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Research Article

Machine Learning for Predicting Natural Disasters: Techniques and Applications in Disaster Risk Management

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Abstract

Natural catastrophes pose a serious threat to property, human life, and vital infrastructure wherever they are found. The need to create effective disaster management systems derives from the growing frequency and intensity of disasters. This study explores the application of machine learning (ML) and deep learning (DL) techniques for disaster detection and classification in order to enhance disaster preparation and response. In this study, a comprehensive dataset that combines satellite images, meteorological data, and historical catastrophe records is used to investigate predicting natural disasters using Convolutional Neural Networks (CNN). The CNN model performs quite well, attaining 97.27% accuracy, 97.79% precision, 98.15% recall, and 97.97% F1-score. With accuracies of 95.33% and 95.23%, respectively, these results greatly outperform those of conventional models like Logistic Regression (LR) and Vision Transformer (ViT-B-32). A detailed evaluation, including loss and accuracy graphs, confirms the model's efficient learning and stable convergence. These findings highlight CNN's potential as a superior approach for natural disaster prediction, offering improved precision and dependability for disaster preparedness and early warning systems.

Keywords: *Natural disaster, Disaster Risk Management, Disaster Prediction, Disaster Recovery, Machine Learning, Natural Disaster Dataset, Satellite Imagery, Meteorological Data, Disaster Management*

Introduction

As a result, there is an increasing necessity to develop better strategies to tackle environmental and other societal risks within global systems that have grown more and more complex and interconnected. Natural disasters are probably the most severe threats that keep on wreaking havoc with life, property and infrastructure[1]. Disaster risk management is more crucial than ever in light of these disasters being stronger and more frequent as a result of climate change. Natural disasters may be catastrophic events such as earthquakes, floods, hurricanes, fires, tsunamis, landslides, and volcanic eruptions [2]. Immediately and in the longer term, these phenomena constitute equivalent risks to communities, economies and ecosystems. Such disasters result in the deaths of millions of people annually, with substantial injuries and property damage, according to recent data[3]. A key element of the efforts to minimize the impact of these events[4] is the ability to understand the responsible factors and to predict the events when they will occur.

The systematic approach to determine the identified, assessed and mitigated risks of natural hazards is referred to as disaster risk management[5]. It consists of four stages: reaction, recovery, readiness, and mitigation. To ensure effective management, one needs accurate data, timely decisions, as well as coordination of resources across different stakeholders. And while the next disaster is inevitably waiting for humanity, traditional methods of prediction and management of the disaster are based on historical data and experts' analysis, so it can be of very narrow scope and insufficient flexibility[6][7]. It has been demonstrated in recent years that ML and AI have enormous promise to transform catastrophe risk management [8][9]. Moreover, DL methods have been applied to improve forecasting, real-time monitoring, and decision support in disaster [10]. These advanced techniques provide more accurate forecasts of natural disasters to better prepare and very quickly and cooperate.

Motivation and contribution

Timely forecasts are an essential element in reducing the impact of the natural catastrophes that represent major risks to lives and infrastructure. Traditional prediction methods are not very accurate and flexible. This paper attempts to improve natural disaster

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prediction by using a variety of data sources with advanced ML and DL techniques, specifically dealing with data imbalance and high dimensionality. The aim is to build more dependable, information-driven models that assist in better disaster prediction and better preparedness and response necessities. The following are the contributions this paper as follows:

The establishment of a detailed database requires combining satellite images with meteorological data combined with historical documentation for generating reliable disaster prediction.

To improve data quality through the use of sophisticated data preparation methods including min-max normalization, category filtering, and missing value imputation.

To address class imbalance using SMOTE, ensuring an equitable distribution of disaster categories.

To enhance model efficiency by reducing dimensionality using feature selection approaches.

To assess how well ML and DL models, such as CNN, ViT-B-32, and LR, perform.

To evaluate the model's efficacy by calculating loss, confusion, F1-score, recall, accuracy, and precision matrices for in-depth insights into categorization.

Structure of the paper

The study is organized in Section II, the existing literature on natural disaster prediction. In section III, the methodology was utilized to compile the data for this study. Section IV provides the results and analysis of text classification. Finally, Section V provides the conclusion.

Literature Review

The literature review part discusses ML for disaster risk management and how it may be used to forecast natural catastrophe protocols. Also, Table I provides a summary of these literature reviews discussed below:

Laya et al. (2021) an unexpected occurrence known as a natural catastrophe may harm both people and the environment. In order to categorise natural disasters, It is necessary to have an automated system that gathers news from several web sources and locates articles pertinent to these occurrences. This is because people are finding it increasingly difficult to find news that is pertinent to these events among the increasing number of online news stories. Results for three categories of natural catastrophes demonstrate that relevant Indonesian web news may achieve an accuracy of around 96% when utilizing the SVM[11].

Ilukkumbure et al. (2021) look at constructing a strategy for managing and reducing flood risks both before and after the impact of floods by using ML, DL, the IoT, and crowdsourcing. The aforementioned elements, when combined with ML methods and the accessible historical data set, may accurately predict the occurrence of floods and catastrophic weather events in some regions of Sri Lanka with an accuracy of above 0.70[12].

Ehara et al. (2020) The proposed system provides automated recognition capabilities that teams can use for disaster rescue through UAV equipment. Test outcomes showed that the system achieved 95.6% accuracy in classification thus proving its usefulness for post-disaster situations in both awareness and rescue operations enhancement[13].

Munawar et al. (2019) merging image processing with ML to identify flood-impacted regions is a novel approach for efficient flood control. Experimental results demonstrate an accuracy of 90%, showcasing the potential of this approach to enhance flood management and improve disaster response strategies[14]

Song and Park (2019) This research suggested disaster management strategies for 187 nations worldwide, taking into account economic indicators and natural catastrophe damage records from 1900 to 2017. It developed a methodology for damage prediction by using national economic data, damage reports from previous natural disasters, and basic indicators like disaster management procedures. Area, GDP, and population are independent variables in the damage prediction model. Using multiple regression analysis, it determined the average number of fatalities, impacted individuals, and damage expenses by nation[15].

Arinta & Andi W.R. (2019) This study will concentrate on carrying out a review procedure and comprehending the function of big data and ML in the context of natural disasters and disaster management. This paper's outcome is to shed light on the application of big data, ML, and DL in six different disaster management domains. Early warning damage, damage assessment, monitoring and detection, forecasting and prediction, post-disaster coordination and response, and long-term risk assessment and reduction are all included in this six-disaster management domain[16].

Table I provides an overview of recent research on ML in the context of disaster management and prediction, describing datasets, methodologies, results, and limits. It also highlights data sources, future research paths, and accuracy advancements.

Table 1 Summary of Literature Review on Machine Learning for Predicting Natural Disasters and Disaster Risk Management

Author	Dataset	Methods	Key Findings	Limitation/Future scope
Laya et al. (2021)	Indonesian online news about natural disasters	Support Vector Machine (SVM)	Achieved 96% accuracy in categorising news from internet sources related to disasters.	Explore news sources from other countries; increase dataset diversity.
Ilukkumbure et al.	Historical flood and rainfall data, weather	ML, DL, IoT, Crowdsourcing	Integrated ML/DL algorithms, IoT, and crowdsourcing to predict flood risks	Consider more diverse geographical areas; enhance

(2021)	information from IoT and crowdsourcing		with 70%+ accuracy.	crowdsourcing data.
Ehara et al. (2020)	UAV-captured images in natural disaster areas	Supervised Machine Learning	Achieved 95.6% accuracy in classifying individuals' statuses (standing, sitting, lying) in post-disaster environments.	Extend to other disaster types and improve real-time processing.
Munawar et al. (2019)	Flood-affected area images	Image Processing, Machine Learning	Achieved 90% accuracy in detecting flood-affected areas to aid flood management and response efforts.	Extend method to other natural disasters and improve real-time detection.
Song and Park (2019)	Disaster damage documents, economic indicators, population, GDP data	Multiple Regression Analysis	created a method for predicting natural catastrophe damage based on GDP, population, and area; R2 = 0.893.	Further exploration of other factors influencing damage prediction; improve formula accuracy.
Arinta & Andi W.R., (2019)	Sensor data, satellite images, social media, historical records	ML, Big Data, DL	Useful in six key areas of disaster management, improving prediction, response, and recovery	Data quality, real-time processing, and integration challenges; need for more adaptive and explainable models

Methodology

The methodology for predicting natural disasters follows a methodical process that starts with gathering information from several sources, such as historical documents, satellite photography, and weather data.

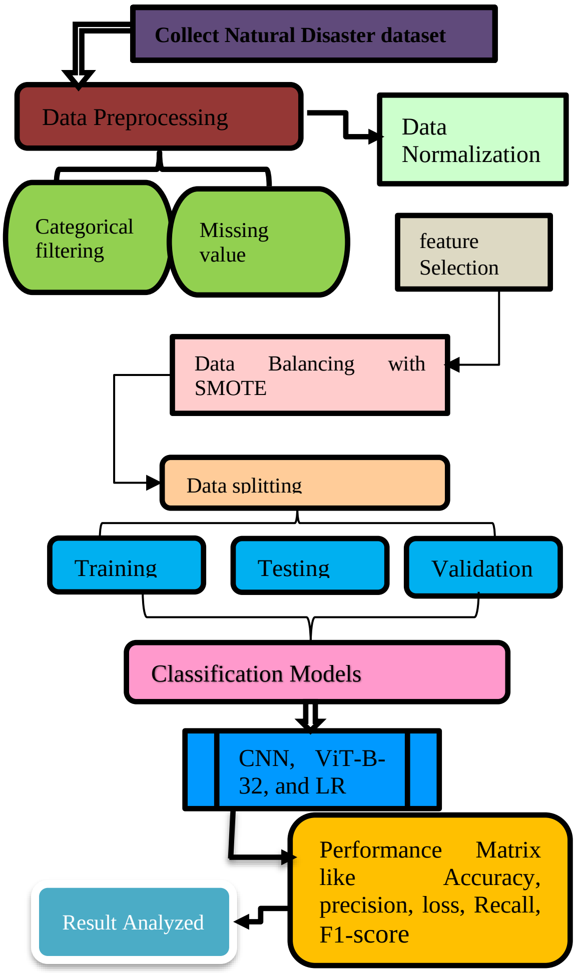

Figure 1 Flowchart of Natural disaster dataset

To improve data quality and standardization, preprocessing methods, including min-max normalization, missing value imputation, and categorical filtering, are then used. Then, by creating synthetic samples, SMOTE is used to rectify class imbalance and guarantee a fair distribution of disaster categories. For model construction, the dataset is then divided into subgroups for training (60%), testing (23%), and validation (17%). In order to reduce dimensionality and increase model performance, redundant characteristics are now removed using feature selection. For classification, ML and DL models such as CNN, ViT-B-32, and LR are used. The models are assessed using the following final metrics: F1-score, accuracy, precision, recall, and loss; confusion matrices, however, give details on the models' classification skills. These steps are displayed in Figure 1.

The following describes the flowchart's further stages.

Data collection

The Natural disaster dataset was compiled from Google Images, yielding 4428 images in various categories. Historical records, satellite images, meteorological data, and social media reports are some sources used to compile the natural disaster prediction dataset. The collection was then separated into four groups, each containing 928, 1350, 1073, and 1077 images: flood, wildfire, earthquake, and cyclone. The following classes of datasets are shown in Figure 2.

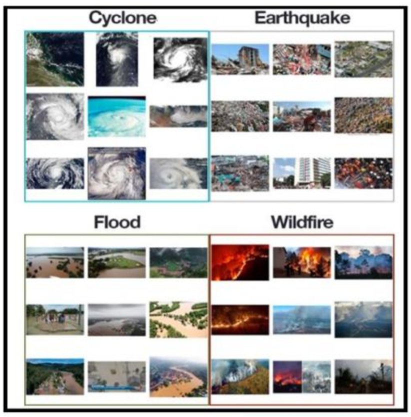

Figure 2 Classes of natural disasters dataset

A visual depiction of the dataset used in the research is shown in Figure 2. Four categories comprise the dataset flood, wildfire, earthquake, and cyclone. Each category is represented by a grid of images showcasing diverse examples of the respective disaster, offering a glimpse into the visual characteristics and variations within each class.

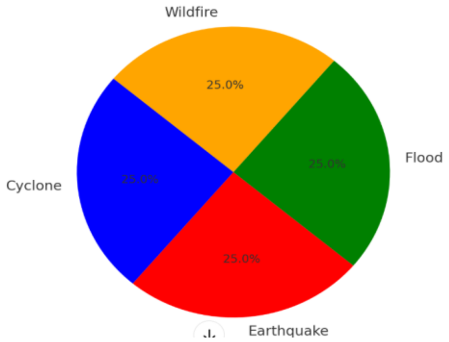

Figure 3 Different types of natural disasters

The following Figure 3 illustrates the many kinds of natural catastrophes. A pie chart that illustrates how the four natural catastrophes depicted in the picture are distributed: Wildfire, Flood, Earthquake, and Cyclone a fair allocation of 25% to each Natural disaster intensity analysis and categorization using multispectral images and a multilayered deep CNN.

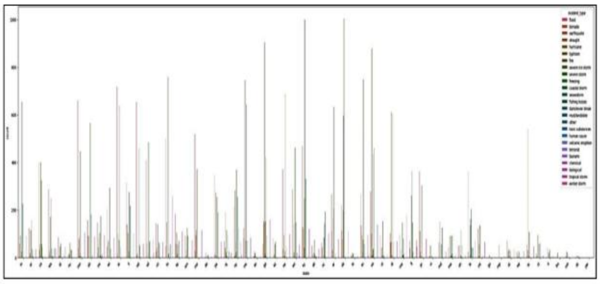

Figure 4 Bar chart for distribution disaster

Figure 4 represents a bar chart illustrating the frequency of different incident types over time. The number of occurrences is shown on the y-axis, while dates are shown on the x-axis. Each bar is color-coded to represent a different incident type, such as flood, terrain-related incidents, drought, hurricane, storm, fire, freezing, coastal storm, landslide, mining accident, transportation accident, industrial accident, collapse, human-caused accident, radiation, chemical, biological, and winter storm. The chart shows the fluctuations in the occurrence of these incidents over the period.

Data preprocessing

The pre-processing task includes the alterations implemented to the data before dispensing it to the algorithm. It is a kind of data preparation for the process[17]. Raw data gets transformed into a clean data set using pre-processing. The pre-processing processes outlined below are as follows:

Categorical Filtering: This step involves filtering or selecting specific categorical values from nominal data (data without an inherent order).

Missing Value Imputation: Removing rows with missing data or imputing them using methods like the mean, median, or mode are common approaches.

Data Normalization

While standardization transforms, data normalization is used to standardize and place the dataset inside a specified range[18]. This procedure improves the data's uniformity and accuracy[19]

An often-used method for normalizing numbers between 0 and 1 is min-max normalization. Equation (1) shows that this method resists outliers since it employs statistical methods that do not affect data variance.

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

Where x stands for the initial worth, $x_{normalized}$ represents the scaled value, min is the lower bound, and max is the top limit of the feature value.

Feature selection

Since overfitting can occur as a result of the curse of dimensionality reduction, feature selection is an essential component of data preparation [20]. A key feature selection component is eliminating superfluous or irrelevant elements.

Data Balancing with SMOTE

The dataset used in this is uneven, which is problematic because most machine learning methods assume that the majority and minority classes are distributed evenly. Inaccurate judgements and poor predictive modelling skills result from this. Synthetic minority sampling is what the SMOTE approach is. SMOTE reduces majority-class bias and levels the playing field in the dataset by creating synthetic samples for under-represented groups.

Data splitting

Training, testing, and validation were the three categories into which the data was separated. Training utilized 60% of the dataset, testing 23%, and validation 17%.

Convolution neural network (CNN) Model

A class of neural algorithms known as CNNs uses local information processed by many layers of convolving filters [21]. Distributed word representations are the most common input text characteristics in NLP[22]. Specifically, with a tokenized text T = {t1,..., tL} as input, a CNN takes a text matrix A as input, where the itch row Equation (2) contains the word vector representations of the itch character in the input text:

$$P(Y_i = yi) = \left(1 - \overline{\Lambda}\dot{i}\right)^1 - y_i \pi_i^{y_i}) \quad (2)$$

A series of filters is used to achieve convolution. The use of convolution filters in computer vision. The number of neighboring rows (or tokens) that the filter considers collectively are represented by their heights, which are a model hyperparameter instead. Here is the Equation (3) to calculate the output of a strainer W ∈ Rd×h (i.e., with height h)

$$C_i = f(W.A[i{:}j] + b) \quad (3)$$

where $A[i{:}j]$ represents The submatrix of A that spans rows I through J has a bias term (b ∈ R) and a nonlinear function (f), such as the hyperbolic curve[23]. This filter is used to create a convolutional feature map $c = [c1, c2, \dots, csh + 1]$ for every potential word window in the text $\{A\ [1{:}\ h], A\ [2{:}\ h\ +\ 1], \dots, A\ [s\ -\ h\ + 1{:}\ s]\}$. Next, feature map c is subjected to a pooling function ito extract a single scalar c hat. he CNN design is made up of many filters, each with a different width, which are used to extract different characteristics. The probability distribution among the classification labels is produced by combining these qualities in the penultimate layer and sending them to a fully linked SoftMax layer.

Performance metrics

A collection of assessment measures, also called performance metrics, was utilized to assess how well phishing email detection performed. A confusion matrix is a table that compares the predicted and actual outcomes to assess how well the model performed. Five assessment metrics accuracy, precision, recall, and F1-score were used to evaluate the final models. Classes in the confusion matrix come first: The number of cases that were accurately predicted to be the actual class is known as the TP. The number of instances from the real class that were mistakenly projected to belong to a different class is simultaneously shown by FN. The number of records successfully identified as normal is known as TN, whereas the number of non-class instances that are mistakenly believed to belong to the target class is known as FP.

Accuracy (ACC): The ratio of the model's absolute number of accurate detections (TP and TN) to its overall number of detections. It is expressed Equation (4).

$$Accuracy = \frac{TP+TN}{N} \times 100 \quad (4)$$

Precision (P): The precision of the Equation (5) is the percentage of favorable observations that accurately calculate the overall number of favorable projections.

$$Precision = \frac{TP}{TP+FR} \times 100 \quad (5)$$

Recall (R): The fraction of properly detected positive observations is called recall, and it is computed using Equation (6).

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (6)$$

F1-Score (F1): The F1 Score, which may be computed as follows Equation (7), is a thorough assessment and balancing of recall and precision values.

$$F1 - \text{score} = \frac{2 \times recall \times precision}{recall + precision} \quad (7)$$

Loss: A model's loss is the quantitative measure of the discrepancy between its actual and anticipated values. It is used as an optimization metric during training. The evaluation of models is successful with the help of these performance parameters.

Experiment Results

The experiment results of the model that is utilized are provided in this section. The proposed model CNN are trained on the Natural disaster dataset and evaluated with F1-score, recall, accuracy, and precision, shows in Table II. The following proposed model is compared with ViT-B-32[19], and LR[20], as shown in Table II.

Table 2 Result of CNN model on Natural disaster dataset for Predicting Natural Disasters

Evaluation Measure	Convolutional Neural Network (CNN)
Accuracy	99.92
Precision	97.79
Recall	98.15
F1-score	97.97

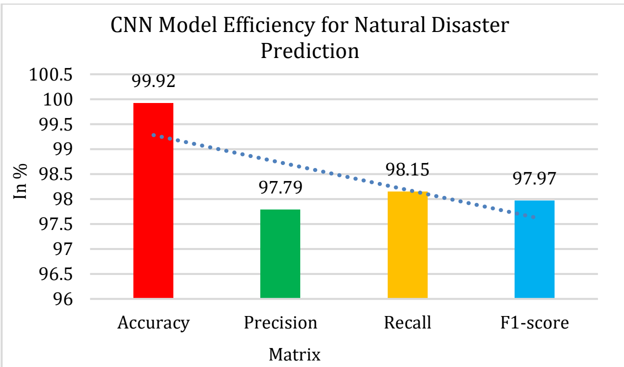

Figure 5 Bar Graph for CNN model

The following The CNN bar graph is shown graphically in Figure 5, and the Natural Disaster dataset performance of the CNN model is displayed in Table II. This graph shows how well the CNN model does overall in classification tasks, with an accuracy of 99.92%, precision of 97.79%, recall of 98.15%, and F1-Score of 97.97% for natural disasters.

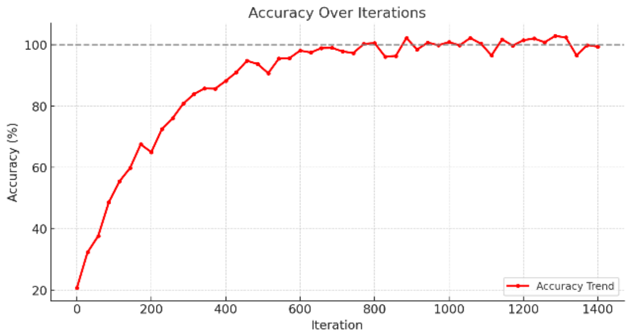

Figure 6 Accuracy graph of CNN Model

Figure 6 illustrates the accuracy trend over multiple iterations, showing a steady increase from around 20% to nearly 100% as the iterations progress. The red line with markers represents accuracy improvements, with minor fluctuations due to variations in learning. The accuracy stabilizes near the 100% mark after approximately 1000 iterations. A dashed gray line highlights the 100% accuracy level for reference. The visualization includes labeled axes, a legend, and a grid for clarity, making it easy to interpret the model's performance improvement over time.

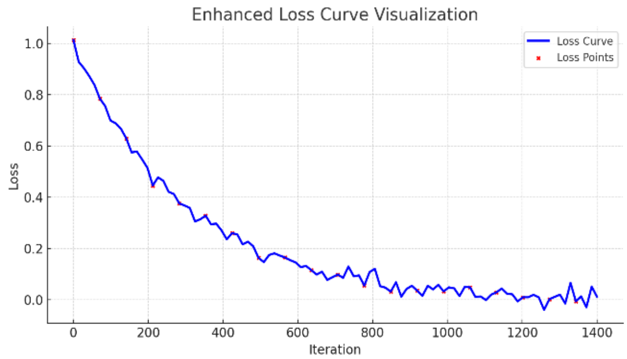

Figure 7 Loss graph of CNN Model

The learning development displayed by the model appears in Figure 7 through multiple iterations as it demonstrates significant initial loss reduction that stabilizes toward an optimized solution. Loss reduction appears as a smooth blue line curve across the graph alongside key red markers used to indicate important points on the curve. The model demonstrates effective error minimization through training because it produces increasingly lower loss values when making predictions. The final stage of the learning curve shows minimal changes indicating a stabilized state of learning.

Figure 8 illustrates how the model performs its classifications for the Cyclone, Earthquake and Flood, along with the Wildfire categories. The model accurately classifies data points, which appear as green cells across the diagonal area, thus demonstrating high reliability across all categories.

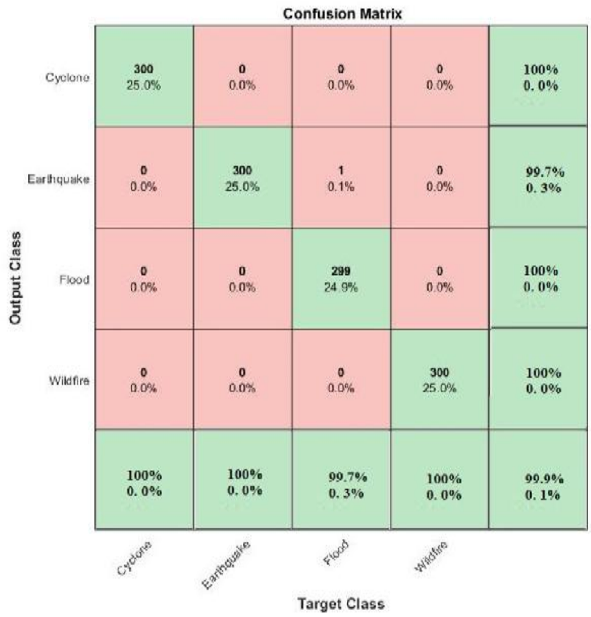

Figure 8 Confusion matrix on Testing Model

The off-diagonal red cells demonstrate few misclassifications where minor mistakes involve classifying one earthquake incident as a Flood (0.3%). The model shows exceptional performance because it achieves a classification accuracy of near 100% for each category.

Table 3 Comparison between CNN and existing model performance for Natural Disaster Prediction

Models	Accuracy
LR[24]	95.33
ViT-B-32[25]	95.23
CNN	99.27

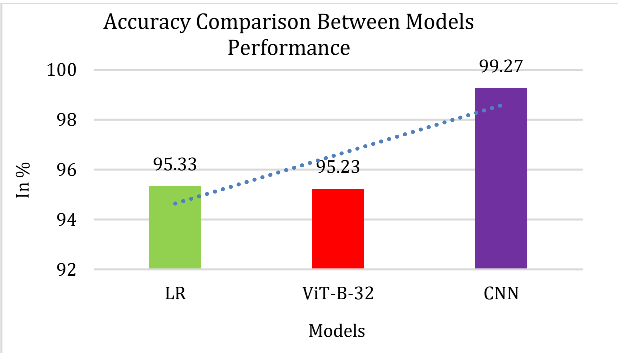

Figure 9 Bar Graph for Accuracy Comparison

Table III and Figure 9 present a comparative analysis of the performance of various models, focusing on accuracy as the evaluation metric. The LR model achieved an accuracy of 95.33%, while the Vision Transformer (ViT-B-32) model earned a little lower 95.23%. But CNN fared much better than these models, with the greatest accuracy of 99.27%. This demonstrates the superior capability of CNN in capturing complex patterns and features, making it a more effective approach for natural disaster prediction tasks.

Conclusion and Future Work

A system to avoid, reduce, or cope with catastrophes is necessary due to the increasing risks of economic, social, and environmental losses from disasters. Existing research, however, has shown that there aren't many useful instruments and systems for disaster risk management. Predicting natural catastrophes accurately is essential to managing them effectively and lessening their effects. This study evaluated the performance of CNN in predicting natural disasters using a diverse dataset comprising satellite imagery, meteorological data, and historical records. The CNN model outperformed more conventional models like LR and ViT-B-32, which had accuracies of 95.33% and 95.23%, respectively, with 97.27% accuracy, 97.79% precision, 98.15% recall, and 97.97% F1-score instead. The findings of this study prove CNN stands as a promising technology for natural disaster prediction because it produces more accurate and reliable results than existing approaches. Future research may concentrate on integrating more data sources, optimizing model hyperparameters, and exploring alternative deep learning architectures in order to enhance prediction performance and robustness.

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