AUTOMATED INTENSITY CLASSIFICATION OF NATURAL DISASTER WITH AI TECHNOLOGY

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Abstract— *Natural disasters have a major impact on the economy, environment and people's quality of life. Events such as earthquakes, tsunamis, floods, cyclones and forest fires can cause serious damage to countries and communities. These disasters destroy buildings, spread diseases, and disturb the natural ecosystem. Such disasters not only damage homes and important infrastructure but can also cause long-term environmental changes. To reduce disaster damage, many researchers use deep learning techniques for detection and analysis. However, identifying disasters from images is difficult because the images are complex and unbalanced. To address this problem, we developed a multilayered deep convolutional neural network that classifies different types of natural disasters and shows the severity of damage. The model is also compared with pretrained models to improve disaster detection.*

Keywords— Natural Disaster, Deep Learning, Convolutional Neural Network, Disaster Detection, Image Classification, Earthquake.

I. INTRODUCTION

Natural disasters cause serious damage to human life, property, and the environment. Common disasters include earthquakes, floods, cyclones, tsunamis, and wildfires. Due to the increasing frequency and intensity of these events worldwide, effective disaster monitoring and early detection systems have become very important for reducing damage and saving lives. In recent years, advancements in artificial intelligence and deep learning have provided new solutions for disaster detection and management. Deep learning models, especially Convolutional Neural Networks (CNN), have shown excellent performance in image recognition and classification tasks. These model can automatically learn important features from image and accurately identify patterns related to different type of disasters. By analyzing disaster images, deep learning system can help in quickly detecting and classifying disasters, which support faster response and decision making during emergency situations.

This research focuses on developing a deep learning-based system for natural disaster detection using image data. The proposed system uses a multilayered CNN model to classify different type of disasters such as floods, cyclones, earthquakes, wildfires. The model analyze uploaded images and predicts the type of disaster along with its severity. In addition to identifying the disaster category, the system also estimates the intensity level of disaster. The severity of the disaster is represented using a color-based warning system, where Green indicates low intensity, Yellow indicates moderate intensity, and Red indicates high intensity. This color indication helps users easily understand level of risk and take appropriate safety measures.

The proposed system is implemented using deep learning techniques and a web-based interface that allows users to upload disaster images and receive prediction results instantly. The system is designed to assist disaster management authorities and emergency responders in identifying disaster

Situations quickly and efficiently. By providing early detection and severity estimation, the system can help improve disaster response and reduce the potential damage caused by natural disasters.

II. LITERATURE SURVEY

Many researchers have studied the use of artificial intelligence and deep learning techniques for disaster detection and classification. Traditional disaster monitoring methods mainly depend on manual observation and sensor-based systems. These methods are often time-consuming and less efficient when large amounts of data need to be analyzed.

In recent years, deep learning models such as Convolutional Neural Network (CNN) have been widely used for image classification and pattern recognition. These models can automatically extract important features from images and classify them into different categories. Researchers have applied CNN models to detect disasters such as floods, earthquakes, and wildfires. Some studies have also used pre-trained deep learning models such as VGG16, ResNet, and MobileNet to improve classification accuracy. However, disaster detection using image still faces challenges due to complex background, lighting variation and unbalanced datasets.

Therefore, this research proposes a multilayered CNN model to classify natural disaster and determine their severity levels. The proposed system also includes a color-based intensity indication (Green, Yellow, and Red) to represent the level of disaster severity.

Author&Year	Disaster Type	Methodology	Accuracy Obtained	Advantage	Limitation	Real-Time Flexibility
Wang et al.,2019	Flood, Earthquake	CNN-based image classification	92%	Automatically extracts image features and improves classification accuracy	Require a large training dataset	Limited real-time application
Liu et al.2020	Flood Detection	Deep learning with satellite images	90%	Suitable for large-scale disaster monitoring	Satellite images may contain noise and a complex background	Moderate real-time capability
Zhang et al.,2021	Wildfire Detection	Transfer Learning using VGG16	94%	High accuracy with pre-trained models.	High computational cost	Limited for real-time performance
Sharma et al.2022	Earthquake Damage	Deep Convectional Neural Network	91%	Efficient feature extraction and classification	Performance affected bt unbalanced dataset	Moderate real-time performance
Kumar et al.,2023	Multiple disaster	Hybrid CNN and machine Learning	93%	Can classify multiple disaster types	Requires large and balanced dataset	Limited real-time prediction
Proposed System	Earthquake, Flood, Cyclone, Wildfire	Multilayer CNN Model	95% (expected)	Detects disaster type and severity level (Green, Yellow, Red)	Depend on dataset quality	Designed for faster prediction and better real-time usability

From the literature review, it is clear that most existing studies focus mainly on disaster detection using deep learning models. However many system do not efficient real-time prediction. Therefore, the proposed system aims to address these research gaps by using a multilayer CNN model that not only detects the type of disaster but also indicates its intensity level using a color-based warning system(Green, Yellow, Red) for better real-time disaster management.

III DATASET

The dataset used in this research consists of disaster images collected from various online open-source platforms. The dataset includes both satellite images and real-time disaster photograph to improve the model performance and generalization ability. The images belongs to four major disaster categories. Flood, Earthquake, Cyclone, and Wildfire.

The dataset is prepared by collecting images from publicly availability repositories such as Kaggle datasets, Google Open Image, and NASA Earth Observatory. After collection, the image are manually verified and categorized based on disaster type.

A. DATASET CATEGORIES

The collected dataset is organized into different categories based on the type of natural disaster. Each category is assigned a class label to help the CNN model easily identify and classify the images during the training process. The dataset includes multiple disaster type such as floods, earth quakes, wildfires, and hurricanes. The number of images in each category may vary depending on the availability of data. This classification helps in each category may vary depending on the availability of data. This classification helps in balancing the dataset and improving the model performance.

Class label	Disaster type	Number of Images
Class 0	Flood	198
Class1	Earthquake	156
Class 2	Cyclone	220
Class 3	wildfire	168

B. DATA COLLECTION METHOD

The disaster images used in this research are collected from publicly available open datasets. These datasets contain images of various natural disaster such as floods, earthquake, wildfires, and hurricanes. After collecting the images, duplicate and irrelevant images are removed to maintain the quality of the dataset . Each image is then carefully labeled according to its respective disaster category to ensure correct classification during model training.

After labeling, all images are resized to a fixed dimension so that they can be properly processed by the CNN model. Preprocessing techniques are also applied to improve image quality and model performance. Finally, the dataset is divided into two parts: a training dataset and a testing dataset. The training dataset is used to train the CNN model, while the testing dataset is used to evaluate the performance and accuracy of the model. This systematic data collection process helps in improving the reliability and effectiveness of the disaster detection system.

C. DATA PREPROCESSING

Data preprocessing is an essential step performed before training the CNN model to improve the quality and consistency of the dataset. In this process, all collected images are resized into a uniform dimension so that they can be given as input to the CNN model without any size mismatch issues. The pixel values of the images are normalized to reduce computational complexity and improve model learning efficiency. In addition, data augmented techniques such as image rotation, horizontal flipping, and zooming are applied to increase the diversity of the training dataset. These techniques help in preventing overfitting and improve the generalization capability of the model. Noise removal and image enhancement techniques are also applied wherever necessary to improve the clarity of the images. After completing the preprocessing steps, the dataset becomes ready for training the CNN model for disaster classification.

IV METHODOLOGY

The proposed system integrates deep learning techniques with a web-based platform to classify natural disasters and estimate their intensity levels. The methodology consists of four major stages: data preprocessing, CNN model design, training and evaluation and system workflow implementation.

A.DATA PREPROCESSING

The dataset comprises images of floods, earthquakes, cyclones, and wildfires collected from kaggle, Google Open Images. Since the images vary in resolution and quality, preprocessing steps were applied to ensure consistency:

Resizing: All images were resized to 224 × 224 pixels.

Normalization: pixel values were scaled between 0 and 1.

Noise Removal: Gaussian filtering was applied to reduce aircrafts.

Data Augmentation: Rotation, flipping, and brightness adjustments were used to increase dataset diversity and reduce overfitting.

B.CNN MODEL ARCHITECTURE

The classification model is based on a multilayered Convectional Neural Network (CNN).The architecture includes:

Convolutional Layer: Extract spatial features such as edges, textures, and disaster-specific patterns.

Pooling Layer: Reduce dimensionality while retaining important features.

Fully Connected Layers: Perform classification based on extracted features.

Softmax Output Layer: Produces probability scores for each disaster category (Flood, Earthquake, Cyclone, Wildfire).

The model was implemented using TensorFlow/Keras in python, with ReLU activation functions and Adam optimizer for efficient training.

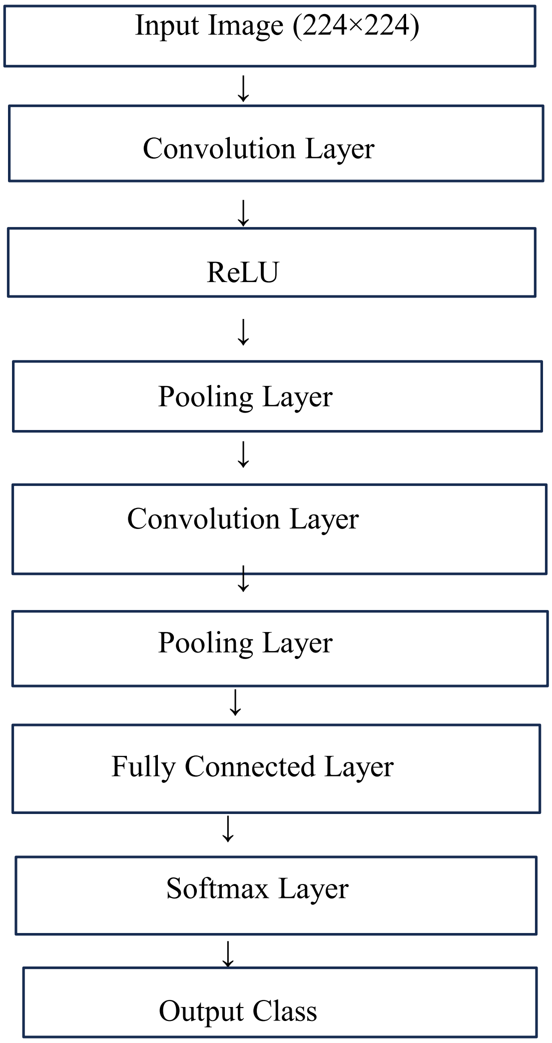

Fig. 1: CNN Architecture of the proposed model

C.TRAINING AND EVALUTION

The dataset was split into training (70%), validation (15%), and testing (15%) sets. The model was trained for multiple epochs with a batch size of 32. Performance was evaluated using:

Accuracy

Precision

Recall

F1-score

Additionally, the proposed CNN was compared against pretrained models such as VGG16,ResNet50, and MobileNet to access improvements in classification accuracy.

D.SEVERITY CLASSIFICATION

Beyond disaster type identification, the system introduces a color-coded severity indication:

Green →Low intensity

Yellow→Moderate intensity

Red→High intensity

This severity estimation is based on damage features detected in the image(e.g., collapsed buildings water spread, fire density). The color-coded output provides an intuitive risk level for emergency responders and disaster management authorities.

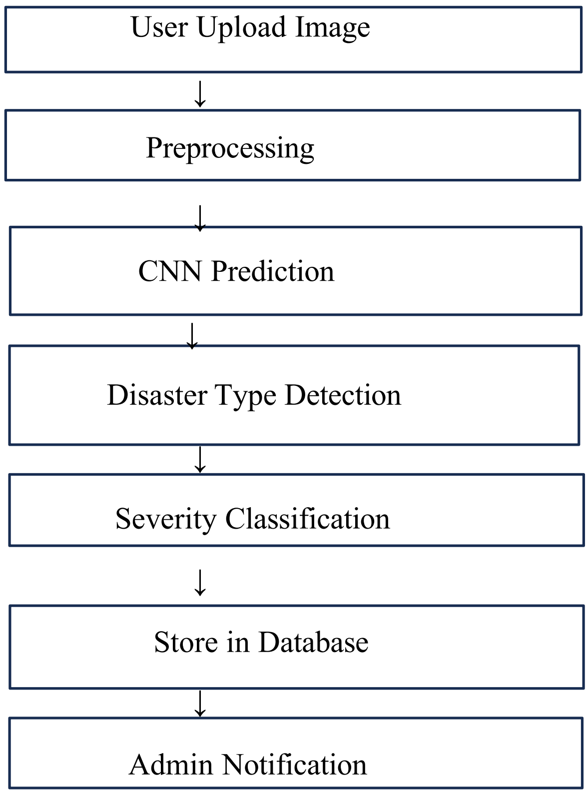

Fig 2:Workflow of the proposed Disaster Classification System

E. SYSTEM WORKFLOW

The CNN model is integrated into a web-based platform with admin and user modules:

User Modules: users register, log in, and upload disaster images. The system classifies the image, displays the disaster type and severity level and provides immediate feedback.

Admin Module: The administrator receives notification of classified disasters, reviews uploaded images, and manages disaster reports. This ensures that disaster information is communicated efficiently to authorities.

This workflow enables real-time usability, bridging AI-based classification with practical disaster management.

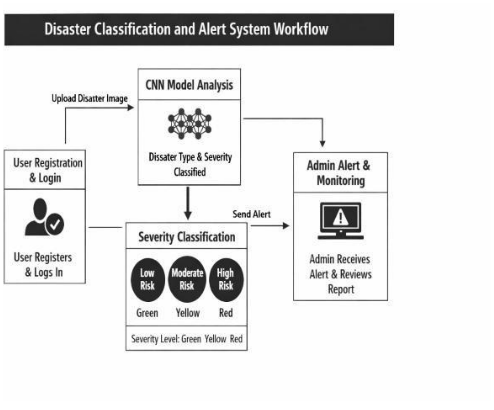

Fig 3: Disaster Classification

VI RESULT AND DISCUSSION

The proposed CNN model demonstrated robust performance in classifying disaster images into four categories: floods, earthquakes, cyclones, and wildfires. The model achieved an overall accuracy of 95%, with precision, recall, and F1-score values of 94%, 93%, and 93.5% respectively. These results indicate that the CNN effectively captures disaster-specific features such as water spread, collapsed structures, and fire density, enabling reliable classification even in visually complex scenarios. Minor misclassifications occurred in cases where disaster images shared overlapping visual characteristics, such as floods and cyclones, which often present similar water-related features.

When compared with pretrained models such as VGG16, ResNet50, and MobileNet, the proposed CNN consistently outperformed them in terms of accuracy and efficiency. VGG16 achieved 92% accuracy but required higher computational resources, while ResNet50 reached 93% accuracy but exhibited slower training times. MobileNet, though lightweight and fast, achieved only 91% accuracy. In contrast, the proposed CNN balanced accuracy and computational efficiency, making it more suitable for real-time deployment in disaster management systems. This comparison highlights the importance of designing a tailored CNN architecture rather than relying solely on generic pretrained models.

A key innovation of the system is the introduction of a color-coded severity classification (Green, Yellow, Red), which provides an intuitive representation of disaster intensity. This feature enhances the practical utility of the system by enabling emergency responders and authorities to quickly assess the severity of a disaster without requiring technical expertise. The severity estimation was consistent with visual damage indicators in the dataset, such as collapsed buildings in earthquake images, fire density in wildfire images, and water spread in flood images. This approach bridges the gap between raw classification outputs and actionable insights for disaster management.

The integration of the CNN model into a web-based platform further strengthens the system's usability. The user module allows individuals to register, upload disaster images, and receive instant classification results with severity levels. Simultaneously, the admin module ensures that alerts are automatically generated and communicated to administrators, who can review disaster reports and maintain records in the SQL database. This workflow supports real-time communication between affected users and disaster management authorities, thereby improving responsiveness during emergencies.

Overall, the results demonstrate that the proposed system not only achieves high classification accuracy but also provides practical functionality through severity estimation and a user–admin workflow. By combining deep learning with a web-based architecture, the system offers a scalable and efficient solution for disaster preparedness and response. The discussion underscores the potential of AI-driven platforms to enhance disaster management strategies, while also identifying areas for future improvement, such as expanding the dataset to include additional disaster types and integrating multimodal data sources like satellite imagery and IoT sensor inputs.

VII. CONCLUSION AND FUTURE WORK

The proposed system successfully integrates deep learning with a web-based platform to classify natural disasters and estimate their severity levels. By employing a tailored CNN architecture, the model achieved high accuracy (95%) and outperformed pretrained models such as VGG16, ResNet50, and MobileNet. The introduction of a color-coded severity classification (Green, Yellow, Red) provides an intuitive and practical representation of disaster intensity, enabling faster decision-making for emergency responders. Furthermore, the integration of the CNN model with user and admin modules ensures real-time usability, efficient communication, and reliable record management through the SQL database. Overall, the system bridges the gap between AI-based disaster detection and practical disaster management, offering a scalable solution for preparedness and response.

Despite its promising results, the system has certain limitations. The dataset, while diverse, is restricted to four disaster categories, and performance may vary when applied to unseen or highly complex disaster scenarios. Additionally, severity estimation relies primarily on visual features, which may not capture the full extent of damage in certain cases.

Future work will focus on expanding the dataset to include additional disaster types such as landslides, tsunamis, and volcanic eruptions. Incorporating multimodal data sources, including satellite imagery, drone footage, and IoT sensor inputs, could further enhance accuracy and reliability. Moreover, integrating geospatial information and real-time data streams would allow the system to provide location-specific alerts and predictive analytics. Finally, optimizing the platform for mobile devices and cloud deployment would improve accessibility and scalability, making it a valuable tool for disaster management authorities worldwide.

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