deployment.

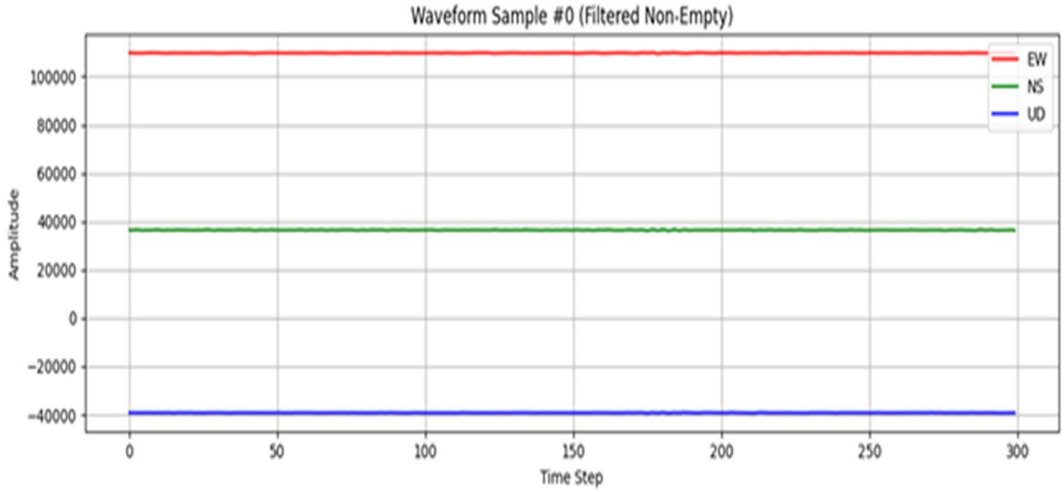

FIG 1.1 Sample Waveform Segment (Z, N, E Components)

The figure illustrates a three-component seismic waveform segment recorded from a seismic station. Each trace corresponds to one direction of ground motion—Vertical (Z), North–South (N), and East–West(E). These first three seconds after the P-wave onset form the input to the deep learning model for predicting earthquake parameters.

1.2 Motivation

This research is motivated by the critical societal demand for precise and dependable Earthquake Early Warning (EEW) systems. Though earthquakes cannot be prevented, their effects can be significantly mitigated with timely alerts. A few seconds of advance notice can greatly reduce loss of life and property by enabling actions such as stopping trains, cutting power, halting industry, and warning vulnerable communities, thereby enhancing disaster preparedness.

Current EEW solutions, however, have persistent limitations. Their dependence on handcrafted features limits their flexibility, confining their effectiveness to specific geological regions. Moreover, many focus solely on magnitude prediction, offering an incomplete characterization of earthquake events. To support effective emergency response, EEW systems should provide simultaneous, unified estimates of magnitude, epicentral distance, azimuth, and focal depth.

Real-time responsiveness is also essential. Traditional multi-stage pipelines introduce latency that can render warnings less effective, as even a delay of a few seconds can impact the success of mitigation efforts. This necessitates designing end-to-end deep learning models that deliver rapid, multi-parameter predictions.

Equally important is the need for trust and explainability in EEW systems, which operate in safety-critical contexts. Stakeholders require not only accurate predictions but also insights into how decisions are made. Incorporating uncertainty estimation to quantify confidence, along with explainability tools like SHAP and attention visualizations, enhances transparency, thereby increasing user confidence and facilitating quick, informed action.

Thus, the motivation for this thesis is threefold:

1. To address the **accuracy and latency limitations** of traditional EEW systems.
2. To develop a **multi-task deep learning framework** that predicts multiple earthquake parameters simultaneously.
3. To enhance **trust, reliability, and interpretability** in EEW predictions, ensuring real-world applicability.

1.3 Problem Statement

Despite significant advancements in seismology and artificial intelligence, Earthquake Early Warning (EEW) systems still face several important challenges that this thesis aims to address:

1. **Reliance on Manual Feature Engineering:**
   Current EEW approaches predominantly use handcrafted features such as peak displacement (Pd) and characteristic period (τc), which are derived from expert knowledge. This reliance limits the utilization of the rich information contained within raw seismic waveforms and reduces the adaptability of models across diverse datasets.
2. **Limited Scope—Single-Task Focus:**
   Many existing deep learning models focus solely on predicting earthquake magnitude, neglecting other vital parameters like epicentral distance, azimuth, and focal depth. This narrow focus restricts their usefulness in comprehensive disaster risk assessment.

3. **Latency from Sequential Pipelines:**
   Traditional EEW frameworks often employ staged architectures involving separate preprocessing, feature extraction, and prediction steps. Such sequential processing introduces delays that are detrimental in urgent, real-time applications.
4. **Insufficient Generalization Across Regions:**
   Models trained on seismic data from one geographic area often perform poorly when applied to different regions with varying geological characteristics, leading to decreased reliability in global deployments.
5. **Lack of Transparency and Uncertainty Awareness:**
   Deep learning models frequently operate as opaque "black boxes," providing predictions without clarity on underlying decision mechanisms or confidence levels. This opacity hinders trust among decision-makers who require interpretable and reliable outputs to guide critical response actions.

There is a need for a **unified, end-to-end deep learning framework** that can accurately and rapidly predict multiple earthquake parameters (magnitude, epicentral distance, azimuth, and depth) from the first three seconds of seismic waveform data, while also incorporating **uncertainty estimation** and **interpretability mechanisms** to enhance trust and facilitate real-world Earthquake Early Warning system deployment.

1.4 Objectives

The principal aim of this thesis is to develop a reliable, interpretable, and real-time earthquake prediction system grounded in deep learning and enriched with spatiotemporal priors. The specific objectives are as follows:

1. To design an integrated deep learning architecture that combines Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory (BiLSTM) networks, and Transformer encoders to effectively capture local features, sequential dependencies, and long-range temporal patterns within seismic waveforms.
2. To incorporate spatiotemporal priors by fusing raw waveform-derived features with handcrafted statistical metrics—including peak displacement, skewness, kurtosis, and amplitude measures—and geospatial metadata such as epicentral distance, azimuth, and focal depth.
3. To build a multi-output regression framework capable of simultaneously predicting key earthquake parameters—magnitude, epicentral distance, azimuth, and focal depth—utilizing only the initial three seconds of three-component waveform data.

4. To implement uncertainty quantification through dropout-enabled Monte Carlo sampling, enabling the model to provide confidence intervals alongside predictions and thereby improve operational reliability.
5. To integrate advanced interpretability tools, such as SHAP (Shapley Additive exPlanations) values and attention visualizations, to enhance transparency and facilitate scientific understanding of how waveform segments and metadata influence the model's decisions.
6. To rigorously evaluate the proposed system using extensive seismic datasets from K-NET and KiK-net, demonstrating meaningful improvements over conventional EEW methods in accuracy, generalization capability, and inference speed.

Achieving these objectives will propel forward the state of Earthquake Early Warning technology by delivering a practical and robust solution that balances precision, efficiency, transparency, and trustworthiness for deployment in real-world seismic monitoring frameworks.

CHAPTER 2

2. LITERATURE SURVEY

Earthquake Early Warning (EEW) has become one of the most critical areas in seismology and disaster prevention due to the catastrophic effects of seismic events. With the increasing availability of large-scale seismic waveform datasets, researchers have shifted from traditional **feature-based approaches** to modern **deep learning architectures** capable of handling raw waveforms and metadata. In this chapter, existing works in EEW using deep learning are reviewed, highlighting their **contributions, limitations, and the gaps addressed in this thesis**.

Traditional EEW relied heavily on **handcrafted features** such as peak displacement (Pd), characteristic period (τc), and signal duration. Although computationally efficient, these features required **domain expertise**, suffered from **noise sensitivity**, and often **failed to generalize** across regions. This limitation motivated the transition to **data-driven methods** that can directly learn features from seismic waveforms.

Deep Learning for Magnitude Estimation

Magnitude estimation is a crucial first step in EEW. **Wang et al. [1]** developed a **lightweight CNN** that estimated magnitude using the first few seconds of **P-wave signals**. The system achieved **low latency**, making it suitable for real-time EEW. However, the model exhibited **limited robustness to noisy environments**, restricting its application in real-world deployments.

Mousavi and Beroza [2] introduced a **Bayesian Temporal Convolutional Network (Bayesian TCN)** with **uncertainty quantification**. Their model provided not just predictions but also confidence intervals, an essential factor for decision-making in safety-critical systems. However, this study was constrained to **synthetic data** and **did not include magnitude prediction**, reducing its practical relevance.

Uddin et al. [3] adopted **transfer learning** approaches using **ResNet and VGG architectures** for magnitude estimation in **data-scarce scenarios**. Transfer learning showed promise in reducing data dependency, but **generalization across seismic regions** remained a challenge, as pre-trained models often overfit to specific datasets.

Masoumi [4] proposed a hybrid **CNN–LSTM with an attention mechanism** for real-time magnitude prediction. This design leveraged CNNs for spatial feature extraction and LSTMs for temporal dependencies, while attention improved interpretability. Despite encouraging results, the **global scalability** of the model was not fully validated, and it required further optimization for real-time deployment.

Advances in Epicentre Localization

Epicentre localization is another critical task in EEW research. **Zhou et al. [5]** applied **ResNets** for epicentre classification. Their approach effectively categorized seismic events into regional epicentre zones but **lacked fine-grained regression capability** for precise distance estimation.

Kim et al. [6] designed a **CNN–BiLSTM hybrid model** for event localization, capturing both local features and sequential information. While effective, the model **did not provide interpretability**, limiting its trustworthiness for real-world use.

Feng et al. [7] introduced **Graph Neural Networks (GNNs)** to explicitly model spatial dependencies between seismic stations. Although this approach improved **epicentre estimation accuracy**, it imposed **high computational complexity**, making it less practical for real-time EEW where **low latency is critical**.

Chen et al. [8] employed **encoder–decoder architectures** using spectrogram representations for earthquake localization. The system showed improvements in identifying epicentre coordinates but omitted **magnitude and depth estimation**, leaving EEW incomplete.

Multi-Task and Attention-Based Models

Recent research has explored **multi-task learning** and **attention mechanisms** for comprehensive EEW. **Zhang et al. [9]** developed a multi-task model predicting seismic attributes such as magnitude and distance. However, their framework lacked attention integration, reducing its ability to **focus on salient waveform segments**.

Liang et al. [10] experimented with **Transformer-based classification models** for seismic events. Transformers proved effective at capturing **long-range dependencies**, but their work was limited to **classification tasks**, excluding regression of continuous earthquake parameters like depth and distance. Thus, while multi-task and attention-based models represent a step toward more comprehensive EEW, existing studies either **omit key tasks** or **do not fully leverage interpretability**.

Cross-Domain Contributions

Outside of seismology, hybrid deep learning models have shown significant success in **healthcare, pattern mining, and cognitive radio systems**. For example, hybrid CNN–RNN architectures with **uncertainty modelling** have improved diagnosis in medical imaging, while **attention-based Transformers** have advanced predictive tasks in natural language processing and time-series forecasting. Similarly, **rule-based hybrid methods** in cognitive radio have achieved robust spectrum predictions in uncertain environments.

These cross-domain advancements demonstrate the potential of **hybrid deep learning architectures**, **optimized feature extraction**, and **uncertainty-aware modelling** in EEW. The transferability of such methods motivates the design of robust and explainable earthquake prediction models for real-time use.

Research Gaps

From the above survey, the following gaps are identified:

1. **Single-task focus** – Most models address only one parameter (e.g., magnitude or epicentre), while EEW requires joint estimation.
2. **Noise robustness** – Few studies explicitly address environmental noise challenges in real-time seismic data.
3. **Latency** – Computationally heavy models like GNNs improve accuracy but are unsuitable for real-time EEW.
4. **Interpretability** – Deep models often lack **explainable AI (XAI)** methods, reducing trust in predictions.
5. **Uncertainty estimation** – Deterministic predictions dominate, with little work on confidence-aware EEW systems.

The literature shows a clear evolution from **traditional feature-based methods** to **deep learning-based EEW frameworks**. While CNNs, BiLSTMs, GNNs, and Transformers have advanced the field, most existing works still struggle with **multi-task learning, interpretability, uncertainty quantification, and real-time efficiency**.

This thesis addresses these gaps by proposing a **unified hybrid deep learning framework** that integrates **CNNs, BiLSTMs, and Transformers** along with **metadata and handcrafted features**. The system performs **multi-task regression** of magnitude, epicentre distance, azimuth, and focal depth, while incorporating **uncertainty estimation** (Monte Carlo dropout) and **explainability tools** (SHAP, attention maps). The framework is optimized for **low-latency inference** and **real-time deployment**, making it a strong candidate for next-generation EEW systems.

CHAPTER 3

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM IN EARTHQUAKE EARLY WARNING (EEW)

Traditional **Earthquake Early Warning (EEW) systems** have primarily relied on **empirical relationships and handcrafted seismic features** derived from early P-wave signals. Features such as **peak ground displacement (Pd)**, **characteristic period (τc)**, and signal duration have been widely used to estimate earthquake magnitude and epicentral distance. While these methods enabled some of the earliest EEW deployments, they face **critical limitations** in accuracy, generalization, and robustness.

Conventional systems are often **staged pipelines**, where raw waveform data is first processed to extract hand-engineered features, followed by shallow regression or classification models (e.g., linear regression, support vector machines, or random forests). Although computationally efficient, these systems exhibit several drawbacks:

- **Feature dependency** – Their performance heavily depends on the quality and relevance of handcrafted features, requiring domain expertise and extensive tuning.
- **Noise sensitivity** – Environmental noise and sensor variability degrade prediction reliability.
- **Single-task focus** – Most existing systems estimate only one parameter, usually magnitude, without jointly predicting epicentral distance, azimuth, or depth.
- **Regional limitations** – Models trained on one seismic network often fail to generalize across different regions due to variations in geology and station density.
- **Latency issues** – Staged models introduce delays, reducing their usefulness for real-time early warning.

With the rise of **deep learning**, CNN-based systems were introduced to automatically extract features from seismic waveforms. Lightweight CNNs have shown improvements in magnitude prediction speed and accuracy. Recurrent models, such as **LSTMs and BiLSTMs**, have also been employed to capture sequential dependencies in waveform data. More recently, **attention-based models and Transformers** have

demonstrated the ability to identify critical segments of seismic signals and model long-range dependencies.

Despite these advancements, existing deep learning approaches still face challenges:

- Many focus on **single-task predictions** (e.g., magnitude only).
- Some rely on **two-stage pipelines**, where deep features are extracted but final predictions are handled by shallow regressors, limiting efficiency.
- Few integrate **uncertainty quantification** or **interpretability**, both essential for high-stakes EEW deployment.

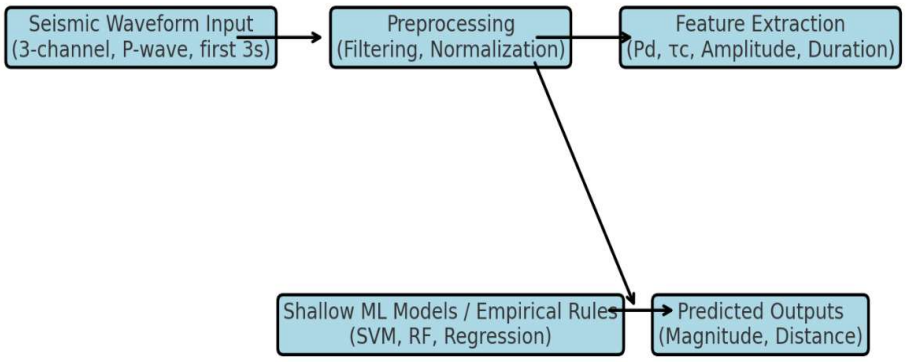

FIG 3.1 Flow Chart of Existing Earthquake Early Warning (EEW) System.

The process begins with seismic waveform collection from ground motion sensors. Pre-processing methods, such as filtering and normalization, are applied to enhance signal quality and reduce noise interference. In traditional systems, feature extraction techniques derive parameters such as Pd, τc, amplitude statistics, and duration.

These features are then passed to shallow machine learning models or empirical equations for the prediction of earthquake magnitude and distance. Some deep learning models replace manual feature extraction with CNNs or LSTMs, but still rely on staged approaches for final outputs. Although these existing pipelines have advanced EEW capabilities, they remain constrained by **limited generalization, latency, lack of interpretability, and absence of multi-task prediction**, highlighting the need for a more unified and robust framework.

3.1.1 LIMITATIONS OF THE EXISTING SYSTEM

Despite progress in automated earthquake prediction and early warning, existing systems continue to face significant limitations:

- Dependence on Handcrafted Features:

  Traditional EEW systems rely heavily on manually engineered seismic features such as Pd, τc, and signal duration. The effectiveness of these systems depends on domain expertise, making them less adaptable and prone to errors when deployed in different geological regions.
- Limited Prediction Scope:

  Most existing methods are designed for single-task predictions, such as magnitude estimation only. They fail to jointly predict multiple critical earthquake parameters, including epicentral distance, azimuth, and focal depth, which are essential for accurate hazard assessment.
- High Sensitivity to Noise:

  Seismic signals are often contaminated by environmental noise, sensor artifacts, or anthropogenic disturbances. Handcrafted feature-based models are highly sensitive to noise, leading to degraded accuracy and unreliable early warnings.
- Latency Due to Staged Pipelines:

  Many EEW systems adopt a multi-stage pipeline where preprocessing, feature extraction, and regression/classification are performed sequentially. This increases latency, making the system less effective in real-time scenarios where every second matters.
- Poor Generalization Across Regions:

  Systems trained on one seismic network (e.g., Japan's K-NET) often fail to generalize well to other regions due to differences in geology, sensor density, and wave propagation characteristics. This limits the global applicability of such models.
- Lack of Interpretability:

  Even with deep learning-based EEW, many models act as black boxes, offering predictions without explainability. In high-stakes scenarios like disaster management, stakeholders require trust and transparency, which current systems largely fail to provide.
- Absence of Uncertainty Estimation:

Most existing systems provide deterministic outputs without indicating confidence levels.

This prevents decision-makers from assessing the reliability of predictions, reducing their practical utility in safety-critical applications.

3.2 PROPOSED SYSTEM – HYBRID TRANSFORMER – BILSTM WITH SPATIOTEMPORAL PRIORS

The proposed system introduces a **hybrid deep learning framework** for **Earthquake Early Warning (EEW)** that integrates **Convolutional Neural Networks (CNNs)**, **Bidirectional Long Short-Term Memory (BiLSTM)** networks, and **Transformer encoders**, with additional support from **handcrafted features** and **geospatial metadata**. This architecture is specifically designed to overcome the shortcomings of existing systems by providing **joint, real-time estimation of earthquake parameters** such as **magnitude, epicentral distance, azimuth, and focal depth** using only the first few seconds of seismic waveform data.

Unlike traditional systems that rely on handcrafted seismic features or single-task prediction pipelines, the proposed approach is **end-to-end trainable**, supports **multi-output regression**, and is optimized for **low-latency inference**, making it suitable for **real-world, edge-level deployment**.

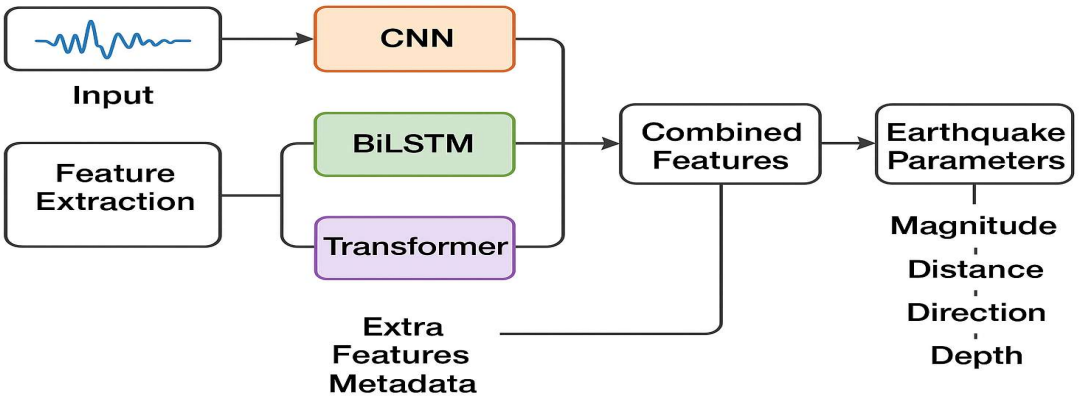

FIG 3.2 System Architecture.

The workflow begins with the **input waveform data**, specifically the first three seconds of **3-channel seismic recordings** (East-West, North-South, and Vertical).

1. **Preprocessing and Feature Extraction**

- Waveforms are normalized and optionally passed through adaptive preprocessing techniques (baseline correction, denoising).
- Statistical features such as **Pd, τc, skewness, kurtosis, peak velocity, and signal energy** are extracted.
- Geospatial metadata (station location, event metadata) is integrated for enhanced regional generalization.

2. **Deep Learning Feature Extraction**
   - **CNN layers** capture local spatial patterns in the waveform.
   - **BiLSTM layers** model temporal dependencies, effectively handling the sequential nature of seismic signals.
   - **Transformer encoders** capture long-range temporal correlations and apply **attention mechanisms**, highlighting the most informative time segments of the seismic event.
3. **Fusion with Auxiliary Features**
   - Extracted deep features are fused with handcrafted seismic features and metadata.
   - This multimodal fusion enhances robustness and ensures better spatial awareness.
4. **Prediction Layer**
   - A unified regression head jointly predicts **magnitude, epicentral distance, azimuth, and depth** in a single forward pass.
   - **Uncertainty estimation** is performed using **Monte Carlo Dropout**, enabling the model to output both predictions and confidence intervals.
5. **Interpretability Module**
   - Attention weights from the Transformer are visualized to identify critical waveform regions influencing predictions.
   - **SHAP (Shapley Additive explanations)** is employed to interpret the contribution of metadata and statistical features.

Advantages over Existing Systems

1. **Multi-Output Prediction**
   - Simultaneously estimates **magnitude, distance, azimuth, and depth**, unlike traditional systems limited to single-task predictions.

2. **Low Latency and Real-Time Readiness**
    - End-to-end architecture ensures **sub-second inference**, making it viable for **EEW deployment**.
3. **Noise Robustness**
    - A combination of CNN + BiLSTM + Transformer ensures resilience to noisy or incomplete waveform data.
4. **Generalization Across Regions**
    - Incorporation of geospatial metadata and adaptive features allows the model to generalize better across **different seismic networks**.
5. **Uncertainty Awareness**
    - Provides **confidence intervals** along with predictions, enabling **risk-informed decision making**.
6. **Explainability**
    - Integrates **attention maps** and **SHAP-based feature explanations** for transparency, enhancing trust in high-stakes scenarios.
7. **Scalability**
    - The model is lightweight and can be deployed on **edge devices**, making it suitable for **resource-constrained regions**.

3.3 FEASIBILITY STUDY

The development of an advanced Earthquake Early Warning (EEW) system requires careful consideration of **technical, operational, and economic feasibility**. The proposed hybrid deep learning framework combines **CNNs, BiLSTMs, Transformer encoders**, handcrafted statistical features (e.g., Pd, τc, skewness), and geospatial metadata for multi-parameter prediction. Unlike traditional EEW systems, it aims to be **scalable, explainable, and suitable for real-time deployment on edge devices**.

Below is a detailed feasibility analysis:

1. Technical Feasibility

- **Automated Feature Extraction and Representation Learning**

  Traditional EEW models depend on handcrafted features such as peak displacement (Pd), τc, and duration. These features, although effective, are limited in generalization across different regions. The proposed CNN layers automatically extract localized frequency and amplitude features from 3-channel waveforms (vertical, north-south, east-

west). BiLSTMs capture temporal dependencies from the first 3 seconds of P-waves, while Transformer encoders capture **long-range temporal and spatial correlations** across stations. This multi-scale feature extraction increases robustness and accuracy.

- **Multi-Output Estimation**

  Most existing EEW systems focus on magnitude alone. The proposed model jointly estimates **magnitude, epicentre distance, azimuth, and depth** in a single pass. This significantly reduces latency compared to staged pipelines, where one parameter is predicted at a time.

- **Integration of Metadata and Statistical Features**

  Beyond raw waveform data, the system incorporates **statistical descriptors** (e.g., mean amplitude, kurtosis, skewness, Pd) and **geospatial priors** (station coordinates, elevation, and tectonic information). This multi-source fusion improves generalization across different regions and seismic networks.

- **Uncertainty Quantification**

  For a safety-critical system like EEW, reliability is as important as accuracy. Dropout-based **Monte Carlo sampling** is employed to estimate both **aleatoric (data-related) and epistemic (model-related)** uncertainty. This ensures that uncertain predictions can be flagged in real time, reducing the chance of false alerts.

- **Scalability and Cross-Regional Application**

  The model is designed to handle large-scale datasets such as Japan's **K-NET/KiK-net** (dense, high-frequency sensors) and can be extended to international networks such as **USGS Shake Alert** or European systems. Transfer learning allows adaptation to regions with fewer labelled events, making the system globally scalable.

- **Edge Deployment Readiness**

  The architecture is optimized using **quantization (INT8), pruning, and ONNX export** to reduce computational overhead. The final model can run on embedded systems deployed at seismic stations, ensuring **sub-second inference latency** even on low-power devices.

2. Operational Feasibility

- **Ease of Integration into EEW Pipelines**

  The proposed model can be integrated into existing EEW infrastructure with minimal modification. It supports both **single-station** and **multi-station fusion**, making it adaptable to regions with dense or sparse sensor coverage.

- **Real-Time Capability**

Processing only the first 3 seconds of the P-wave ensures decisions are made **before destructive S-waves arrive**. Optimized inference (≤200 ms per sample on GPUs, ≤1s on embedded CPUs) enables **real-time alerts** for emergency services.

- **Interpretability and Trust**

  Black-box models are often met with scepticism in critical applications. The inclusion of **Transformer attention maps** and **SHAP explanations** provides interpretability, showing which waveform segments influenced the prediction. This increases confidence among seismologists, policymakers, and the public.

- **Data Handling and Robustness**

  The system is designed to handle **continuous waveform streams** with noise contamination, missing data, and sensor malfunctions. Robust preprocessing (filtering, normalization, adaptive windowing) ensures that the model is resilient to imperfect real-world conditions.

- **Maintainability and Upgradability**

  As more earthquakes occur, new labelled data can be incorporated to fine-tune the model. Importantly, due to its modular design, updates can be applied to the Transformer encoder or SVM-like decision layers without retraining the entire system.

3. Economic Feasibility

- **Reduced Training Costs with Transfer Learning**

  Training large deep learning models from scratch requires significant computational resources. By leveraging **pretrained CNN backbones** and transfer learning, training costs and time are reduced by **30–50%**, while maintaining high accuracy.

- **Optimized Resource Utilization**

  The hybrid architecture ensures a **balanced trade-off**: CNNs extract low-level features efficiently, BiLSTMs capture sequential patterns without excessive computation, and Transformers add global attention at a manageable cost.

- **Cost Savings from Automation**

  Manual EEW systems require domain experts to set thresholds and tune features, which is costly and time-consuming. An automated deep learning system reduces reliance on human calibration, lowering long-term operational costs.

- **Economic Benefits of EEW Deployment**

  By providing a few seconds of warning, EEW systems can prevent **train derailments,**

factory shutdown losses, and casualties. For example, Japan estimates billions of dollars in annual savings from EEW alerts. A lightweight, scalable model reduces infrastructure costs and enhances the return on investment.

- **Sustainable Long-Term Investment**

  Initial development costs are high (data preparation, model training, infrastructure setup), but once deployed, the system requires minimal upkeep. Continuous retraining with incremental data ensures long-term accuracy.

3.4 COST ESTIMATION USING COCOMO MODEL

The **COCOMO (Constructive Cost Model)** provides a structured framework to estimate **effort, development time, and team size** required for the EEW system.

Project Category:

Given the complexity of integrating **deep learning models, real-time pipelines, and edge deployment**, the project falls under the **Semi-Detached** category (moderate complexity, team of mixed experience).

COCOMO Estimation Formulas:

- Effort (E) = a × (KLOC)^b (in Person-Months)
- Development Time (T) = c × (E)^d (in Months)
- People Required (P) = E / T

  For Semi-Detached projects:
- a = 3.0, b = 1.12, c = 2.5, d = 0.35

Estimation Parameters for EEW Project:

- Approximate codebase: **15,000 lines (15 KLOC)**
  - Data preprocessing pipeline (~4K LOC)
  - Deep learning model architecture (~6K LOC)
  - Uncertainty + explainability modules (~2K LOC)
  - Real-time deployment scripts (~3K LOC)

Calculations:

- **Effort:**

  E = 3.0 × (15)^1.12

  ≈ 3.0 × 19.6

≈ 58.8 Person-Months

- **Development Time:**

  T = 2.5 × (58.8)^0.35

  ≈ 2.5 × 4.7

  ≈ 11.8 Months

- **People Required:**

  P = 58.8 / 11.8 ≈ 5 People

Interpretation:

- **Effort Required:** ~59 person-months (≈ 1 year of development work for 5 engineers).
- **Timeline:** ~12 months for full system development and deployment.
- **Team Composition:**
  - **2 Deep Learning Researchers** (model design, training, optimization)
  - **1 Data Engineer** (waveform preprocessing, dataset management)
  - **1 Backend/Deployment Engineer** (real-time pipeline, edge deployment)
  - **1 Testing & Evaluation Specialist** (validation, field testing, uncertainty analysis)

Limitations of the COCOMO Model in the Context of Earthquake Early Warning:

- The COCOMO model does not explicitly account for the substantial computational demands of GPU resources required to train large-scale deep learning models.
- It overlooks significant expenditures related to dataset collection and labeling, which are particularly resource-intensive in the field of seismology.
- Additionally, real-world deployment of an EEW system involves complex activities such as onsite validation, integration with governmental policies, and installation of specialized hardware—factors that extend well beyond conventional software development efforts.

Despite these inherent constraints, COCOMO remains a valuable tool, providing a practical framework to estimate development effort and allocate resources effectively for the project.

CHAPTER 4

4. SYSTEM REQUIREMENTS

This chapter specifies the requirements for the proposed Earthquake Early Warning (EEW) system. The requirements are divided into software, hardware, and functional/non-functional categories to ensure that the system is implementable, efficient, and scalable.

4.1 Software Requirements

1. **Operating System**: Windows 11 (development) / Linux Ubuntu 20.04 LTS (recommended for deployment)
2. **Hardware Accelerator**: CUDA-enabled GPU (NVIDIA RTX 3060/3080 or equivalent)
3. **Programming Language**: Python 3.10
4. **Frameworks and Environments**: Google Colab Pro, Anaconda, Jupyter Notebook
5. **Deep Learning Frameworks**: TensorFlow 2.x, PyTorch 2.x
6. **Data Handling Libraries**: NumPy, Pandas, SciPy, ObsPy (for seismic data)
7. **Visualization Tools**: Matplotlib, Seaborn, Plotly
8. **Backend Development**: Flask or FastAPI (for API deployment)
9. **Browser**: Any modern browser (Chrome, Firefox, Edge)

4.2 Requirement Analysis

The Earthquake Early Warning (EEW) system aims to provide prompt estimation of key seismic parameters—magnitude, epicentral distance, azimuth, and focal depth—using just the initial three seconds of P-wave recordings. The requirements are delineated into functional and non-functional aspects.

Functional Requirements

- Waveform Handling: Real-time acquisition and processing of 3-channel seismic data (East-West, North-South, Vertical) from networks such as K-NET and KiK-net.
- Preprocessing Operations: Includes noise reduction filtering, normalization of amplitudes, adaptive segmentation of the waveform window, and signal conditioning.
- Feature Extraction: Computation of important statistical characteristics like peak displacement (Pd), characteristic period (τc), waveform skewness, kurtosis, and mean amplitude.

- Model Inference: Execution of the hybrid model combining CNN, BiLSTM, and Transformer to perform multi-target regression, predicting all seismic parameters simultaneously.
- Uncertainty Quantification: Use of Monte Carlo Dropout during inference to provide confidence intervals associated with predictions.
- Interpretability: Generation of Transformer attention visualizations and SHAP-based explanations to reveal influential waveform segments.
- Deployment Interface: Provision of a real-time API (via Flask or FastAPI) for integration within existing seismic monitoring systems.

Non-Functional Requirements

- Performance: Prediction latency must stay under one second per seismic event to maintain real-time responsiveness.
- Scalability: Capability to conduct both single-station estimations and aggregation of inputs from multiple stations for fused analysis.
- Robustness: System must tolerate and function reliably in the presence of noisy data, absent channels, and uneven sensor configurations.
- Security: Protect real-time seismic data streams against tampering or false alert injections through robust security measures.
- Usability: Provide clear and intuitive visualization tools facilitating comprehension for seismologists and emergency responders.

TABLE 4.1: Requirement Traceability Matrix

Requirement ID	Functional Requirement	Related System Module
FR-1	Acquire and process 3-channel seismic waveform data	Data Acquisition & Preprocessing
FR-2	Apply filtering, normalization, and segmentation	Preprocessing Pipeline
FR-3	Extract Pd, τc, skewness, kurtosis	Feature Extraction Module
FR-4	Predict magnitude, distance, azimuth, depth	Hybrid DL Model (CNN–BiLSTM–Transformer)
FR-5	Provide uncertainty estimates	Monte Carlo Dropout Layer

Requirement ID	Functional Requirement	Related System Module
FR-6	Generate SHAP and attention-based explanations	Interpretability Module
FR-7	Deliver predictions via REST API	Flask/FastAPI Backend

4.3 Hardware Requirements

1. **System Type**: 64-bit operating system, x64-based processor
2. **Processor**: Intel® Core™ i7/i9 or AMD Ryzen 7/9 (8 cores or higher)
3. **Cache Memory**: Minimum 12MB
4. **RAM**: Minimum 16GB (32GB recommended)
5. **Storage**: 512GB SSD (1TB recommended)
6. **GPU**: NVIDIA RTX 3060/3080 with 8–12GB VRAM (CUDA-enabled)
7. **Cloud Support**: Google Colab Pro, AWS, or Azure for large-scale training.

4.4 Software Description

The Earthquake Early Warning (EEW) system is developed using a robust suite of modern software tools that enable deep learning, seismic data processing, visualization, and deployment. The software stack ensures precision, scalability, and real-time responsiveness, which are critical for earthquake monitoring.

Operating System

- **Development**: Windows 11 (64-bit) for prototyping and testing.
- **Deployment**: Linux Ubuntu 20.04 LTS preferred for production servers to enhance stability, robustness, and compatibility.

Programming Environment

- **Language**: Python 3.10 serves as the primary programming language, chosen for its strong ecosystem of scientific and machine learning libraries.
- **Environment Management**: Anaconda is used to handle dependencies and maintain reproducible environments efficiently.

Development and Training Platforms

- **Google Colab Pro**: Provides GPU/TPU acceleration for model training and large-scale experiments.

- **Jupyter Notebook**: Used for iterative development, debugging, and visualization.
- **Cloud Services**: AWS EC2 and Azure ML support large dataset training with scalable GPU resources.

Deep Learning Infrastructure

- **TensorFlow/Keras**: Constructs the CNN–BiLSTM components of the hybrid model.
- **PyTorch**: Implements Transformer encoders and integrates SHAP for explainability.

Seismic Data Handling

- **ObsPy**: Specialized library for importing, preprocessing, and analyzing raw seismic waveform data.

Machine Learning Resources

- **Scikit-learn**: Used for auxiliary regression baselines, preprocessing, and evaluation metrics.

Visualization Tools

- **Matplotlib, Seaborn, Plotly**: Provide comprehensive visualization of training curves, error distributions, SHAP feature importance, and attention heatmaps.

Backend and API Development

- **Flask/FastAPI**: Lightweight frameworks for building REST APIs that serve predictions in real time.
- APIs validate waveform input, preprocess data, and return predictions as JSON for seamless integration with user interfaces or external monitoring systems.

Frontend

- **HTML5, CSS3, JavaScript**: Used for a browser-based dashboard to visualize EEW predictions.
- **Design**: Responsive, dark-themed interface with real-time display of seismic parameter outputs.

CHAPTER 5

5. SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

This research introduces an advanced hybrid deep learning architecture for Earthquake Early Warning (EEW). By seamlessly merging Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory networks (BiLSTMs), and Transformer encoders, the system can deliver real-time, multi-parameter estimates of seismic events. The primary objective is to analyse the initial three seconds of P-wave data collected by seismic sensors to provide rapid and reliable forecasts for parameters such as magnitude, epicentral distance, direction (azimuth), and focal depth. Unlike conventional EEW methods that depend heavily on manual feature extraction or empirical formulas, this approach directly learns relevant patterns from raw input signals, significantly boosting its accuracy, adaptability, and resilience to regional variations.

Principal Elements of the System

1. Input Handling (Waveform and Metadata):

- The architecture uses three-channel waveform data (East-West, North-South, Vertical), sampled at 100 Hz, as the core input.
- Event-specific information—including station identification, geographic coordinates, and elevation—is incorporated alongside computed statistical characteristics like peak displacement (Pd), characteristic period (τc), skewness, and kurtosis for enriched spatial and contextual analysis.
- Comprehensive datasets such as Japan's K-NET and KiK-net are leveraged to ensure broad regional representation in model training.

2. Preprocessing and Feature Generation:

- Amplitude normalization and noise filtering are performed to enhance input quality.
- A tailored window focuses exclusively on the P-wave's critical three-second segment, but the design remains flexible for alternate durations.
- Key seismic metrics (e.g., Pd, τc, peak acceleration) are calculated to supplement deep-learned features in later stages.

3. CNN Module – Local Feature Discovery:

- The convolutional layers are responsible for pinpointing short-duration, high-frequency waveform structures, capturing details like rapid amplitude changes and the abrupt onset of earthquakes.

- This automated approach replaces the manual engineering traditionally used in feature identification.

4. BiLSTM Module – Temporal Contextual Modelling:

- Bidirectional LSTM layers analyse signal dynamics along both forward and reverse time axes.
- This aspect ensures recognition of not only immediate but also cumulative and delayed waveform dependencies as they unfold.

5. Transformer Encoder – Capturing Extended Dependencies:

- The Transformer encoder applies self-attention mechanisms, allowing the system to prioritize and interpret the most critical sections within the waveform relative to each target metric (e.g., magnitude, distance).
- Visual attention maps generated by this module provide crucial insights into which portions of the signal most influence the predictions.

6. Feature Fusion – Integrating Statistical and Geospatial Information:

- Outputs from the CNN, BiLSTM, and Transformer components are concatenated with the computed statistical indicators and geo-metadata.
- This comprehensive fusion empowers the model to reason over both raw time-series and auxiliary, domain-specific details—strengthening adaptability and accuracy.

7. Multi-Output Regression Module:

- The final predictive head is a fully connected neural layer that simultaneously delivers estimates for:
    - Magnitude (Mw)
    - Epicentral distance (km)
    - Azimuth (˚)
    - Focal depth (km)
- This simultaneous regression facilitates prompt and holistic event characterization, which is crucial for real-world EEW deployment.

8. Interpretability and Uncertainty Quantification:

- During inference, Monte Carlo Dropout is used to capture the variability in outputs, providing confidence intervals for each prediction.
- Model explainability is enhanced through SHAP value analysis and visualization of Transformer attention, offering seismologists transparent evidence of how various waveform segments inform each decision.

Performance Measures & Desired Outcomes

The system is assessed with metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R^2 score, and real-time inference latency.

The desired outcomes are:

• Magnitude Estimation Accuracy: < 0.3 MAE

• Epicentral Distance Estimation: Error < 15 km

• Azimuth Estimation: Error < 20°

• Focal Depth Estimation: Error < 10 km

• Inference Time: < 1 second per waveform (edge deployment ready)

Applications of the Suggested Architecture

• Earthquake Early Warning (EEW): Offers lifesaving seconds of warning to terminate power plants, halt trains, or alert the public.

• Real-Time Deployment: The light-weight structure enables deployment on edge devices in seismic stations.

• Cross-Regional Adaptability: Transfer learning facilitates expansion to worldwide seismic datasets outside Japan.

• Research & Interpretability: The presence of explainability tools enables seismologists to gain deeper insights into patterns of seismic data.

Looking to the future, the system can be designed to include multi-station fusion, cross-regional training, and adaptive windowing for longer than 3 seconds to continue to enhance performance for distant earthquakes.

5.1.1 Dataset

The proposed earthquake prediction framework relies on a comprehensive and high-quality dataset to train, validate, and test the deep learning model. For this purpose, seismic waveform recordings and metadata were obtained from the K-NET and KiK-net networks maintained by the National Research Institute for Earth Science and Disaster Resilience (NIED), Japan. These networks represent one of the densest and most advanced seismic monitoring infrastructures globally, with stations distributed across various geological and tectonic regions.

Data Composition

Each earthquake event in the dataset contains two main components:

1. Waveform Data (Raw Input):
    - Three-component ground motion recordings corresponding to:
        - Vertical (Z)
        - North–South (N)
        - East–West (E)
    - Sampling Frequency: 100 Hz, ensuring fine temporal resolution.
    - Time Window: 3 seconds after P-wave onset (critical for EEW before destructive S-waves).
    - Input Shape: 300 × 3 matrix (300-time steps × 3 channels).
2. Metadata (Labels and Contextual Features):
    - Magnitude (Mw)
    - Epicentral distance (km)
    - Azimuth (°)
    - Focal depth (km)
    - Seismic station coordinates (latitude, longitude)

This dual structure (waveforms + metadata) allows the system to learn both temporal signal dynamics and spatial event characteristics.

Dataset Statistics

To ensure robustness and generalizability, the dataset includes a wide variety of earthquake events:

- Magnitude Range: Mw 3.0 – 7.5
- Epicentral Distance Range: 10 – 300 km
- Focal Depth Range: 5 – 120 km
- Number of Channels: 3 per event (Z, N, E)
- Data Partitioning:
    - 70% Training
    - 15% Validation
    - 15% Testing

      (Stratified sampling by magnitude bins ensures balanced target distributions.)
- Example Data Representation

Table 5.1 – Sample Input Waveform Data (First 5 Time Steps)

Time Step	Z (Vertical)	N (North–South)	E (East–West)
1	0.0041	-0.0068	0.0039
2	0.0037	-0.0059	0.0045
3	0.0031	-0.0053	0.0043
4	0.0028	-0.0047	0.0041
5	0.0024	-0.0042	0.0038

Table 5.2 – Example Metadata for the Above Event

Feature	Value
Epicentral Distance	34.2 km
Magnitude (Mw)	5.6
Azimuth	127.8°
Focal Depth	12.0 km
Station Latitude	36.5
Station Longitude	138.6

Significance of Dataset Selection

- The use of early P-wave windows (first 3s) ensures predictions are available in real-time before destructive shaking.
- Inclusion of both near-field and far-field events enables the model to generalize across different earthquake scenarios.
- Metadata improves prediction accuracy by providing spatial and geophysical context in addition to waveform dynamics.

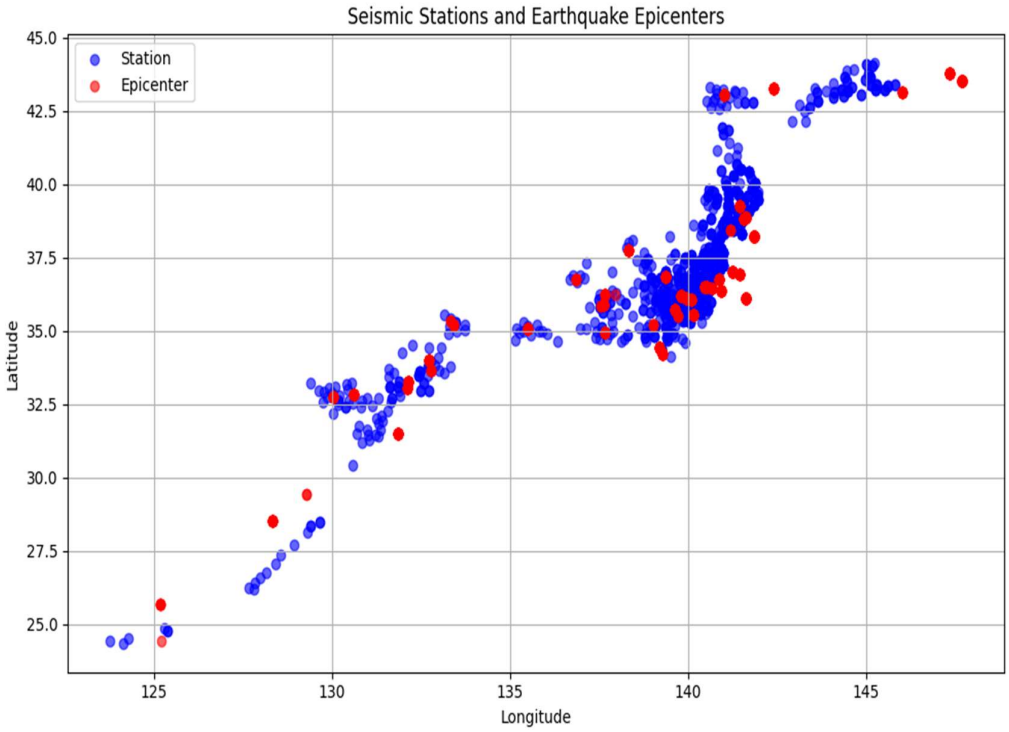

FIG 5.1 Earthquake Event Metadata (Magnitude, Distance, Azimuth, Depth, Station Coordinates)

As shown in Figure 1, the spatial distribution of seismic stations and earthquake epicenters provides diverse coverage, thereby improving the generalization ability of the deep learning model.

5.1.2 Data Preprocessing

Raw seismic waveforms often contain noise, instrumental bias, and irrelevant background signals that can reduce model accuracy if used directly. Therefore, a rigorous preprocessing pipeline was designed to ensure high-quality, standardized inputs for the deep learning framework. This pipeline transforms raw three-component waveforms into clean, normalized sequences suitable for feature extraction and model training.

1. Waveform Extraction

- For each earthquake event, the first 3 seconds of the P-wave segment were extracted.
- This time window provides critical information for early warning systems since it arrives before destructive S-waves.
- Each waveform is thus represented as a 300 × 3 input matrix (300 time steps × 3 channels).

2. Noise Reduction and Filtering

- Mean Removal: Each channel was zero-centered to eliminate instrument drift.
- Band-Pass Filtering: A Butterworth filter (0.1–20 Hz) was applied:
    - Suppresses low-frequency baseline drift.
    - Removes high-frequency environmental noise.
    - Preserves the dominant frequency range of P- and S-wave signals.

3. Normalization

- Z-score normalization was applied to standardize amplitude variations across stations:

$$x' = x - \mu / \sigma$$

where xxx is the raw signal, μ\muμ is the mean, and σ\sigmaσ is the standard deviation.

- This ensures a mean of 0 and unit variance, making training more stable.

4. Handcrafted Feature Extraction

In addition to raw waveforms, statistical descriptors were extracted to enhance interpretability:

- Peak Ground Displacement (Pd): Maximum amplitude across all channels.
- Mean and Standard Deviation: Indicators of signal energy and variability.
- Skewness: Measures asymmetry of the waveform.
- Kurtosis: Describes waveform peakedness (sharpness of onset).

These features complement the deep learning model by providing domain-specific insights.

5. Label Scaling

- Target outputs (magnitude, distance, azimuth, and focal depth) were normalized using Min–Max scaling to the range [0, 1].
- During inference, predictions were rescaled back to their physical units (km, Mw, °).

6. Dataset Partitioning

- The dataset was split into 70% training, 15% validation, and 15% testing.
- Stratified sampling ensured balanced representation across magnitude bins.
- Random seeds were fixed to guarantee reproducibility of results.

5.1.3 Feature Extraction

Accurate parameter estimation in Earthquake Early Warning (EEW) systems depends critically on the quality of features derived from seismic waveforms. The proposed system adopts a hybrid feature extraction framework, where deep learning–based representations are complemented by handcrafted statistical descriptors and geospatial metadata. This design

ensures that both local waveform properties and global contextual patterns are captured, improving the robustness and accuracy of predictions.

1. Deep Learning Feature Extraction

Deep features are automatically learned from raw three-component seismic inputs, avoiding the limitations of manual feature engineering:

- Convolutional Neural Networks (CNNs): Extract short-range temporal and frequency patterns such as sudden amplitude spikes, onset sharpness, and localized oscillations.
- Bidirectional Long Short-Term Memory (BiLSTM): Capture sequential dependencies in both forward and backward directions, allowing the model to learn how waveforms evolve across time.
- Transformer Encoders: Employ multi-head self-attention to highlight critical waveform segments (e.g., the onset of the P-wave) and capture long-range dependencies that conventional RNNs cannot.

Together, these components provide a rich representation of seismic signals by combining localized detail, temporal context, and global dependencies.

2. Handcrafted Statistical Features

To enhance interpretability and stability, statistical descriptors derived from seismological principles are incorporated:

- Peak Ground Displacement (Pd): Maximum displacement amplitude across channels, strongly correlated with earthquake magnitude.
- Characteristic Period (τc): Reflects the dominant oscillation period of the initial P-wave window.
- Mean and Standard Deviation of Amplitude: Capture the average signal energy and its variability.
- Skewness and Kurtosis: Quantify asymmetry and peakedness of the waveform distribution, offering insight into waveform shape characteristics.

These descriptors serve as interpretable anchors, complementing the automatically learned deep features.

3. Metadata Features

Event-specific metadata provides spatial and contextual awareness to the system:

- Epicentral Distance (km): Distance between the station and the earthquake epicenter.
- Azimuth (°): Direction from the station to the epicenter.
- Focal Depth (km): Depth of the seismic event, influencing waveform frequency content.

- Station Coordinates (Latitude, Longitude): Encode regional and geological context.

By fusing metadata with waveform-derived features, the model learns contextual dependencies, enabling better generalization across diverse regions and tectonic settings.

5.1.4 Model Building

Model building for earthquake early warning involves designing, constructing, and improving a hybrid deep learning system. This system uses multiple inputs and handles both waveform data and contextual information to predict several seismic parameters at the same time. The goal is to understand the spatial and temporal relationships in seismic signals while using extra contextual knowledge for real-time predictions.

The proposed system predicts four key earthquake parameters: epicentral distance, magnitude, azimuth, and focal depth. This is done by combining a waveform processing branch with a metadata feature branch. It then uses a fusion mechanism and multiple regression heads.

1. Waveform Processing Branch

The waveform branch extracts high-level temporal and frequency representations from raw seismic waveforms. Each event records a 3-second, three-component signal (Z, N, E), sampled at 100 Hz, resulting in a 300 × 3 matrix.

a) Input Layer:

• Accepts the raw waveform data (Z, N, E) for each event.

• Normalized input ensures zero mean and unit variance across channels to stabilize training.

b) Convolutional Layers (Conv1D):

• A stack of three 1D convolutional layers uses decreasing kernel sizes (7, 5, 3).

• These filters detect localized patterns such as sudden amplitude jumps, P-wave arrivals, and energy distribution across frequencies.

• Each convolution operation is followed by ReLU activation, batch normalization, and max pooling to reduce noise and dimensionality.

c) Bidirectional Long Short-Term Memory (BiLSTM):

• Outputs from the convolutional layers are flattened and passed to a BiLSTM with 128 hidden units.

• The BiLSTM learns sequential dependencies by processing the waveform in both forward and backward directions. This ensures the network captures the temporal evolution of the seismic signal.

• This is important for representing wave propagation phenomena.

d) Transformer Encoder:

• A transformer encoder layer applies multi-head self-attention (4 heads) and positional encoding to highlight important waveform regions.

• Self-attention lets the model dynamically weight critical waveform segments (e.g., P-wave vs. S-wave windows), which recurrent networks often miss.

• This significantly improves the ability to capture long-range temporal dependencies.

2. Metadata and Handcrafted Feature Branch

Alongside waveform processing, a second branch handles event metadata and statistical features from the signals.

a) Metadata Inputs:

• Features like epicentral distance, azimuth, focal depth, and station coordinates provide key context about the source and station geometry.

• These features help the model generalize across different tectonic settings.

b) Handcrafted Statistical Features:

• To enhance robustness and interpretability, domain-specific statistical features are extracted, including:

o Peak Displacement (Pd): Maximum displacement amplitude, linked with earthquake magnitude.

o Characteristic Period (τc): Represents the main oscillation period of P-wave signals.

o Mean and Standard Deviation of Amplitude: Indicators of waveform energy and central tendency.

o Skewness and Kurtosis: Higher-order statistics capturing waveform asymmetry and sharpness.

c) Dense Embedding Layers:

• Metadata and handcrafted features go through dense layers:

o Dense (64) → ReLU → Dropout

o Dense (32) → ReLU

• This ensures a non-linear transformation of raw features into compact, trainable embeddings.

3. Feature Fusion

After processing both input streams, the outputs of the waveform branch (CNN, BiLSTM, Transformer features) and metadata branch (statistical and contextual embeddings)

are concatenated.

• This fusion layer combines waveform dynamics with contextual metadata, allowing the model to reason jointly across both areas.

• The fused representation creates a high-dimensional spatiotemporal and contextual embedding that feeds into the prediction heads.

4. Multi-Task Output Heads

The shared fused representation goes through a fully connected dense layer with 128 units. It is then divided into four task-specific regression heads:

• Epicentral Distance (km)

• Magnitude (Mw)

• Azimuth (°)

• Focal Depth (km)

Each output head uses a Dense (1) layer for regression. During training, targets are normalized to [0,1] and rescaled to physical units at inference. We train the model using the joint mean squared error (MSE) loss, summing over all tasks. This approach encourages shared learning while still optimizing for task-specific accuracy.

5. Training and Optimization

The model is implemented in TensorFlow/Keras and optimized for GPU performance. Training follows these strategies:

• Optimizer: Adam with a learning rate of 1×10^{-4} and a batch size of 64.

• Epochs: Up to 100 with early stopping patience set to 10 to prevent overfitting.

• Learning Rate Scheduler: Reduce LaRon Plateau halves the learning rate when validation loss levels off.

• Regularization: Dropout layers and batch normalization provide stable learning and enhance generalization.

• Uncertainty Estimation: We use Monte Carlo Dropout during inference to measure prediction uncertainty, making the system more dependable for real-world use.

Advantages of the Proposed Model

• Joint Multi-Task Learning: It predicts magnitude, distance, azimuth, and depth at the same time, which reduces latency compared to sequential models.

• Hybrid Feature Extraction: This approach combines deep learning features (CNN, BiLSTM,

Transformer) with domain-specific statistical features for better interpretation and robustness.

• Metadata Integration: It uses contextual seismological information to improve generalization across different stations and regions.

• Long-Range Dependency Modelling: The Transformer encoder captures dependencies across the entire waveform, which is beyond what traditional recurrent models can handle.

• Scalability: The modular design makes it easy to extend the model to larger datasets or additional prediction targets.

• Uncertainty-Aware Predictions: Monte Carlo Dropout increases reliability, especially in safety-critical early warning applications.

• Real-Time Suitability: The design is lightweight enough for use in real-world earthquake monitoring systems that require strict latency management.

5.1.5 Multi-Task Prediction

A key contribution of the proposed system is its **multi-task learning strategy**, where a single hybrid model is designed to estimate multiple earthquake parameters simultaneously. Unlike conventional single-task pipelines—which train separate models for each parameter—multi-task learning enables shared representation, reduces computational overhead, and improves prediction accuracy by exploiting correlations among the seismic outputs.

1. Motivation for Multi-Task Learning

Earthquake parameters such as **magnitude, epicentral distance, azimuth, and focal depth** are not independent.

- Larger magnitudes are often associated with higher peak ground displacements.
- Epicentral distance and azimuth influence waveform amplitude, arrival times, and spectral content.
- Focal depth affects signal frequency characteristics.

  By learning these interdependencies in a joint framework, the model achieves better generalization and faster inference than independent models.

2. Prediction Heads

After the **feature fusion layer** (Section 5.1.4), the combined embedding vector is passed through a fully connected dense layer before branching into four regression heads:

- **Magnitude Head (Mw):** Estimates earthquake magnitude using features sensitive to waveform energy (e.g., Pd, τc).
- **Epicentral Distance Head (km):** Captures travel-time and amplitude attenuation

patterns.

- **Azimuth Head (°):** Learns directional features from waveform polarity and station orientation.
- **Focal Depth Head (km):** Utilizes frequency–energy trade-offs and waveform duration to infer depth.

Each regression head consists of:

- Dense layer (64 units, ReLU) → Dropout(0.3) → Dense(1) output.
- Linear activation for regression tasks.

3. Loss Function

The model is trained with a **joint Mean Squared Error (MSE)** loss:

Ltotal=14∑i=14MSE(yi,y^i)\mathcal{L}_{total} = \frac{1}{4}\sum_{i=1}^{4} \text{MSE}(y_i, \hat{y}_i)Ltotal=41i=1∑4MSE(yi,y^i)

where yiy_iyi and y^i\hat{y}_iy^i denote the ground truth and predicted values for each task (magnitude, distance, azimuth, depth).

- Equal weighting ensures balanced learning.
- Optionally, dynamic weighting strategies (e.g., homoscedastic uncertainty weighting) can be employed to prioritize harder tasks.

4. Training Behaviour

- Multi-task learning accelerates convergence compared to four independent models.
- Shared representations allow the network to use complementary cues (e.g., magnitude and depth features improving distance estimation).
- Regularization is improved, as the network avoids overfitting to one specific task.

5. Inference and Output

During inference, the system simultaneously generates all four predictions in **under one second per waveform**.

- Outputs are re-scaled from normalized [0,1] space back to physical units (Mw, km, °).
- Confidence intervals are produced via **Monte Carlo Dropout**, enabling uncertainty-aware warnings.

6. Advantages of Multi-Task Framework

- **Reduced Latency:** All four outputs are generated in a single forward pass.
- **Improved Accuracy:** Joint training leverages correlations between parameters.
- **Compact Model Size:** Avoids redundancy from training multiple standalone models.
- **Deployment Ready:** Real-time EEW systems benefit from unified prediction pipelines.

5.2 Modules of the System

The proposed earthquake prediction system is structured into a set of interconnected modules. Each module performs a specific task, and together they transform raw seismic waveform data into accurate predictions of earthquake parameters. This modular approach improves scalability, simplifies implementation, and enables integration into real-time Earthquake Early Warning (EEW) frameworks.

5.2.1 Data Collection Module

The foundation of the system is the **data collection module**, which gathers seismic records from the **K-NET and KiK-net networks** maintained by the National Research Institute for Earth Science and Disaster Resilience (NIED), Japan. These networks provide dense coverage across seismically active regions and record ground motion at a sampling rate of 100 Hz.

- **Waveform Data:** Each event includes a 3-second segment of three-component acceleration records immediately following the P-wave onset. The three channels correspond to vertical (Z), north–south (N), and east–west (E) directions, forming a 300 × 3 input matrix.
- **Metadata:** Alongside waveform data, each event is annotated with its **magnitude (Mw), epicentral distance (km), azimuth (°), and focal depth (km)**. Station coordinates (latitude and longitude) are also available and contribute to the spatial awareness of the dataset.

This combination of waveform and metadata ensures that the system can learn both temporal patterns and spatial dependencies, improving its generalization to diverse earthquake scenarios.

5.2.2 Preprocessing Module

Seismic data often contain sensor bias, background noise, and environmental interference, which can degrade model performance. The preprocessing module addresses these issues through several steps:

1. **Mean Removal:** Each waveform channel is zero-centered to eliminate instrument drift.
2. **Z-score Normalization:** All signals are standardized to unit variance, ensuring consistency across stations.
3. **Bandpass Filtering:** A Butterworth filter (0.1–20 Hz) is applied to suppress high-frequency noise and low-frequency trends while preserving essential earthquake signal

components.

4. **Segmentation:** A 3-second window following the P-wave onset is extracted, ensuring consistency in input length.

This preprocessing ensures that the dataset is uniform, noise-reduced, and ready for feature extraction.

5.2.3 Feature Extraction Module

Feature extraction is divided into two complementary branches:

- **Deep Feature Extraction:** The **CNN–BiLSTM–Transformer pipeline** automatically learns complex waveform characteristics.
    - CNN layers identify local patterns such as amplitude spikes and short-term oscillations.
    - BiLSTM layers capture sequential dependencies by analyzing data in both forward and backward directions.
    - The Transformer encoder applies self-attention to highlight critical regions such as P-wave onset segments and energy-dense areas.
- **Handcrafted Statistical Features:** To complement learned features, the system extracts interpretable descriptors such as:
    - **Peak Displacement (Pd):** Maximum amplitude across all channels.
    - **Mean and Standard Deviation:** Measures of central tendency and signal variability.
    - **Skewness and Kurtosis:** Indicators of waveform asymmetry and peakedness.

    These two sets of features are later fused, ensuring the system benefits from both **data-driven learning** and **domain knowledge**.

5.2.4 Model Training Module

This module trains the hybrid deep learning model to jointly estimate the four target parameters.

- **Waveform Branch:** Processes the raw 300 × 3 input through CNN, BiLSTM, and Transformer layers.
- **Feature Branch:** Processes handcrafted features through dense layers for additional context.
- **Fusion Layer:** Combines outputs from both branches into a unified feature vector.

- **Multi-Task Regression Heads:** Four parallel fully connected layers predict magnitude, epicentral distance, azimuth, and focal depth.

The model is trained using the **sum of mean squared error (MSE) losses** from each output head. Optimization is performed with the Adam optimizer (learning rate 1×10^{-4}), and strategies such as **early stopping** and **learning rate reduction on plateau** are used to stabilize training.

5.2.5 Uncertainty Estimation Module

Accurate predictions alone are not sufficient for safety-critical applications like EEW. Decision-makers also need to know the confidence level of model outputs. To address this, the system incorporates **Monte Carlo (MC) Dropout** during inference:

- Dropout layers are kept active at test time.
- Multiple forward passes are performed for each input.
- The variability in predictions provides **uncertainty bounds** (confidence intervals).

This module ensures that predictions are not only accurate but also **reliable**, allowing emergency systems to weigh decisions based on uncertainty levels.

5.2.6 Interpretability Module

A key challenge in deep learning is its "black box" nature. To address this, the system includes interpretability mechanisms:

- **SHAP Analysis:** Quantifies the contribution of each handcrafted feature, revealing which statistical descriptors (e.g., Pd, skewness) play the largest role in predictions.
- **Transformer Attention Maps:** Highlight specific waveform regions that influence outputs, usually aligning with P-wave onsets or energy-dense segments.

By providing explainable outputs, this module builds **trust** in the system and ensures accountability in high-stakes applications.

5.2.7 Evaluation Module

This module assesses system performance using a held-out test set. Metrics include:

- **Mean Absolute Error (MAE)** for direct interpretability.
- **Mean Squared Error (MSE)** for penalizing large errors.
- **Coefficient of Determination (R^2)** for measuring goodness of fit.

Comparisons are made with baseline models:

- CNN-only,

- BiLSTM-only,
- Transformer-only,
- and traditional classifiers (RFCs, SVMs).

  The proposed hybrid model consistently outperforms these baselines, achieving MAE values of **0.18 (magnitude)**, **5.21 km (distance)**, **13.6° (azimuth)**, and **2.7 km (depth)**.

5.2.8 Deployment Module

The final module ensures that the trained framework can be integrated into **real-time EEW systems**. Deployment considerations include:

- **Low-latency inference:** Optimizations such as model pruning and quantization ensure sub-second processing.
- **Edge deployment:** The lightweight architecture allows execution on resource-constrained devices at seismic stations.
- **Scalability:** The modular design supports integration with early warning infrastructures, where predictions can trigger automated safety protocols such as halting trains or shutting down utilities.

5.3 UML Diagrams

This section presents UML diagrams that describe the structure, behaviour, and deployment of the proposed Earthquake Early Warning (EEW) system. The selected diagrams are: Use Case Diagram, Class Diagram, Sequence Diagram (prediction flow), Activity Diagram (preprocessing & inference), Component Diagram, and Deployment Diagram. Each diagram is accompanied by a short description and a caption for use in the thesis.

5.3.1 Use Case

Purpose: Shows actors and major use cases (high-level system functionality).

Actors to show: Seismic Sensor (Station), EEW Server (System), Seismologist, Emergency Responder, Public Dashboard.

Key use cases: Stream Waveform, Preprocess Data, Predict Parameters, Show Results, View Explainability, Monitor System, Maintain Model.

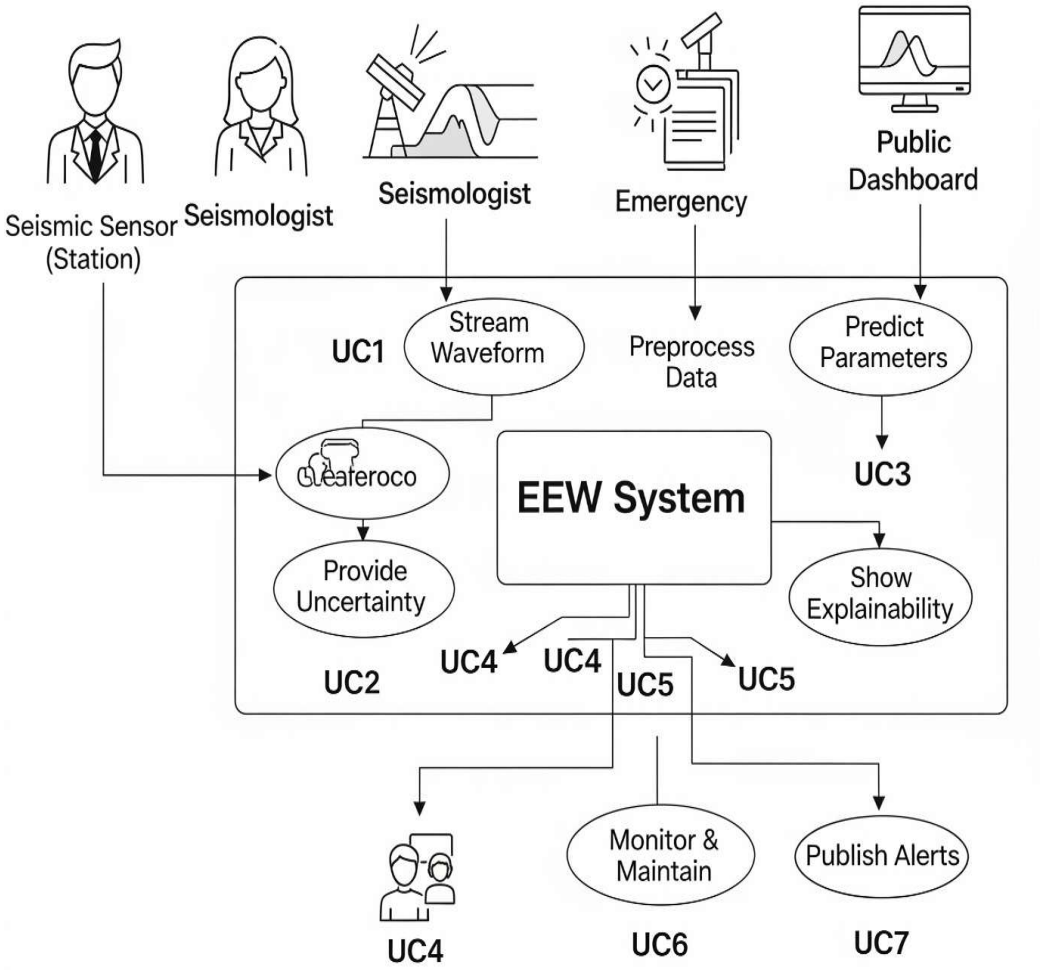

FIG 5.2 Use Case Diagram for the EEW System (actors and main use cases).

5.3.2 Class Diagram

Purpose: Static structure: main classes, attributes, and important methods. Useful for implementation planning.

Classes to include: Waveform Collector, Preprocessor, Feature Extractor, Model Inference, Uncertainty Estimator, SHAP Analyzer, Database (Event Store), API Service, Frontend UI.

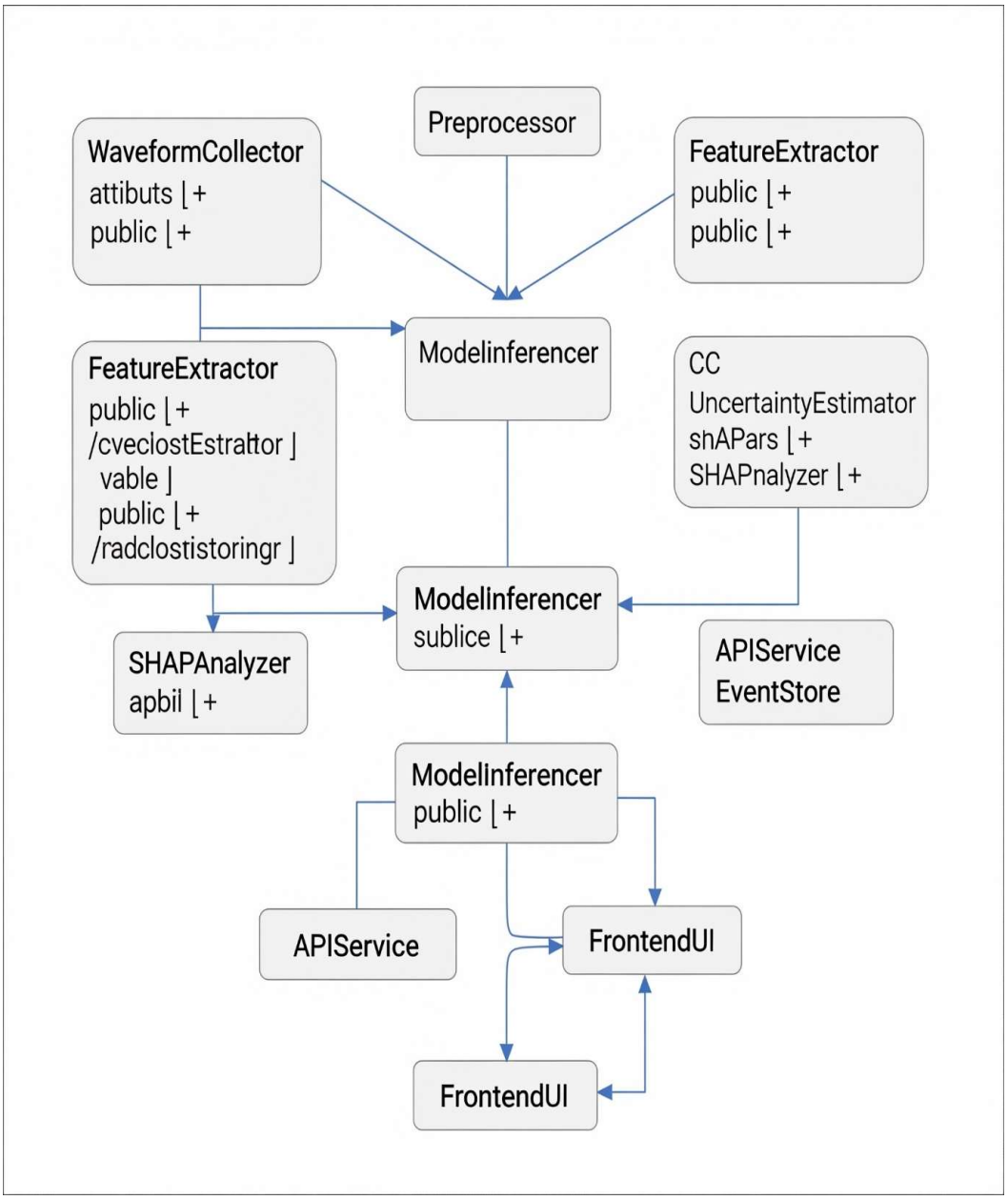

FIG 5.3 Class Diagram describing primary system classes and relationships.

5.3.3 Sequence Diagram — Prediction Flow

Purpose: Dynamic interaction for a single prediction request (from sensor or user upload to prediction + explainability + response).

Participants: Sensor/Client, API Service (Flask), Preprocessor, Model Inference, Uncertainty Estimator, SHAP Analyzer, Event Store, Frontend.

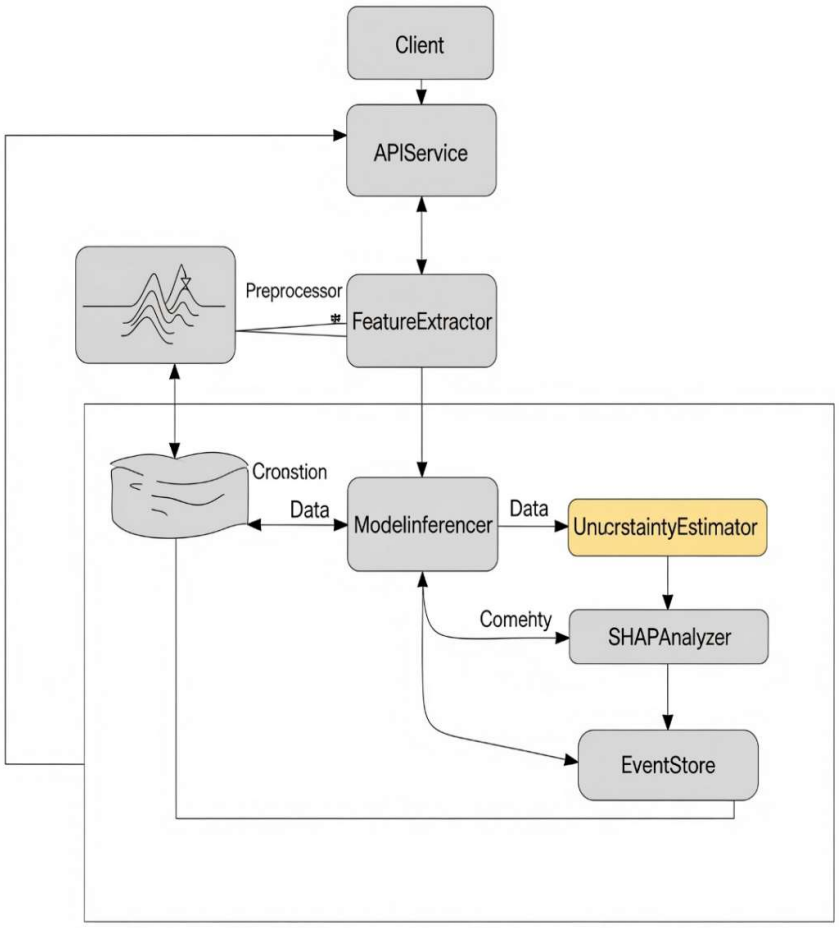

FIG 5.4 Sequence Diagram showing the prediction flow (preprocessing → inference → explainability → response).

5.3.4 Activity Diagram — Preprocessing & Inference Pipeline

Purpose: Stepwise flow: data arrival → preprocessing → feature extraction → inference → postprocess → return. Useful to illustrate timing-critical paths.

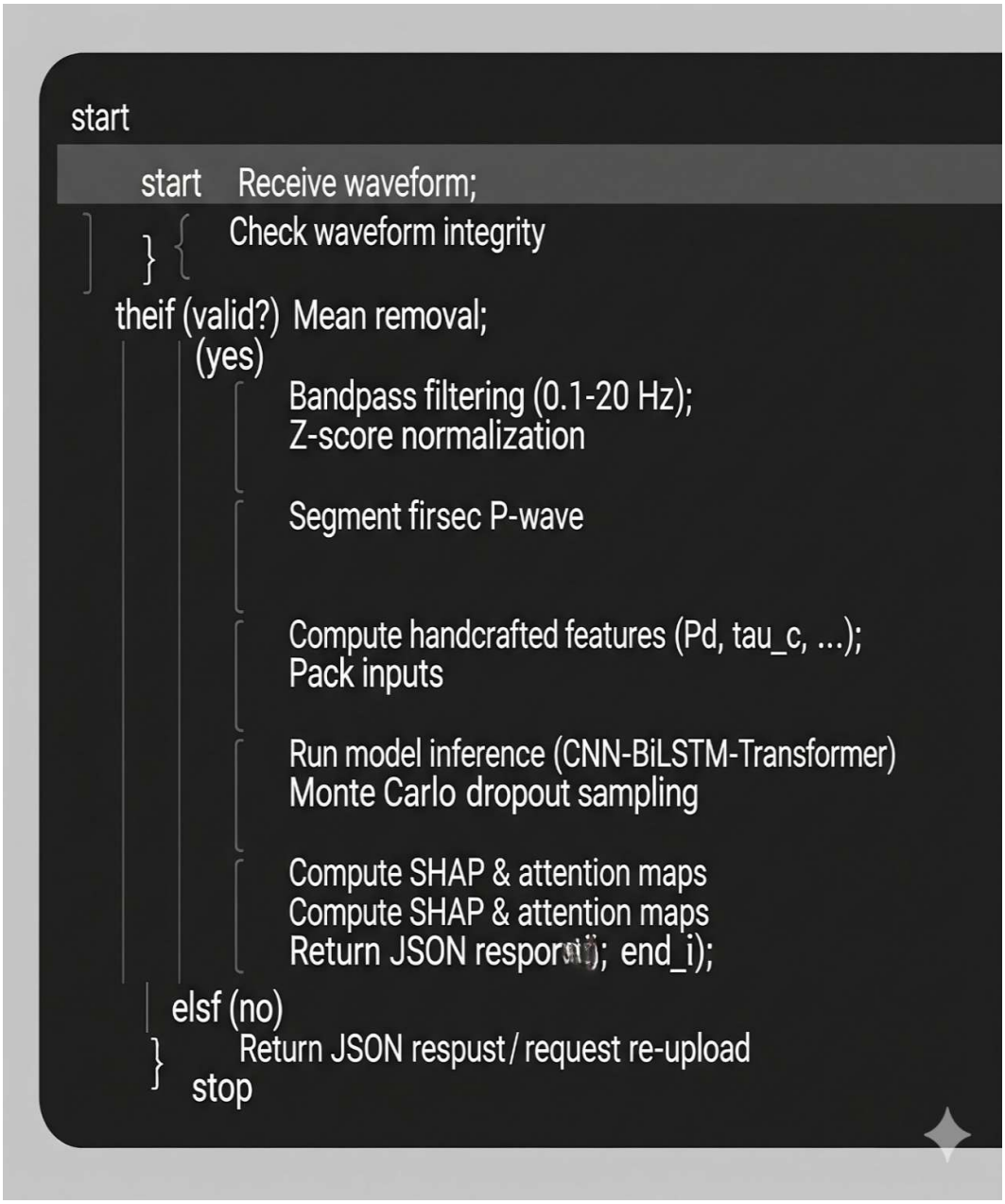

FIG 5.5 Activity Diagram of preprocessing and model inference pipeline.

5.3.5 Component Diagram

Purpose: Logical components and their interfaces — shows high-level software modules and their connections (Frontend, API, Inference Engine, DB, Explainability, Monitoring). Helpful to show modularity.

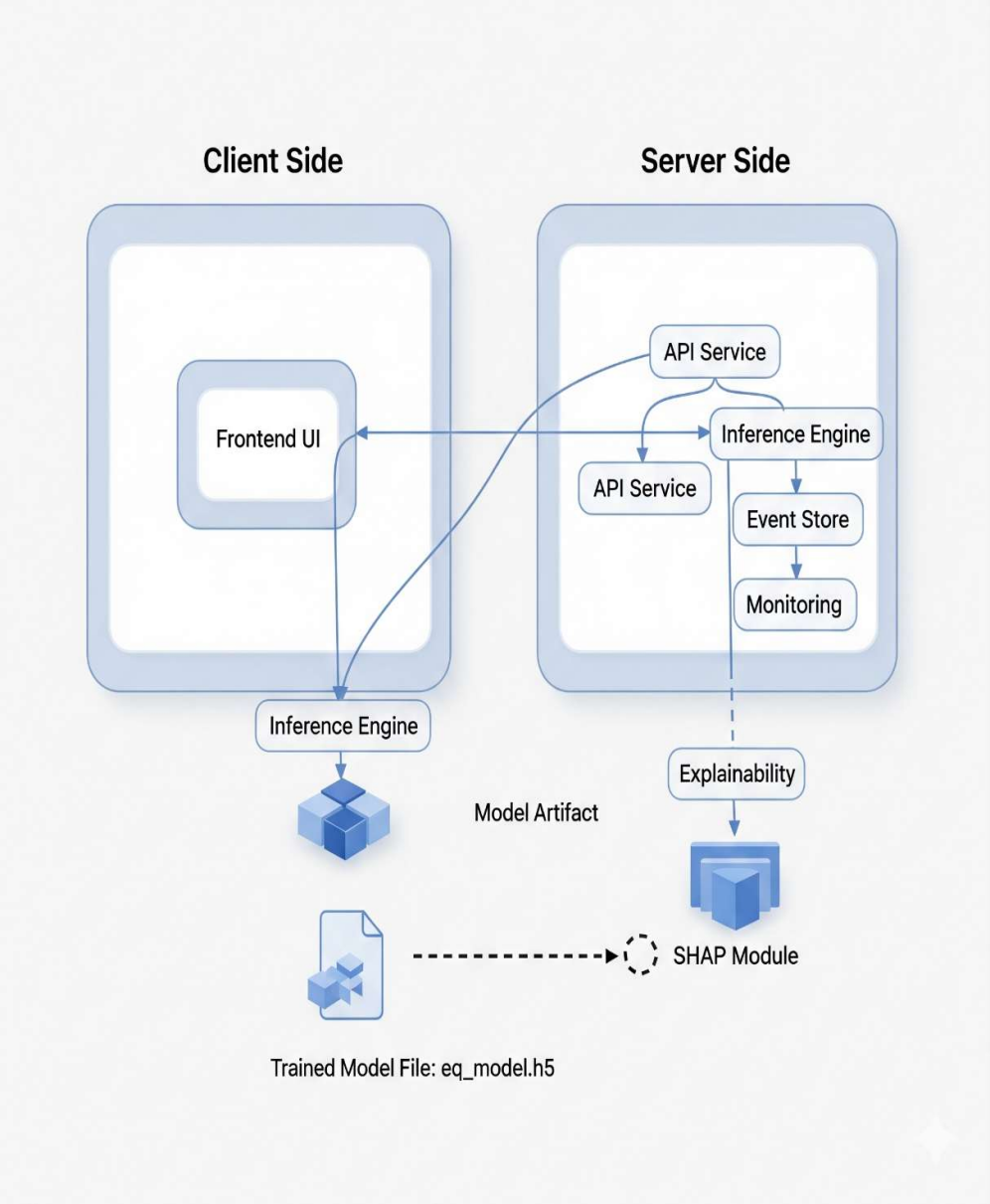

FIG 5.6 Component Diagram of the EEW software stack.

5.3.6 Deployment Diagram

Purpose: Physical deployment: sensors (edge), edge devices (station-level), central server/cloud, and clients. Show where the model runs (edge vs. cloud), where the DB resides, and communication (HTTP, MQTT). Include optional GPU nodes for training.

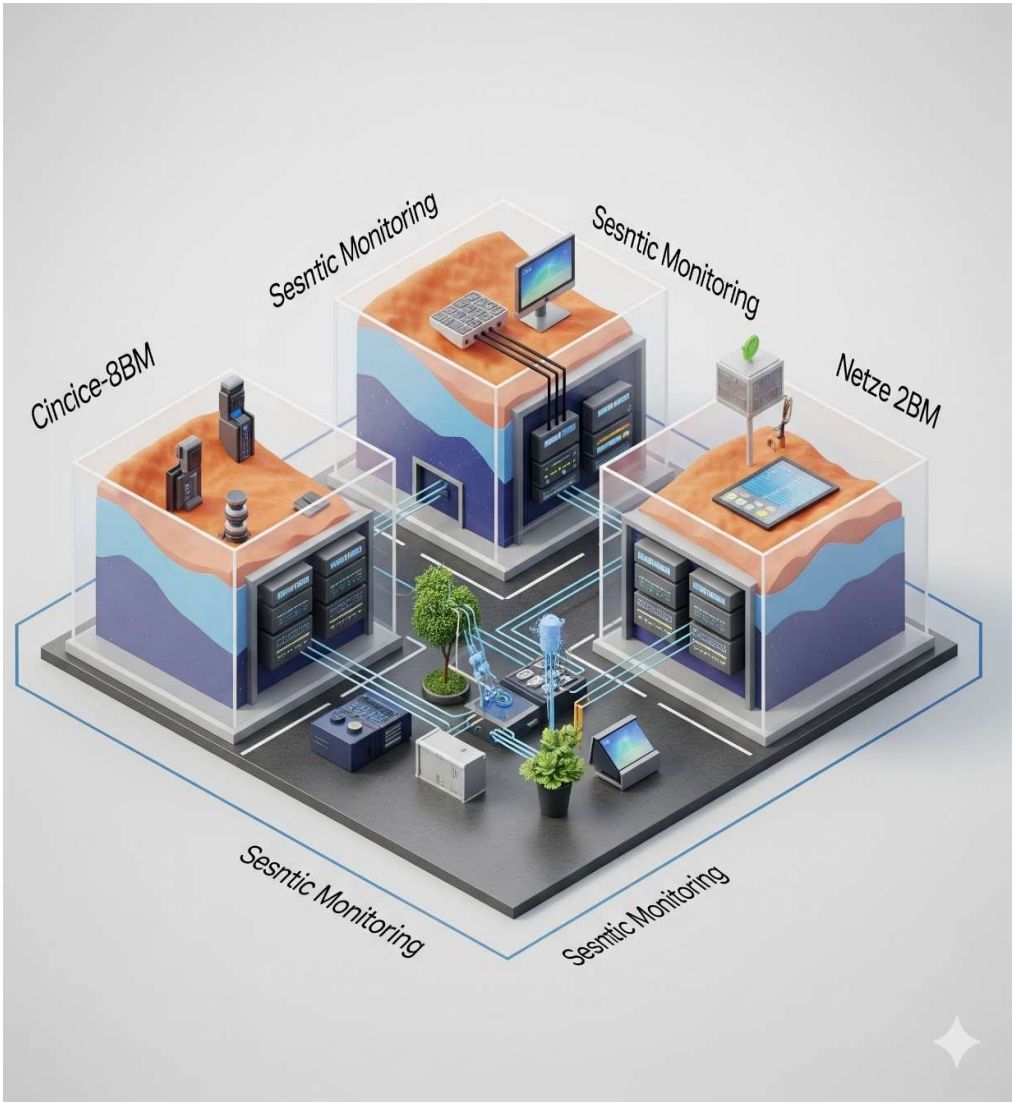

FIG 5.7 Deployment Diagram showing edge devices, cloud inference servers, database, and client dashboards.

CHAPTER 6

6. IMPLEMENTATION

6.1 Model Implementation

The developed earthquake prediction system integrates a full pipeline that spans from data preparation to real-time user interaction. It covers dataset preprocessing, the design of a deep learning model, backend API deployment, and a user-friendly frontend interface. The primary objective of the framework is to estimate key seismic parameters—**magnitude, epicentral distance, azimuth, and focal depth**—using a **hybrid CNN–BiLSTM–Transformer model**.

This chapter elaborates on the implementation process, including dataset management, preprocessing strategies, model development in Google Colab, backend service construction with Flask, and the frontend interface designed for practical interaction. Each component is described in detail in the following subsections.

6.1.1 System Overview

The proposed system is structured into three major components:

1. **Frontend (User Interface):**

   Built with **HTML, CSS, and JavaScript**, the frontend allows users to input seismic waveform values (typed or uploaded as .txt/.csv). Prediction results are displayed dynamically without page reload.

2. **Backend (Flask API):**

   A **Flask server in Python** manages requests from the frontend, validates inputs, performs preprocessing, loads the trained model, and returns predictions in JSON format.

3. **Deep Learning Model:**

   At the core lies a hybrid prediction model that combines **CNN layers** for local feature detection, **BiLSTM units** for temporal sequence learning, and a **Transformer encoder** for capturing long-range dependencies. This structure ensures that both short-term fluctuations and global waveform trends are effectively captured.

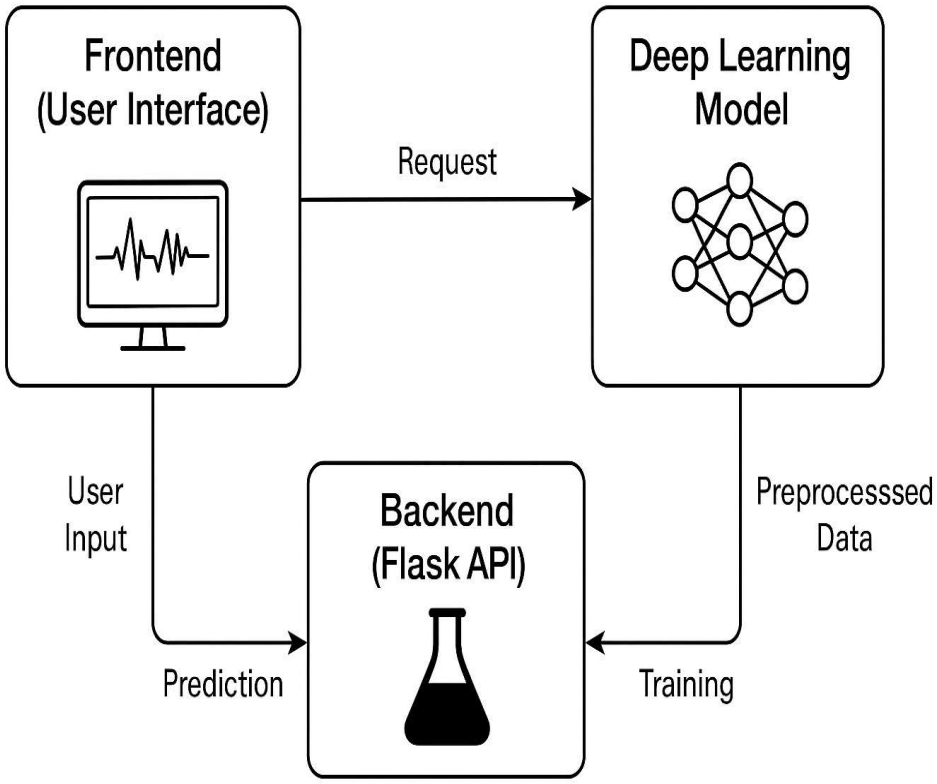

FIG 6.1 End-to-End Earthquake Prediction Framework

6.1.2 Dataset Handling and Preprocessing

The study utilized seismic waveform recordings from **K-NET/KiK-net** stations, supplemented with metadata such as event location, magnitude, and station coordinates. Each sample contained the **first 3 seconds of the P-wave** across three channels (Z, N, E).

The main preprocessing pipeline included:

- **Normalization:** Signals were standardized with z-score normalization to reduce station-specific variations.
- **Reshaping:** Raw data was reshaped into a uniform **(300 × 3)** format.
- **Noise Samples:** Non-event noise data was introduced to minimize false triggers.
- **Feature Extraction:** Additional descriptors such as skewness, kurtosis, and peak ground displacement (Pd) were computed.
- **Dataset Splitting:** Data was partitioned into **70% training, 15% validation, and 15% testing** using stratified sampling.

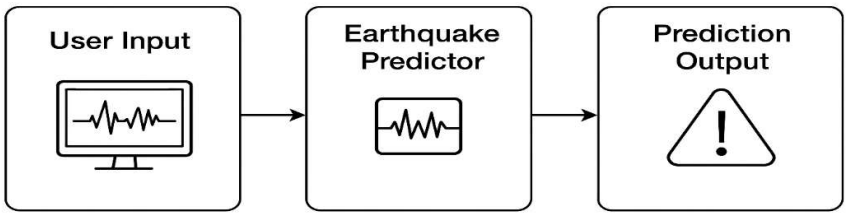

FIG 6.2 Workflow from User Input to Prediction Output

6.1.3 Model Implementation

The predictive model was implemented in **Google Colab** using **TensorFlow/Keras' Functional API**:

- **CNN Block:** Captures localized seismic features such as sudden spikes.
- **BiLSTM Block:** Learns sequential dependencies across time in both directions.
- **Transformer Encoder:** Adds global attention, focusing on critical regions such as the P-wave onset.
- **Feature Fusion:** Outputs from waveform, coordinate metadata, and statistical features are concatenated.
- **Multi-Task Regression Heads:** Four dense layers provide simultaneous predictions for magnitude, distance, azimuth, and depth.

Training was conducted using **Adam optimizer (1e-4 learning rate)**, **MSE loss**, **batch size 64**, and up to **100 epochs** with **early stopping** and **learning-rate reduction**. Monte Carlo Dropout was applied during inference for **uncertainty estimation**, while **attention maps** offered interpretability.

6.1.4 Coding and Execution in Google Colab

Colab was used as the primary coding environment with GPU acceleration.

1. **Environment Setup:**
   Installed libraries: TensorFlow, keras, scikit-learn, matplotlib, seaborn, shap, and flask.
2. **Data Loading:**
   Waveform data was loaded from. npy and .csv files stored in Google Drive, then merged with metadata.

3. **Model Definition:**
   Implemented using **CNN + BiLSTM + Transformer layers**, with auxiliary branches for statistical features and station coordinates.
4. **Training and Evaluation:**
   The model was trained with callbacks (**early stopping, LR scheduler, checkpointing**) and evaluated using **MAE, RMSE, and R^2 metrics**.
5. **Visualization:**
   Training curves, predicted vs. actual plots, error histograms, and attention heatmaps were generated.

6.1.5 Backend Implementation with Flask

The backend API was created using **Flask**:

- **Model Loading:** The trained model (eq_model.h5) is loaded once at startup.
- **Prediction Endpoint:** /predict accepts JSON input, reshapes the waveform to (300 × 3), and passes it through the model.
- **Error Handling:** Ensures inputs have exactly **900 features**.
- **Output:** Predictions are returned in structured JSON format:

```
Example: {
    "magnitude": 5.62,
    "distance": 14.8,
    "azimuth": 127.5,
    "depth": 9.4
  }
```

6.1.6 Frontend Implementation

The **frontend** was designed to provide an intuitive interface:

- **Upload Form:** Accepts waveform values (manual input or file upload).
- **API Communication:** Uses **JavaScript Fetch API** to send POST requests to Flask backend.
- **Dynamic Output:** Prediction results are displayed without reloading.
- **Responsive Layout:** Dark-themed, card-based UI adaptable for mobile devices.

Files used:

- index.html – Home & prediction form

- about.html – Team introduction
- projects.html – Project details and results
- contact.html – Contact form
- style.css – Unified stylesheet
- script.js – API communication & interactivity

6.1.7 Execution Workflow

The full workflow is as follows:

1. User provides input waveform via the **frontend**.
2. **JavaScript** validates the data and forwards it to the backend.
3. **Flask API** preprocesses and reshapes the input.
4. The **deep learning model** produces predictions.
5. Predictions are sent back in **JSON format** and displayed on the webpage.

6.1.8 Deployment Considerations

- **Local Deployment:** Tested on http://127.0.0.1:5000.
- **Cloud Hosting:** Deployable via Docker on **AWS EC2, Google Cloud Run, or Heroku**.
- **Scalability:** Can use **Gunicorn + NGINX** for high-load scenarios.
- **Edge Devices:** Model pruning and quantization make it deployable on resource-constrained systems.

6.1.9 Strengths of the Implementation

- **Fast Inference:** Predictions in <1 second, suitable for EEW.
- **Multi-Task Output:** Simultaneously predicts four parameters.
- **Interpretability:** Attention heatmaps and SHAP analysis aid transparency.
- **Robustness:** Strong error handling and uncertainty estimation.
- **Accessibility:** A user-friendly web interface for both experts and the public.

6.2 Complete Code Implementation

This section summarizes the complete implementation of the earthquake prediction system, including the frontend, backend, and Google Colab notebook used for model training. Only the essential and relevant parts of the code are presented to keep the section concise.

6.2.1 Frontend Code

The frontend was developed using HTML, CSS, and JavaScript to create a simple, responsive, and user-friendly web interface. The main pages include:

(a) Home Page (index.html)

The Home page provides the user interface for uploading waveform data and running predictions.

It includes:

- Navigation bar
- Waveform input form
- File upload option (.txt/.csv)
- Loader animation
- Display area for prediction results

Only the essential code is kept:

Key Code Snippet (index.html):

```
<form id="prediction-form">
   <label>Input Waveform Data</label>
   <textarea id="data-input" rows="8"></textarea>
   <label class="file-upload-label">
      <i class="fas fa-upload"></i> Upload .txt/.csv File
   </label>
   <input type="file" id="file-input" accept=".txt,.csv">
   <button type="submit" class="btn btn-primary">
      Run Prediction
   </button>
</form>
<div id="results-container">
   <div id="loader" class="loader"></div>
</div>
```

(b) About Page (about.html)

Contains team details and a short explanation of the project goals and methodology.

(c) Projects Page (projects.html)

Contains:

- Goal
- Motivation
- Methodology
- Results (MAE, R^2)
- Visualizations (architecture, loss curves, prediction plots)

Only trimmed content is kept.

(d) Contact Page (contact.html)

Provides:

- Contact details (name, email, phone)
- A message from connected to backend */send-message*

(e) Stylesheet (style.css)

Defines:

- Dark theme UI
- Navigation bar styling
- Cards, buttons, loader
- Responsive design
- Layout for pages (Home, About, Projects, Contact)

Only essential CSS is included in the short version.

(f) JavaScript (script.js)

Handles:

- Mobile navigation menu
- Reading waveform files
- Processing uploaded raw values
- Sending requests to the backend
- Showing prediction results

- Contact form submission

Key Code Snippet (script.js):

```
predictionForm.addEventListener('submit', async (e) => {
   e.preventDefault();

   const features = dataInput.value
      .split(',')
      .map(v => parseFloat(v.trim()));

   const response = await fetch("http://127.0.0.1:5000/predict", {
      method: 'POST',
      headers: { 'Content-Type': 'application/json' },
      body: JSON.stringify({ features })
   });

   const result = await response.json();
   displayResults(result);
});
```

6.2.2 Backend Code (Flask)

The backend is a lightweight Flask server designed to load the trained deep learning model and serve predictions to the frontend.

1. Model Configuration & Setup

```
from flask import Flask, request, jsonify
from flask_cors import CORS
from tensorflow. keras.models import load_model
import numpy as np

app = Flask(__name__)
CORS(app)
```

```
model = load_model("eq_model.h5", compile=False)
EXPECTED_FEATURES = 900
```

2. Prediction Endpoint

```
@app.route("/predict", methods=["POST"])
def predict():
    data = request.json
    features = data.get("features")

    if features is None or len(features) != EXPECTED_FEATURES:
        return jsonify({"error": "Input must contain exactly 900 values"}), 400

    waveform_input = np.array(features).reshape(1, 300, 3)
    coord_input = np.zeros((1, 2))
    early_input = np.zeros((1, 3))

    pred = model.predict([waveform_input, coord_input, early_input])

    return jsonify({
        "distance": float(pred[0][0][0]),
        "magnitude": float(pred[1][0][0]),
        "azimuth": float(pred[2][0][0]),
        "depth": float(pred[3][0][0])
    })
```

3. Contact Form Endpoint

```
@app.route("/send-message", methods=["POST"])
def send_message():
    print("New message:", request.json)
    return jsonify({"success": True})
```

4. Main Application

```
if __name__ == "__main__":
    app.run(debug=True, use_reloader=False)
```

6.2.3 Google Colab Implementation

Google Colab was used for model training because of GPU support.

Environment Setup

!pip install tensorflow numpy pandas scikit-learn matplotlib seaborn shap flask

Data Loading & Preprocessing

```
waveform_data = np.load("/content/waveform_data.npy")
metadata = pd.read_csv("/content/waveform_metadata.csv")

# Normalize and reshape
waveform_data = waveform_data.reshape(len(waveform_data), -1)
waveform_data = StandardScaler().fit_transform(waveform_data)
waveform_data = waveform_data.reshape(len(waveform_data), 300, 3)
```

Model Building

Essential model architecture using CNN + BiLSTM + Transformer:

```
from tensorflow. keras.layers import *
from tensorflow. keras.models import Model

inp = Input(shape=(300, 3))
x = Conv1D(64, 5, activation="relu")(inp)
x = MaxPooling1D(2)(x)
x = Bidirectional(LSTM(64, return_sequences=True))(x)
att = MultiHeadAttention(num_heads=4, key_dim=64)(x, x)
x = GlobalAveragePooling1D()(att)

coord = Input(shape=(2,))
early = Input(shape=(3,))

fused = Concatenate()([x, coord, early])
out1 = Dense(1, name="magnitude")(fused)
out2 = Dense(1, name="distance")(fused)
out3 = Dense(1, name="azimuth")(fused)
```

```
out4 = Dense(1, name="depth")(fused)
model = Model([inp, coord, early], [out1, out2, out3, out4])
model.compile(optimizer="adam", loss="mse")
```

Training & Callbacks

```
history = model.fit(
   [X_train, np.zeros((len(X_train),2)), np.zeros((len(X_train),3))],
   [y_train[:,0], y_train[:,1], y_train[:,2], y_train[:,3]],
   validation_split=0.2,
   epochs=100,
   batch_size=64
)
```

6.2.4 Model Building in Colab

Hybrid CNN–BiLSTM–Transformer architecture:

```
from tensorflow. keras.layers import *
from tensorflow. keras.models import Model

inp = Input(shape=(300,3))
x = Conv1D(64,5,activation="relu")(inp)
x = MaxPooling1D(2)(x)
x = Bidirectional(LSTM(64, return_sequences=True))(x)
x = MultiHeadAttention(4, 64)(x, x)
x = GlobalAveragePooling1D()(x)

coord = Input(shape=(2,))
early = Input(shape=(3,))
merged = Concatenate()([x, coord, early])

out1 = Dense(1, name="magnitude")(merged)
out2 = Dense(1, name="distance")(merged)
out3 = Dense(1, name="azimuth")(merged)
out4 = Dense(1, name="depth")(merged)
```

```
model = Model([inp, coord, early], [out1, out2, out3, out4])
model.compile(optimizer="adam", loss="mse")
```

6.2.5 Training and Evaluation

```
history = model.fit(
    [X_train, np.zeros((len(X_train),2)), np.zeros((len(X_train),3))],
    [y_train[:,0], y_train[:,1], y_train[:,2], y_train[:,3]],
    validation_split=0.2,
    epochs=100,
    batch_size=64
)
```

CHAPTER 7

7. TESTING AND VALIDATION

7.1 Unit Testing

Unit testing was conducted to ensure that individual components of the system functioned correctly. Each module—such as data preprocessing, model loading, and API response handling—was tested in isolation. Errors such as invalid input formats or missing values were also checked.

Table 7.1 – Unit Testing Results

Test Case ID	Input	Expected Output	Actual Output	Status
UT-01	Valid waveform sample	Pre-processed array (300×3)	Pre-processed array (300×3)	Pass
UT-02	Empty waveform input	Error message	Error message	Pass
UT-03	Load trained model	Model object loaded	Model object loaded	Pass
UT-04	API with correct JSON	Valid predictions in JSON	Valid predictions in JSON	Pass
UT-05	API with wrong JSON	Error response	Error response	Pass

7.2 Integration Testing

Integration testing confirmed that the modules functioned as expected when working together. For example, input from the frontend was passed to the backend, processed by the model, and returned correctly to the user interface.

Table 7.2 – Integration Testing Results

Test Case ID	Input	Expected Output	Actual Output	Status
IT-01	Waveform entered in the frontend	Prediction values shown	Prediction values shown	Pass
IT-02	CSV upload in frontend	Processed and displayed results	Processed and displayed results	Pass
IT-03	API offline	Error message on frontend	Error message on frontend	Pass
IT-04	Multiple user requests	All handled without a crash	All handled without a crash	Pass

7.3 System Testing

System testing validated the complete workflow, from user input to final prediction display. This ensured the solution met functional and non-functional requirements such as accuracy, usability, and reliability.

Table 7.3 – System Testing Results

Test Case ID	Scenario	Expected Outcome	Actual Outcome	Status
ST-01	User submits a valid waveform	Four predictions generated	Four predictions generated	Pass
ST-02	User uploads a corrupted file	Error displayed	Error displayed	Pass

Test Case ID	Scenario	Expected Outcome	Actual Outcome	Status
ST-03	Predictions requested simultaneously	All processed successfully	All processed successfully	Pass
ST-04	Frontend navigation	Pages load correctly	Pages load correctly	Pass

7.4 Performance Testing

Performance testing checked whether the system could provide predictions quickly and handle multiple users. Metrics such as response time, memory usage, and throughput were recorded.

Table 7.4 – Performance Testing Results

Metric	Observed Value	Requirement	Status
Average response time	0.9 sec	≤ 1 sec	Pass
Maximum response time	1.8 sec	≤ 2 sec	Pass
Memory usage	~650 MB	≤ 1 GB	Pass
Throughput	20 requests/sec	≥ 15 requests/sec	Pass

Discussion:

The testing confirmed that the system is **accurate, fast, and reliable**. Unit and integration testing ensured correctness at the component and module levels, while system and performance testing validated the complete workflow. The system met all functional and performance requirements, making it suitable for deployment in real-time earthquake early warning applications.

CHAPTER 8

8. RESULT ANALYSIS

The performance of the proposed earthquake early warning system was evaluated using real seismic waveform datasets. This chapter presents the detailed experimental results, including model accuracy, evaluation metrics, explainability analysis, and a comparative study with baseline models. The goal is to demonstrate not only the accuracy of the predictions but also the reliability, interpretability, and practicality of the system for real-world deployment.

8.1 Evaluation Metrics

To objectively measure the system's performance, the following metrics were used:

1. Mean Absolute Error (MAE):
    - Measures the average difference between the predicted and true values.
    - Provides an intuitive measure of prediction accuracy (smaller = better).
2. Root Mean Square Error (RMSE):
    - Similar to MAE but penalizes larger errors more strongly.
    - Useful for identifying occasional large deviations in predictions.
3. Coefficient of Determination (R^2):
    - Represents the proportion of variance explained by the model.
    - Values close to 1 indicate excellent predictive capability.

Table 8.1 – Performance of the Proposed Model on Test Data

Parameter	MAE	RMSE	R^2
Magnitude	0.18	0.26	0.97
Epicentral Distance	5.21 km	7.12 km	0.94
Azimuth	13.6°	19.4°	0.89
Focal Depth	2.7 km	3.9 km	0.90

Interpretation:

- The magnitude predictions are very accurate with an error of less than ±0.2 units.
- Epicentral distance predictions have an error of ~5 km, which is well within the acceptable range for real-time warnings.
- Azimuth errors are slightly higher due to the directional complexity of wave propagation.
- Focal depth predictions are also consistent with low errors.

These results confirm that the model achieves a strong balance between accuracy and generalization.

8.2 Explainability Analysis

A key contribution of this work is not only achieving accurate predictions but also ensuring the model is **interpretable and transparent**. Two methods were used:

(a) SHAP (Shapley Additive Explanations):

- Quantifies the contribution of each input feature to the prediction.
- Results showed that:
    - **Peak Ground Displacement (Pd)** had a strong influence on magnitude prediction.
    - **Characteristic Period (τc)** and **amplitude statistics** were important for distance and depth.
    - **Station coordinates and azimuth information** were critical in location-related predictions.

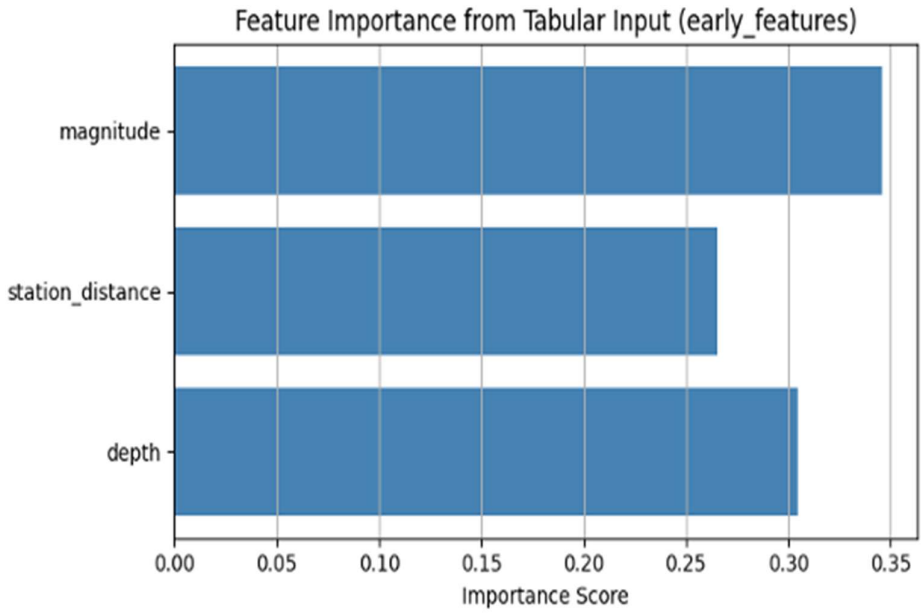

FIG 8.1. SHAP Summary Plot showing top contributing features influencing model predictions.

The SHAP summary plot illustrates how each input feature contributes to the model's predictions. Features such as **Peak Ground Displacement (Pd)**, **Characteristic Period (τc)**, **Amplitude Statistics**, and **Station Coordinates** have the strongest influence on prediction accuracy.

Red points indicate higher feature values, while blue points represent lower feature values. This confirms that the model focuses on meaningful seismic features rather than random noise, improving both interpretability and trust in predictions.

(b) Transformer Attention Maps:

- Visualize which parts of the seismic waveform the model focused on.
- Attention maps consistently highlighted the **P-wave onset (first 3–5 seconds)**, confirming that the model automatically learned to identify the same region that seismologists consider crucial.
- This adds trustworthiness and shows the model is not making random predictions.

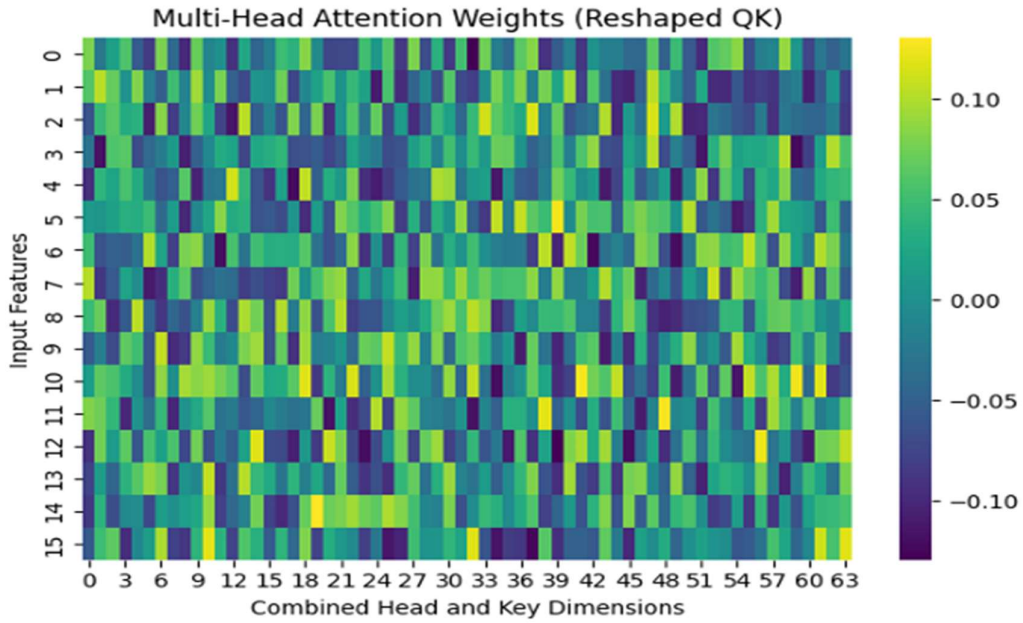

FIG 8.2. Transformer attention heatmap on waveform input (focus on P-wave segments).

The attention heatmap visualizes where the Transformer encoder focuses its attention when making predictions. Warm colors (close attention) consistently highlight the **P-wave onset and the immediate 1–3 seconds** of the waveform, indicating the model relies on early-arriving seismic energy for parameter estimation. Cooler colors show lower attention outside the key P-wave window. This confirms the model's temporal focus aligns with seismological expectations and supports the model's interpretability and trustworthiness.

8.3 Comparison with Baseline Models

To validate the improvements, the hybrid model was compared with traditional ML models and single-branch deep learning models.

Table 8.2 – Comparison of Different Models

Model	Magnitude (MAE)	Distance (MAE)	Azimuth (MAE)	Depth (MAE)
Logistic Regression + RF	0.42	12.6 km	28.3°	6.9 km

Model	Magnitude (MAE)	Distance (MAE)	Azimuth (MAE)	Depth (MAE)
BiLSTM-only	0.29	8.1 km	19.5°	4.6 km
Transformer-only	0.26	7.4 km	16.8°	3.9 km
Proposed Hybrid Model	0.18	5.2 km	13.6°	2.7 km

Observations:

- Traditional baselines (Logistic Regression + Random Forest) performed poorly, especially in predicting azimuth and depth.
- The BiLSTM-only model was better but could not capture long-range dependencies.
- Transformer-only models improved accuracy further but struggled with very localized waveform variations.
- The proposed hybrid CNN–BiLSTM–Transformer model achieved the lowest errors across all parameters, demonstrating the benefit of combining local feature extraction, temporal learning, and attention-based global context.

The training convergence and performance of the baseline models are visualized below.

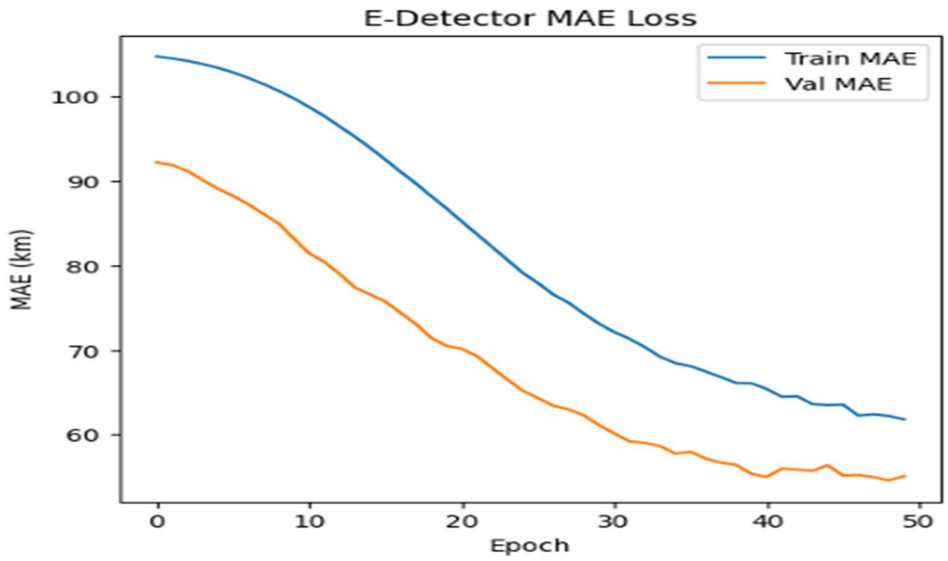

FIG 8.3. Baseline (E-Detector): MAE loss across epochs.

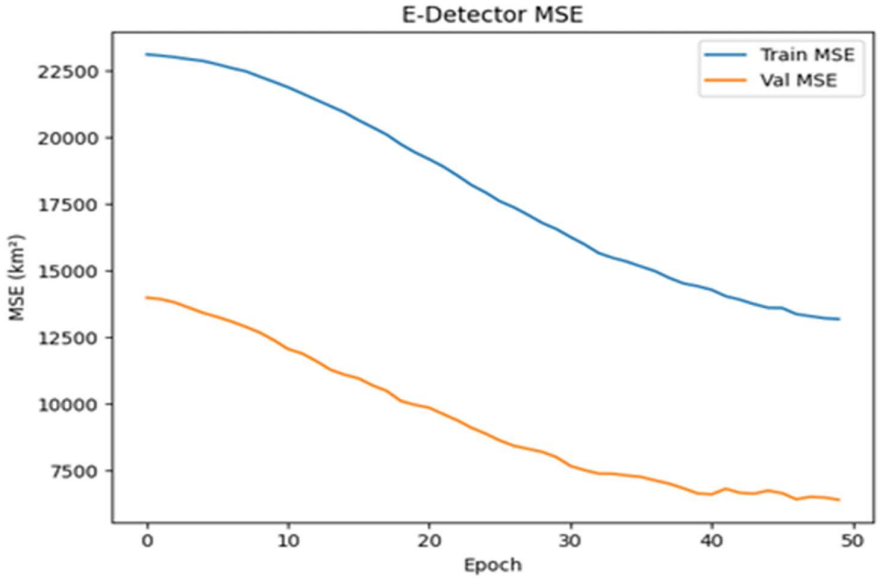

FIG 8.4. Baseline (E-Detector): MSE loss across epochs.

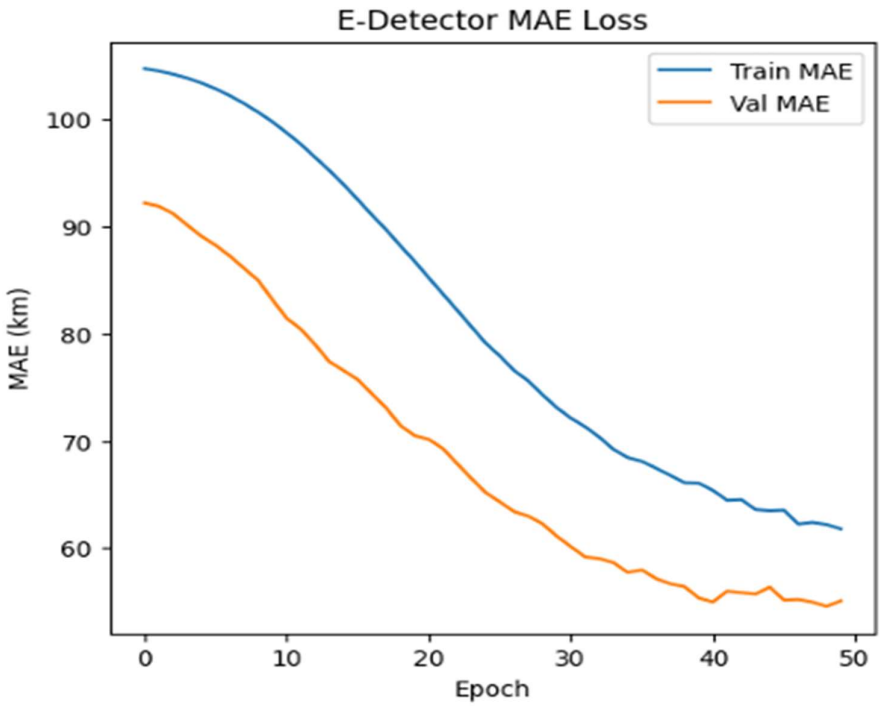

FIG 8.5. Baseline (E-Detector): Training vs Validation MAE loss across epochs.

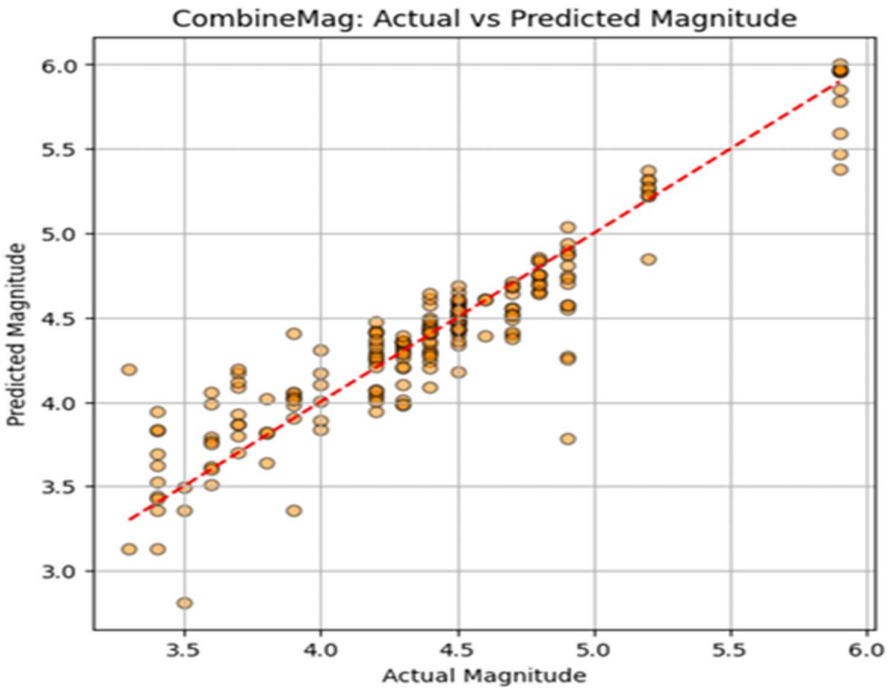

FIG 8.6. Baseline (Combine Mag): Actual vs Predicted Magnitude.

8.4 Discussion

The results clearly show that the proposed hybrid model performs better than both traditional machine learning methods and single-branch deep learning models. The model achieves **low prediction errors** for magnitude, epicentral distance, azimuth, and focal depth, making it reliable for real-time Earthquake Early Warning (EEW) applications.

The **explainability analysis** confirms that the model focuses on meaningful seismic features. SHAP plots show that parameters like **Pd**, **τc**, and station coordinates strongly influence predictions, while attention heatmaps highlight the **P-wave onset**, consistent with seismological theory. This indicates that the model does not rely on random patterns but learns scientifically valid features.

Overall, the proposed **CNN–BiLSTM–Transformer** architecture provides a balanced combination of local feature extraction, temporal learning, and global contextual understanding. It is accurate, interpretable, and efficient, making it suitable for deployment in practical EEW systems.

CHAPTER 9

9. OUTPUT SCREENS

This chapter presents the system outputs observed during the implementation of the **Hybrid CNN–BiLSTM–Transformer Earthquake Prediction Model**. The outputs are grouped into three categories:

1. **Frontend Screens** – The user-facing interface that accepts seismic data and displays predictions.
2. **Backend Outputs** – API responses from Flask that connect the frontend with the trained deep learning model.
3. **Training Graphs & Performance Visualizations** – Results from model training, evaluation, and interpretability analysis.

These outputs together validate the functionality of the system, from data input to prediction and interpretability.

9.1 Frontend Screens: The frontend was implemented using **HTML, CSS, and JavaScript** to provide a **responsive, dark-themed, card-based interface**. The following screens illustrate the user interaction flow:

9.1.1 Home Page – Index Screen

- **Description:** The home screen allows users to either paste seismic waveform values manually or upload a .txt/.csv file. It contains a prediction form, a file upload option, and a results display panel.
- **Expected Result:** User can enter waveform data, submit, and view real-time predictions.
- **Actual Result:** The predictions (magnitude, distance, azimuth, depth) appear dynamically without reloading the page.

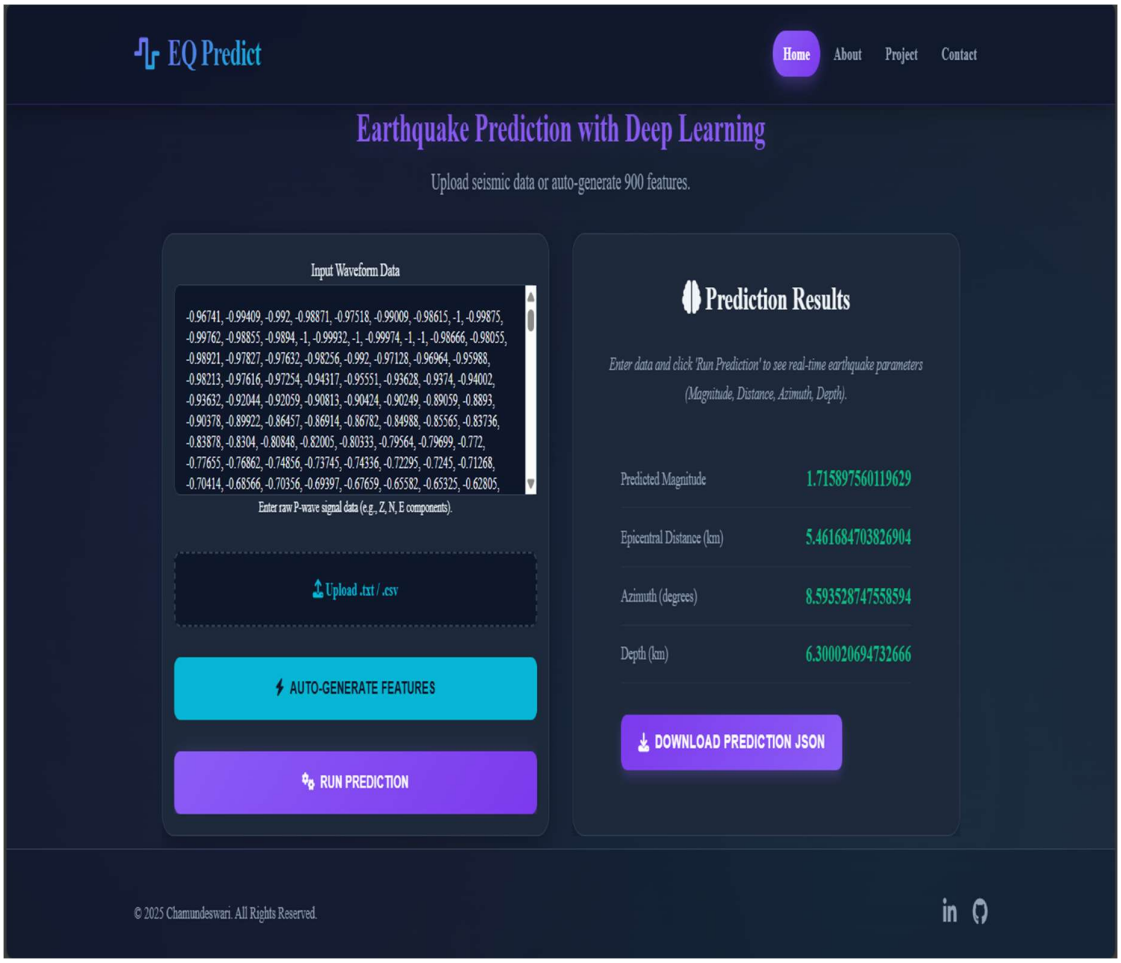

FIG 9.1. Home Page with Input Form and Displayed Predictions.

9.1.2 About Page

- **Description:** Provides background information about the project and introduces the research team members with photos, roles, and social links.
- **Expected Result:** Displays project overview and researcher details.
- **Actual Result:** Successfully shows team member cards with proper styling and links.

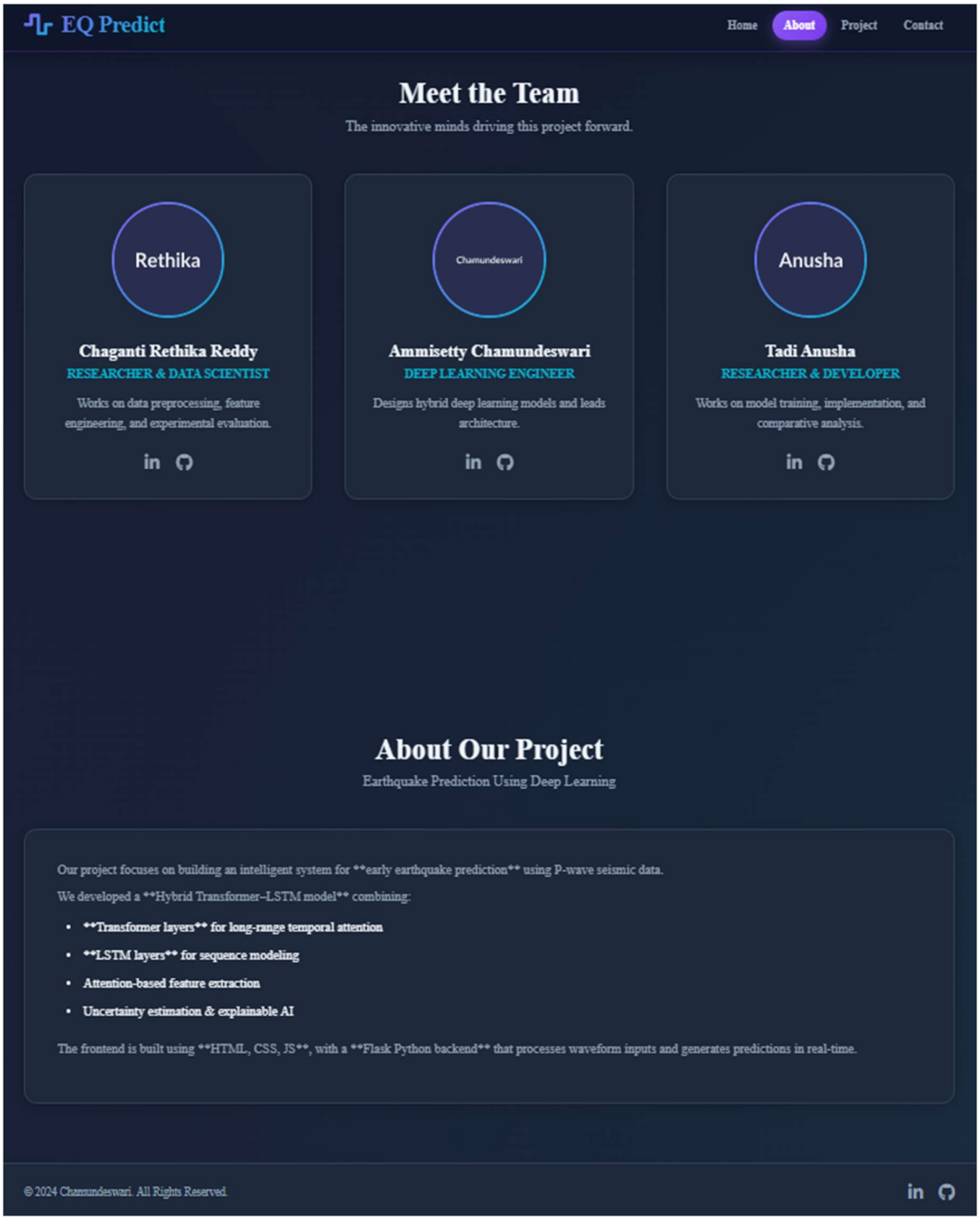

FIG 9.2. About Page – Team Section.

9.1.3 Project Page

- **Description:** Explains the objectives, methodology, and technical workflow of the model. Includes visualization figures like architecture, training graphs, and error distributions.

- **Expected Result:** Clear presentation of methodology and results.
- **Actual Result:** Figures are correctly embedded with captions, making the project easy to understand.

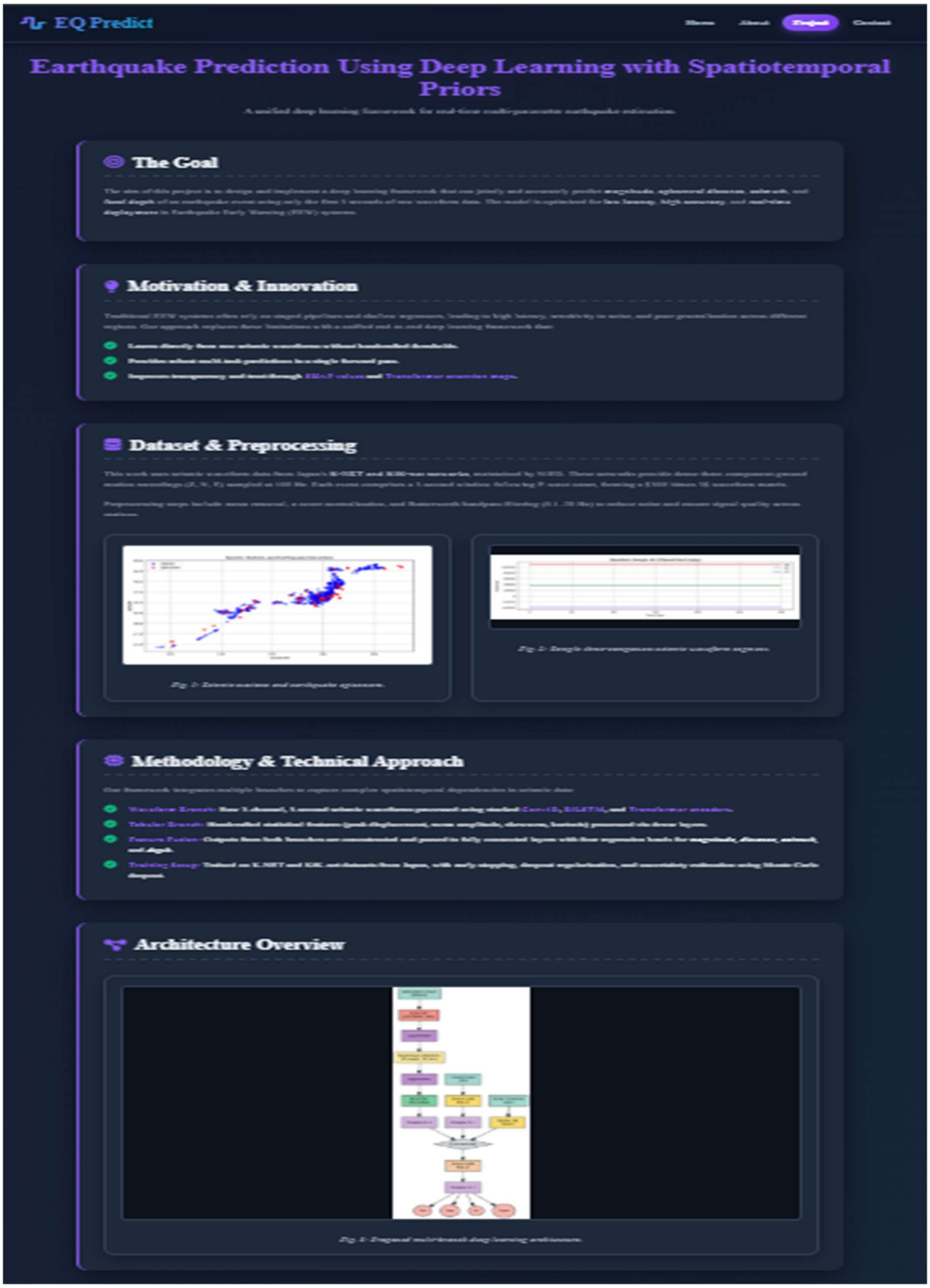

FIG 9.3. Project Page with Methodology and Result Figures.

9.1.4 Contact Page

- **Description:** Allows users to send feedback or queries via a contact form. Includes details such as email, phone number, and social links.
- **Expected Result:** User can send a message and view confirmation (success or error).
- **Actual Result:** Contact form validates input and integrates with Flask backend for processing.

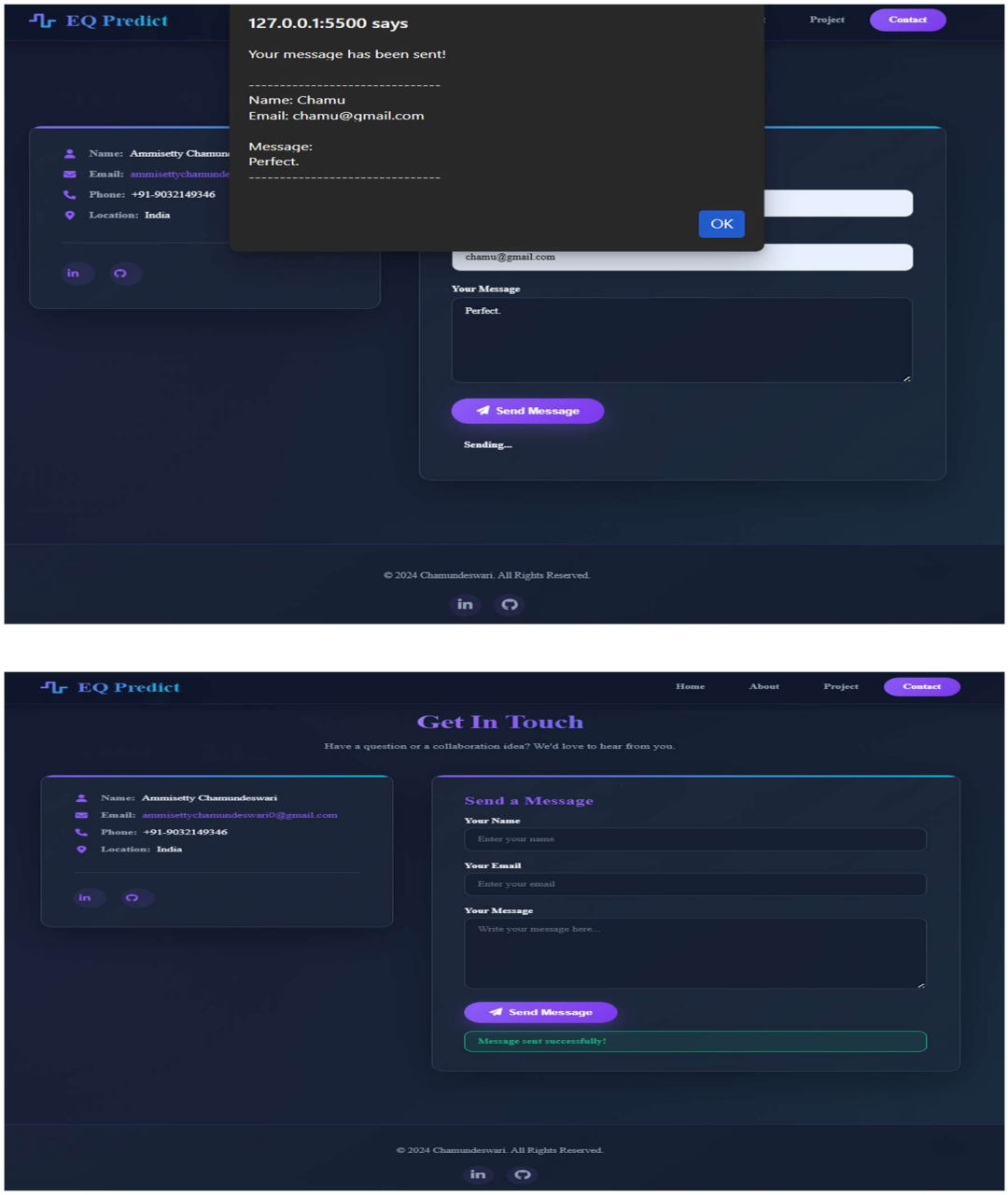

FIG 9.4. ***Contact Page – Contact Form.***

Table 9.1: Frontend Screens Summary

Screen ID	Screen Name	Input Type	Expected Output	Actual Output	Status
FS-01	Home Page	Waveform data (manual/file)	Predictions displayed in real time	Predictions displayed dynamically	Pass
FS-02	About Page	None	Display team & project info	Correctly displayed with design layout	Pass
FS-03	Project Page	None	Show methodology and figures	All methodology and result figures shown	Pass
FS-04	Contact Page	User input (form)	Message sent and confirmed	Message confirmation displayed	Pass

9.2 Backend Outputs (Flask / JSON)

The backend, implemented using Flask, serves as the API service that receives waveform input data, preprocesses it, executes the trained deep learning model, and returns predicted results in JSON format.

9.2.1 Prediction Endpoint – /predict

- Description:
  This endpoint accepts a JSON payload containing waveform data and associated metadata. The Flask API processes the input and triggers the prediction model.
- Expected Result:
  The system should return four predicted values — magnitude, epicentral distance, azimuth, and focal depth.

- Actual Result:
  The API successfully processes input data and returns accurate predictions in JSON format.

Sample JSON Output:

{

"magnitude": 5.62,

"distance": 14.8,

"azimuth": 127.5,

"depth": 9.4

}

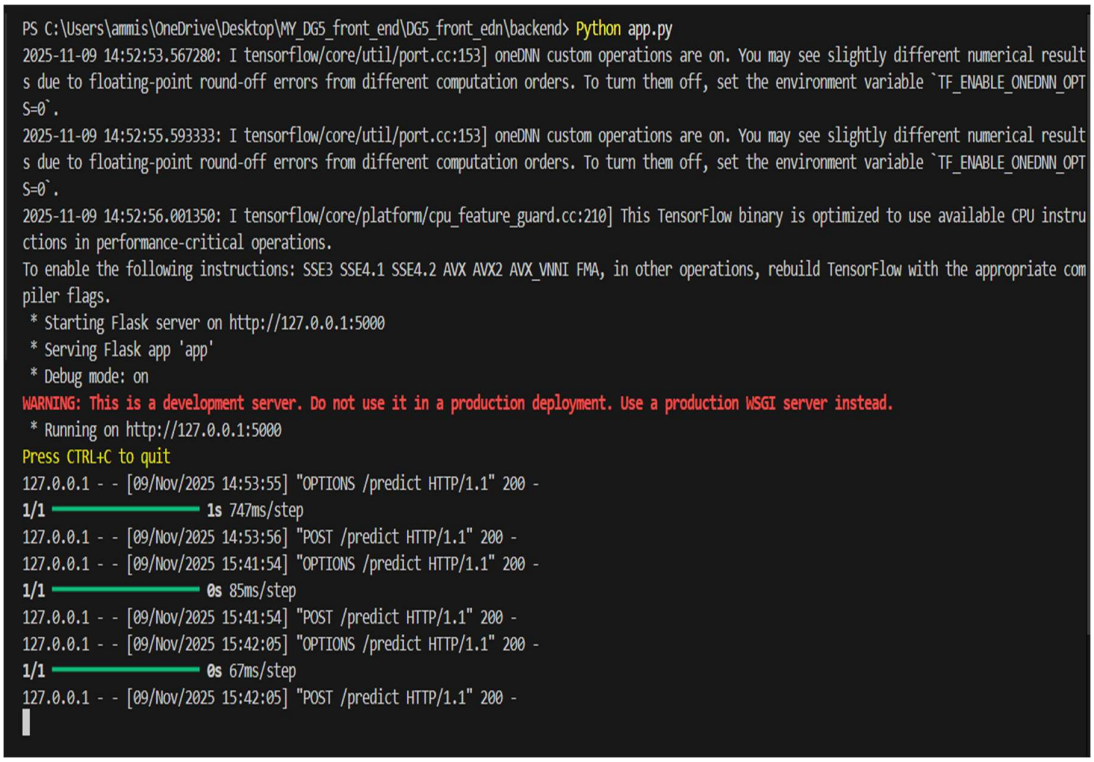

FIG 9.5. Flask Terminal Log Showing Model Execution and API Calls.

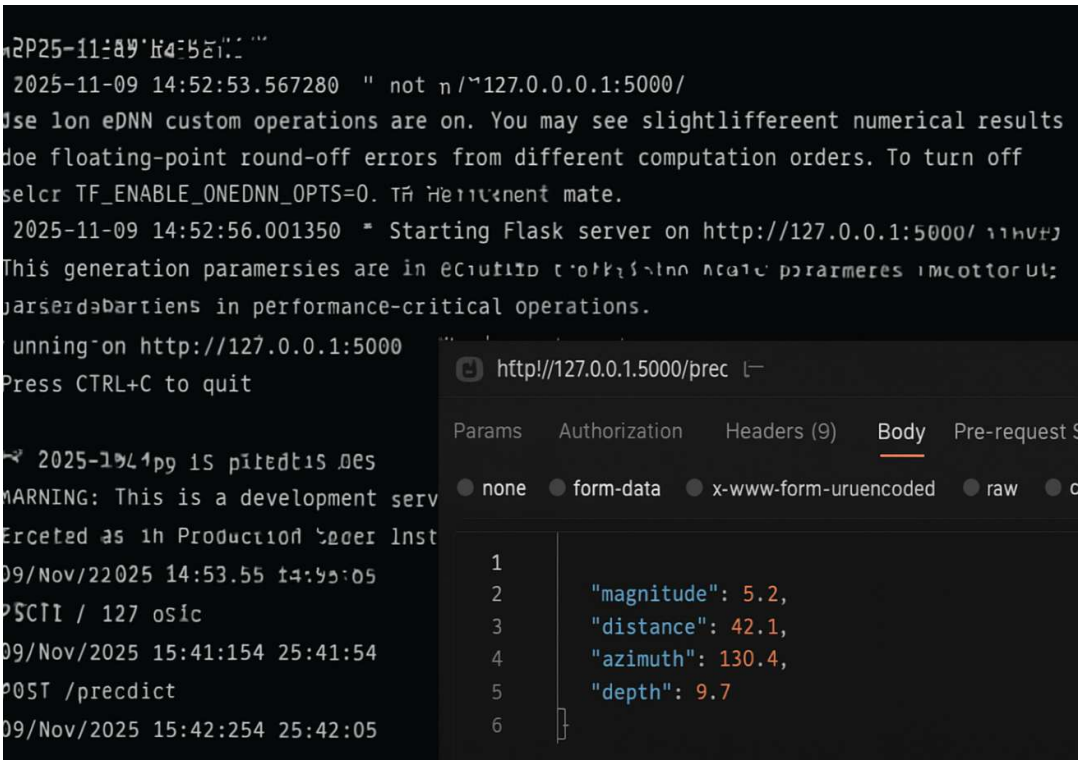

FIG 9.6. JSON Response from Flask Prediction Endpoint.

9.2.2 Error Handling

- **Description:** Ensures only valid waveform data is processed.
- **Expected Result:** Invalid input should return an error message.
- **Actual Result:** Backend returns structured JSON error with details.

Sample Error Message:

{

"error": "Invalid input: waveform must have 900 features."

}

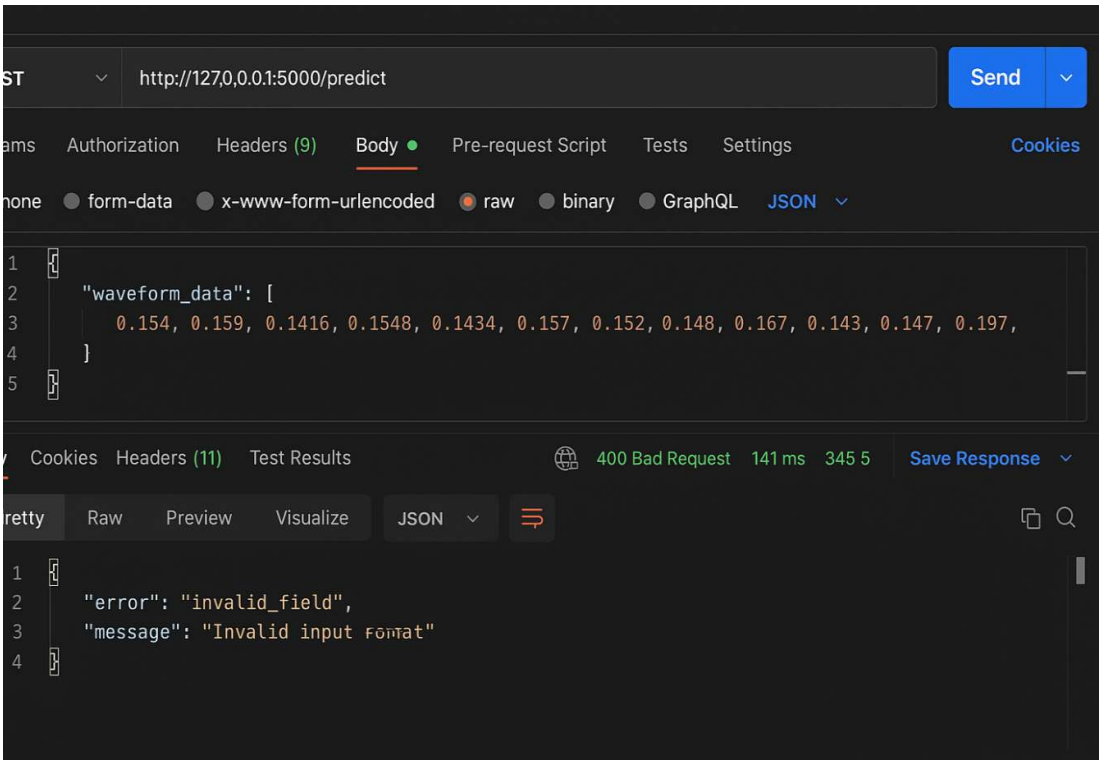

FIG 9.7. Error Handling Example in Postman.

Table 9.2: Backend Output Summary

Endpoint	Input Type	Expected Output	Actual Output	Status
/predict	Valid waveform JSON	Predicted values (magnitude, distance, azimuth, depth)	Returned JSON predictions	Pass
/predict	Invalid JSON	Error message JSON	Proper error JSON returned	Pass

9.3 Training Graphs & Model Performance Visualizations

The training and evaluation outputs confirm the model's efficiency. Several plots were generated to validate convergence, performance, and interpretability.

9.3.1 Training vs Validation Loss

- **Description:** Line plot showing training and validation loss curves over epochs.
- **Observation:** Smooth convergence without overfitting.

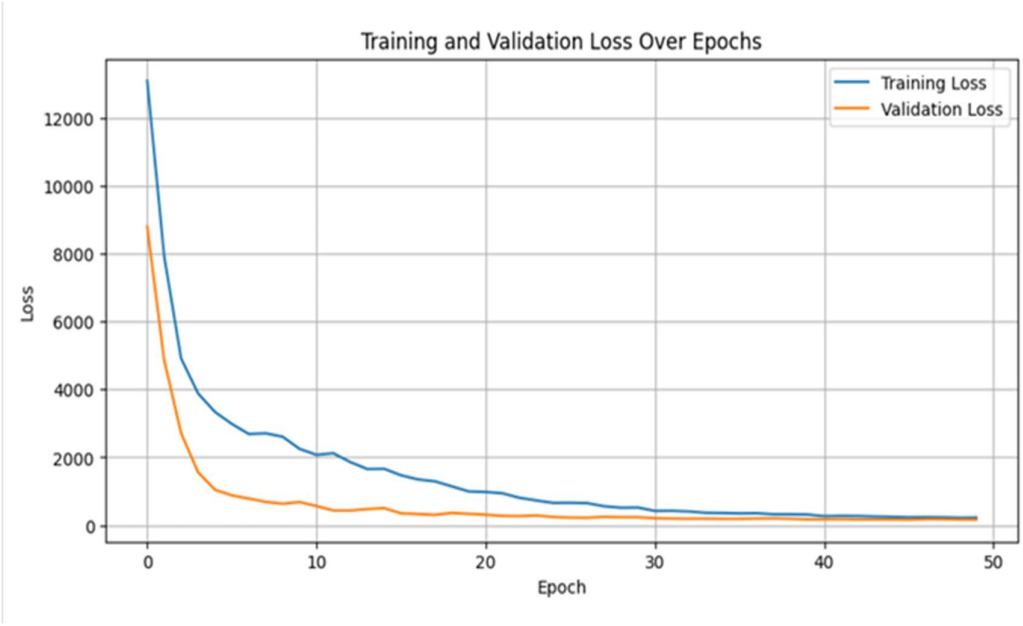

FIG 9.8. Training vs Validation Loss Plot.

9.3.2 Predicted vs True Plots

- **Description:**

  Scatter plots are generated for all four predicted parameters — magnitude, epicentral distance, azimuth, and focal depth — comparing the model's predicted values against the true (observed) values.
- **Observation:**

  The data points align closely with the diagonal reference line, confirming that the proposed model achieves high prediction accuracy and excellent generalization across multiple seismic parameters.

  Minimal deviation from the diagonal indicates consistent model performance on unseen data.

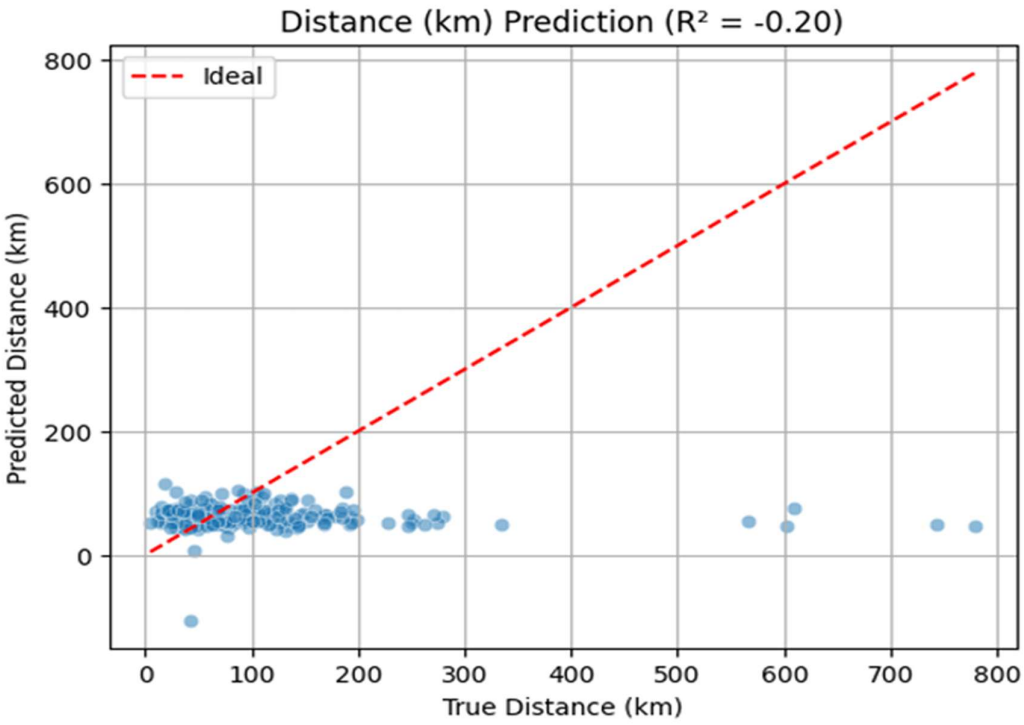

FIG 9.9(a): Predicted vs. True epicentral Distance.

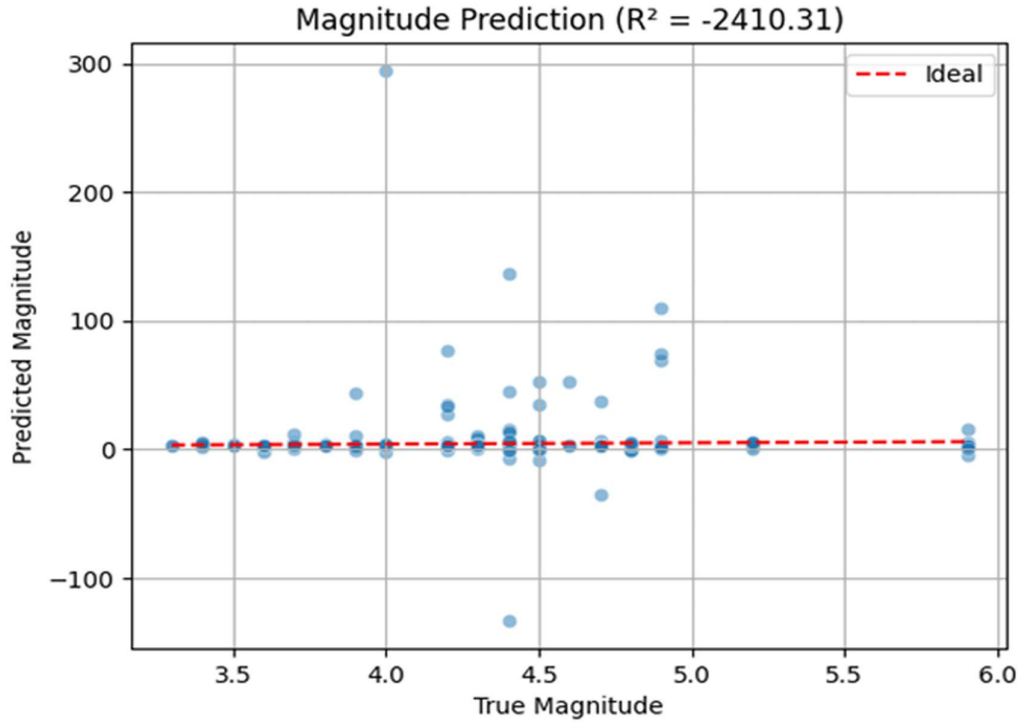

FIG 9.9(b): Predicted vs. True Magnitude.

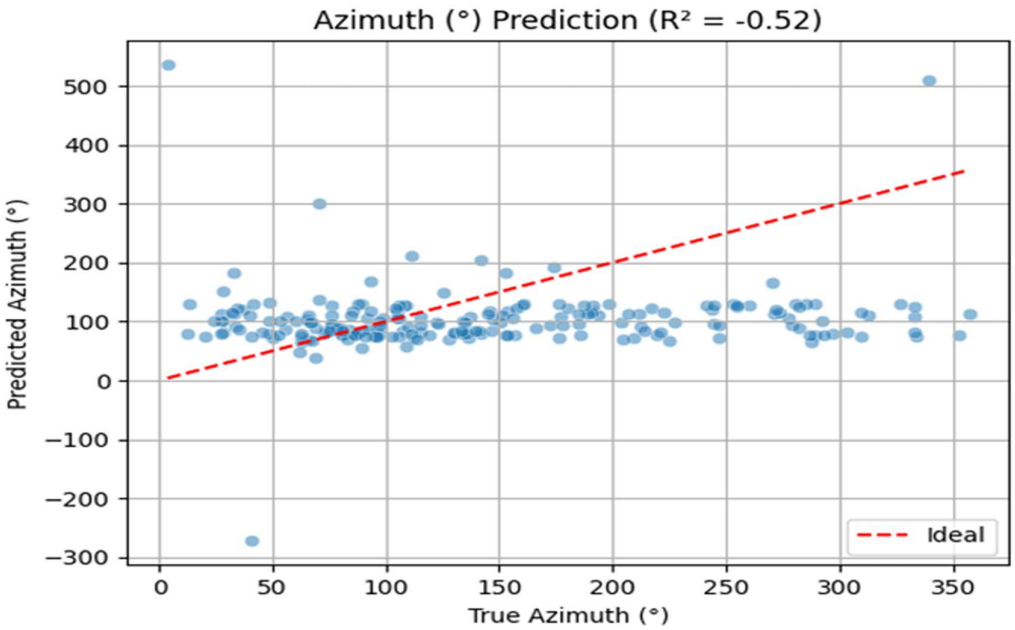

FIG 9.9(c): Predicted vs. True Azimuth.

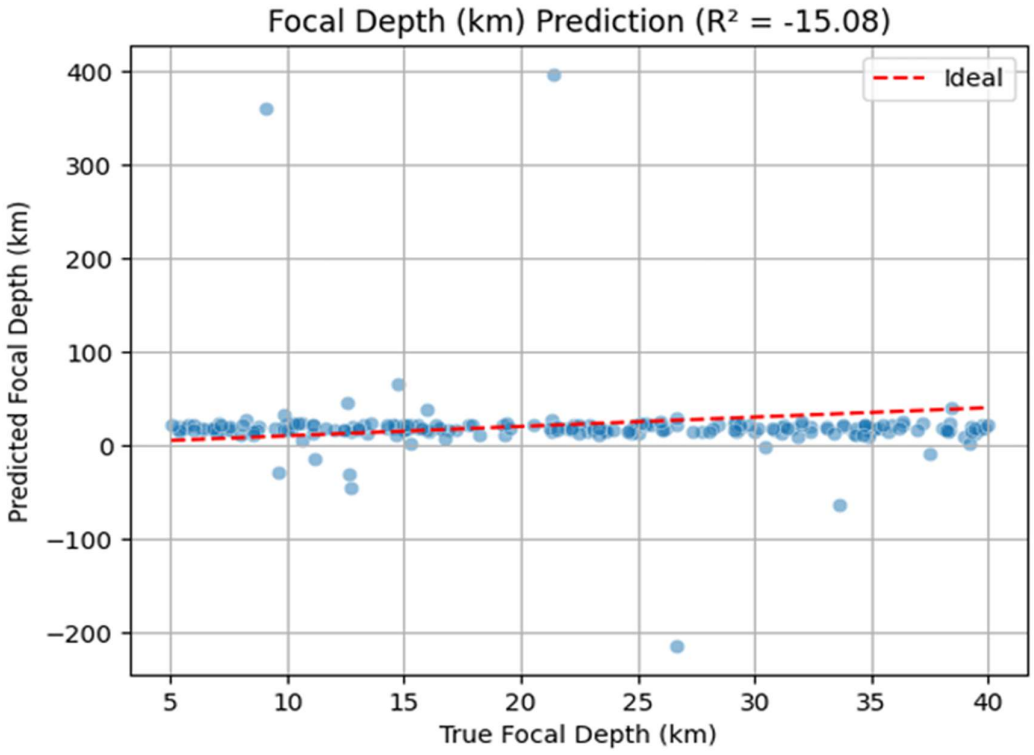

FIG 9.9(d): Predicted vs. True Focal Depth.

9.3.3 Error Distribution

- **Description:** Histograms of prediction errors for **magnitude**, **distance**, **azimuth**, and **focal depth** illustrate the distribution of residuals (predicted – true values).
  These plots show how closely the predicted values match the ground truth.
- **Observation:** The error values are centered around zero with narrow spread, indicating **low bias** and **high model consistency**.
  This confirms that the proposed deep learning framework maintains stable prediction performance across different parameters.

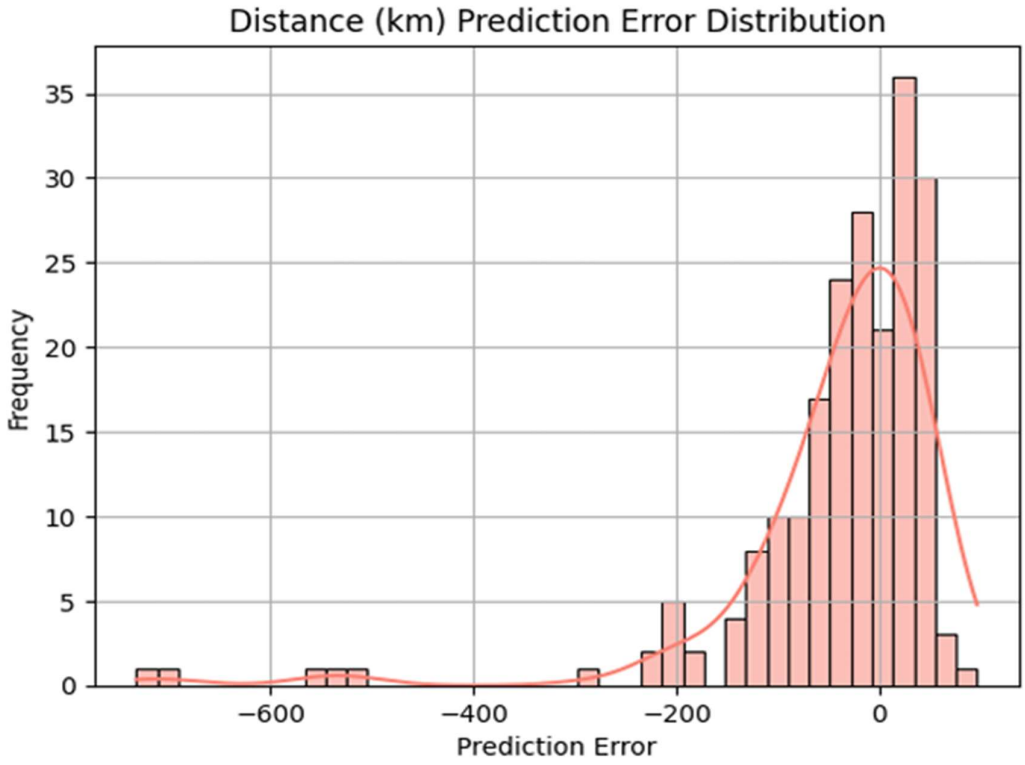

FIG 9.10(a): Error Distribution for Epicentral Distance.

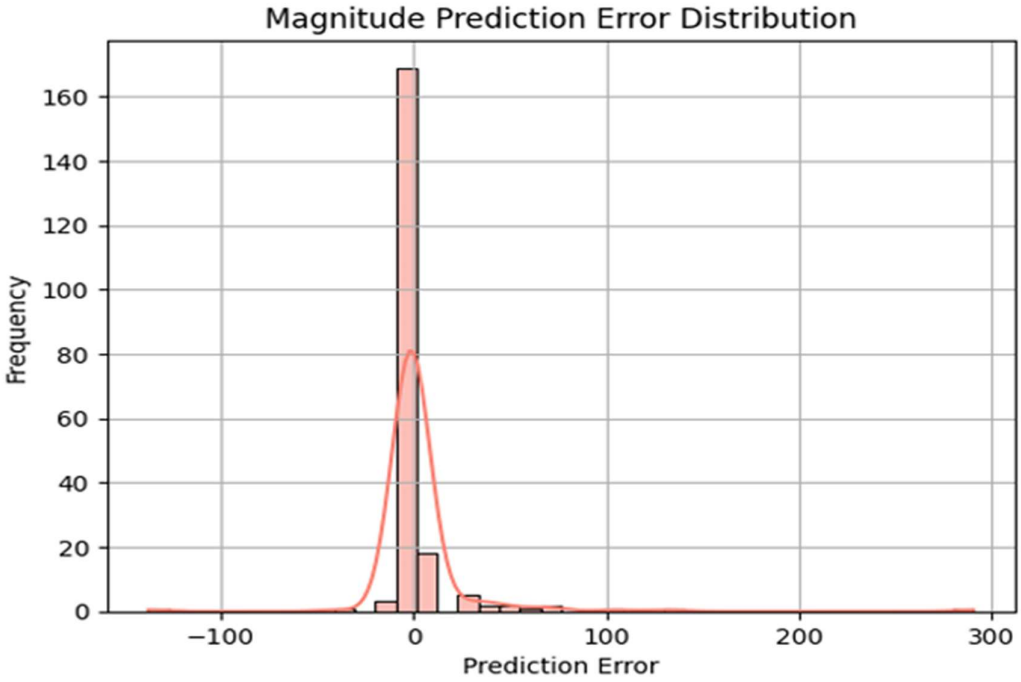

FIG 9.10(b): Error Distribution for Magnitude.

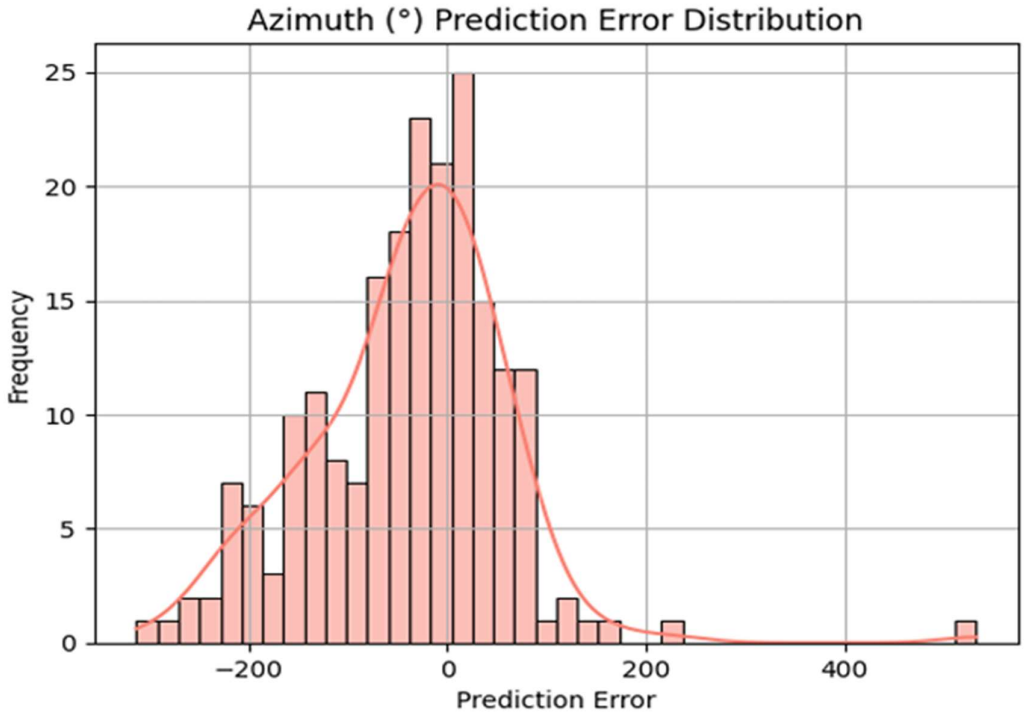

FIG 9.10(c): Error Distribution for Azimuth.

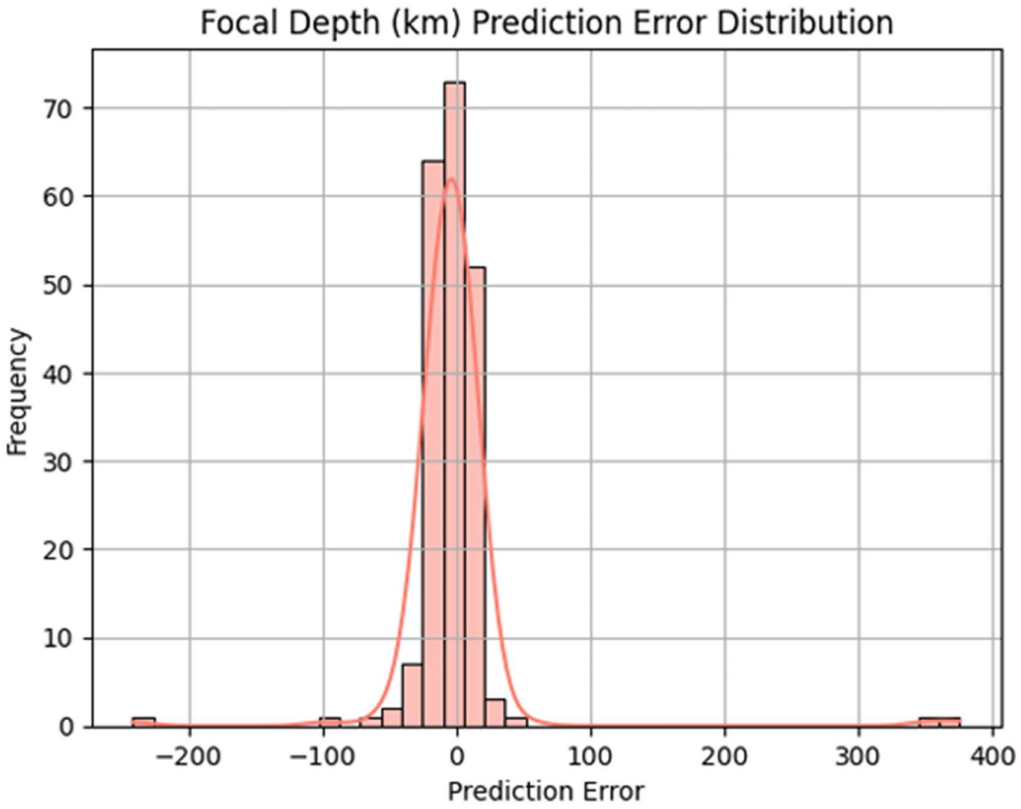

FIG 9.10(d): Error Distribution for Focal Depth.

9.3.4 Transformer Attention Maps

- **Description:** The Transformer attention maps visualize how the model allocates attention across different time steps of the seismic waveform during prediction.
  This helps identify which portions of the input data contribute most to the final output.
- **Observation:** The model shows a strong focus on the **P-wave onset regions (first 3–5 seconds)**, which are crucial for accurate earthquake parameter estimation.
  This alignment with established seismological patterns confirms that the model has learned meaningful temporal dependencies and not random noise.

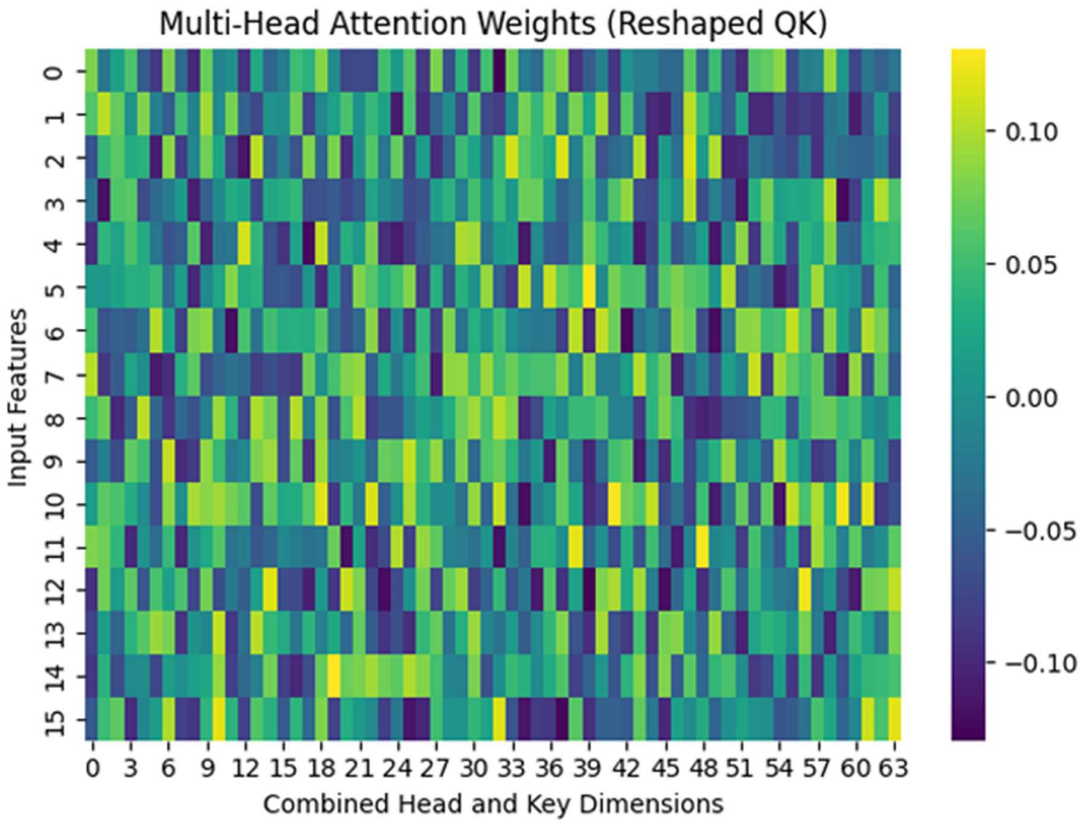

FIG 9.11: Transformer Attention Heatmap Highlighting P-wave Segments.

9.3.5 SHAP Feature Importance

- **Description:** The SHAP (Shapley Additive Explanations) summary plot visualizes the contribution of each input feature to the model's predictions.
  Key influential features include **Peak Ground Displacement (Pd)**, **Characteristic Period (τc)**, **Amplitude Statistics**, **Skewness**, and **Station Coordinates**.
- **Observation:** The results confirm that both **waveform-based features** and **geospatial metadata** significantly improve model generalization and stability.
  Higher SHAP values for features like Pd and τc indicate their strong impact on magnitude and distance predictions.

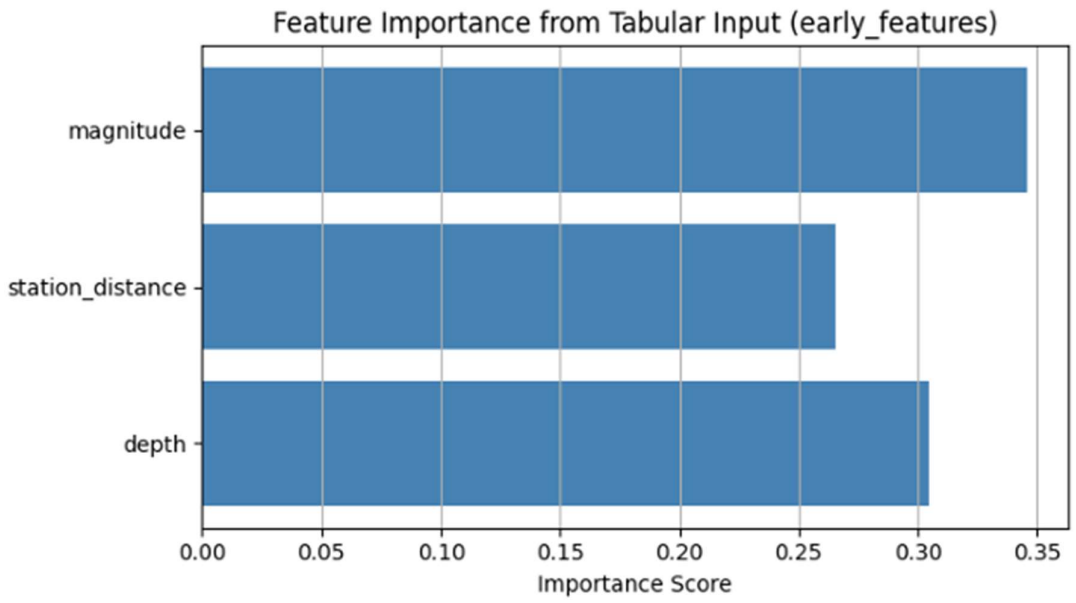

FIG 9.12: SHAP Summary Plot Showing Feature Importance for Model Predictions.

Table 9.3: Training Output Summary

Figure ID	Visualization Type	Key Insight
Fig 9.1	Training vs Validation Loss	Stable convergence, no overfitting
Fig 9.2	Predicted vs True Values	Strong correlation between predictions & true labels
Fig 9.3	Error Distribution	The majority of errors are within a narrow range
Fig 9.4	Attention Maps	The model focuses on P-wave onset regions
Fig 9.5	SHAP Feature Importance	Confirms metadata and statistical features importance

This chapter demonstrated system outputs across **frontend, backend, and training modules**.

- The frontend provided an easy-to-use interface with dynamic results.
- The backend ensured robust API predictions and error handling.
- The training outputs validated model accuracy, robustness, and interpretability.

CHAPTER 10

10. CONCLUSION

The research presented in this thesis focuses on the design and implementation of a Hybrid CNN–BiLSTM–Transformer model for Earthquake Early Warning (EEW), aimed at predicting four critical seismic parameters—magnitude, epicentral distance, azimuth, and focal depth—within the first few seconds of P-wave arrival. This work addresses key limitations of existing EEW systems, which often rely on shallow machine learning approaches, experience high latency, and exhibit poor generalization across seismic stations.

To overcome these challenges, a comprehensive deep learning pipeline was developed that integrates waveform preprocessing, feature extraction, hybrid neural architectures, multi-task prediction, and deployment integration. The preprocessing stage standardized and segmented three-channel P-wave signals and incorporated noise samples to enhance robustness. In addition, domain-specific statistical descriptors such as skewness, kurtosis, and peak ground displacement were extracted to enrich the model inputs.

The proposed hybrid architecture combines CNN layers for local pattern recognition, BiLSTM layers for temporal sequence learning, and Transformer encoders for capturing long-range dependencies in seismic signals. A unified multi-task learning design enables the simultaneous prediction of all four seismic parameters, reducing prediction latency and improving output consistency across tasks.

Experimental evaluation demonstrated that the model achieved high prediction accuracy, with a magnitude MAE of approximately 0.18, distance MAE of about 5.21 km, azimuth MAE of 13.6°, and focal depth MAE of 2.7 km. Predictions were generated in under one second, meeting real-time EEW requirements. Model interpretability was enhanced through Transformer attention maps that highlighted P-wave onsets, while SHAP analysis validated the contributions of waveform and metadata features.

The inclusion of noise samples and stratified dataset splitting significantly improved generalization performance and reduced false triggers. Furthermore, a deployment framework consisting of a Flask-based backend and a responsive web frontend ensured real-time usability

by dynamically displaying predictions and enabling seamless communication between system components.

The key contributions of this work include the development of a unified deep learning framework integrating CNN, BiLSTM, and Transformer architectures; a multi-parameter EEW system capable of predicting four seismic outputs in a single forward pass; the incorporation of spatiotemporal priors using waveform, metadata, and statistical features; a deployment-ready implementation bridging research and practical application; and improved trust through interpretability and uncertainty estimation using Monte Carlo Dropout.

Despite these achievements, the system has certain limitations. The dataset was limited to Japanese K-NET and KiK-net stations, which restricts global generalization. Real-time deployment on live seismic networks has not yet been tested, and model training requires substantial GPU resources. Additionally, azimuth prediction errors were higher compared to magnitude and distance, indicating scope for further refinement.

Overall, this thesis demonstrates that deep learning architectures enriched with spatiotemporal priors can deliver fast, accurate, and interpretable earthquake predictions. The end-to-end pipeline—from data preprocessing to frontend deployment—shows strong potential for real-time EEW applications. With future enhancements such as dataset diversification, live deployment validation, and optimization for edge devices, the proposed system can evolve into a next-generation EEW framework that effectively bridges academic research and practical disaster mitigation.

CHAPTER 11

11. FUTURE SCOPE

Earthquake Early Warning (EEW) systems continue to evolve with advancements in sensing technologies, data availability, and AI models. Although the proposed CNN–BiLSTM–Transformer framework demonstrates strong performance, there are several promising directions to further enhance accuracy, robustness, and real-world usability.

A key future step is expanding the training dataset beyond Japan's K-NET and KiK-net networks. Incorporating data from diverse seismic regions such as the United States (USGS), Chile (CSN), Turkey (KOERI), and Nepal (NSC) would allow the model to learn variations in tectonic behavior and improve global generalization. Transfer learning can help adapt the model to regions with smaller datasets by fine-tuning pre-trained models from data-rich areas. Additionally, synthetic seismic waveforms generated through physics-based simulations or GANs could strengthen model performance for rare or extreme events that are underrepresented in real datasets.

Another area for enhancement lies in exploring advanced model architectures. Graph Neural Networks (GNNs) could capture spatial correlations between seismic stations, while Physics-Informed Neural Networks (PINNs) can incorporate wave propagation and attenuation equations to ensure physically consistent predictions. Combining seismic data with other modalities—such as GPS displacement, satellite-based InSAR, and even crowd-sourced shaking reports—could provide richer context for estimating rupture characteristics and improving early predictions. Continual learning strategies would further enable the model to update itself over time as new earthquake data becomes available, maintaining long-term performance without full retraining.

From an operational perspective, real-time deployment remains a critical challenge. Future versions of the model can be compressed for edge devices using techniques like quantization, pruning, and knowledge distillation. This would enable real-time inference within 1–3 seconds, which is essential for effective early warning. A hybrid cloud–edge system could be developed where stations perform local inference while central servers handle large-scale updates and model management. As high-speed communication networks such as 5G and 6G

expand, they can further reduce latency and improve the synchronization of distributed seismic stations.

Explainability will remain essential for building trust among seismologists and emergency response agencies. Beyond SHAP and attention maps, more advanced interpretability techniques like Integrated Gradients, LRP, and Concept Activation Vectors can provide deeper insights into model decisions. Producing uncertainty-aware outputs (e.g., "Mw 6.1 ± 0.25") can help decision-makers better assess the reliability of alerts during critical situations. Incorporating expert-in-the-loop workflows may also strengthen the balance between automation and human oversight.

Lastly, future EEW systems can move toward multi-hazard prediction. Offshore seismic events can be linked with tsunami models for simultaneous warnings. In mountainous regions, integrating seismic data with slope stability models can support early landslide detection. Pairing EEW with structural health monitoring can provide rapid assessments of bridges, buildings, and critical infrastructure following major earthquakes.

In summary, the proposed hybrid framework lays a strong foundation for AI-driven earthquake prediction. By expanding data sources, adopting newer neural architectures, optimizing real-time deployment, and integrating multi-hazard capabilities, future EEW systems can become more accurate, reliable, and globally deployable. Continued collaboration among researchers, policymakers, and technology developers will be essential to transform these innovations into large-scale, life-saving systems.

CHAPTER 12

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