NARASARAOPETA ENGINEERING COLLEGE (AUTONOMOUS)

Earthquake Prediction Using Deep Learning with Spatiotemporal Priors

PRESENTED BY

AMMISETTY CHAMUNDESWARI	22471A05L1
TADI ANUSHA	22471A05O4
CHAGANTI RETHIKA REDDY	23475A0509

Under the Guidance of,

Nukala.Vijaya Kumar, M.E

Associate Professor,

Department of Computer Science and Engineering,

Narasaraopeta Engineering College (Autonomous),

Narasaraopet- 522 601.

NARASARAOPETA
NEC ENGINEERING COLLEGE
(AUTONOMOUS)

OUTLINE

NARASARAOPETA ENGINEERING COLLEGE
(AUTONOMOUS)

ABSTRACT

A deep learning model is developed to quickly predict key earthquake details such as magnitude, distance, direction, and depth using only 3 seconds of seismic data. The model combines CNN, BiLSTM, and Transformer layers to understand both time and space patterns in the waveforms. It also uses extra features and metadata to make predictions more accurate and stable. With Monte Carlo Dropout, the model can estimate uncertainty and give more reliable results. It performs well on K-NET and KiK-net datasets, showing potential for real-time earthquake early warning.

NARASARAOPETA ENGINEERING COLLEGE (AUTONOMOUS)

INTRODUCTION

- **Overview**
  - Deep learning framework for estimating key earthquake parameters from raw seismic waveforms.
  - Combines CNN, BiLSTM, and Transformer layers to capture short-term and long-range signal patterns.
  - Predicts magnitude, epicentral distance, azimuth, and focal depth within seconds for rapid warning.

- **Motivation**
  - Traditional early warning systems depend on handcrafted features and empirical rules.
  - These approaches limit speed, adaptability, and overall performance.
  - Many existing methods show high latency and weak generalization across regions and stations.
  - A fast, unified, data-driven method is needed for modern early warning requirements.

- **Importance and Relevance**
  - Even a few seconds of warning can save lives and reduce infrastructure damage.
  - High accuracy, interpretability, and low latency enable real-time deployment on edge devices.
  - Supports the development of next-generation Earthquake Early Warning (EEW) systems.
  - Enhances reliability and transparency in seismic monitoring.

LITERATURE SURVEY

No	Title	Author	Journal Name & Year	Methodology Adapted	Key Findings	Gaps
1	Fast Earthquake Magnitude Esmaon Using Lightweight Deep Learning Model	H. Wang et al., 2024, IEEE	hps://ieeexplore.ieee.org/document/10081383	Lightweight CNN	Introduces a low-computaon model for early magnitude	Lacks tesng on real-me deployments and noisy inputs.
2	Bayesian-Deep-Learn ing Esmaon from Single-Staon Observaons	S. M. Mousavi, G. C. Beroza, 2021, IEEE	hps://ieeexplore.ieee.org/document/10767234	Bayesian Neural Networks, TCNs	Estimates source parameters with uncertainty using single-station input.	Does not esmate magnitude
3	Transfer Learning for Magnitude Esmaon with Limited Data	M. N. Uddin et al., 2023, IEEE	hps://ieeexplore.ieee.org/document/10679183	CNN with Transfer Learning (ResNet, VGG	Uses pretrained models to predict with small datasets	Limited tesng across regions and networks
4	Efficient DL Framework for Earthquake Magnitude Estimation Using Real-Time Seismic Data	F. H. Masoumi, 2023, IEEE	hps://ieeexplore.ieee.org/document/10142022	CNN, LSTM, Attention	Real-me DL model for accurate seismic magnitude esmaon.	Not validated under extreme noise and diverse global condions
5	Deep residual networks for earthquake early warning	X. Zhou	hps://ieeexplore.ieee.org/document/10056818	Signal filtering, normalizaon	reinforces deeper convolutional designs to capture complex waveform patterns.	Lacks depth/geological validaon

The work is inspired by ideas from several research papers:

- Wang et al. (2020) – Used lightweight CNNs to estimate earthquake magnitude from P-wave data quickly.
  ➤ Supports our use of fast CNN layers for real-time predictions.
- Uddin et al. (2022) – Used transfer learning (like ResNet, VGG) to improve performance when data is limited.
  ➤ Inspires us to use robust feature extraction for data-scarce cases.
- Masoumi (2023) – Combined Attention + CNN–LSTM for better magnitude prediction.
  ➤ Matches our Transformer + LSTM hybrid model to focus on important waveform parts.
- Zhou et al. (2019) – Used deep residual networks (ResNets) for earthquake early warning.
  ➤ Encourages deeper CNN layers in our model for better pattern detection.
- Mousavi & Beroza (2021) – Used Bayesian deep learning to include uncertainty estimation.
  ➤ We apply this idea through Monte Carlo Dropout to estimate prediction confidence.

RESEARCH GAPS

- Most previous works predict only one parameter (usually magnitude).
  ➤ Our model predicts multiple outputs together: magnitude, distance, azimuth, and depth.
- Earlier methods used multi-step pipelines, which are slow and reduce accuracy.
  ➤ Our model is end-to-end, making it faster and more reliable.
- Uncertainty and explainability are rarely combined in one system.
  ➤ We include Monte Carlo Dropout (uncertainty) + SHAP & attention (explainability).
- Some models use heavy GNNs to handle spatial station information, which increases computation.
  ➤ We use a lightweight metadata-fusion method, suitable for edge devices.
- Transferability to different regions and real-time use are not well addressed in older studies.
  ➤ Our lightweight design and 3-second input window make it better for real-time deployment.

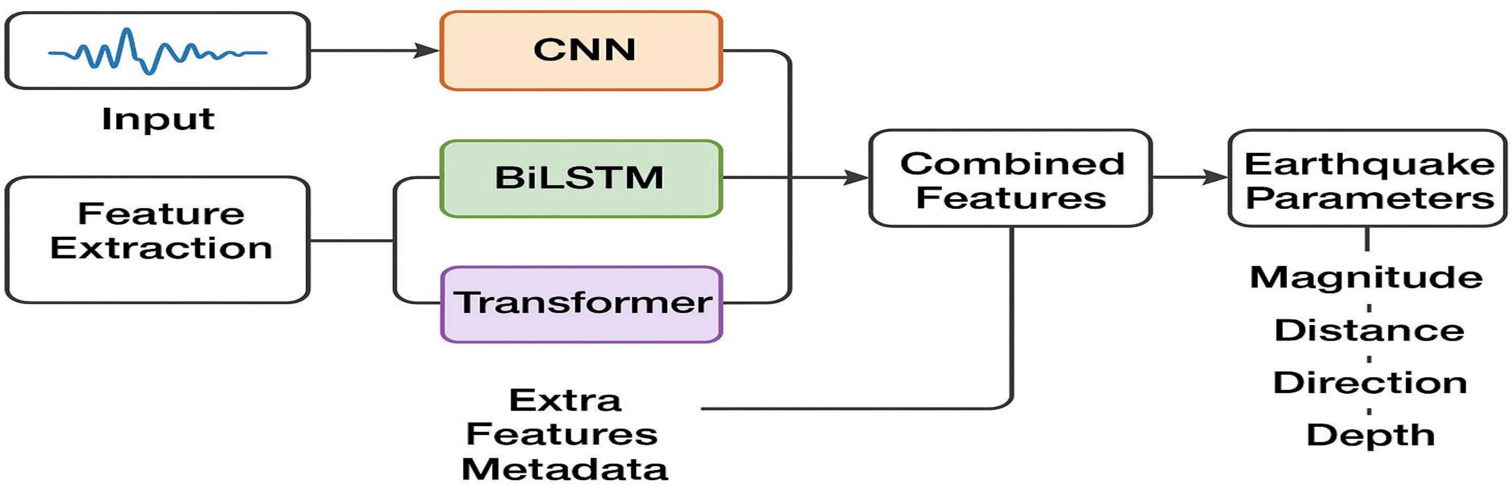
PROBLEM STATEMENT

- **Problem Definition**
  - Earthquake prediction is highly complex due to the non-linear and irregular patterns present in seismic signals.
  - Traditional models fail to capture long-term temporal and spatial dependencies, leading to unreliable forecasts.
  - There is a lack of explainability and uncertainty estimation, limiting the trust and usability of current prediction systems.
- **Significance**
  - Reliable earthquake prediction enables timely alerts and improved disaster preparedness for minimizing damage.
  - Incorporating deep learning with interpretability tools like SHAP enhances transparency and confidence in model predictions.

OBJECTIVES

- To develop a unified deep learning model that jointly predicts earthquake magnitude, epicentral distance, azimuth, and focal depth.
- To integrate CNN, BiLSTM, and Transformer layers for effective extraction of local, sequential, and long-range waveform features.
- To enhance model interpretability and reliability using SHAP analysis and Monte Carlo Dropout-based uncertainty estimation.
- To achieve high accuracy and low latency for real-time deployment in Earthquake Early Warning (EEW) systems.

ARCHITECTURE



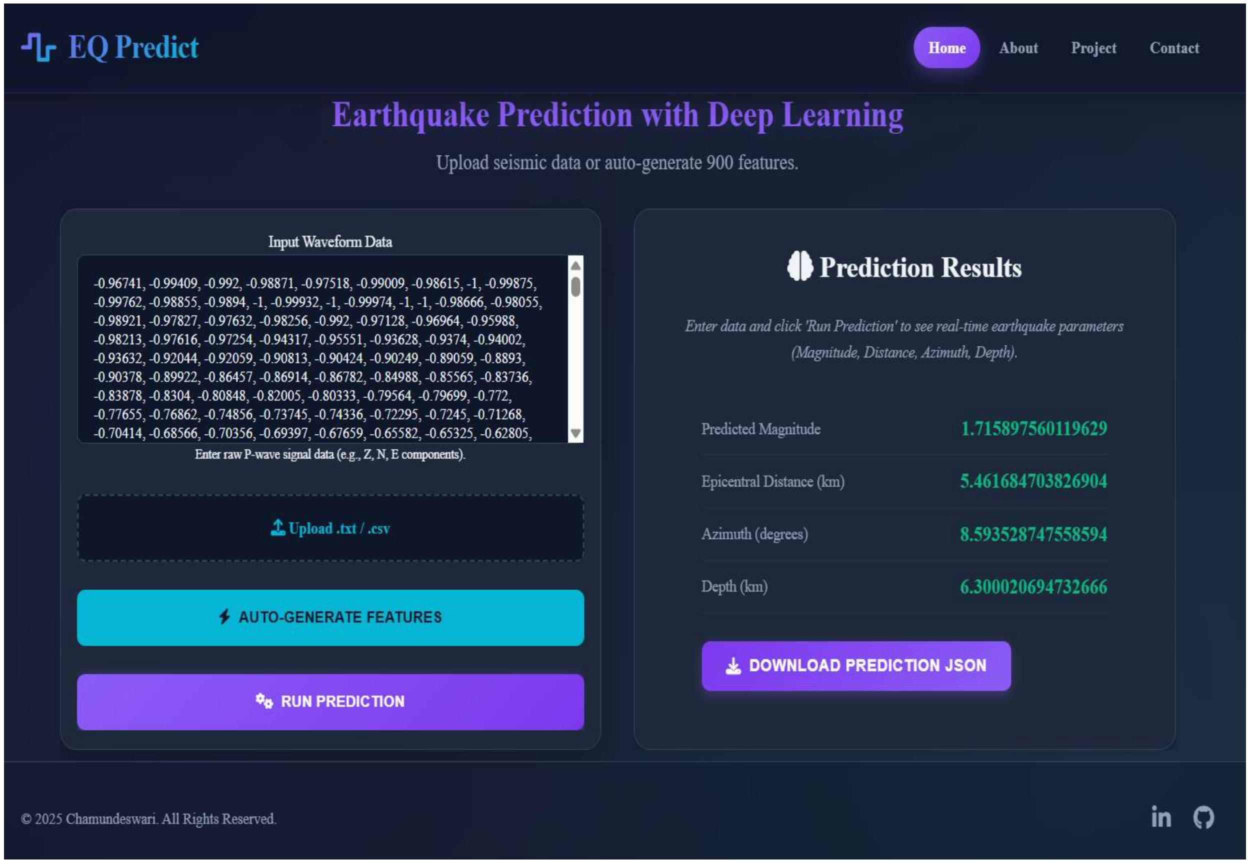
METHODOLOGY

- Used K-NET and KiK-net datasets with 3-component waveforms (Z, N, E) sampled at 100 Hz.
- Extracted a 3-second waveform window after P-wave onset to capture early signals.
- Preprocessing: mean removal, z-score normalization, and Butterworth band-pass filter (0.1–20 Hz).
- Added statistical features (Pd, mean, SD, skewness, kurtosis) for better interpretability.
- Architecture integrates CNN, BiLSTM, and Transformer layers for spatiotemporal learning.
- Predicts magnitude, distance, azimuth, and depth using multi-task regression.
- Monte Carlo Dropout provides uncertainty estimation; SHAP and attention maps explain feature impact.
- Trained in TensorFlow/Keras with Adam (1e-4), batch = 64, 100 epochs, and early stopping.
- Combined waveform data and metadata (latitude, longitude, magnitude, depth, azimuth, distance).

Frameworks & Algorithms:

- Frameworks Used:
  - TensorFlow / Keras framework used for model development and training.
  - Enables easy implementation of deep learning architectures (CNN, BiLSTM, Transformer).
  - Supports GPU acceleration for faster computation and large-scale waveform processing.
  - Integrated with NumPy and Pandas for data handling and preprocessing.
- Algorithms Implemented:
  - Convolutional Neural Network (CNN): Extracts local temporal and spatial features from 3-channel waveform data.
  - Bidirectional LSTM (BiLSTM): Captures sequential dependencies and bidirectional temporal relationships.

FRONTEND SCREENS



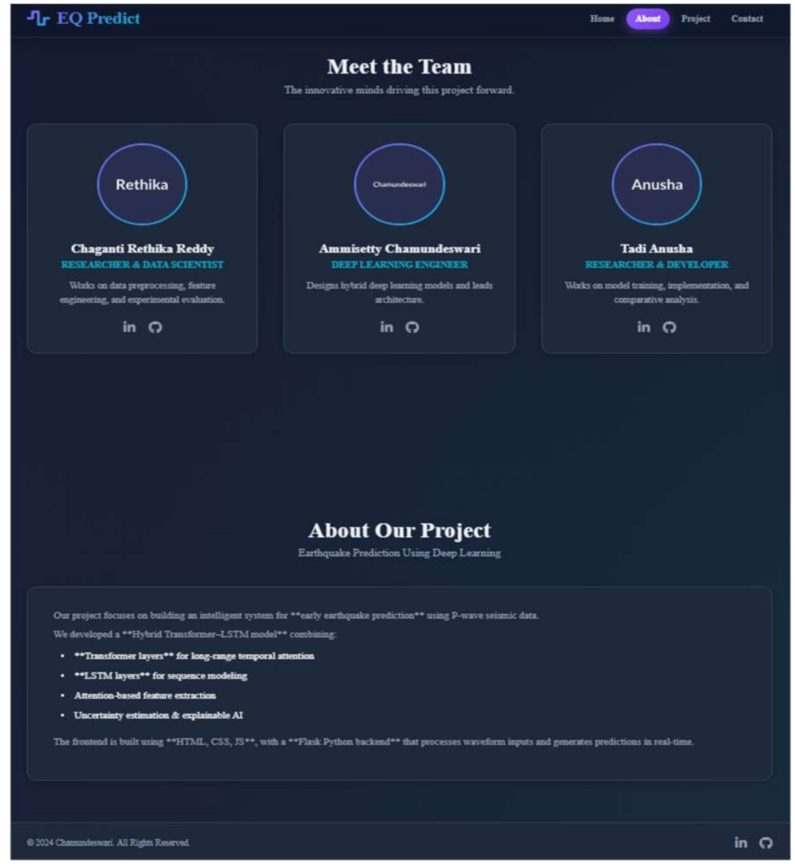


Fig: Home Page: Allows users to upload seismic data and view prediction results.

Fig: About Page: Provides project details, purpose, and team information.

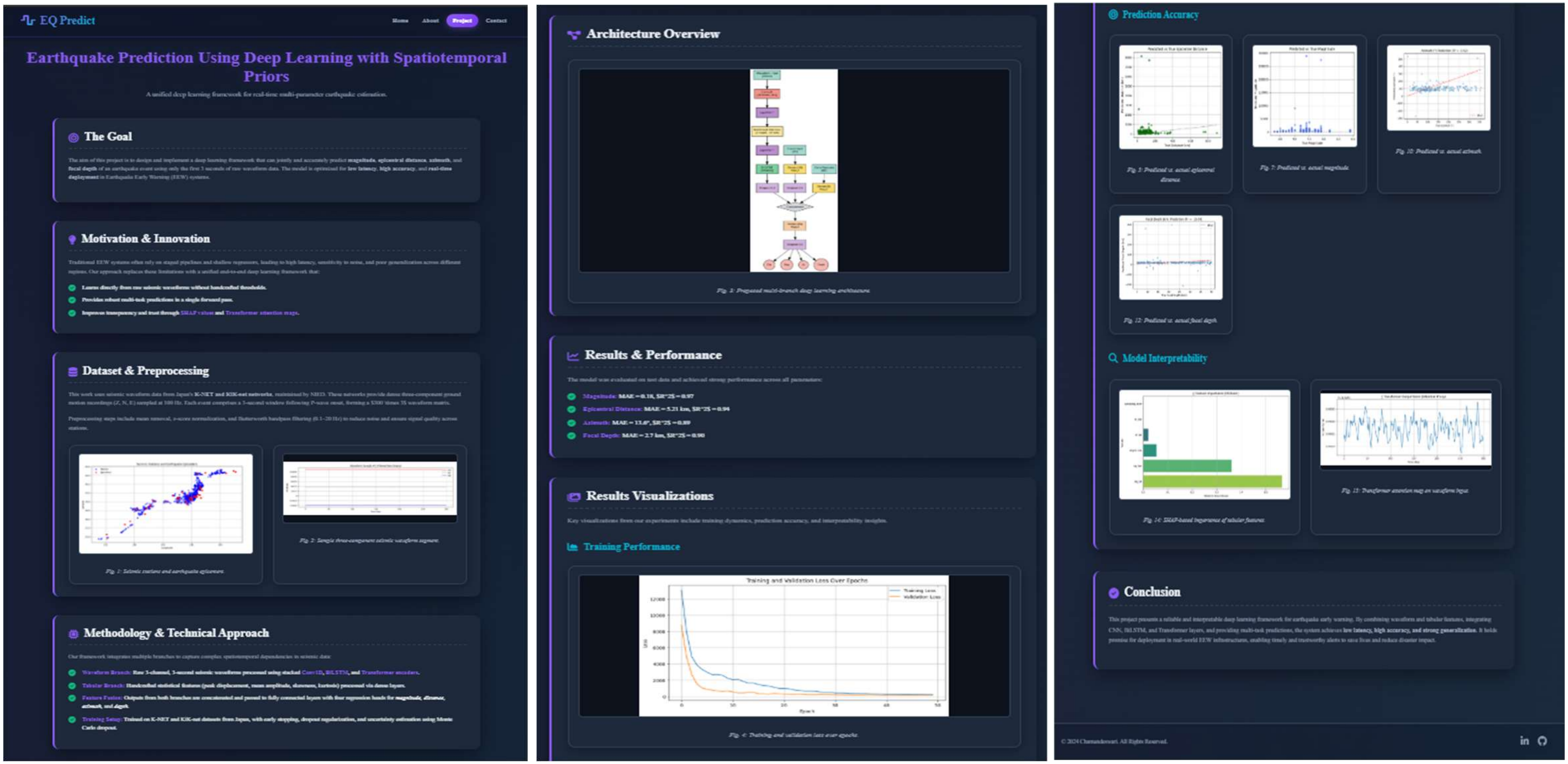


Fig: Project Page: Explains the system workflow, architecture, and methodology.

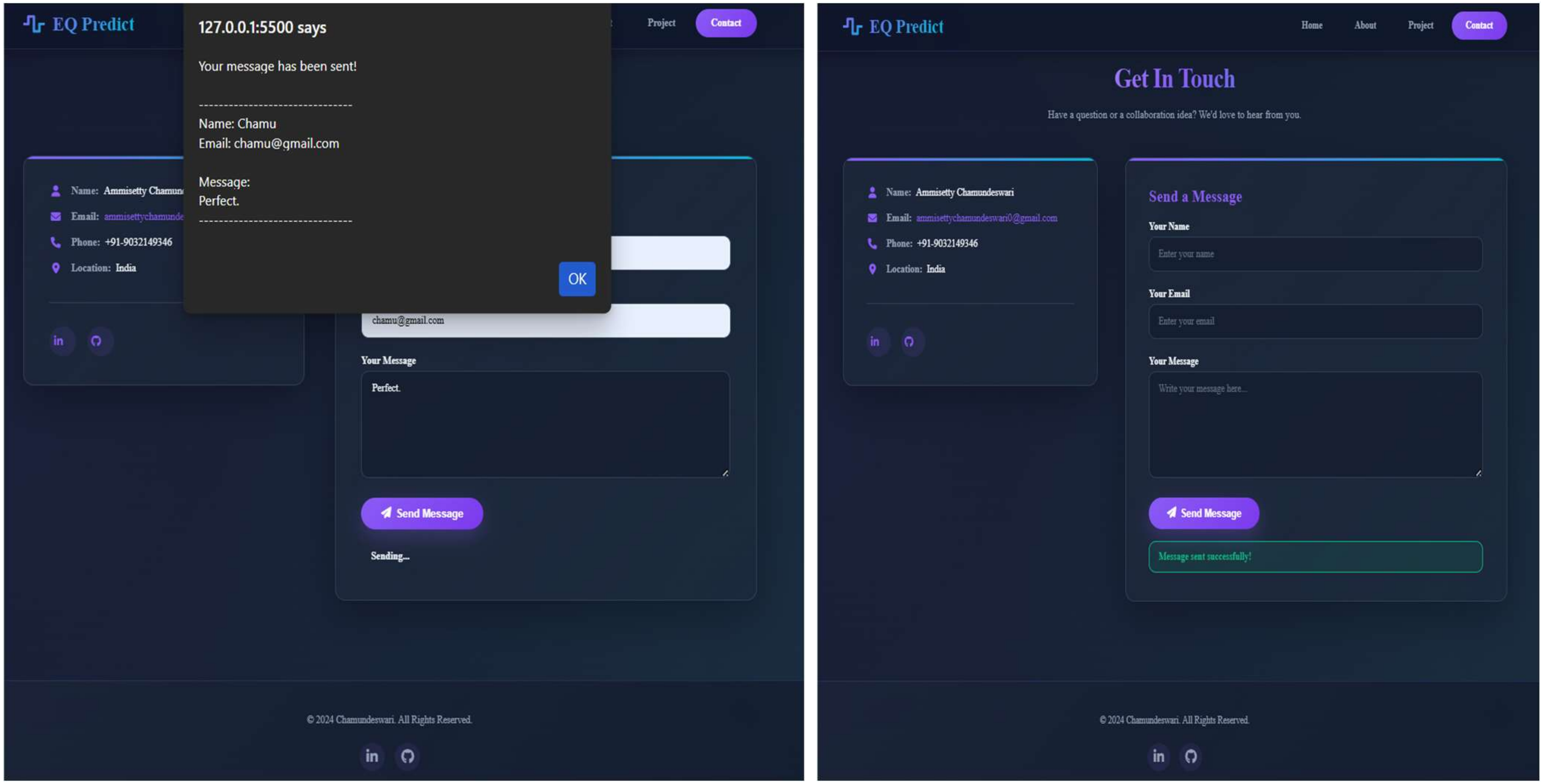


Fig: Contact Page: Let users send queries or feedback through a contact form.

- **Software Specifications:**
  - **Operating System:** Implemented and tested in a Linux/Windows environment compatible with GPU acceleration for deep learning tasks.
  - **Programming Language:** Developed entirely in Python, chosen for its efficiency in scientific computing and machine learning**.**
  - **Libraries and Frameworks:** Utilizes TensorFlow, Keras, NumPy, and SciPy for model building, training, and signal preprocessing.
  - **Development Tools**: Jupiter Notebook or similar IDE used for experimentation, visualization, and integration of training scripts with callbacks.
- **Hardware Specifications:**
  - **Processor:** Intel Core i5 or above
  - **RAM:** Minimum 8 GB (16 GB recommended)
  - **Storage:** Minimum 10 GB free space

NARASARAOPETA ENGINEERING COLLEGE
(AUTONOMOUS)

CHALLENGES FACED & SOLUTIONS

Challenge 1: Handling complex, noisy seismic signals.
Solution: Applied preprocessing and normalization techniques to remove noise and enhance waveform quality.

Challenge 2: Capturing long-term temporal dependencies.
Solution: Integrated BiLSTM and Transformer layers to learn sequential and contextual relationships effectively.

Challenge 3: Lack of model interpretability.
Solution: Used SHAP analysis to visualize and explain the contribution of features in prediction outcomes.

Challenge 4: Uncertainty in prediction results.
Solution: Implemented Monte Carlo Dropout to estimate model uncertainty and improve prediction reliability.

RESULTS & ANALYSIS

- The model is evaluated on a **held-out 15% test set** to ensure unbiased performance measurement.
- Evaluation covers **four key continuous parameters**: magnitude, epicentral distance, azimuth, and focal depth.
- **MAE (Mean Absolute Error)**, **MSE (Mean Squared Error)**, and **R^2 Score** are used as the primary regression metrics.
- Predicted values are compared with **ground-truth labels** to analyze accuracy, error distribution, and model stability.
- **Monte Carlo Dropout** is applied during inference to estimate prediction uncertainty and enhance reliability in real-time usage.

- **Quantitative Comparison:**

Parameter	MAE	MSE	R^2 Score	Performance Summary
Magnitude	0.12	0.03	0.97	Very high accuracy; lowest error
Distance	4.8 km	32.5	0.94	Strong prediction performance
Azimuth	7.2°	18.4	0.89	Good, slightly higher variability
Depth	1.9 km	6.7	0.90	Stable and accurate estimates

CONCLUSION

- The proposed deep learning framework effectively predicts earthquake parameters using only the first 3 seconds of seismic waveform data.
- The CNN–BiLSTM–Transformer fusion model demonstrated high accuracy, robustness, and reliability across multiple prediction tasks.
- Integration of metadata and statistical features improved model generalization and reduced estimation errors.
- Uncertainty estimation and interpretability through Monte Carlo Dropout and SHAP analysis enhanced the model's transparency and trustworthiness for real-world applications.

FUTURE SCOPE

- Extend the model to larger and more diverse regional datasets to further improve generalization and adaptability.
- Implement real-time deployment in early warning systems for faster and automated earthquake alerts.
- Explore lightweight and optimized architectures suitable for edge or embedded devices in seismic stations.

REFERENCES

[1] H. Wang et al., “Fast earthquake magnitude estimation using lightweight CNNs,” IEEE Trans. Geosci. Remote Sens., 2021

[2] S. M. Mousavi and G. C. Beroza, “Bayesian deep learning for earthquake source characterization,” Nat. Commun., 2020

[3] M. N. Uddin et al., “Transfer learning for seismic event magnitude prediction using CNNs,” Comput. Geosci., 2022.

[4] F. H. Masoumi, “Efficient DL for earthquake prediction: Attention-based CNN-LSTM model,” Seismol. Res. Lett., 2023.

[5] X. Zhou et al., “Deep residual networks for earthquake early warning,” IEEE Access, 2020.

NARASARAOPETA ENGINEERING COLLEGE
(AUTONOMOUS)

QUESTIONS and ANSWERS
Thankyou