NATURAL DISASTERS INTENSITY ANALYSIS AND CLASSFICATION USING ARTIFICAL INTELLIGENCE PREPARED SOLUTION

Abstract: Natural disasters not only disturb the human ecological system but also destroy the properties and critical infrastructures of human societies and even lead to permanent change in the ecosystem. Disaster can be caused by naturally occurring events such as earthquakes, cyclones, floods, and wildfires. Many deep learning techniques have been applied by various researchers to detect and classify natural disasters to overcome losses in ecosystems, but detection of natural disasters still faces issues due to the complex and imbalanced structures of images. To tackle this problem, we propose a multilayered deep convolutional neural network. The proposed model works in two blocks: Block-I convolutional neural network (B-I CNN), for detection and occurrence of disasters, and Block-II convolutional neural network (B-II CNN), for classification of natural disaster intensity types with different filters and parameters. The model is tested on 4428 natural images and performance is calculated and expressed as different statistical values: sensitivity (SE), 97.54%; specificity (SP), 98.22%; accuracy rate (AR), 99.92%; precision (PRE), 97.79%; and F1-score (F1), 97.97%. The overall accuracy for the whole model is 99.92%, which is competitive and comparable with state-of-the-art algorithms.

Keywords: deep learning; natural disasters intensity and classification; convolutional neural network

1. Introduction

Natural disasters are inevitable, and the occurrence of disasters drastically affects the economy, ecosystem and human life. Buildings collapse, ailments spread and sometimes natural disasters such as tsunamis, earthquakes, and forest fires can devastate nations. When earthquakes occur, millions of buildings collapse due to seismological effects [1]. Many machine learning approaches have been used for wildfire predictions since the 1990s. A recent study used a machine learning approach in Italy. This study used the random forest technique for susceptibility mapping of wildfire [2]. Floods are the most devastating natural disaster, damaging properties, human lives and infrastructures. To map flood susceptibility, an assembled machine learning technique based on random forest (RF), random subspace (RS) and support vector.

The proposed multilayered deep convolutional neural network method works in two blocks of convolutional neural networks. The first block, known as Block-I Convolutional Neural Network (B-I CNN), detects the occurrence of a natural disaster and the second one, known as Block-II Convolutional Neural Network (B-II CNN), defines the intensity of the natural disaster. Additionally, the first block consists of three mini convolutional blocks with four layers each and includes an image input and fully connected layers. On the other hand, the second block also consists of three mini convolutional blocks with two layers each, including an image input layer and fully connected layer.

The remaining paper is divided into four sections: Section 2, describes the related work. Section 3 presents the methodology which elaborates on the proposed technique. The results and discussion are presented in Section 4 to explore the overall research outcomes and describe the used dataset. Finally, the proposed work is concluded in Section 5.

2. Related Work

Studies analyzing the intensity of natural disasters have gained significant attention in the current decade. A. Ashiquzzaman et al. [6] utilized a video source for fire detection; processing video sources is a feasible task due to convolutional neural networks (CNNs),which require high performance computational resources including graphics hardware, and thus a smart and cost-effective fire detection network is proposed based on architectureof convolutional neural networks.

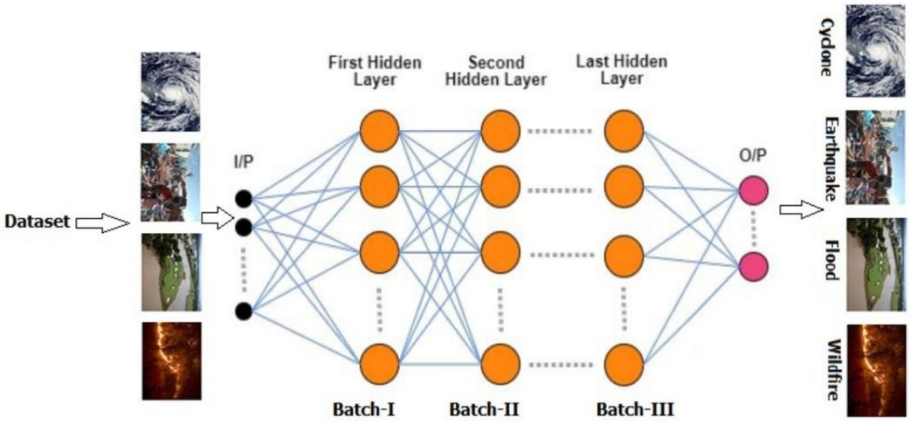
In convolutional neural networks, a model to detect wildfire smoke named wildfire smoke dilated dense net was proposed by Li et al. [7], consisting of a candidate smoke region segmentation strategy using an advanced network architecture. Mangalathu et al. [8] performed an evaluation of building clusters affected by earthquakes by exploring the deep learning method, which uses long short-term memory.

Methodology

This section defines the overall method for natural disaster intensity analysis and classification based on multispectral images using a multilayered deep convolutional neural network. Moreover, this method consists of two blocks of a convolutional neural network. The first block detects a natural disaster occurring and the second one defines the intensity type of the natural disaster. Additionally, the first block consists of three miniconvolutional blocks with four layers each, including an image input and fully connected layers. On the other hand, the second block also consists of three miniconvolutional blocks with two layers each and includes an image input layer and fully connected layer. The overall flow of methodology is shown in Figure 1 and explained below.

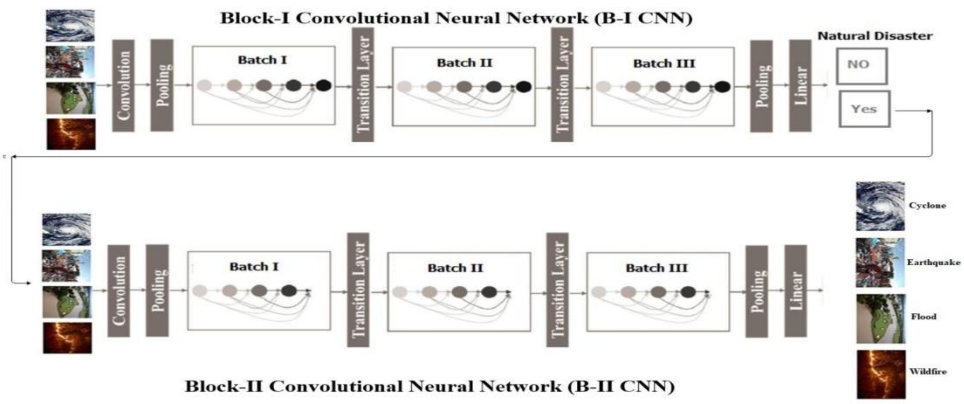
Block-I Convolutional Neural Network (B-I CNN)

According to block-I of the convolutional neural network, only a detection process occurred in this phase. However, this block also consists of three small batches having four layers each. Moreover, an image input layer and fully connected layers are present. Additionally, some parameters are also defined with learning rate 0.001 and epoch size 40. On the other hand, the convolutional layers use a filter size of 3 × 3, stride 1 and eight filters that increase in number from 16 to 32 for the second and third minibatches of convolutional neural networks,



Block-II Convolutional Neural Network (B-II CNN)

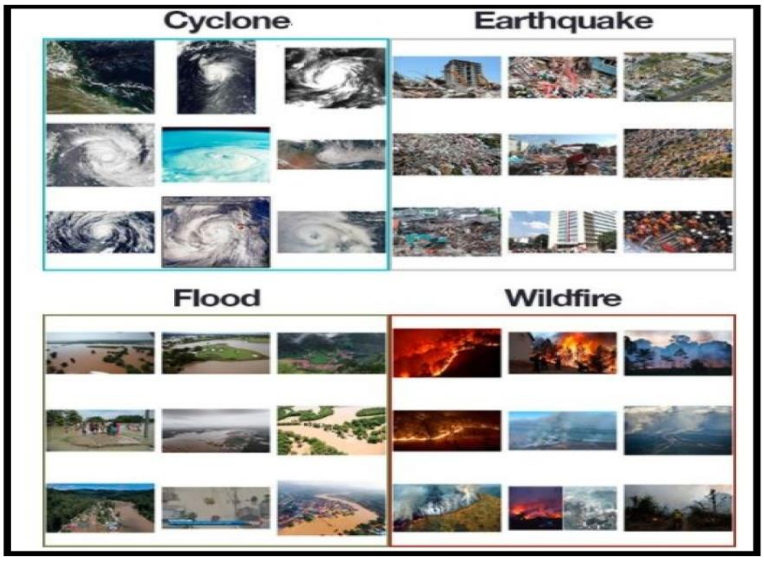
The block-II convolutional neural network takes the output from the first block and finds the types of natural disaster with intensity. Moreover, this block also consists of three minibatches having three layers each with two extra layers such as image input and fully connected layers. Additionally, the same parameters as block-I have been defined for this block also.



Dataset and Preprocessing:

In our research, the dataset used was collected from PyImage Search readers, who used Google Images to collect the total number (4428) of images in different classes. The dataset was separated into four classes: cyclone, earthquake, flood and wildfire, with 928, 1350, 1073 and 1077 images, respectively, as shown in Figure 3. The dataset was preprocessed to remove the noise by using an adaptive histogram equalizer. The whole dataset was divided into three groups: training, testing and validation. In total, 60% of the dataset was used for training, 23% for testing and 17% for validation. These percentages of the dataset were used to inform the machine on the percentage values of the dataset to be used for testing, training and validation purposes. The validation set was used to count the number of epochs for the whole training process. The details of the dataset are shownin Table 4.

Disaster Type	Total	Training	Test	Validation
Cyclone	928	500	300	128
Earthquake	1350	600	300	450
Flood	1073	600	300	173
Wildfire	1077	600	300	177
Total	4428	2300	1200	928



Evaluation Criterion:

To evaluate the performance of the proposed multilayered deep convolutional neural network, uses a train–test validation schema. To train the whole model, the training dataset was used, while for the fine-tuning of model the validation set was used. The performance of the whole framework was calculated on the basis of the test dataset. For the evaluationof the proposed model on the given dataset of classification for positive and negative values, four types of data were accrued: true positive (TP), the number of correctly positive classified images; true negative (TN) the number of correctly negative classified images; false positive (FP), the number of incorrectly positive classified images; and false negative (FN), the number of images that are incorrectly classified as negative images. The confusion matrices for these values are shown in Figures 4 and 5. To calculate the performance of the model, the specificity (SP), sensitivity (SE), accuracy rate (RR), precision (PRE) statisticalvalues were adopted as a criteria. The F1 score was used when a conflict occurred between accuracy and sensitivity to evaluate the performance. The equations are given below.

$$Sensitivity\ (SE) = \frac{TP}{TP + FN} \tag{1}$$

Equation (3) gives the value of accuracy rate (AR), which is equal to the

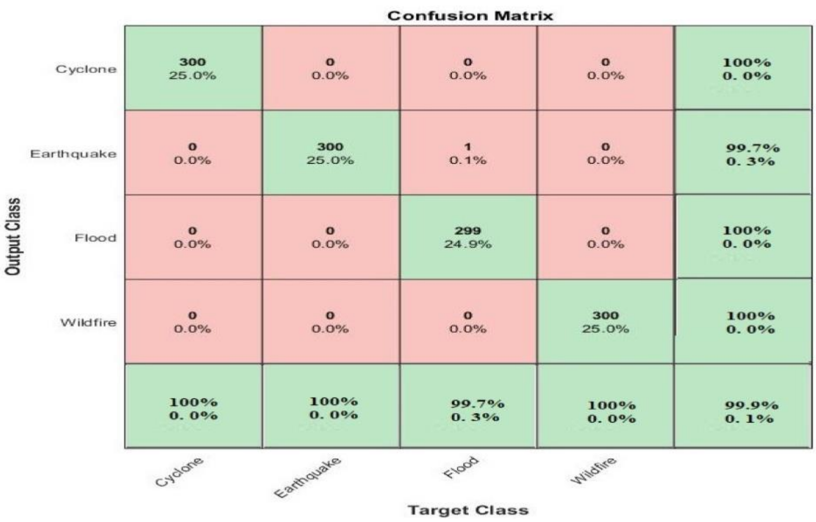
$$Precision\ (PRE) = \frac{TP}{TP + FP} \tag{4}$$

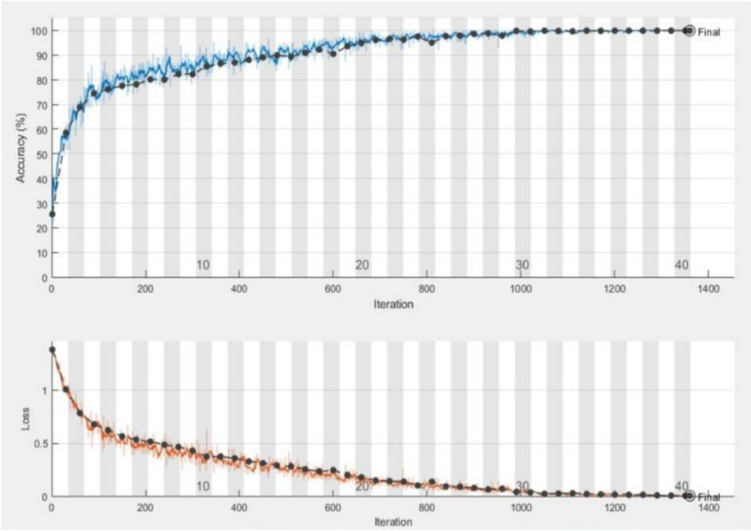
The precision (PRE) in Equation (4) explains the proportion of closeness in measure-ment values.

$$SE + PRE \tag{5}$$

The $F1$–Score ($F1$) in Equation (5) is the proportion of recall and precision which actually measure the model accuracy for the dataset.

(2)





The training and validation accuracy rate, which is 99.92%, and also shows the validation and training loss. Moreover, a complete training process is represented in Figure 6. The smooth line shows the training process and the dotted line shows the validation process for natural disasters dataset. Table 5 shows the calculated results in the shape of average statistical values: SE, 97.54%; SP, 98.22%; AR, 99.92%; PRE, 97.79%; and F1, 97.97% for the proposed model. The obtained results are comparable with the state-of-the-art techniques and solved the complex queries related to analysis of the natural disasters.

Cited	Technique Used	Accuracy-Rate (%)	Year
[43]	CNN	84.00	2015
[44]	Feed-Forward neural network	92.00	2016
[45]	Support Vector Machine	87.00	2016
[46]	CNN	90.00	2016
[47]	Glaucoma-Deep (CNN, DBN d, Softmax)	99.0	2017
[48]	RestNet-50	96.02	2018
[7]	WSDD-Net	99.20	2019
[49]	OCT Probability map using CNN	95.7	2019
[50]	Attention Guided Convolutional Neural Network	95.3	2019
[51]	ML-DCNN	99.39	2020
[52]	ML-DCNNet	99.14	2020
Proposed Multilayered Deep Convolutional Neural Network		99.92	2021

Conclusions:

Many researchers have attempted to use different deep learning methods for detection of natural disasters. However, the detection of natural disasters by using deep learning techniques still faces various issues due to noise and serious class imbalance problems.To address these problems, we proposed a multilayered deep convolutional neural net- work for detection and intensity classification of natural disasters. The proposed method works in two blocks—one for detection of natural disaster occurrence and the second block is used to remove imbalanced class issues. The results were calculated as average statistical values: sensitivity, 97.54%; specificity, 98.22%; accuracy rate, 99.92%; precision, 97.79%; and F1-score, 97.97% for the proposed model. The proposed model achieved the highest accuracy as compared to other state-of-the-art methods due to its multilayered structure. The proposed model performs significantly better for natural disaster detection and classification, but in the future the model can be used for various natural disaster detection processes.

Author Contributions: M.A. and T.A. conceptualized the research and methodology. The data gathering was performed by M.I. and A.S. The technical and theoretical framework was prepared by M.Z.A. and A.G. The technical review and improvement were performed by F.B. The overall technical support, guidance and project administration was conducted by W.G. and T.A. The final editing and reviewing were carried out by S.R. and S.A. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare that they have no conflict of interest.

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