Civic Centered Heuristic Early Warning System Fashioned using Artificial Intelligence and Internet of Things

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***Abstract*— Nowadays, countries are suffering from a significant problem of natural disasters worldwide. Natural disasters happen due to environmental imbalance. The previously developed models do not have substantial results. The early warning system (EWS) comprises artificial intelligence (AI) and the internet of things (IoT) technologies. The EWS is tracing the climatic/weather conditions and accordingly floats an intimation to humans geographically through network-connected mobile devices. EWS gets trained using a 2D convolution neural network (CNN) of deep learning (DL) algorithms on collected data from different weather sensors. It classifies the weather conditions accurately. The proposed design is an EWS prediction model for detecting future natural disasters by following past and current climatic data details. It attains 93% training accuracy, 90% validation accuracy, 22% training losses, and 34% validation losses approximately. Also, to measure the model's performance for multiclassification on the validation dataset, find the precision, recall, and f1-score for each class, respectively. Then, calculate the accuracy, macro average (macro avg) and weighted average (weighted avg) on the whole testing dataset. All of the following results are explained in the classification report section. Simultaneously, this system provides a warning message to society geographically through IoT devices.**

Keywords*— *Early Warning System (EWS), Natural Disasters, Disaster Risk Reduction (DRR), Internet of Things (IoT), Artificial Intelligence (AI)

I. Introduction

The climate on earth suffers a lot due to the development of unethical infrastructure. Human beings are cutting the trees, polluting the rivers, pollutes the air for monetary gains. These day-by-day changes are the fundamental cause of global warming noticed worldwide. It significantly unfavourable weather conditions and creates severe reasons for natural disasters [1]. It adversely affects in excessive melting of glaciers and the increase in snowfall [2]. Both cases are harmful to life on the planet.

India's developing country suffers from above 40 million hectares of land prone to natural floods. Due to a lack of information about natural disaster preparedness, floods have wreaked havoc in these communities. The mortality in Kedarnath, Uttarakhand, India, was caused by cloudburst floods. There is no system to send out alerts in advance of natural disasters [3].

Human beings cannot stop natural calamities, hazards, and analysis of abrupt real-time weather changes. To overcome this problem, provide an alert to the citizens before the problem happens through the internet of things (IoT) or mobile devices geographically. In this regard, technology helps monitor and community awareness about upcoming mishappenings. It can handle through disaster risk reduction (DRR). The EWS is a helping system for sending warning messages to flood-affected regions [4], [5].

Nowadays, the social media revolution plays a prominent role in rapidly spreading information to society. The telecommunication network is a backbone for EWS alerts. The short message system (SMS) extends the knowledge of the severity of natural hazards like a flood to readiness for evacuation to the nearby harmless station. The early warnings help save a life, environment, and worldly things [6].

It is research for designing an artificial intelligence-based EWS to secure and save lives smartly. This system works with minimum human intervention and aids climatic information in detail. It analyzes the weather forecasting variables such as atmospheric pressure, temperature, humidity, wind speed, and wind direction [7].

EWS facilitates information to the stakeholders like agriculturists, farmers, scientists, meteorologists, departments, disaster management teams, climatic change activists, and researchers. This research provides a case study of the EWS concept in action. The EWS is a hybrid model that combines elements from artificial intelligence and the Internet of Things. The machine learning and deep learning algorithms assist in training the system (or hardware) to work unnaturally intelligently in sharing alerts to IoT devices spatially according to concerned areas.

II. Previous Studies

The authors showed interest in connecting local citizens to spread early messages to locale and stakeholders using existing IoT resources and telecommunication infrastructures for better timely responses [4]. The authors describe an EWS prototype consisting of a liquid crystal display (LCD) and a light-emitting diode (LED) to monitor the water level in a river or on the land in this article. If the system finds the water level in dangerous mode, it directly shares warnings through the global system for mobile (GSM) technology to the community [5].

The authors examined a geographic information system (GIS)-based decision support system (DSS) for disaster risk reduction. Practiced above makes the data details perfect and incorporate all agencies associated with disaster administration services [8]. The various sensors (like rain gauges, weather radars, ultrasonic, and pressure) measured certain variables. The authors classified the weather variables monitored in real-time while the rain fell to observe rainfall and water level outlay. Collecting all of the variables' real-time data from different sensors allows the stakeholders to save lives, the environment, and necessary things. However, weather detectors secure more coverage regions than rainfall standards. After all, rainfall measures are more costly and need higher technological implementation [9].

The author proposed an EWS by analyzing twelve environmental indicators: four pressure, five states, and three responses. Also did a thorough study for leading and concluding indicators: precipitation, vegetation covering status, and soil brightness with remote-sensing. The significant point in this method is electing the signs based on the environmental stipulations concerning each region. It shows the ecological imbalance through remote-sensing technology to collect data regarding rainfall, arid or semiarid regions. It was research conducted with the least number of intimations for EWS. Hence more investigation required more gauges to improve the research's result [10].

The researcher introduced an automatic weather system (AWS) to analyze weather variables, and ultrasonic sensors help read water levels. Accordingly, the EWS communicates a message with safe, standby, warning, and danger (flash flood) knowledge. The results AWS achieved 80% well, and the flash-flood early warning system favoured 70% [11]. In this study, the scholars categorized rainfall into three patterns, like 70–160 mm, 161–250 mm, and >250mm, as low, medium, and high simultaneously for five successive days. Due to this, landslides would notice in Chittagong Hill Districts of Bangladesh. Here landslides EWS designed by Web-GIS technologies to reach the policymakers and regional people. It highlights constraining fake alerts. The effort mentioned above was co-produced by experts, social personalities, and stakeholders to overwhelm the deficiencies in landslide warning integration at the regional scale [12], [13].

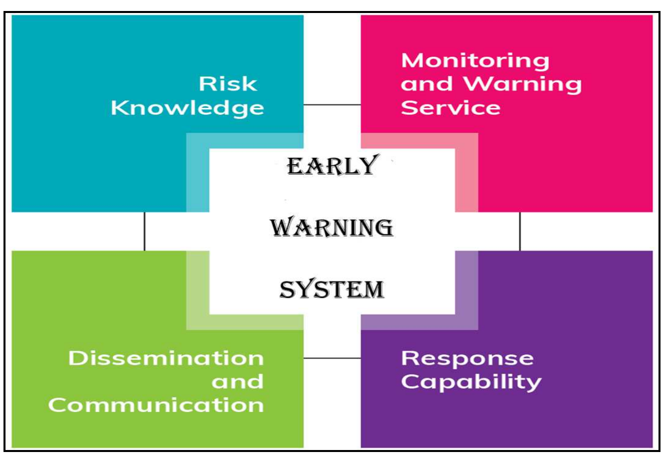

Fig. 1. Early Warning System Life-cycle.

It signified the EWS life-cycle to handle natural hazards. This life-cycle, see Figure-1, comprises four steps: 1. Risk knowledge; 2. Monitoring and warning services; 3. Dissemination and communication, and; 4. Response potential building. The authors concentrated on a clear sense and accurate message floating to the community. If possible, design a warning in local languages. It is easy to understand in a non-well-educated society [13], [14].

Here authors described data collection and analysis through remote sensing (RS) and geographic information system (GIS) techniques. RS technology facilitates recognition changes on the ground surface effectively. The RS arrangement may additionally be a vital monitoring agent if significant exposure frequently comes at a suitable time. GIS technology favours data collection, analysis, and visualization for spatial surfaces. It helps analyze the threshold for rainfall and soil humidity [14].

Scholars described a successful development of a wireless sensor network, which regulates many accurate parameters that lead to disaster. The connection comprises a slope sensor, humidity sensor, temperature sensor, and soil moisture sensor. The sensed data was compared to the exact previously collected data into the Internet cloud by a GSM transmission medium [15]. The authors demonstrated android and website technologies for sending early notifications to the community toward saving a life, culture, environment, and worldly things [16]. Android devices comprise Google Map (GM) applications. It facilitates human beings to find harmless stations to evacuate themselves with necessary items. It also supports the stakeholders in providing needed help to the citizens stuck in the disaster-affected area [17].

III. Methodology to Design and Implement EWS Model

This methodology represents a new early warning system (EWS), which facilitates saving the life and worldly things. The following method uses five steps process, such as:

Step 1 Start the process.

Step 2 To input weather data from multiple sensors for distinct locations.

Step 3 To prepare Weather Image Classification Model by using deep learning neural network (DNN).

Step 4 Display the forecast climatic conditions detail to the internet of things (IoT) devices for a specific location.

Step 5 End.

A. Input Weather Data for EWS Model

Firstly, input the weather image dataset from the Kaggle website (https://www.kaggle.com/vijaygiitk/multiclass-weather-dataset). This dataset uses to make the model perform correctly and classify any weather conditions accurately. The real-time implementation collects data from sensors, geographical information systems (GIS), and geostationary satellites.

The Kaggle dataset specifies the different climatic conditions and contains 1531 labelled images. Images categorize into six directories as cloudy, foggy, rainy, shine, sunrise, and alien-test. With these directories, it consists of one test.csv file for validating the label of the image.

B. AI-based Weather Image Data Classification Model

This paradigm is a convolution neural network (CNN), a deep learning model. See Figure-2, Step-2. It classifies all of the images accurately and predicts the weather conditions perfectly. This EWS model facilitates the community by providing early notifications regarding mishappening to the harmful spots.

C. Pseudocode for Weather Image Data Classification Model

The pseudocode of the proposed algorithm for a weather image-data classification model, such as.

Step 1 *Begin by creating a model.*

Step 2 *Include all of the necessary built-in libraries, including TensorFlow, Keras, NumPy, Pandas, Sklearn, OS, and Matplotlib.*

Step 3 *Gather data for the model's training and validation.*

⇒ *Specify a location for collecting image data.*

⇒ *To split up image data into distinct classes, i.e., TRAINING DATASET and VALIDATION DATASET, classify the image data into five classes, such as cloudy, foggy, rainy, shine, and sunrise.*

Step 4 *Show the graphs in a bar chart format.*

⇒ *Plot a bar-graph for the training dataset's classification and a bar-graph for the validating dataset's classification.*

Step 5 *Using the data augmentation technique, add to an existing dataset to produce more data.*

Step 6 *CNN has created a new Weather Classification model.*

⇒ *Create a sequential model with FIVE convolution 2D filters, kernel-size, activation function 'relu,' and padding function 'same; FIVE maximum pooling sizes of 2D images; ONE flatten layer; THREE dense layers with activation function 'softmax.'*

⇒ *Summarize the model.*

Step 7 *Compile the Weather Image Data Classification model that is just implemented.*

Step 8 *Run the collected images dataset through a newly implemented Weather Image Data Classification model.*

Step 9 *Validate the performance of a newly designed Weather Image Data Classification model by comparing it to the collected image dataset.*

Step 10 *Plot the line graphs to show how 'Training and Validation Accuracy' and 'Training and Validation Loss' performed.*

Step 11 *End.*

D. Results and Discussion for Weather Image Data Classification Model

The recommended weather image-data classification model is a step-by-step review. It consists as:

1. **Prepare Data:** At the start, require factual data to process further for modelling an architecture. The Kaggle data details provide in the initial phase of the methodology section.
2. **Classification of Training and Validation datasets:** It divides into two parts after the dataset is provided: The Training Dataset is 80% and the Validation Dataset is 20% of the total. This step graphically displays the diversity of the splitting images dataset. The data in a bar graph chart is described as per group in this case. Separate data sets for training and validation datasets are displayed in the bar, such as cloudy, foggy, rainy, shine, and sunrise image data. Individual classifications of the Training and Validation Datasets can be found in Table-1.

TABLE I. TRAINING AND VALIDATION DATA CLASSIFICATION

Dataset	*Types of images*	*No. of images*
Training	cloudy images	240
	foggy images	240
	rainy images	240
	shine images	200
	sunrise images	280
Validation	cloudy images	60
	foggy images	60
	rainy images	60
	shine images	50
	sunrise images	70

3. **Analysis for Performance of Model:** After implementation, compiling, and training a weather image-data classification model, focus on analyzing the performance of the same model on a split dataset.

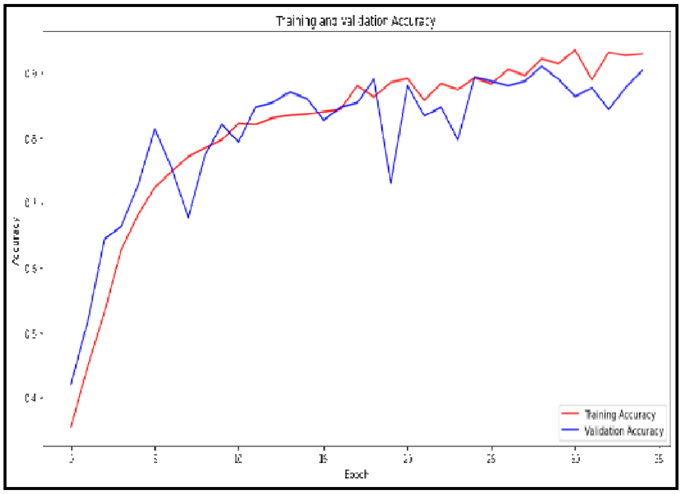

Fig. 2. Training and Validation Accuracy.

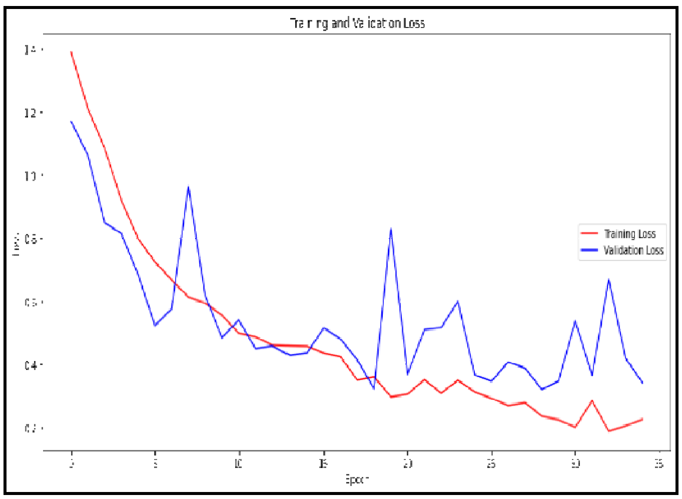

Fig. 3. Training and Validation Loss.

In the above figures, see Figure-2 and Figure-3 separately for training and validation accuracy; training and validation loss. This action demonstrates the result in 'Training and Validation Accuracy' and 'Training and Validation Loss.' It sequentially confers accuracy 93%, validation accuracy 90%, losses 22%, and validation losses 34% approximately. It represents no overfitting and underfitting in the proposed model for weather image-data categorization. So, it defines that the model's performance is acceptable for further testing on data.

4. **Confusion Matrix:** The confusion matrix represents the accuracy of image data prediction. Here, Figure-4 confusion matrix shows all of the performance of the proposed model. On a testing data, this describes that for cloudy: out of four images, it predicts two images correctly; for foggy: out of ten shots, it indicates seven precisely; for rainy: out of six shots, it represents six accurately; for shine: out of three images, it displays three correctly; for sunrise: out of seven ideas, it indicates seven correctly.

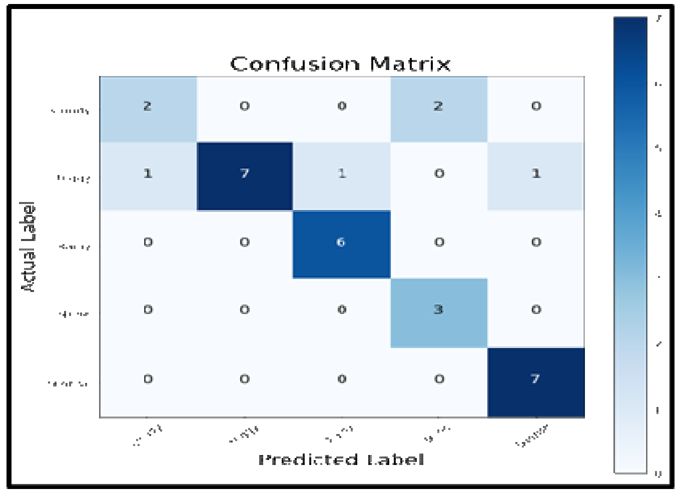

Fig. 4. Confusion Matrix.

5. **Classification Report:** The classification report represents the accuracy of image data prediction. Here, the TABLE II classification report summarizes the proposed model's performance. The validation dataset is identical to the confusion matrix dataset described above.

In this case, TP denotes True Positives, TN denotes True Negatives, FP denotes False Positives, and FN denotes False Negatives.

Precision assesses the proportion of positive class predictions that are genuinely positive class predictions.

Precision equals (TP) / (TP+FP) (1)

Recall is a metric that expresses the number of positive class predictions made from all positive examples in the dataset.

Recall equals TP / (TP+FN) (2)

The f1-score is used to calculate the harmonic mean of precision and recall. The scores assigned to each class indicate the classifier's accuracy in classifying the data points within that class in comparison to all of the other classes.

The F1-score is calculated in the conventional manner as follows::

F1-Score equals (2 * Precision * Recall) / (Precision + Recall) (3)

The support is the number of true response selections that match into that class.

The accuracy of a weather classification model is calculated by dividing the total number of valid forecasts by the total number of dataset values, such as:

Accuracy equals (Sum of TP of each class) / (TP + TN + FP + FN) (4)

Macro-averaging scores are the arithmetic mean of the precision, recall, and f1-scores for each individual class, such as:

Macro average equals (Sum of all classes precision or recall or f1-score values) / (Total number of classes)

(5)

In case of class inequalities like different numbers of data for various class labels, then use weighted average or weighted macro-averaging score to analyze the model's performance for each precision, recall and f1-score individually. Multiply each number by its weight to obtain a weighted average, and then aggregate the results, such as:

Weighted average = ∑ (Total number of each class data / Total classes dataset) * (Each class precision or recall or f1-score values separately) (6)

It is shown below in TABLE II for performance metric of multiclass (cloudy, foggy, rainy, shine, and sunrise) models with parameters like precision, recall, f1-score, accuracy, macro-avg and weighted-avg.

For example, firstly calculate accuracy for cloudy class to predict the true information. Here,

TP = 2; FP = 1; FN = 2; TN = 25

from “(1)”, we get,

Precision (cloudy dataset) = 2 / (2 + 1) => 0.6666 => 0.67

from “(2)”, we get,

Recall (cloudy dataset) = 2 / (2 + 2) => 0.5

from “(3)”, we get,

F1-score (cloudy dataset) = (2 * 0.67 * 0.5) / (0.67 + 0.5) => 0.5726

As of the above, follow the same procedure to calculate for other classes like foggy, rainy, shine and sunrise. For complete details, check for TABLE II below.

from “(4)”, we get,

Accuracy (weather classification model)

= (2 + 7 + 6 + 3 + 7) / (4 + 10 + 6 + 3 + 7) => 25 / 30

=> 0.83

from “(5)”, we get,

Macro average = (0.67 + 1.00 + 0.86 + 0.60 + 0.88) / 5

=> 0.80 (for precision)

Similarly, for recall and f1-score are 0.84 and 0.80 simultaneously.

from “(6)”, we get,

Weighted average = {(4 / 30) * 0.67 + (10 / 30) * 1.00 + (6 / 30) * 0.86 + (3 / 30) * 0.60 + (7 / 30) * 0.88}

=> 0.86 (for precision)

Similarly, for recall and f1-score are 0.83 and 0.83 simultaneously.

TABLE II. DATA CLASSIFICATION REPORT

Classification Report				
	Precision	**Recall**	**F1-score**	**Support**
cloudy	0.67	0.50	0.57	4
foggy	1.00	0.70	0.82	10
rainy	0.86	1.00	0.92	6
shine	0.60	1.00	0.75	3
sunrise	0.88	1.00	0.93	7
accuracy			0.83	30
macro avg	0.80	0.84	0.80	30
weighted avg	0.86	0.83	0.83	30

E. *Receive Early Alert Notifications for Natural Disaster*

Thirdly, after analyzing the climatic behavior, this early warning system activates. These warnings receive on the internet of things (IoT) devices or mobile devices. It supports human life to decide before natural disasters happen and evacuate from dangerous areas to safe spots with worldly things. It provides excellent help in disaster risk reduction (DRR). As a proposed model, while mis-happenings will notice, EWS analyzes the problem geographically and warns the people, stakeholders, and emergency services accordingly. If it predicts the weather is not fruitful to the region as per setting the instruction, it directly connects to the mobile network and floats the notifications around harmful spots.

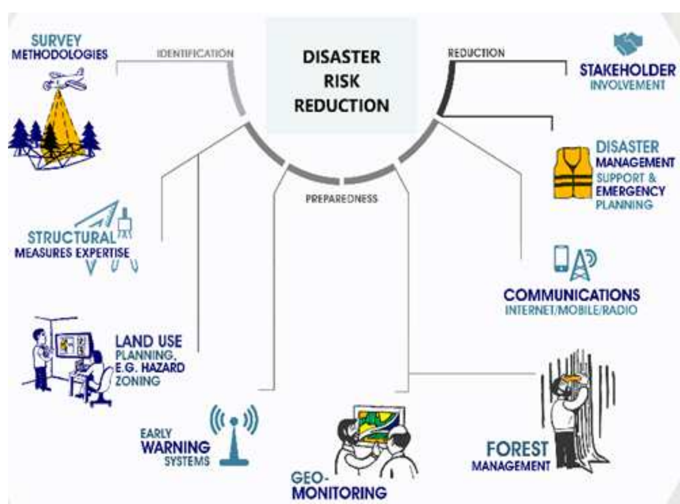

Fig. 5. Disaster Risk Reduction (DRR).

IV. DISCUSSION ABOUT EWS MODEL

EWS is a supervised communication to avoid old-fashioned care challenges for detecting natural disasters. It facilitates detecting the weather conditions on time and notifications to different authentic bodies to save a life, environment, and practical matters. It is a three steps process, as: Collect the input from relevant resources; Create an AI deep learning CNN model for classifying the weather conditions for accurate forecasting; Spread the alerts to the society to transfer themselves and their necessary things before a disaster happens in the specific region, plus provide the announcement to the stakeholders and emergency ser-vices to support the community in real-time. The means of transferring the alarms on IoT types of equipment use any of the services such as short message service (SMS) alert system, social media system (Facebook, Twitter, WhatsApp, so on), and geographic information system (GIS).

V. CONCLUSION AND FUTURE WORK

This practice concludes the proposed EWS for climatic conditions classification using a deep learning CNN sequential model and sharing the information on affected areas. It defines the model as classifying weather details correctly with great accuracy. After following all of the processing steps, it shows beautiful outcomes. This model implements using a clean dataset from the Kaggle website to train and validate the model. The solved confusion matrix explains the performance of the model on the test dataset very adequately. It improves training accuracy by 93%, validation accuracy by 90%, training losses by 22%, and validation losses by 34%. During the training and validation steps, there was no overfitting or underfitting report. As a result, the model's performance is extremely pleasing.

In the future, this strategy will be more practical to put up a temporary mobile network infrastructure in unstable natural areas by leveraging robots technology to inform people during disasters. It helps more on early alerts and saves a life on the planet.

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