Predicting Levels of Damages To Buildings Caused By Earthquake

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Abstract- *Earthquakes are among the most devastating natural disasters, causing extensive damage to infrastructure and posing severe threats to human life. Predicting the level of building damage resulting from an earthquake can greatly enhance disaster preparedness and response. This project explores the use of advanced deep learning techniques—such as CNN, BLSTM, GBNN, TabNet, TabPFN, and NODE—for classifying damage levels into three categories: low, medium, and high. Using the 2015 Nepal Earthquake dataset, which includes over 25,000 records and 39 features, our models demonstrate improved performance, achieving accuracy rates of over 74.5% in some cases. These findings highlight the potential of deep learning for effective structural damage assessment.*

Keywords- Earthquake, building damage, deep learning, CNN, BLSTM, GBNN, TabNet, TabPFN, NODE, Nepal earthquake dataset

I. INTRODUCTION

Earthquakes are among the most catastrophic natural disasters, often resulting in severe loss of human life, displacement, and economic instability. The 2015 Nepal earthquake, which registered a magnitude of 7.8, serves as a stark reminder of the devastating power of seismic events. This tragedy caused widespread destruction, with over 9,000 fatalities, hundreds of thousands of buildings either partially or completely destroyed, and entire communities left in ruins. It highlighted not only the vulnerability of the built environment in earthquake-prone regions but also the urgent need for advancements in disaster preparedness and damage mitigation strategies.

In the field of disaster management, the ability to accurately predict the extent of structural damage caused by earthquakes is pivotal. Such predictions play a critical role in prioritizing rescue operations, allocating emergency resources efficiently, and guiding long-term urban planning decisions. However, traditional methods of damage prediction often lack the precision and adaptability required for real-time decision-making, especially in scenarios where each second counts. Advancements in machine learning and deep learning techniques have opened new doors to address these limitations, offering the potential to model complex relationships within seismic data and predict damage levels with unprecedented accuracy. This study leverages cutting-edge artificial intelligence methodologies, specifically tailored for tabular datasets, to predict the levels of damage sustained by buildings during seismic events. By utilizing the Nepal Earthquake dataset, which encompasses structural details, building materials, geographical attributes, and damage, grades, our work seeks to identify underlying patterns and insights that influence building vulnerability. Unlike previous approaches, this research emphasizes the comparative analysis of multiple models, including Convolutional Neural Networks (CNN), Gradient Boosted Neural Networks (GBNN), and Long Short-Term Memory Networks (LSTM).

Furthermore, it explores the capabilities of emerging transformer-based architectures such as TabNet, TabPFN, and Neural Oblivious Decision Ensembles (NODE), which have demonstrated exceptional performance in handling tabular data. This paper's primary objective is to determine the most effective model for accurately classifying earthquake-induced building damage levels. Through meticulous experimentation, we aim to not only evaluate these models' performances but also provide actionable insights for policymakers, urban planners, and first responders. Beyond its immediate applications in earthquake-prone regions, the findings from this work can serve as a blueprint for disaster resilience in other contexts, fostering safer and more sustainable communities. In the sections that follow, we provide a comprehensive review of related work, detail the methodologies employed, present experimental results, and discuss the implications of our findings. This research represents a step forward in the integration of advanced machine learning techniques into disaster management, offering hope for a future where communities are better equipped to withstand the devastating impacts of earthquakes.

II. LITERATURE REVIEW

Earthquake damage prediction has been a crucial area of research for decades, evolving from traditional engineering-based assessments to advanced data-driven methodologies. Accurate predictions of building damage levels enable proactive disaster management, saving lives and minimizing economic losses. This section reviews key studies and approaches, highlighting the advancements in modeling techniques and datasets relevant to seismic damage assessment. Traditional Approaches to Earthquake Damage Assessment Early studies focused on structural engineering models, which relied on physical simulations and empirical formulas to predict building vulnerability. These methods utilized seismic design parameters, such as Peak Ground Acceleration (PGA), soil type, and building codes, to estimate the potential damage. While effective for general risk assessment, they often lacked precision when applied to diverse urban environments due to variability in construction practices and building materials. Emergence of Machine Learning in Seismic Damage Prediction The introduction of machine learning revolutionized earthquake damage prediction by enabling the extraction of complex patterns from vast datasets.

Techniques such as Support Vector Machines (SVM) and Random Forests demonstrated their ability to analyze non-linear relationships between building features and damage levels. However, these methods required extensive feature engineering and were often constrained by the limitations of tabular data. Deep Learning Applications Deep learning has emerged as a powerful tool for earthquake damage prediction, particularly for handling large and complex datasets. Convolutional Neural Networks (CNNs) have been applied to geospatial data, utilizing their capability to extract spatial patterns and correlations. Long Short-Term Memory Networks (LSTMs) introduced temporal dynamics, allowing models to capture sequential dependencies in earthquake sequences. Gradient Boosted Neural Networks (GBNNs) further extended deep learning applications by modeling relational dependencies between buildings and seismic zones. Advancements with Transformer-Based Models Recent studies have explored transformer-based architectures, such as TabNet and NODE, for tabular data classification. TabNet, leveraging attention mechanisms, prioritizes critical features and effectively handles imbalanced datasets—a common challenge in disaster prediction. TabPFN introduced zero- shot learning capabilities, offering competitive accuracy with minimal training effort. These models address the limitations of traditional deep learning techniques, providing interpretable and scalable solutions for earthquake damage assessment. Comparative Analysis Comparing traditional machine learning approaches with deep learning and transformer-based models reveals significant advancements in prediction accuracy and model efficiency. For example, studies show that transformer-based architectures outperform CNNs and LSTMs in tabular data tasks, as demonstrated by their robust performance in handling diverse features such as building characteristics, geographical attributes, and structural integrity scores. Gaps and Research Opportunities 3 Despite the progress, challenges remain in improving the interpretability and scalability of advanced models. Existing research rarely incorporates ensemble techniques or optimization strategies to enhance accuracy. Additionally, few studies address the integration of disaster resilience metrics, such as urban planning recommendations, into prediction models. This project aims to fill these gaps by conducting a comparative analysis of traditional and transformer-based models, focusing on their ability to predict damage levels in real- world scenarios. Future studies can explore the incorporation of **real-time seismic wave monitoring** to refine predictive models. Additionally, leveraging edge computing with **distributed AI architectures** could enhance earthquake damage predictions in regions with limited data access. Emerging advancements in **quantum computing** may also accelerate model training, further refining the precision of earthquake damage forecasting.

III. METHODOLOGY

This study utilizes advanced deep learning and transformer-based techniques to predict earthquake induced building damage levels. The methodology consists of systematic data preprocessing, model selection, training procedures, and performance evaluation.

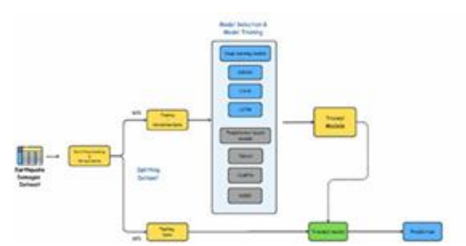

Figure 3.1: Proposed System Architecture for Building Damage Prediction caused by Earthquake

Dataset Description: The dataset used in this study is sourced from DrivenData and contains detailed structural, geographical, and engineering features of buildings affected by the 2015 Nepal earthquake. The dataset includes the following key features: [1]. Building Characteristics: Foundation type, roof material, wall material, number of floors, age, and ground floor type. [2]. Geographical and Location-Based Data: GPS coordinates, soil type, urban/rural classification, and proximity to fault lines. [3]. Structural and Engineering Factors: Compliance with building technical standards, structural integrity scores, and the presence of reinforcement materials. [4]. Target Variable: Damage levels classified into Low (Grade 1), Medium (Grade 2), and Severe (Grade 3).

Data Preprocessing Data preprocessing ensures that the dataset is structured, cleaned, and normalized for effective model training.

Handling Missing Data: [1]. Dropping Features: Features with excessive missing values were removed if deemed non-critical. [2]. Imputation: Missing numerical values were replaced using mean or median methods, while categorical variables were imputed using mode or assigned a placeholder category labeled "Unknown."

Encoding Categorical Variables: [1]. One-Hot Encoding: Applied to categorical variables with a limited number of unique values, such as foundation type and roof material. [2]. Label Encoding: Used for ordinal features like damage levels. [3]. Embedding Representations: Dynamic relationships between categorical variables were learned through embedding layers in transformer models such as TabNet.

Feature Scaling: [1]. Min-Max Scaling: Numerical features were rescaled to a range between 0 and 1 to ensure compatibility with deep learning frameworks.

Dataset Splitting A stratified split was performed to ensure class balance across subsets: [1]. Training Set (80%): Used for model training. [2]. Validation Set (20% of Training Data): Reserved for hyperparameter tuning. [3]. Test Set (20%): Used for final model evaluation.

Model Selection This study explores six machine learning models categorized into traditional deep learning and transformer-based architectures. Traditional Deep Learning Models:

[1]. Convolutional Neural Networks (CNN): CNN reshapes tabular data into spatial-like representations to identify patterns across features. A typical CNN model includes convolutional layers followed by ReLU activations, max pooling, flattening, and dense output layers for classification.

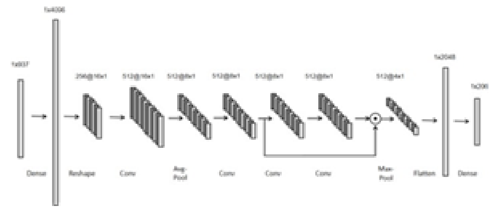

Figure 3.2: CNN Architecture

[2]. Gradient Boosted Neural Networks (GBNN): GBNN combines neural networks with the structure of gradient boosting. It uses multiple shallow networks trained in succession to correct the errors of previous ones.

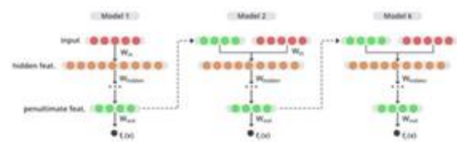

Figure 3.3: GBNN Architecture

[3]. Bidirectional Long Short-Term Memory Networks (BLSTM): BLSTM captures bidirectional dependencies in sequential data and is well-suited for encoding the relationship between building features. The architecture includes forward and backward LSTM layers feeding into a dense classification layer.

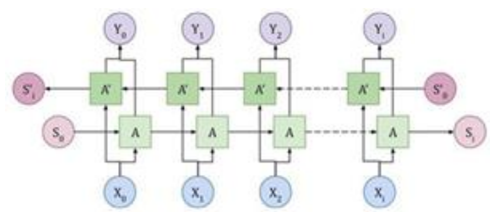

Figure 3.4: B-LSTM Architecture

Here; *Xi* is the input token, *Yi* is the output token, A and A’ *A*’ are Forward and backward LSTM units The final output of *Yi* is the combination of *A* and *A*’ LSTM nodes.

[4]. TabNet: TabNet leverages attention mechanisms to select the most important features during training. It consists of a series of decision steps with feature transformers and attentive transformers.

Matrix: Highlights the classification performance of each model. [2]. Performance Metrics: Accuracy: Percentage of correct predictions,

$TN + TP$

$_{Accuracy =} TN + FP + TP + TN$

Precision: Quality of positive predictions for each class,

$Precision =$

TP

$TP + FP$

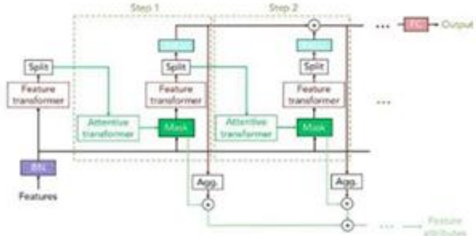

Figure 3.5: TabNet Architecture

[5]. TabPFN: TabPFN is a transformer-based model pretrained to rapidly predict with minimal data. It is especially suitable for few-shot learning tasks in tabular domains.

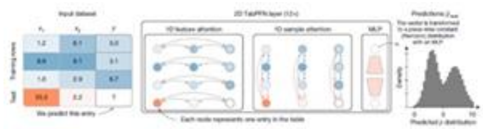

Figure 3.6: TabPFN Architecture

[6]. NODE (Neural Oblivious Decision Ensembles): NODE replaces traditional decision trees with a neural ensemble approach, where differentiable oblivious decision trees are arranged in layers.

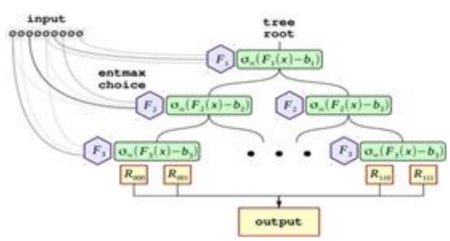

Figure 3.7: NODE Architecture

Training Process All models were implemented using TensorFlow and TabularML frameworks, following a structured training procedure: [1]. Hyperparameter Tuning: Learning rate, batch size, and number of epochs were optimized using a grid search method. [2]. Training Metrics: Accuracy, precision, recall, F1-score, loss, and validation accuracy were monitored across epochs. [3]. Early Stopping: Training was halted when validation loss plateaued to prevent overfitting.

Prediction and Evaluation Post-training, predictions were made on the test set, classifying buildings into Low, Medium, and Severe damage levels. Model performance was evaluated using the following criteria: [1]. Confusion Matrix: Highlights the classification performance of each model. [2]. Performance Metrics:Accuracy: Percentage of correct predictions,

$$Accuracy=\frac{TN+TP}{TN+FP+TP+TN}$$

Precision:Qualityofpositivepredictionsfor eachclass,

$$Precision=\frac{TP}{TP+FP}$$

Recall:Model'sabilitytocorrectlyidentifytruepositives,

$$Recall=\frac{TP}{TP+FN}$$

F1-Score:Balancebetweenprecisionandrecall.

$$F1-Score=2\times\frac{Precision\times Recall}{Precision+Recall}$$

IV. PREDICTION AND EVALUATION

After training each model, we performed predictions on the test set. The following evaluations were made for each model: [1]. Confusion Matrix: To visualize class-wise prediction accuracy. [2]. Training History Curves: Validation accuracy and loss curves were plotted to monitor training dynamics.

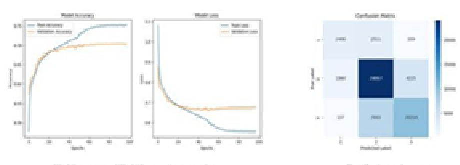

Figure 4.1: CNN Model Performance — Accuracy and Loss Curves with Confusion Matrix

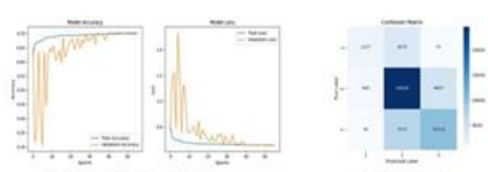

Figure 4.2: GBNN Model Performance — Accuracy and Loss Curves with Confusion Matrix

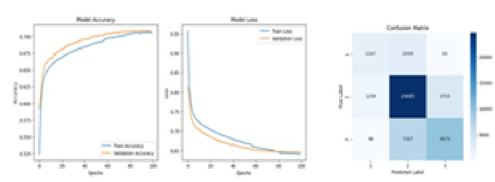

Figure 4.3: BLSTM Model Performance — Accuracy and Loss Curves with Confusion Matrix

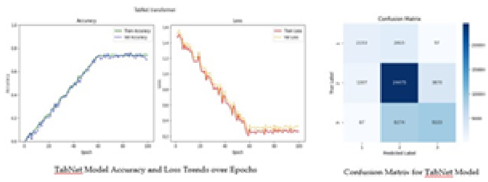

Figure 4.4: TabNet Model Performance — Accuracy and Loss Curves with Confusion Matrix

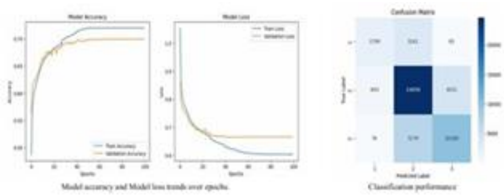

Figure 4.5: TabPFN Model Performance — Accuracy and Loss Curves with Confusion Matrix

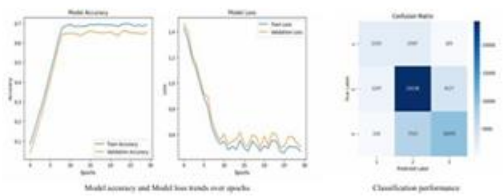

Figure 4.6: NODE Model Performance — Accuracy and Loss Curves with Confusion Matrix

This section presents the performance results of the models employed in predicting building damage levels caused by earthquakes, alongside detailed analysis of their effectiveness. The evaluation is based on key metrics, including accuracy, precision, recall, F1-score, and confusion matrices. Graphical representations of training history (accuracy and loss curves) and confusion matrices provide a visual understanding of the models' predictive capabilities.

Performance Metrics Each model's performance was assessed using the following metrics: [1]. Accuracy: Measures the overall correctness of the model. [2]. Precision: Evaluates the quality of predictions by focusingon minimizing false positives. [3]. Recall: Assesses theMmodel's ability to identify true positives. [4]. F1-Score: Represents the harmonic mean of precision and recall, ensuring balanced evaluation.

Table 4.1: Summarizes the results for all models

Models	Accuracy	Recall (Weighted Average)	F1-Score (WeightedAverage)	Precision (WeightedAverage)
CNN	0.70182	0.693	0.702	0.691
GBNN	0.70131	0.701	0.691	0.701
BLSTM	0.70921	0.689	0.697	0.702
TabNet	0.7401	0.7461	0.72	0.734
TabPFN	0.7052	0.691	0.681	0.703
NODE	0.6970	0.681	0.681	0.691

From the results, it is evident that TabNet outperformed all other models, achieving the highest accuracy of 74.10%, along with strong recall and F1-score values. Transformer- based models showed significant superiority over traditional deep learning models for tabular data classification.

Comparative Analysis: Classification performance Transformer-based models, particularly TabNet, significantly outperformed traditional models (CNN, GBNN, BLSTM). TabNet’s attention-driven learning enabled effective prioritization of critical features such as structural integrity and geographical location. The following key observations were made: [1]. CNN struggled with non-spatial data, limiting its performance. [2]. TabPFN provided competitive results but was slightly less effective in handling imbalanced datasets. [3]. NODE demonstrated potential through hierarchical feature learning but requires further optimization for tabular classification tasks.

Key Takeaways: [1]. Transformer-Based Models Lead: TabNet emerged as the best-performing model, highlighting its suitability for earthquake damage prediction. [2]. Challenges with Severe Damage Classification: Most models faced difficulty in accurately classifying severe damage levels due to class imbalance. This challenge can be mitigated using data augmentation or resampling techniques. [3]. Potential for Improvement: Ensemble methods and explainable AI techniques can further enhance model accuracy and interpretability.

V. CONCLUSION AND FUTURE WORK

This study explored six state-of-the-art deep learning models—**CNN, GBNN, BLSTM, TabNet, TabPFN, and NODE**—for predicting the severity of building damages resulting from earthquakes, using the comprehensive **2015 Nepal Earthquake** dataset. Among these, **TabNet** achieved the highest overall performance with an accuracy of **74.01%**, a recall of **74.61%**, and an F1-score of **0.720**, followed closely by CNN and GBNN. These results validate the use of deep learning techniques, particularly attention-based and boosting-inspired models, in handling complex tabular disaster datasets.

The performance differences across models illustrate that: [1]. **TabNet's** feature selection mechanism significantly benefits structured data learning. [2]. **CNN** and **BLSTM** performed competitively, showcasing their ability to learn spatial or sequential representations of tabular data. [3]. **GBNN** and **TabPFN**, while slightly behind in accuracy, still demonstrated strong generalization ability and precision. [4]. **NODE**, despite its novelty, showed room for improvement with the lowest scores, highlighting potential areas for optimization or tuning.

These findings emphasize the practical applicability of AI- based predictive systems in urban planning and disaster risk management. Accurate prediction of building damage can streamline emergency logistics, improve resource allocation, and ultimately save lives during seismic crises.

Key Findings: [1]. Transformer-based models outperformed traditional deep learning approaches by effectively capturing complex interactions within tabular datasets. [2]. Class imbalance challenges, particularly in predicting severe damage levels, affected model performance, emphasizing the need for further optimization. [3]. Feature selection played a crucial role in predictive performance, as evidenced by TabNet's superior results.

Real-World Implications: The findings of this study have significant applications: [1]. Emergency response teams can use predictive models to prioritize rescue operations in high-risk areas. [2]. Urban planners and policymakers can integrate these insights to design safer buildings and infrastructure. [3]. Disaster management authorities can develop resource allocation strategies based on predicted damage levels.

Future Research Directions: [1]. Exploring ensemble methods to combine the strengths of multiple models for enhanced predictive performance. [2]. Incorporating explainable AI techniques to ensure model transparency and foster trust in real world applications. [3]. Integrating real-time seismic data to improve model robustness and predictive accuracy.

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Forest were used to predict Nepal earthquake damage levels. Models provided reliable damage level classification.

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