MONITORING AND PREDICTION OF NATURAL DISASTER USING MULTI-KERNEL INCEPTION VGGNet-16 CLASSIFICATION

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Abstract— **The whole world is revealed to the disaster that causes severe damage to the life, infrastructure, and injury to the public. Human capabilities can be extended to predict and manage natural disasters with the help of the Internet of things and technology. The main objective of this paper is to design and implement sensor-based natural disaster monitoring and predicting methods in the regions of Krishna Godavari region of Andhra Pradesh state which helps to alert peoples at the correct time and provide the right decision. Initially, the datas from the cloud storage are acquired in the form of satellite images that are associated to the natural disasters. The collected data is preprocessed and then the feature extraction is employed using Matrix-based Fisher discriminant analysis and feature selection is performed by Adaptive Entropy-based PCA for Feature Selection method. The best resultant features were then optimized using the Heuristic Echolocation BAT optimization algorithm. The optimized output can be given as an input for the process of classification. The classification process is enhanced using Multi-kernel Inception VGGNet-16 classification. The output after classification is subjected to the alert system which is responsible for offering warning messages and for the detection and prediction of the natural disasters in order to make the right decisions. The performance analysis and the estimation of accuracy are done to prove the effectiveness of the proposed technique. The recommended technique proves to be favorable in monitoring and predicting natural disasters.**

Index Terms— **Natural Disaster, Artificial Intelligence, Matrix-based Fisher discriminant analysis for feature extraction, Adaptive Entropy-based PCA for Feature Selection, Heuristic Echolocation BAT optimization algorithm, Multi-kernel Inception VGGNet-16 classification**

I. INTRODUCTION

Natural processes often result in disasters such as earthquakes, thunderstorms, floods, wildfires, and landslides, which cause severe loss of life, widespread destruction, and substantial economic damage. The frequency and intensity of these disasters have been increasing in recent years. Therefore, effective disaster management has become a crucial responsibility to safeguard communities through improved strategies and technologies.

The latest studies emphasize the increasing use of Artificial Intelligence (AI) in disaster management as a data analyzer to assess the disaster-related information and aid its timely decision-making. AI solutions cover all four disaster management stages preparedness, mitigation, response, and recovery, allowing predicting events much faster, distributing the resources effectively, and recovering much quicker. The collection of accurate and real-time data on disaster impact is, however, a big task although it is critical in determining the extent of damage, justification of losses and making effective recovery decisions [1].

Artificial Intelligence (AI) can be defined as a machine or a computer system that simulates human mental processes including learning, thinking, and solving problems. The AI-based computational methods span the spectrum of rule-based expert systems to sophisticated deep learning systems. Many of the ways we use modern technologies, such as robotics, self-driving cars, chatbots, smart homes, and smart data analytics, are based on these technologies.

When it comes to natural disasters, AI is vital in gathering, processing and interpreting bulk information to predict the calamities, determine the resilience of society and their effects on the society as a whole. The majority of the current disaster monitoring methods are based on change detection algorithms with identification of the affected regions based on complex analysis of post- and pre-event satellite images or other sensor data.

Disaster management is a complex problem of the real world that requires the implementation of modern technologies. Since natural disasters have become a common occurrence in the world with more intensity and frequency, their effects have become more serious and unpredictable. AI offers efficient solutions to handle large amounts of heterogeneous data, derive meaningful information, and facilitate credible monitoring and predictive analysis especially in seismology. The AI-based seismology protocols that can be applied to the field include machine learning (ML) and deep learning (DL), which improve the interpretation of data by separating the region earthquake activity signal and the background noise, thereby increasing the detection accuracy and timeliness of the events.

Likewise, AI-based spatial prediction and risk evaluation have been effectively applied in the process of landslide susceptibility modeling, such as statistical and expert system methods. Artificial Neural Networks (ANNs) have been best known as one of the most reliable algorithms among other algorithms especially in prediction of shallow landslides.

The occurrence rate of natural disasters will increase even more because of the consequences of climate change. This has heightened studies towards the creation of AI-based systems of disaster monitoring, early detection, and prevention. Artificial Intelligence based wireless applications in Natural Disaster Management (NDM) have been on the forefront because of the high speed, accuracy, and simplicity of implementation. In general, AI is a smart computational component that can be used to improve real-time detection, situational awareness, and informed decision-making in case of disasters.

The main goal of the given work is to design AI-driven technologies that would be used to monitor and identify natural disasters with the help of sensed data, thus providing timely notifications and warnings to protect human life and infrastructure.

The remainder of this paper is organized as follows: **Section II** presents a review of existing methods; **Section III** describes the proposed approach; **Section IV** discusses performance analysis and result evaluation; and **Section V** concludes the study.

II. Related Works

This paper provides an in-depth overview of literature and methods of using Artificial Intelligence (AI) to predict, detect, and track natural disasters. The studies mentioned below point out the development of AI-based disaster management models in different settings and disaster types.

[1] The research was aimed at implementing AI and, specifically, Machine Learning (ML) to increase flood preparedness and resilience. This research was a product of the BRIM (Building Resilience into Risk Management) project and applied ML algorithms to big amounts of historical flood data to find unnoticeable trends and actions. These understandings were then applied to avoid possible damages, predict future floods, and enhance resilience of the communities.

[2] In this work, the authors addressed the possibility of artificially intelligent cities based on the use of AI to protect societies against natural disasters and pandemics. It talked about the disruptive possibilities of AI technologies in the urban setting, tracing the history of AI use, and looking at how it may impact disaster preparedness and preparedness, as well as urban resilience.

[3] An integrated solution was suggested to enhance early disaster detection, recovery and management. The paper has taken a critical analysis of the current systems and technologies like Remote Sensing, Wireless Sensor Network (WSN), Internet of Things (IoT), Artificial Intelligence (AI), Unmanned Aerial Vehicles (UAV), and satellite imagery. It highlighted the need of having alternative communication networks that will keep situational awareness during times of emergency when the normal communication networks are disrupted.

[4] This study introduced examples on the application of Information Technology (IT) in disaster management phases which include response, recovery, preparedness and risk control. It pointed at the fact that AI-powered information systems can scan through records of disasters and issue real-time notifications. One of such events was the integration of the AI platform that can identify an increase in the water level based on social media posts. Disaster preparedness was also increased among communities due to sensor networks.

[5] The case has mentioned that there has been a growing challenge in forecasting extreme disasters as a result of climate change and environmental degradation. It suggested adopting the latest technologies including WSNs, next-generation IoT, big data analytics, and 5G communication systems to reinforce the structures of predictive modeling and disaster response.

[6] AI was presented as an instrument of properly detecting seismic activity under the traditional detection level. The paper has examined the published work on AI-powered seismology and analyzed the performance of diverse key algorithms, such as ML and DL models, to identify weak seismic signals in the presence of background noise.

[7] The paper described a methodological paradigm through the state-of-the-art AI methods, both unsupervised and supervised learning, to analyze social media data in case of disasters. Based on the case studies of Hurricanes Harvey, Maria, and Irma, the study showed that AI-based social media analysis can be used to enhance crisis awareness and support humanitarian organizations.

[8] The study examined the risk of disaster in the Himalayan state of Uttarakhand that is extremely prone to earthquakes, floods, landslides, and forest fires. It highlighted the use of the WSNs in early warnings and disaster management operations like monitoring the level of rivers, glaciers and the safety of tourists.

This study explored landslides susceptibility mapping on the Muong Lay district, Vietnam, in several artificial intelligence methods namely Artificial Neural Networks (ANN), Support Vector Machines (SVM), Reduced Error Pruning Tree (REPT), and the Logistic Regression (LR). The paper proved that the models based on AI significantly increase the accuracy of landslide forecasting and hazard mapping.

The paper has analysed the synergies of UAVs and WSNs in managing natural disasters by categorising the applications of the technologies in different disaster management stages. It also recognized the current research and development issues, where the use of integrated UAV-WSN system is necessary to enhance disaster response and citizen safety.

A number of developed AI models were used to compare and contrast the daily rainfall prediction in Hoa Binh province, Vietnam, namely, PSO-ANFIS (Particle Swarm Optimization-based Adaptive Neuro-Fuzzy Inference System), ANN, and SVM. The study used climatic parameters to include temperature, humidity, wind velocity and solar radiation as inputs and gave the study the highest accuracy and strength in rainfall prediction using SVM.

[12] The article was a review of the rising contribution of AI and ML to geohazard modeling, including earthquakes, landslides, droughts, debris flows, glaciers, and floods. Because these types of geohazards are responsible in almost 80 percent of an economic loss related to natural disasters, the research focused on applying deep learning to long-term forecasting and classification and detecting temporal changes.

The article introduced a farsighted idea of a Disaster City Digital Twin, a system in one, powered by AI, dedicated to making decisions, assessing the situation, and coordinating stakeholders in the event of a disaster. It allowed convergence between ICT and crisis informatics and enhanced visibility of networked disaster response and humanitarian activity.

[14] UAV systems based on deep learning and neural networks were suggested to detect and control floods within a short period. The paper employed aerial imagery that has been operated by Convolutional Neural Networks (CNN) to identify flood-related patterns as a less expensive approach compared to the classical flood monitoring system, which is based on expensive satellite or GIS networks.

[15] This systematic review has explored the application of AI in the creation of smart cities that are resilient, adaptive and sustainable. It has emphasized the role of AI applications in planning, environmental sustainability, healthcare, governance, and disaster risk management in cities. Inadequate research on the ethical and social consequences of massive deployment of AI in cities was also a finding made in the study.

[16] Established that Artificial Intelligence (AI) methods are capable of using large, complex, and nonlinear datasets, which leads to a greater efficiency and accuracy, making Artificial Intelligence an optimal choice to use disaster predictions and disaster monitoring. The paper has highlighted that AI-supported Natural Disaster Management (NDM) received a lot of research interest in the past few years; nevertheless, a review of the literature in the given area was not systematic. To fill this gap, the paper has retained a systematic review of AI applications in the different stages of NDM, in accordance with the literature on SpringerLink and Elsevier databases.

The review (1) identified existing research gaps, (2) provided enhanced visibility into the application of AI models across different types and stages of disaster management from both procedural and contextual perspectives, and (3) offered valuable recommendations for improving AI model performance and advancing the quality of disaster modeling.

III. Proposed Work

This section gives a description of the overall workflow of the proposed system in detail. Figure 1 shows the schematic view of proposed methodology, which gives its process sequences and mode of operation.

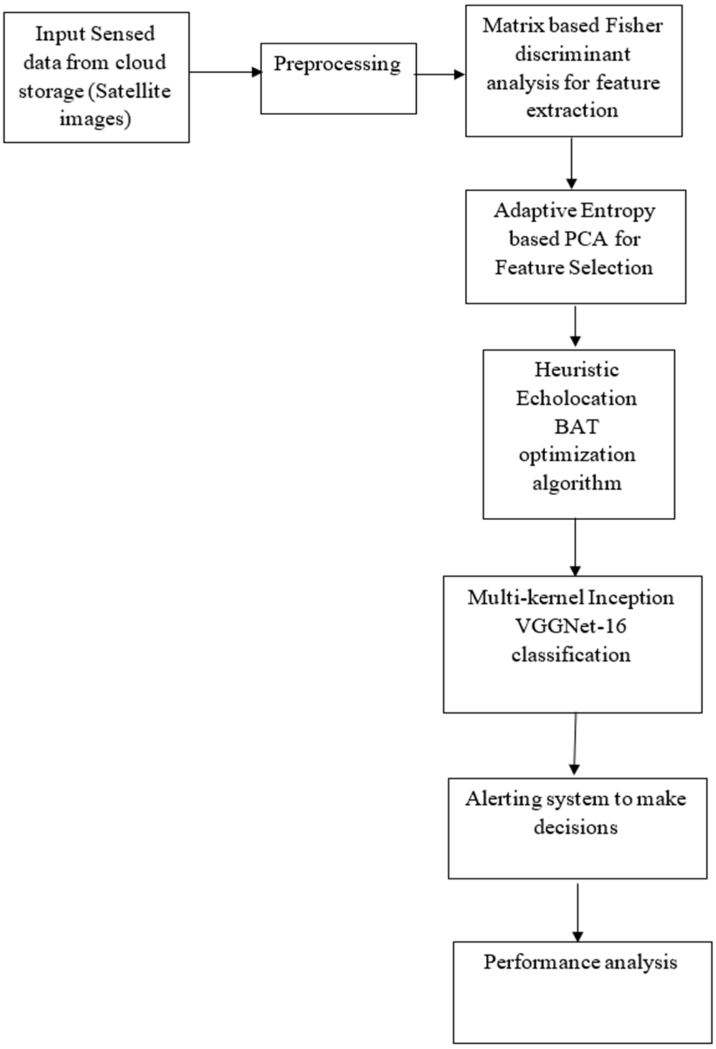


Figure 1 Flow of suggested Scheme

A. Input data acquisition from cloud storage and Preprocessing

The input received is first the sensed data that is stored in the cloud storage. In particular, the satellite images related to the natural disasters are read off the cloud and are used as the main input in the further processing. Preprocessing is done to the retrieved data to eliminate irrelevant, redundant and noisy data. In this phase, feature extraction is done in order to determine and select the most meaningful attributes that will be needed in the analysis.

Preprocessing guarantees the quality of data by making sure that duplicates, incomplete, or inconsistent data are removed so that the results obtained may be ambiguous and unreliable. In order to maintain the atomicity and integrity of the data, normalization methods are used. Unnecessary information doubles computation and storage space, therefore, syntactic and semantic verification are introduced to reduce redundancy.

Normalization (also known as data standardization) converts the data to a common scale, generally between [0,1], so that once one source of data is incorporated with another, the data can be compared. This is especially essential with datasets that have attributes of different scale where a standard threshold value is required to be able to compare them properly.

$$S_A = \frac{1}{n}(|P_1 - \mu| + |P_2 - \mu| + \cdots .|P_n - \mu|) \quad (1)$$

$$P_i' = \frac{\mathrm{P_i - \mu}}{S_A} \quad (2)$$

$$T_i = \frac{1}{5} P_i' \quad (3)$$

$$\text{NDS} = T_i + 0.5 \quad (4)$$

μ is the mean of the data set

Pn denotes the values of the dataset.

s_A represents the Mean Absolute Deviation value of the specified data set.
P_i denotes the old values of the dataset
$P_i^{'}$ represents new values of the dataset
NDS- Normalized Data set
After the z-score normalization, the value lies between $[-2 \sim 2]$. To change the values to the range of $[0 \sim 1]$, first, divide the values by 5 to get the range. We added 0.5 to all values of the normalized values.
Z-score normalization (also referred to as zero-mean normalization) is used in this work. It normalizes the data set by the mean and one of the Mean Absolute Deviation (MAD) or the Standard Deviation (σ). Normalization of Z-score mathematically can be as:

$$Z = \frac{(x-\mu)}{\sigma}$$

where $x$denotes the data value, $\mu$is the mean of the dataset, and σrepresents the standard deviation.

B. Matrix based Fisher discriminant analysis for feature extraction & Adaptive Entropy based PCA for Feature Selection

In order to extract features, this paper uses Matrix-based Fisher Discriminant Analysis (MFDA). Under this method, features are directly obtained based on the matrix representation of the processed data, as opposed to transforming them into vector patterns. Fisher Discriminant Analysis (FDA) is a supervised learning method, which makes use of available prior class information to implicitly identify the most discriminative properties amongst the different classes.
Suppose that there are Mdistinct classes of matrix-patterns to be analysed, and which are instances of a particular category or type of disaster-related data. The MFDA approach attempts to maximize the separability of these classes and minimize the variance within each class in order to guarantee that each of the classes is well represented by features that will be used to classify them later.

$$\omega = \{A_{ij}\}_{j=1}^{T_i}, \text{ i=1, 2,… M} \tag{5}$$

represents the ith class, the means of class are,

$$A_i = \frac{1}{T_i}\sum_{j=1}^{T_i} A_{ij}, i = 1,2, \dots \text{ M}, \tag{6}$$

and the total mean of a sample is represented as A.
Let p be a vector with m components. Matrix based Fisher Discriminant analysis projects A, a matrix pattern onto the p that satisfies the constraint that $p^T p = 1$ using the linear transformation

$$q = p^T A \tag{7}$$

q is an extracted feature matrix.
Hence each $A_{ij}, i = 1,2, \dots . M; j = ,2, \dots . T_i$, all the projected values are in the form of

$$q_{ij} = p^T A_{ij}, i = 1,2, \dots . M; j = ,2, \dots . T_i \tag{8}$$

In order to get optimal vector p, were present the objective function ,

$$J_{Mat}(p) = \frac{tr(p^T C_b^{Mat} p)}{tr(p^T C_w^{Mat} p)} \tag{9}$$

Where $C_b^{Mat} = \sum_{i=1}^{M} T_i(\bar{A_\iota} - \bar{A})(\bar{A_\iota} - \bar{A})^{\mathrm{T}}$ (10)

is the sum of between scatter matrix class and

$$C_w^{Mat} = \sum_{i=1}^{M}\sum_{j=1}^{T_i}(A_{ij} - \bar{A}_i)(A_{ij} - \bar{A}_i)^{\mathrm{T}} \tag{11}$$

the sum within- scatter matrix class.
By maximizing $J_{Mat}(p)$, we achieve two points in the space of projection. one is between-class scatter as large, another is within-class scatter as small.
Differentiating $J_{Mat}(p)$ with respect to p under the constraint of $p^T p = 1$, we can represent the following eigenvalue-eigenvector equation that p satisfies

$$C_b^{Mat} p = \lambda C_w^{Mat} p \tag{12}$$

The feature selection is utilized in order to extract the dimensionality of the data thus limiting the number of computational and sensor resources. Such a process similarly removes irrelevant or redundant features and basically removes noise thus improving upon the accuracy of the model. The process of feature selection by the removal of non-contributory information results in the more efficient and accurate outcomes of classification.

A subset of the most important features are then selected out of the original high-dimensional feature space to enhance the performance of the model without discarding the important discriminative features. The most important task of feature selection is to determine the minimum possible feature set that will provide the maximum classification accuracy and system overall efficiency.

Adaptive Entropy-based Principal Component Analysis (AEPCA) is applied to select the features in this work. The algorithm starts with an initial calculation of the distance between the combined features and then the best subset is identified using the minimum distance criterion. This is an adaptive strategy that makes sure that the chosen features retain as much information content as possible and reduce redundancy amongst components**.**

$$\vec{D}=\sqrt{\sum_{c=1}^{n}(C(\emptyset)_{i+1}-C(\emptyset))^2} \tag{13}$$

$C(\emptyset)_{i+1}$ represents i+1frame and $C\ (\emptyset)$ is the current frame, n is the dimension of feature vector.

$$\mathrm{M}\ (\vec{D}) = \text{minimum}\ (\vec{D}\ ,\beta) \tag{14}$$

Where β is the parameter = 400. Then entropy is employed on features and the best 356 features are chosen for recognition and classification.

$$Entropy = \sum_{c_1}^{n}\sum_{c_2}^{n} F(c_1,c_2)\ \log \mathrm{F}(c_1,c_2) \tag{15}$$

c_1, c_2 are the present and previous minimum distance.

C. Heuristic Echolocation BAT optimization algorithm

The algorithm is based on a biological ability of bats, which is called echolocation. Bats find their way and locate prey by sending out ultrasonic pulses and based on the reflection of the echo it sends back, they develop a highly accurate spatial map of their environment. With the help of comparing the emitted pulse with the echo, bats could differentiate the prey and obstacles correctly and estimate the distance and direction.

The **Bat Algorithm** models this natural behavior using three fundamental rules:

1. The bats have an echolocation pulse that each one uses to distinguish between prey and obstacles and also to measure distance towards a target.
2. Bats fly at a velocity $v$and position $x$with a specific frequency f, wavelength λ, and loudness A, dynamically adjusting these parameters during the search process to locate optimal solutions.
3. The pulse emission rate $r_i$varies within the range [0,1], allowing adaptive exploration and exploitation of the search space.

As there are varied directions of soundness, it is assumed that it decays gradually to reach a maximum positive value to a minimum threshold as the bat approaches its prey. This is an adaptive process that is used to help the algorithm to balance global exploration and local exploitation to increase optimization.

Algorithm 1 Heuristic Echolocation BAT optimization Algorithm

Set the populations of bat at positions xi (i = 1, 2, 3,…,n) and velocity V
Initialize pulse emission rate ri , frequency f , and loudness A
While (ti < the maximum number of iterations)
Create new values by the frequency adjustment
Create location and new velocity
If (random > ri)
Choose a value among the best data
Create new solution among the chosen best solution
End if
Get a new value for random flying
If (random < A & f(xi) < f(x*))
Agree to take the new value
Increase the value ri and decrease A
End if
put grade for the bats and find the present best x*
End

D. Multi-kernel Inception VGGNet-16 classification

This algorithm is based on deep learning and was employed in this classification. Here, CNN (Convolution Neural Network) enables an evaluation of discrepancies among one or two variables. Multi-kernel Inception Visual Geometry Group (VGGNet-16) gives opportunity and uses a plan in which statistical data are used. CNN reads and resizes the data and then calculates the similarities in the phase. An advanced residual Inception VGGNet-16 CNN models are arranged in the form of these layers that helps in the recognition and analysis of data.

1. ReLU layers
2. Convolutional layers
3. Pooling layers
4. Fully connected layer

Convolution layer
This focuses on the data in the images. This method finds the input data functions and implements the map. The main phase of CNN is coding.

ReLU layer
To enhance nonlinearity within the network, feature charts include the application technique. Here we can remove the negative values very fast.

Pooling layer
In this, the input scale is reduced slowly. This phase decreases the fit. The appropriate parameters are shown for the increasing number of needed parameters.

Flattening layer
Flattening the map feature in the sequential column statistics is done.

Fully connected layer
The percentage of the inaccuracy of data, the classification process is finalized.

SoftMax

Complete SoftMax is able to estimate the probability chances for every class. It is used to map the unregulated network function to a probability of predicted classes of output.

Algorithm 2: Pseudo code (**Multi-kernel Inception VGGNet-16 classification**)

Input is enhanced features data D_{im}
Output filtered data D_c
Initialize train features data
Initialize l (label)
Initialize the network layers
Test label =30%
Train label =70%
L= single (l)
For ii=1: length (L)
Cl = calculate (l== L (ii))
Train cut=length (cl) – train cut
Tr data= [tr data; train features; class (1: Train cut)]
Predict L=classify (net, tr data)
End
End
For ii=1: size (tr data,1)
Tr data = [tr data; tr features; class (1: Train cut)]
End
For ii=1: size (tr features,1)
Tr data= [tr features; tr features; class (1: Train cut)]
End

E. Alerting system for making decisions

The optimized input data are categorized using a suitable classification algorithm to identify and predict potential natural disasters. In the previous phase, the data were classified into categories based on flood levels and transmitted to the alert system for real-time monitoring and warning dissemination. The warning system builds the sensors, GSM modem, and Ethernet shield to enable the detection and communication.

The sensors constantly determine the distance between the water surface and the sensor and then calculate the height of the water level which is displayed in a real time web interface and updated. The measured water level is then compared against a set limit of water level. When the currency level rises past this set limit, an encoded alert message is automatically created and sent.

Once a sensor notices a change exceeding the threshold, it gives out a signal to the satellite uplink transmitter that sends out data. Every signal sent has a distinct identifier with the sensor and transmitter. It transmits the data via Geostationary Operational Environmental Satellite (GOES), which is in geosynchronous orbit and is linked to a ground station.

The signals received by the satellites are received at the ground station and processed by a computer system which decodes the signals. It will then command the ground unit to relay the decoded and short-coded message back to the alert station through the satellite link. Incoming messages are constantly monitored and decoded by the alert station which has an antenna that is connected to the downlink frequency of the satellite. The processor is selective to the applicable alerts, and it gives a notification message that includes the trigger point location, time of detection, and the emergency management process that ought to be taken by the appropriate authorities.

This is a mechanism as observed in Project Thrust; it is an example of a low-cost, locally-implementable tsunami warning system. The greater goals of such emergency decision-making system are to increase the precision of prediction, preparedness, efficiency of rescue and ability to recover. Real-time monitoring, emergency procedures pre-planned and frequent emergency drills are necessary to reduce the damage and loss in the case of natural disasters.

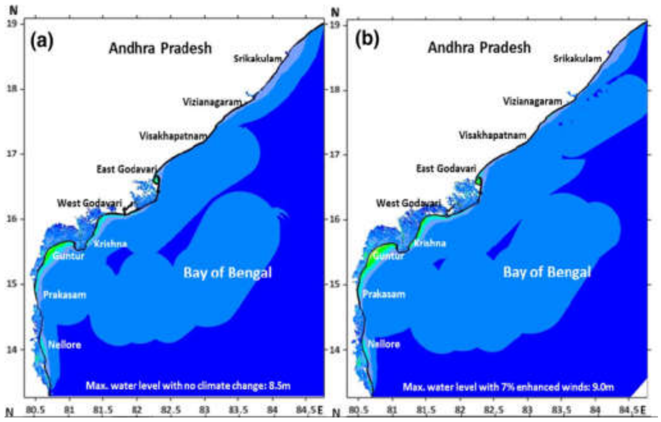
A variety of decision-making models have been addressed to assist these processes including Bayesian Networks, Markov Decision Processes, Fuzzy Logic, and Game Theory which allows the disaster response planning to be dynamic and data-driven.

Performance Analysis

The performance analysis of this proposed work is calculated and the achieved outcomes are explained in this section.

E. Performance analysis of Flood susceptibility by Maximum Water Level (MWL)

The study area is part of the Krishna Godavari region in the state of Andhra Pradesh of India. Due to the event of tropical cyclones, major flood event is noticed and the maximum water level is due to cyclones that cross the Krishna Godavari region Andhra Pradesh coast.



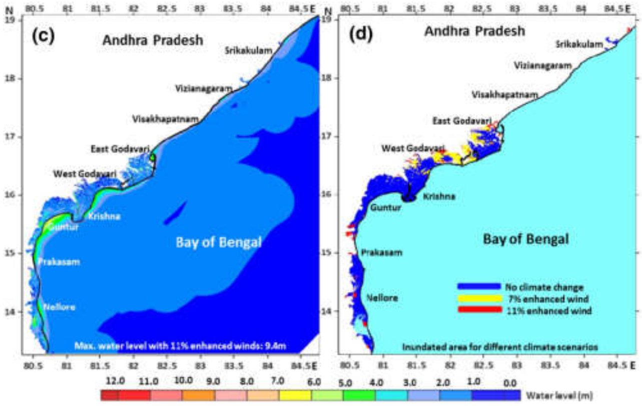


Fig 2 prediction of the maximum rise of water levels due to cyclones that occurs in Krishna Godavari region Andhra Pradesh coast has no climate change, **b** 7% increase in winds **c** 11% increase in winds **d** possible flooded area for climatic scenarios

In AP as given in Fig.2, East Godaveri and West Godavari and Krishna are susceptible to higher tides. Flooding occurs in the coastal area at an range of 60 km is noticed in the districts of Guntur and Krishna since they are situated in the areas of low lying rivers. As seen in Fig. 3d, the West Godavari District is the Climate change scenario as the MWL produces between 5.6 and 7.6 m that leads to flooding.

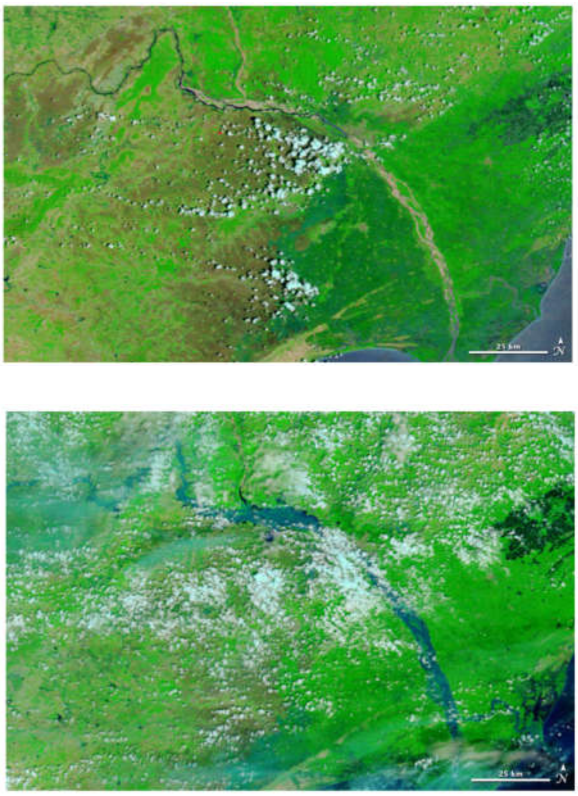


Fig 3 : satellite view for the portion of the Krishna River a) before flooding and b) after flooding

Figure 3 illustrates a section of the Krishna River as it flows into the Bay of Bengal, captured by the Terra satellite. In these satellite images, vegetation appears in green, clouds in pale turquoise, bare ground in pink-beige, and water bodies in blue. Figure 3(a) depicts the river channels in a dry state, whereas Figure 3(b) shows the channels completely filled with water on October 5, 2009, following severe flooding.

During this event, the Krishna and Godavari rivers overflowed, inundating numerous villages and damaging vast stretches of agricultural land across the Guntur, Krishna, West Godavari, and East Godavari districts. It was estimated that more than 20,000 people across 87 villages in the Krishna and Guntur districts were affected. According to the Disaster Management authorities, approximately 4,352 houses were marooned, and crops over 5,311 hectares of agricultural land and 1,400 hectares of horticultural fields remained submerged during August 2020.

Fig 4 Floods on Krishna Godaveri water merging into the Bay of Bengal

Figure 4 illustrates the krishna Godaveri river flood water merging into the Bay of Bengal.

Table 1 Probable maximum water level in Krishna Godaveri and related flooded area (sq. km)

	Maximum water Level (MWL) m	Inundated Area (sq.km)
West Godavari	5.6	430
East Godavari	8.5	1510
Krishna	6.7	2745

Table 1 presents the Maximum Water Level (MWL) measurements for the Krishna and Godavari rivers, along with the corresponding flooded areas under normal conditions. The data indicate that the **East Godavari** and **West Godavari** districts, located within the Godavari River delta, are the most severely affected—experiencing over 50 percent of the total flooded area. This high vulnerability is primarily attributed to the increasing impacts of climatic variations and extreme weather events.

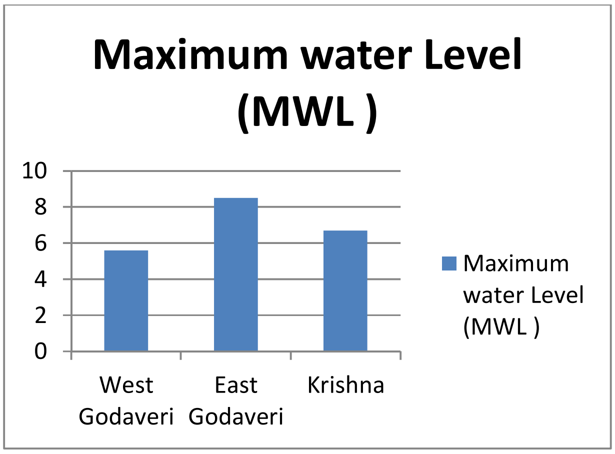


Fig 5 Probable maximum water level in Krishna Godavari region in metre

Fig 5 represents the maximum water level in Krishna Godavari regions such as East Godavari, West Godavari, and Krishna.

F. Cyclone Risk Susceptibility

The cyclone shelters are very important during serious occurrences of natural calamities as they offer safe areas and save human lives. These shelters help minimize casualties and mitigate secondary disaster effects such as food shortages, disease outbreaks, and homelessness. The spatial distribution data of cyclone shelters were obtained from the AP Space application.

The assessment of cyclone risk was carried out by evaluating both the vulnerability of each location and its corresponding hazard zone. The study revealed that a majority of the region falls within the moderate-risk zone, while certain critical areas are classified as high-risk zones. Specifically, approximately 50% of the total area (3,121.07 km²) lies within the moderate-risk category, 17.06% falls under the high-risk category, and 1.65% is identified as a very high-risk zone. Meanwhile, 15.31% of the area is classified as low-risk, and 1.46% as very low-risk, as detailed in Table 2.

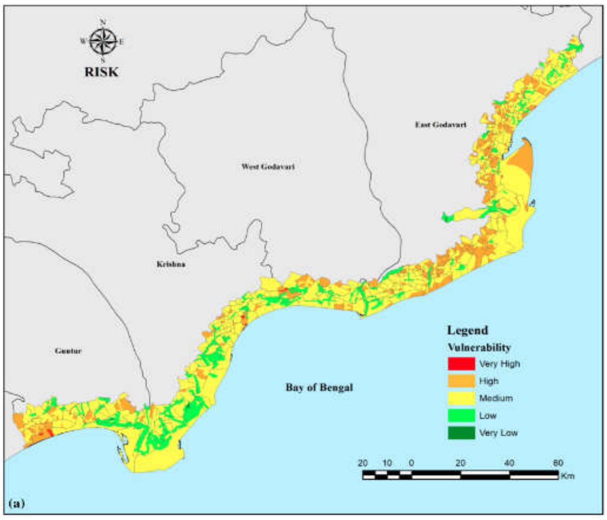


Fig 6 Cyclone risk analysis for various classes of vulnerability.

Analysis of cyclone risk is performed based on the spatial distribution for different classes of vulnerability such as very low, Low, Moderate, High and very High is shown in figure 6.

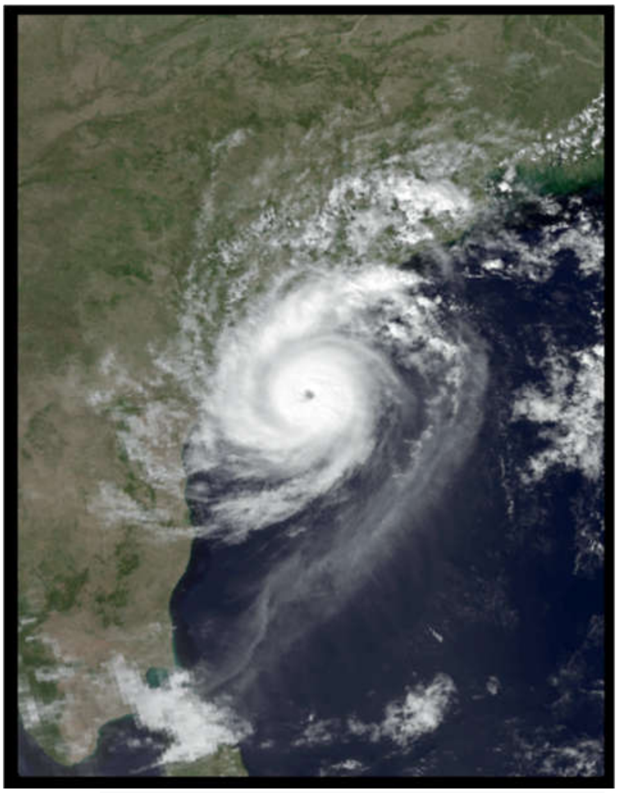


Fig 7 Satellite image of the cyclone prior to landfall in AndhraPradesh

The 1996 Andhra Pradesh Cyclone, also referred to as Cyclone 07B, was a powerful tropical storm that caused extensive damage across the state of Andhra Pradesh. The system originated over the eastern Bay of Bengal on November

4, 1996, and reached its peak intensity before making landfall on November 6, approximately 50 km south of Kakinada. The satellite image depicting Cyclone 07B prior to its landfall in Andhra Pradesh is shown in Figure 7.

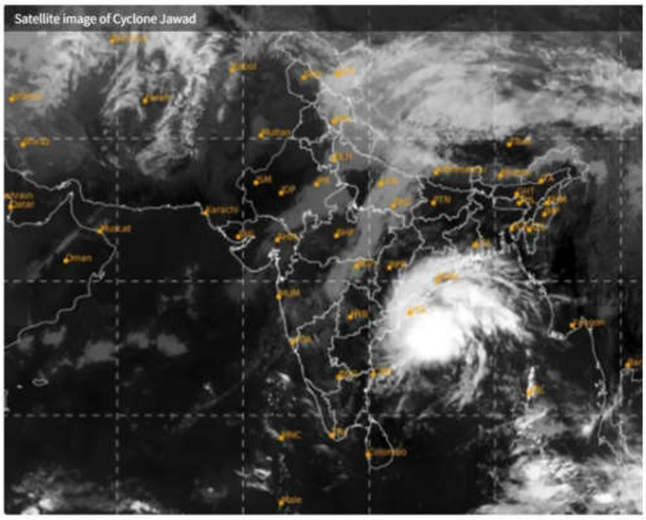


Fig 8 Cyclone Jawad is likely to reach north coastal Andhra Pradesh

The India Meteorological Department (IMD) issued a red alert, forecasting that a low-pressure system over the Bay of Bengal could intensify into a cyclone. The system was observed moving in a northwesterly direction and was expected to make landfall along the North Andhra–Odisha coast, bringing strong winds and heavy rainfall to the East Godavari district. Figure 8 illustrates Cyclone Jawad as it approaches the northern coastal region of Andhra Pradesh.

Table 2 Analysis of Cyclone risk for various risk classes

	East Godaveri	West Godaveri	Krishna	Total	Percentage
Very low	17.9	16.86	18.75	70.7	1.46
Low	207.13	58.02	352.73	740.65	15.31
Moderate	1420.11	234.87	982.55	3121.69	64.52
High	504.92	79.03	93.74	825.45	17.06
Very high	17.52	17.4	21.11	79.97	1.65
Total	2167.56	406.16	1468.94	4838.47	100

The study examined that the district East Godavari are in high-risk cyclone zone and its associated hazards as in Table 2. Table 2 suggested the analysis of cyclone risk under different classes of risk for different districts of East Godavari, West Godavari and Krishna. The study observed areas like Kannuru, Suryalanka, Kalipatnam, Nizampatnam, Uppada, Part of Machilipatnam, etc. are the places that undergoes high and very-high-risk zone.

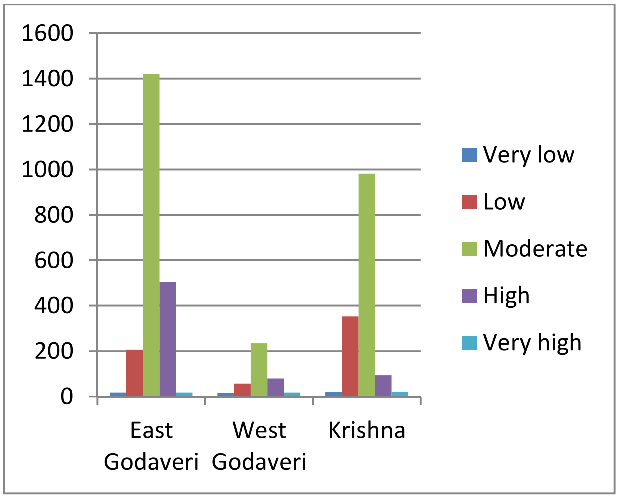


Fig 9 Analysis of cyclone risk for Krishna Godavari region under different classes

Fig 9 shows the graphical representation of the cyclone risk analysis for districts of East Godavari, West Godavari, and Krishna under classes.

Table 3 Comparative analysis of prediction ability of existing and proposed models

Models	Precision	Probability of Detection (POD)	False Alarm Ratio (FAR)	Critical Success Index (CSI)
MARS	.94	.95	.06	.95
CART	.92	.94	.08	.92
RF	.95	.95	.05	.96
SVM	.9	.95	.1	.91
VGGNet-16	.97	.98	.04	.97

Table 3 presents a comparative analysis of the prediction performance between the proposed model and existing approaches. The results of the **VGGNet-16** model are evaluated against established methods such as MARS, CART, Random Forest (RF), and Support Vector Machine (SVM), based on key performance metrics including Precision, Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI). The analysis indicates that the proposed VGGNet-16 model outperforms the existing techniques across all evaluated parameters.

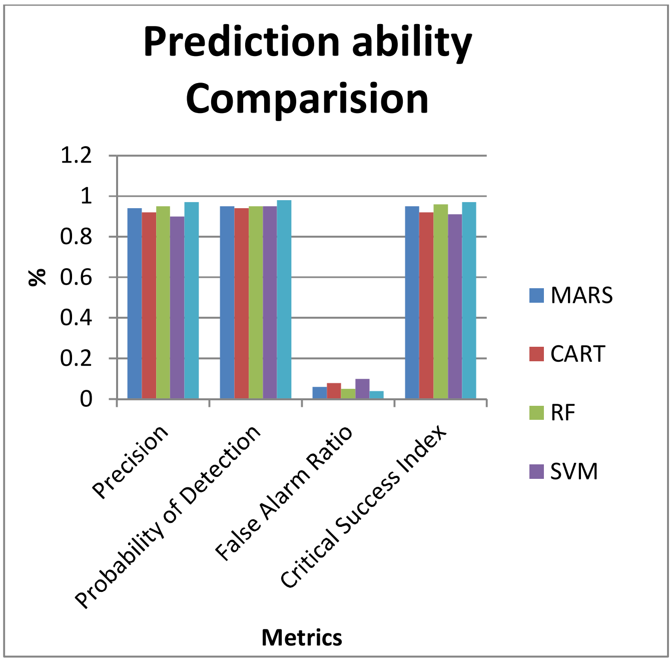


Fig 10 Comparative analysis of prediction ability

The table below (Figure 10) gives a graphical display of the comparative analysis of prediction performance of the proposed and existing models. The VGGNet-16 model is tested against the accepted techniques such as the MARS, CART, Random Forest (RF), and the Support Vector Machine (SVM) in terms of evaluation parameters like Precision, Critical Success Index (CSI), Probability of Detection (POD), and False Alarm Ratio (FAR). As it is evident in the analysis, the proposed VGGNet-16 model can be seen as superior in its performance to the current techniques in all the metrics examined.

Table 4 comparison of predictive analysis of overall accuracy of different techniques[21]

Techniques	Overall accuracy (%)
MARS	95
CART	93
RF	95
SVM	92
VGGNet -16	97.5

Table 4 shows a comparative study of the total predictive accuracy of existing techniques and the proposed model. The current techniques, such as MARS, CART, Random Forest (RF) and Support Vector machine (SVM) are compared with the new developed technique. According to the results the proposed VGGNet-16 model has a higher performance, with the overall accuracy of 97.5, which is better than existing techniques..

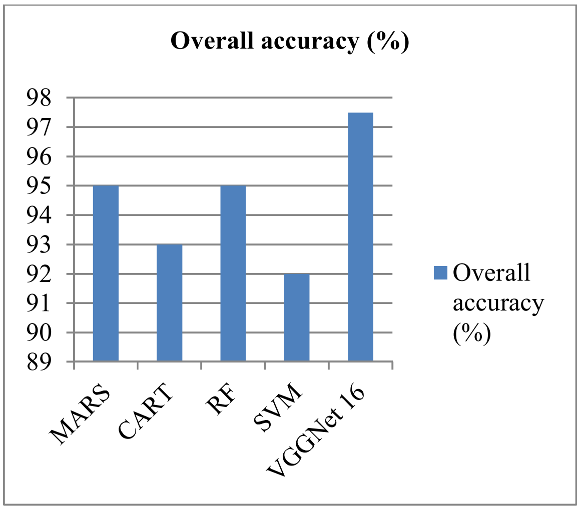


Fig 11 Comparison of accuracy for different techniques

Figure 11 shows the comparison of the accurate rating of the proposed model and the existing techniques. MARS, CART, Random Forest (RF), and Support Vector Machine (SVM) are compared with the proposed approach in terms of the accuracy of their predictions. The findings indicate that the designed VGGNet-16 model is superior to the current methods, and the accuracy of the model is 97.5. Moreover, the results demonstrate that the derived model has a better sensitivity to predict floods, rise in water level, and cyclone risk. Thus, the suggested method is more efficient and valid than the traditional methods.

IV. Conclusion

This approach provides a sensor-based natural disaster monitoring and prediction system i.e. floods and cyclones. First of all, remote sensing data were preprocessed and the feature extraction was implemented by using Matrix-based Fisher Discriminant Analysis. Adaptive Entropy-based Principal Component Analysis (AEPCA) was then used to refine the extracted features in order to effectively select features. In order to improve the accuracy of prediction, optimization was implemented on the Heuristic Echolocation Bat Optimization Algorithm.

Lastly, a Multi-Kernel Inception VGGNet-16 model was used in classification. The classified information was combined with an anti-terrorism alert process which produced real time warning notifications to enlighten the population. Performance assessment was also done to determine the ability of the system to forecast the flood and cyclone prone areas. The results obtained were contrasted with the available processes and it was proven that the proposed system outperformed in terms of Accuracy, Precision, Probability of Detection (POD), False Alarm Ratio (FAR) and Critical Success Index (CSI).

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