REAL TIME EMERGENCY RESPONSE LOCATION TRACKING APP FOR CLIMATE DISASTERS USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Natural disasters such as floods, earthquakes, cyclones, and extreme weather conditions pose significant threats to human life, infrastructure, and the environment. Early detection and timely response are crucial to minimize the impact of such disasters. This project presents a Real-Time Emergency Response Location Tracking System for Climate Disasters using Artificial Intelligence, designed to predict disaster occurrences and facilitate efficient communication between users and administrators. The proposed system utilizes environmental parameters such as temperature, humidity, wind speed, precipitation, seismic activity, and atmospheric pressure to analyze potential disaster situations. Machine learning and deep learning models, including Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN), are implemented to improve prediction accuracy. Among these, the CNN model demonstrates higher performance in identifying disaster patterns. The system is developed using a web-based architecture where users can input environmental data and receive real-time disaster predictions. The backend is implemented using the Flask framework, while SQLite is used for data storage. An administrative module allows dataset uploading, model training, monitoring of user activity, and broadcasting emergency alerts to users. Additionally, the system maintains a history of predictions and provides timely notifications to enhance disaster preparedness. By integrating artificial intelligence with real-time data processing, the proposed system aims to support early warning mechanisms and improve disaster management efficiency

Keywords: Artificial Intelligence, Deep learning, disaster detection,CNN, LSTM

I INTRODUCTION

Disaster management is a multidisciplinary field focused on minimizing the impact of natural and human-induced disasters through preparedness, mitigation, response, and recovery strategies. In recent decades, the world has witnessed a significant increase in the frequency and intensity of disasters such as floods, earthquakes, cyclones, wildfires, landslides, industrial accidents, and pandemics. Rapid urbanization, environmental degradation, and climate change have further amplified vulnerability, particularly in densely populated and developing regions. Traditional disaster management systems rely heavily on manual surveys, sensor networks, meteorological data, and statistical forecasting methods. While these approaches provide valuable insights, they often struggle to handle the massive volume of real-time data generated during emergencies. Delays in data processing and damage assessment can lead to slower response times, increased casualties, and higher economic losses. Therefore, integrating intelligent and automated technologies into disaster management has become essential.

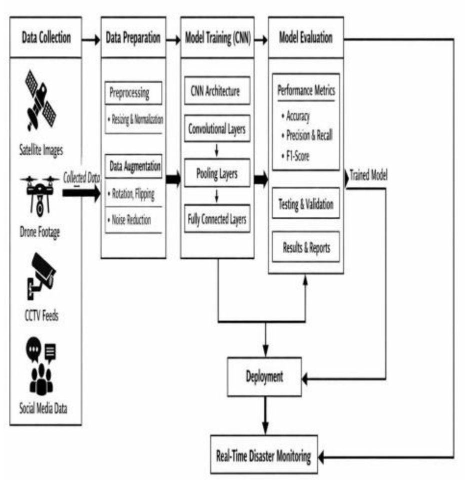

Fig 1: SYSTEM ARCHITECTURE

II LITERATURE SURVEY " .

1:Title:Fully Convolutional Networks for Semantic Segmentation"

Author: J. Long, E. Shelhamer and T. Darrell

Abstract: In this survey, introduced Fully Convolutional Networks (FCN), which became a foundation for image segmentation tasks in disaster management. Their work replaced fully connected layers with convolutional layers, enabling pixel-level prediction for images. In disaster management systems, FCNs are widely used for segmenting flooded regions, burnt forest areas, and damaged buildings from satellite imagery. The authors demonstrated that deep convolutional architectures can learn spatial hierarchies and provide precise localization. This research significantly influenced later disaster detection models by enabling automated mapping of affected regions using remote sensing

data. Their contribution laid the groundwork for semantic segmentation models used in flood mapping and earthquake damage assessment.

2.Title:**"Deep Residual Learning for Image Recognition"**

Author: K. He, X. Zhang, S. Ren and J. Sun

Abstract: proposed the ResNet architecture, which introduced residual connections to overcome the vanishing gradient problem in deep neural networks. The deep residual learning framework allowed training of very deep CNNs with improved accuracy. In disaster management applications, Res Net-based models are widely used for classifying disaster types such as wildfire, flood, cyclone, and landslide from aerial and satellite images. The robustness and high feature extraction capability of Res Net improve detection accuracy in complex environmental conditions. Their work contributed significantly to improving disaster image classification performance and enhancing automated monitoring systems.

3:Title: " **U-Net: Convolutional**

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Network for Biomedical Image Segmentation "
Author: O. Ronneberger, P. Fischer and T. Bro
Abstract: This survey Ronneberger et al. introduced U-Net, a CNN architecture designed for precise image segmentation. Although initially developed for biomedical imaging, U-Net has been extensively adapted for disaster damage detection. The encoder–decoder structure with skip connections allows accurate localization of damaged buildings, flooded areas, and wildfire spread from satellite images. In disaster management systems, U-Net provides high-resolution segmentation maps, which are crucial for emergency planning and rescue operations. The architecture's ability to work with limited training data makes it highly suitable for disaster datasets where labeled data may be scarce.

4:Title: " Learning Building Extraction in Aerial Scenes with Convolutional Networks "
Author: Y. Yuan
Abstract: Yuan focused on building extraction from aerial imagery using CNN based deep learning methods. This research is highly relevant to post earth quake and post-cyclone damage assessment. By automatically identifying buildings and infrastructure from high-resolution satellite images, the system can compare pre- and post-disaster images to estimate structural damage. The study demonstrated improved accuracy in urban feature extraction, which directly supports disaster response teams in identifying heavily affected zones. The work contributes to automated infrastructure monitoring within disaster management frameworks.

III IMPLEMENTATION

MODULES:

1. Upload Historical Trajectory Dataset : Upload Historical Trajectory Dataset' button and upload dataset.
2. Generate Train & Test Model :Generate Train & Test Model' button to read dataset and to split dataset into train and test part to generate artificial intelligence and machine learning train model
3. Run CNN Algorithm: Run CNN Algorithm' button to train CNN model and to calculate its accuracy. .
4. Predict Disaster :Predict Type' button to predict disaster.

IV ALGORITHMS

1. Data Preprocessing Algorithms
preprocessing is essential to standardize input data before feeding it into the CNN model. This stage includes image resizing to a fixed dimension suitable for the neural network, normalization of pixel values to improve convergence during training, and noise removal techniques to enhance clarity. Data augmentation techniques such as rotation, flipping, zooming, and cropping are applied to increase dataset diversity and prevent overfitting. Preprocessing ensures that the model receives clean, consistent, and optimized input data, thereby improving learning efficiency and accuracy.

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2.CONVOLUTIONAL NEURAL NETWORK (CNN) Training Backpropagation Algorithm:

1. CNN consists of convolutional layers that apply filters to extract features such as edges, textures, and shapes. Activation functions introduce non-linearity, allowing the model to learn complex patterns. Pooling layers reduce dimensionality and computational load. Fully connected layers perform classification tasks.The soft max function generates probability distributions across disaster classes. Training is performed using stochastic gradient descent or adaptive optimizers like Adam. Loss functions such as categorical cross-entropy measure prediction error. CNN's hierarchical feature learning capability makes it ideal for image-based disaster detection

2. The first layer of the architecture is the Data Acquisition Layer. In this stage, images and visual data are collected from multiple sources including

V RESULTS

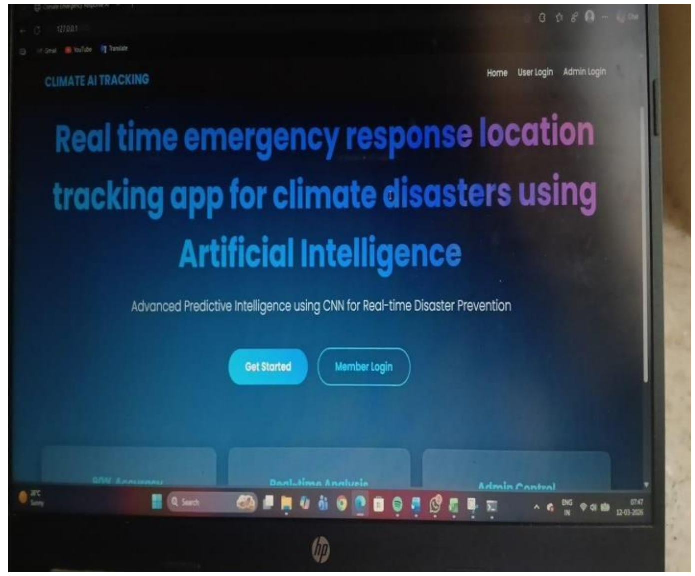

Fig:1 In above screen click on 'member login or Get Started'

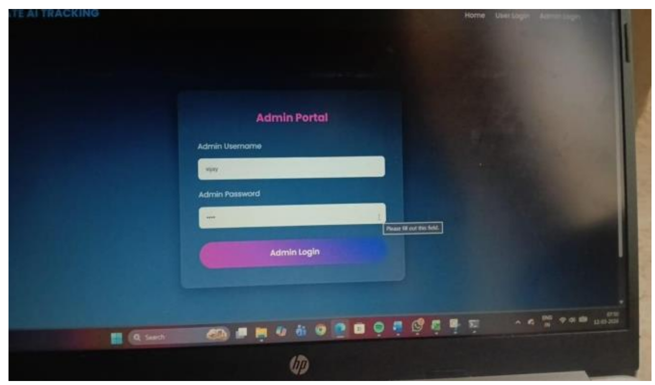

Fig:2 In above screen user is entering sign up details and giving valid user ID tpassword and then press button to complete sign up and get below page

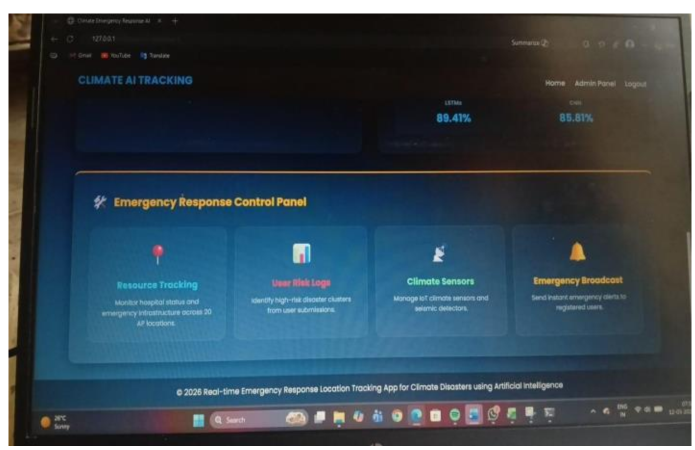

Fig:3, Above username and password we can receive in given email at sign up time

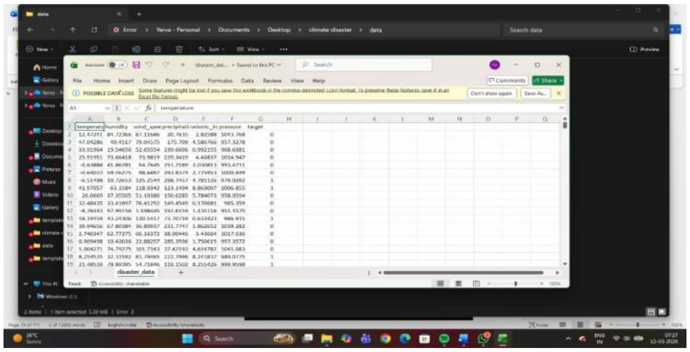

Fig:4, In above screen click on 'Upload Dataset' link to get below page

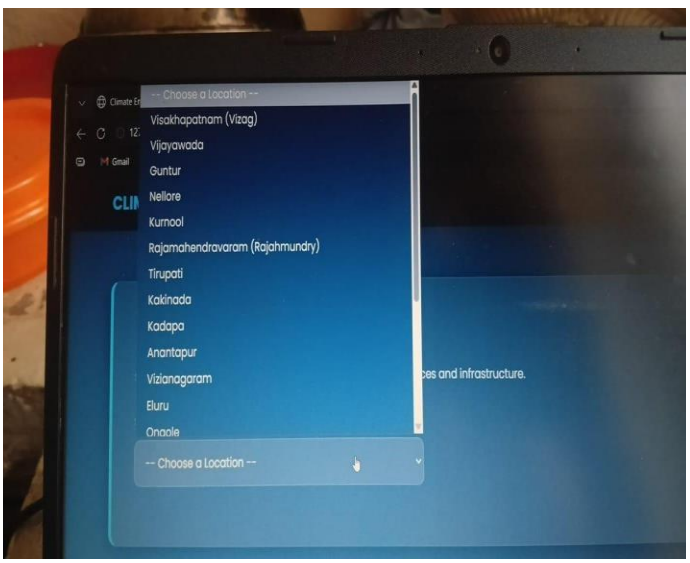

Fig:5.Now click on ' required location to predict disaster or not

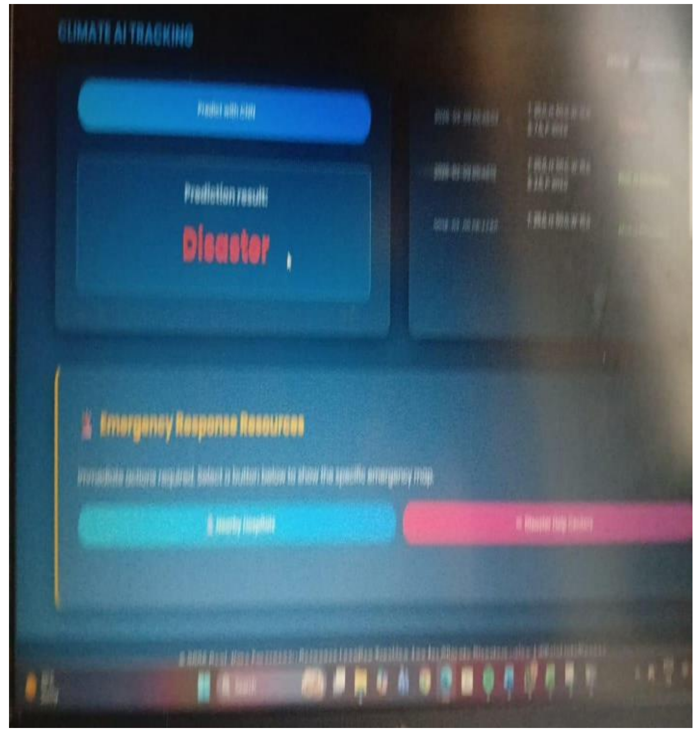

Fig:6,Now displays disaster or not a disaster

Fig:7, In above bar graph represents algorithm names and represents accuracy

CONCLUSION

In conclusion, the "Disaster Management System using Convolutional Neural Networks (CNN) represents a significant advancement in the application of artificial intelligence for emergency response and disaster mitigation. By leveraging deep learning techniques, particularly CNN-based image classification and segmentation models, the system is

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capable of automatically detecting and assessing disaster-affected areas from satellite imagery, UAV images, and real-time camera feeds. Unlike traditional manual monitoring systems that rely heavily on human observation and delayed reporting, the CNN-based system enables rapid identification of disasters such as floods, earthquakes, landslides, wildfires, and cyclones with higher accuracy and reduced response time. The integration of deep learning algorithms enhances pattern recognition capabilities, allowing the system to differentiate between normal environmental conditions and disaster-affected regions. This automated analysis supports government agencies, disaster response teams, and humanitarian organizations in making informed decisions quickly, thereby reducing loss of life and property damage.

FUTURE SCOPE

The future scope for the project " Although the CNN-based Disaster Management System provides promising results, several areas can be explored for further improvement and research. One major direction for future study is the integration of multimodal data sources such as sensor data, weather information, social media feeds, and Internet of Things (IoT) devices along with satellite imagery. Combining multiple data streams can enhance prediction accuracy and provide a more comprehensive understanding of disaster scenarios. Future research can also focus on developing hybrid deep learning models that combine CNN with Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, or Graph Neural Networks (GNN) to incorporate temporal and spatial dependencies for improved forecasting and real-time monitoring.

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