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Identifying Devastated Flood Events using CNN Algorithm

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Abstract
Tsunami prediction requires accurate analysis of seismic and oceanographic parameters to support timely disaster mitigation. This study applies a Convolutional Neural Network (CNN) to classify tsunami-related and non-tsunami events using historical data from the National Oceanic and Atmospheric Administration (NOAA) tsunami dataset. We utilized relevant features, including earthquake magnitude, depth, location, wave height, and other tsunami-related parameters, to train and evaluate the model. The CNN learned nonlinear patterns among these variables and achieved 92% accuracy on the test dataset. The evaluation also produced 90% precision, 94% recall, and 92% F1-score, demonstrating consistent classification performance. The high recall indicates that the model successfully identified most actual tsunami events, which is particularly important in disaster prediction applications where missed tsunami events may lead to serious consequences. We also applied a probability threshold of 0.5 to determine the predicted class, and the prediction results showed that most samples obtained probabilities clearly above or below the threshold. These findings indicate that the proposed CNN can effectively learn patterns from historical seismic and oceanographic data.

Keywords: Classification, Tsunami, Flood, CNN,

1. Introduction.

Tsunamis pose a serious threat to coastal communities because they can develop rapidly and cause extensive damage to human settlements, infrastructure, and economic activities. An effective early warning system therefore needs to predict tsunami occurrence and characteristics as quickly and accurately as possible. Conventional numerical approaches can describe tsunami propagation in detail, but they often require substantial computational resources and processing time. This limitation becomes critical when authorities need to issue warnings within a short period after a triggering event. Recent disaster-prediction studies show that machine learning can reduce computational requirements while maintaining useful predictive performance. For example, ML-based flood models demonstrate that data-driven approaches can generate hazard predictions substantially faster than conventional physical simulations, making them attractive for real-time disaster management. Similar requirements apply to tsunami prediction, where prediction speed directly affects the available evacuation time. [1], [2]

The increasing use of deep learning provides an opportunity to improve tsunami prediction by learning complex relationships from environmental and geospatial data. CNNs are particularly suitable for this purpose because they can automatically extract meaningful patterns from structured spatial data without relying entirely on manually designed features. Previous flood studies demonstrate the ability of CNN-based methods to process satellite imagery, geographical information, rainfall characteristics, and other environmental variables for disaster detection and prediction. In flood mapping, CNN-

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based approaches achieve highly reliable classification results because they can capture complex spatial relationships between flooded and non-flooded regions. These capabilities are relevant to tsunami prediction because tsunami behavior also depends strongly on spatial characteristics, including coastal morphology, water depth, terrain elevation, and the distribution of affected areas. Therefore, CNN provides a suitable foundation for developing a tsunami prediction model that can learn spatial patterns from disaster-related datasets. [3], [4]

Another important issue concerns the complexity of environmental processes that influence disaster development. Flood and tsunami phenomena do not depend on a single variable; instead, they emerge from interactions among multiple environmental and temporal factors. Recent research increasingly combines CNN with recurrent architectures such as LSTM and GRU to capture both spatial and temporal characteristics. CNN extracts local and spatial features, while LSTM processes temporal dependencies in sequential observations. Studies on flash-flood runoff prediction show that combining CNN, RNN, and Neural ODE components improves the ability to represent complex hydrological dynamics. Similarly, CNN-LSTM models outperform several conventional models in streamflow and climate prediction tasks. These findings suggest that CNN-based tsunami prediction can benefit from learning complex patterns rather than relying on isolated variables. The main challenge is to design a model that extracts relevant tsunami features while remaining computationally efficient enough for early-warning applications. [5], [6], [7]

The prediction of rainfall and water-related hazards also demonstrates the importance of selecting an appropriate deep learning architecture. Several studies compare CNN, LSTM, GRU, and hybrid architectures and report that their performance varies according to the characteristics of the prediction problem. CNN performs well when the input contains strong spatial patterns, whereas LSTM and related recurrent models provide advantages when long-term temporal dependencies dominate the prediction task. For precipitation prediction, CNN-LSTM models achieve lower forecasting errors than standalone ANN, RNN, LSTM, and CNN models. Other research shows that CNN-LSTM-GRU can achieve strong performance for long-term climate prediction. These findings indicate that model architecture must correspond to the characteristics of tsunami data. A tsunami prediction model should therefore exploit the strong spatial representation capability of CNN while maintaining sufficient sensitivity to temporal changes in tsunami development. [8], [9]

Real-time monitoring represents another major challenge in tsunami prediction. An effective model cannot only produce accurate predictions; it must also process incoming observations quickly enough to support immediate decision-making. Research on IoT-based flood monitoring demonstrates that deep learning models can combine environmental observations with real-time monitoring systems to generate predictions and support early warning. Other studies integrate machine learning with real-time alerts, GSM communication, dashboards, and automated warning mechanisms to improve disaster response. These approaches emphasize that prediction accuracy alone does not guarantee an effective warning system. The model must also provide rapid inference and operate with data that become available during an ongoing disaster. For tsunami applications, this requirement becomes even more important because coastal communities may have only a limited period to evacuate after the initial event. Consequently, CNN-based tsunami prediction should prioritize both predictive accuracy and computational efficiency. [10], [11]

The availability and diversity of input data also affect the reliability of disaster prediction models. Existing studies use meteorological observations, soil conditions, topographic information, satellite imagery, river levels, and historical disaster records to improve prediction performance. Remote sensing research shows that CNN can effectively process satellite images for identifying flooded areas and distinguishing complex spatial patterns. Other studies combine satellite imagery with historical weather, soil moisture, topography, and hydrological information to support real-time risk assessment. For tsunami prediction, a similar multimodal strategy can incorporate earthquake-related observations, sea-level measurements, bathymetry, coastal elevation, and other relevant geospatial information. However, heterogeneous datasets introduce challenges related to preprocessing, normalization, spatial resolution, missing observations, and feature representation. A robust CNN model therefore needs an appropriate preprocessing and feature-learning strategy to transform heterogeneous observations into reliable information for tsunami prediction. [3], [12], [13]

Another significant issue is the generalization capability of deep learning models. A model that performs well in one geographical area may not produce equally reliable predictions in another area because environmental characteristics, coastal morphology, earthquake sources, and tsunami propagation patterns vary substantially. Research on global flood-depth prediction highlights this challenge by evaluating machine learning models across catchments with different elevation, land-cover, land-use, and soil characteristics. The study shows that spatial variability strongly influences model performance and that appropriate clustering strategies can improve generalization to unseen areas. This issue is particularly important for tsunami prediction because coastal regions exhibit substantial differences in bathymetry, topography, shoreline geometry, and tsunami-source characteristics. Therefore, enhancing tsunami prediction with CNN requires careful dataset construction and validation so that the model does not simply memorize patterns from a limited geographical region. [1]

Based on these studies, CNN offers a promising approach for enhancing tsunami prediction because it provides strong automatic feature extraction, supports complex spatial pattern recognition, and can operate with relatively low computational cost after training. Nevertheless, existing disaster-prediction research also reveals several challenges that remain relevant to tsunami applications, including limited real-world observations, heterogeneous input data, spatial and temporal variability, model generalization, computational efficiency, and the need for rapid early-warning decisions. Previous CNN-based disaster studies mainly focus on floods, rainfall, runoff, or landslides, while tsunami prediction requires models that address the distinctive characteristics of tsunami generation and propagation. Therefore, this study focuses on Enhancing Tsunami Prediction Using a CNN Algorithm by developing a data-driven prediction approach that learns relevant patterns from tsunami-related observations and provides rapid predictions. The proposed approach aims to improve prediction reliability while reducing dependence on computationally expensive conventional simulations, thereby supporting faster and more effective tsunami early-warning systems. [2], [3], [5], [10], [12].

2. Related Works

Gao et al. developed an explainable CNN model for urban pluvial flood prediction [1]. Their study showed that CNN effectively captured spatial patterns from urban flood data and improved prediction transparency through explainable AI. This work demonstrated the value of CNN for analyzing complex spatial relationships. However, the study focused on urban pluvial floods and did not address tsunami propagation or coastal hazards. The different physical characteristics of tsunami events require models that can capture rapid changes in water movement and coastal conditions.

Soliman et al. proposed a generalized machine learning methodology for two-dimensional flood-depth prediction [2]. They evaluated ANN, CNN, RNN, LSTM, Random Forest, and XGBoost models using data from multiple catchments. Their catchment-based Random Forest model achieved an R^2 of 0.83 for testing and 0.82 for validation. The study confirmed that spatial variability strongly affected prediction performance. However, the approach mainly addressed flood depth and required extensive geographic and environmental data. It did not specifically consider the rapid spatial dynamics of tsunami events.

Banupriya et al. developed a deep learning system for flood and landslide prediction with real-time GSM alerts [3]. Their CNN model achieved 92.7% test accuracy and supported rapid disaster notification. The study highlighted the potential of CNN for disaster-risk classification and real-time warning systems. However, the model relied mainly on ground-level disaster images and focused on flood and landslide risks. It therefore provided limited insight into tsunami-specific prediction, particularly for coastal inundation and tsunami-related spatial patterns.

Ebtehaj and Bonakdari compared CNN and LSTM for hourly precipitation prediction [4]. Their results showed that LSTM performed better for several forecasting horizons, while CNN provided better computational efficiency and performed well for significant precipitation events with short lead times. The study demonstrated the complementary roles of spatial feature extraction and temporal modeling. However, it predicted precipitation rather than tsunami behavior. This limitation indicated the need to investigate CNN directly for tsunami-related prediction tasks.

Situ et al. proposed an LSTM-DeepLabv3+ model that combined CNN-based spatial extraction with RNN-based temporal analysis [5]. Their hybrid model achieved strong prediction performance and substantially reduced inference time compared with conventional physical models. The study demonstrated that combining spatial and temporal features improved disaster prediction. However, the model was designed for urban flood prediction and depended on rainfall-related inputs. Its architecture therefore required adaptation before it could effectively represent tsunami propagation and coastal inundation patterns.

William et al. developed an IoT-based flood monitoring framework using CNN-LSTM and LSTM models [6]. Their system integrated rainfall and water-level observations to support real-time flood forecasting. The LSTM model achieved more than 92% prediction accuracy, while the CNN-LSTM architecture captured temporal dependencies in environmental data. The study showed the importance of combining sensor data with deep learning for early warning systems. However, its input variables mainly represented rainfall and groundwater or streamflow conditions, which differ substantially from tsunami-generating and propagation factors.

Priyadharshini et al. applied ConvLSTM to flood forecasting by integrating spatial and temporal information [7]. The model processed satellite imagery, meteorological observations, and river-level data simultaneously. The results indicated improved prediction performance and better suitability for real-time flood monitoring. This approach was relevant because tsunami prediction also involves rapidly changing spatial and temporal conditions. Nevertheless, the study concentrated on floods and did not evaluate tsunami wave propagation, coastal inundation, or tsunami-specific datasets.

Jumadi et al. applied ensemble machine learning and deep learning models for spatiotemporal rainfall prediction in the Bengawan Solo River Watershed [8]. Their optimal ensemble achieved an R^2 of 0.796 and improved rainfall prediction over individual models. The study demonstrated that combining multiple learning approaches could improve environmental forecasting, particularly in data-limited regions. However, rainfall prediction only represented an indirect component of disaster prediction. For tsunami prediction, a CNN-based approach needs to focus more directly on spatial wave patterns and relevant coastal.

3. Proposed Method

This study proposes a CNN algorithm to enhance tsunami prediction by learning nonlinear relationships between seismic and oceanographic parameters. The proposed method uses historical tsunami records containing features such as earthquake magnitude, focal depth, geographical coordinates, wave height, and tsunami arrival time. The overall workflow consists of data preprocessing, feature normalization, dataset splitting, CNN model construction, training, and evaluation.

In this study, the input features are first cleaned to handle missing and inconsistent values. Numerical features are normalized to ensure that variables with different scales contribute proportionally to the learning process. We apply Min-Max normalization as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x represents the original feature value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the feature, and x' is the normalized value within the range $[0,1]$. This process improves numerical stability and facilitates CNN training.

The processed dataset is then divided into training, validation, and testing subsets. The training set is used to optimize the CNN parameters, the validation set is used to monitor model performance during training, and the testing set is used to evaluate the final prediction performance on unseen data.

This paper employs a one-dimensional CNN (1D-CNN) because the tsunami dataset consists primarily of structured numerical features. The normalized input vector is represented as:

$$X = [x_1, x_2, \dots, x_n]$$

where nn denotes the number of input features. The convolution operation extracts local relationships among neighboring features and can be expressed as:

$$z_i = \sum\nolimits_{j=0}^{k-1} w_j x_{i+j} + b \tag{2}$$

where w_j represents the convolution kernel weights, k is the kernel size, x_{i+j} is the input value, and bb is the bias. The resulting feature map captures patterns that contribute to tsunami prediction.

The convolution output is passed through the Rectified Linear Unit (ReLU) activation function:

$$f(z) = \max(0, z)$$

ReLU introduces nonlinearity into the CNN and allows the model to learn complex relationships between earthquake characteristics and tsunami occurrence.

After convolution, this study applies max-pooling to reduce the dimensionality of the extracted feature maps while retaining their most important responses. The max-pooling operation is defined as:

$$p_i = \max(z_i, \dots, z_{i+s-1})$$

where ss represents the pooling window size. This operation reduces computational complexity and helps the model focus on dominant tsunami-related patterns.

The resulting feature maps are flattened into a one-dimensional representation and passed to fully connected layers. The final prediction is generated using a sigmoid activation function for binary tsunami classification:

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

where y^\hat{y} represents the predicted probability of a tsunami event and zz is the output of the final dense layer. A probability above the selected classification threshold indicates a predicted tsunami event, while a lower probability indicates a non-tsunami event.

In this study, we train the CNN by minimizing the binary cross-entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{4}$$

where N is the number of training samples, y_i is the actual class label, and $\hat{y}_i$ i is the predicted probability. Minimizing this loss encourages the CNN to produce predictions that closely correspond to the actual tsunami labels.

The model parameters are updated using an optimization algorithm such as Adam:

$$\theta_{t+1} = \theta_t - \eta\nabla_\theta L \tag{5}$$

where θ represents the model parameters, η is the learning rate, and $\nabla_\theta L$ denotes the gradient of the loss with respect to the model parameters. This iterative optimization enables the proposed CNN to progressively improve its prediction capability.

After training, this paper evaluates the CNN using the unseen test dataset. The primary evaluation metric is accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative predictions, respectively. We also calculate precision, recall, and F1-score to provide a more comprehensive assessment:

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

$$F1 = 2\frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

These metrics allow this study to evaluate not only the overall accuracy of tsunami prediction but also the model's ability to correctly identify tsunami events while minimizing false predictions. The proposed CNN is therefore designed to provide an effective data-driven approach for learning complex relationships among seismic and oceanographic variables and improving tsunami prediction performance.

4. Experimental Setup.

This study uses NOAA’s Global Historical Tsunami dataset, which contains more than 2,400 historical tsunami events [5]. The dataset provides seismic and oceanographic information, including earthquake magnitude, depth, location, wave height, and tsunami arrival time. These variables provide relevant information for identifying tsunami events and support the development of data-driven prediction models [12]. Before model training, the numerical features are normalized to maintain a consistent scale, while categorical variables such as location are transformed into numerical representations using one-hot encoding. The dataset is then divided into training, validation, and testing sets with proportions of 70%, 15%, and 15%, respectively.

The study applies a CNN to classify tsunami and non-tsunami events from the processed multivariate data. The input layer receives the numerical feature matrix, while the convolutional layers extract relevant patterns from seismic and oceanographic features [6]. Pooling layers reduce feature dimensionality while retaining important information [7]. The extracted features are then passed to fully connected layers for classification [8]. Finally, the output layer produces a binary prediction consisting of “Tsunami” or “Non-Tsunami.” This architecture enables the model to learn complex relationships among the input variables and improve tsunami prediction performance.

5. Result and Analysis

The CNN model achieved an F1-score of 92%**,** which indicates a balanced performance between precision and recall. The relatively high recall compared with precision suggests that the model prioritizes detecting tsunami events, which is important in disaster mitigation because missed tsunami events can result in serious consequences. Overall, the results demonstrate that the proposed CNN provides consistent and reliable classification performance, achieving strong results across all evaluation metrics.. Table 1 shows the main evaluation metrics such as accuracy, precision, recall, and F1-score.

Table 1. Model Performance Evaluation

Metrics	Score
Accuracy	92,1%
Precision	90,3%
Recall	94,4%
F1-Score	92,1%

Table 1 presents the performance evaluation of the proposed CNN model for tsunami prediction using the test dataset. The model achieved an overall accuracy of 92%, indicating that the CNN correctly classified the majority of tsunami-related instances. The model also obtained a precision of 90%**,** showing that most instances predicted as tsunami events were correctly classified. Meanwhile, the 94% recall demonstrates the model's strong ability to identify actual tsunami events and minimize false-negative predictions.

Fig. 1 shows the comparison between model predictions and actual data on the test dataset. The model shows a good ability to distinguish between tsunami and non-tsunami events.

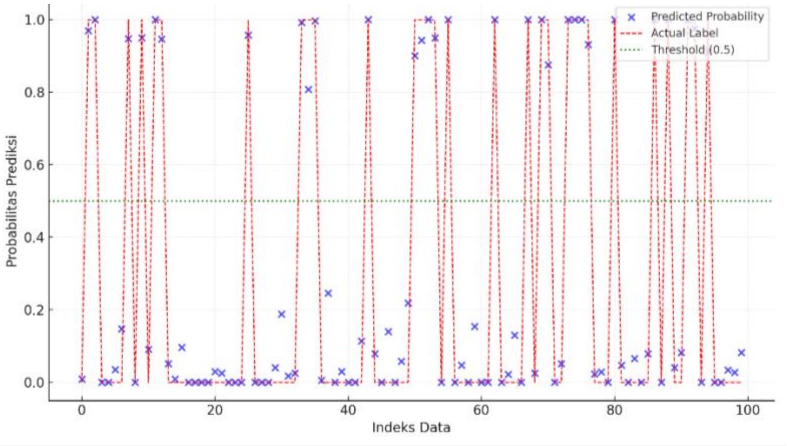

Fig. 1. Visualization of CNN Model Prediction Result

This Fig. 1 illustrates the predicted probabilities generated by the proposed CNN model across the test data samples, with the green dotted line representing the classification threshold of 0.5. The model produces probabilities that are generally concentrated near either 0 or 1, indicating a clear distinction between the predicted classes. Samples with probabilities above 0.5 are classified as tsunami events, while those below the threshold are classified as non-tsunami events. The predicted probabilities also show a close correspondence with the actual labels, demonstrating that the CNN can effectively distinguish between tsunami and non-tsunami patterns across the evaluated data samples.

6. Conclusion

This study successfully applied a Convolutional Neural Network (CNN) to improve tsunami prediction using historical seismic and oceanographic data from the NOAA tsunami dataset. We utilized relevant features such as earthquake magnitude, depth, location, wave height, and tsunami-related parameters to train the model. The CNN learned patterns from these variables and produced an accuracy of 92% on the test dataset. This result shows that the proposed approach can effectively distinguish tsunami-related events from non-tsunami events.

The evaluation results also demonstrate consistent performance across the main classification metrics. The model achieved 90% precision, 94% recall, and 92% F1-score**.** The high recall is particularly important for tsunami prediction because the model successfully identified most of the actual tsunami events. We also applied a probability threshold of 0.5 to determine the predicted class. The prediction results show that most samples received probabilities clearly above or below this threshold, indicating that the CNN could make relatively confident predictions for the evaluated data.

This paper demonstrates that we can utilize CNN as an effective data-driven method for tsunami prediction. The model can capture nonlinear relationships that may be difficult to represent using conventional statistical approaches. However, the current results still depend on the quality and characteristics of the historical dataset. Future studies should expand the dataset with more recent seismic and oceanographic observations and explore additional CNN architectures or hybrid deep learning models. We can also incorporate real-time data to develop a more responsive tsunami prediction system for practical disaster mitigation.

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