NATURAL DISASTER DETECTION FROM IMAGES WITH DEEP LEARNING METHODS

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***Özetçe* —Doğal afetler, insani ve ekonomik açıdan büyük felaketlere sebep olmaları nedeniyle günümüzde küresel bir tehdit olarak yer almaktadır. Doğal afetlerin gerçekleşmesi ve farklı seviyelerde yıkıcı sonuçlara sebep olması kaçınılmaz bir gerçektir. Doğal afetlerin gerçekleşmesini engellemek için alınacak bir aksiyon henüz yokken, oluşan afetlerin yapay zeka tarafından derin öğrenme metodlarıyla tespitinin yapılması için günümüzde pek çok çalışma yapılmaktadır.**

Bu çalışmada, doğal afetlerin gerçekleşmesiyle ortaya çıkan görüntüler seçilmiş ve derin öğrenme algoritmalarından CNN yöntemi kullanılarak sınıflandırılmaları amaçlanmıştır. Kullanılan veri seti, 'Kuraklık', 'Deprem', 'Yangın', 'Sel' ve 'Normal' olmak üzere 5 farklı sınıf ve toplamda 5611 görüntü içermektedir. Veri seti üzerinde implemente edilebilecek derin öğrenme modelleri incelenmiş ve başarılı bir şekilde sınıflandırma yapabilecek model oluşturulmuştur. Oluşturulan modelin implementasyonunda yer alan motivasyon ve modelin başarımı literatürde sıklıkla yer alan metrikler uzerinden değerlendirilmiş olup elde edilen sonuçlar raporlanmıştır. Oluşturulan modelin doğruluğu yüzde 79 olarak hesaplanmıştır.

Anahtar Kelimeler—derin öğrenme, görüntü işleme, doğal afetler, evrişimsel sinir ağları, CNN.

***Abstract*—Natural disasters are a global threat today since they cause great human and economic disasters. It is an inevitable fact that natural disasters occur and cause devastating consequences at different levels. While there is no action to be taken to prevent the occurrence of natural disasters, many studies are carried out today to detect the disasters that occur by artificial intelligence using deep learning methods.**

In this study, images resulting from the realization of natural disasters were selected and it was aimed to classify them using CNN method, one of the deep learning algorithms.The data set used includes 5 different classes as 'Drought', 'Earthquake', 'Fire', 'Flood' and 'Normal' and a total of 5611 images. Deep learning models that can be implemented on the used data set have been examined and a model that can successfully classify has been created. The motivation involved in the implementation of the created model and the performance of the model have been evaluated through the metrics frequently found in the literature, and the results have been reported. The accuracy of the created model was calculated as 79 percent.

Keywords—deep learning, image processing, natural disasters, convolutional neural networks, CNN.

I. Introduction

Natural disasters are a global threat today because they cause great human and economic disasters. It is an inevitable fact that natural disasters occur and cause devastating consequences at different levels. While there is no action to be taken to prevent the occurrence of natural disasters, many studies are carried out today to detect the disasters that occur by artificial intelligence using deep learning methods. [1]

Natural disasters cannot be prevented, but they can be detected. Today, sensors are used to detect natural disasters. Seismic sensors (seismometers) and vibration sensors (seismoscopes) are used to monitor earthquakes. Radar maps are used to detect a hurricane's signature "hook echo". Flood sensors are used to measure humidity levels, while water level sensors are used in rivers, streams, etc. monitors the height of the water throughout. Wildfire sensors are still in their infancy, but will be able to detect traces of smoke and fire in the near future. Each of these sensors is highly specialized for the task at hand. Using computer vision, existing sensors can be strengthened, thereby increasing the accuracy of natural disaster detectors and, most importantly, enabling people to take action, stay safe, and prevent/reduce the number of deaths and injuries caused by these disasters. CNN was chosen as the basic model for the reasons stated in the data set used in the study carried out with this motivation.

CNN is an artificial neural network used for image classification, image segmentation and object recognition with high accuracy and high performance. CNN can learn to detect various images based on the images in the dataset studied. In this direction, images of natural disasters can be detected and classified with CNN.

II. Dataset

There are two approaches in artificial intelligence and deep learning techniques, 'supervised' and 'unsupervised learning'. The main difference between these two approaches is that one uses labeled data while the other produces results by doing the labeling itself. In the 'supervised' model, the data set is labeled from the beginning and it is requested to make the predictions within the framework of these labels. Using labeled inputs and outputs, the model can measure its accuracy and learn over time.

Since our project detects natural disasters from images, it is included in the 'supervised learning' method, one of the deep learning approaches. As a result of the literature review we conducted to determine the model we will use in our own project, we chose to create our own model based on the 'supervised learning' approach. For both models, we

Figure 1 Some examples from the dataset

used a dataset containing 5 different natural disaster classes. These classes are respectively 'Drought', 'Earthquake', 'Fire', 'Flood', and 'Normal'. When we got the data set ready, we saw that the performance of these two classes was low after the first training in our model, since there was not enough data in the 'Drought' and 'Earthquake' classes, and we started collecting data ourselves. We enriched our dataset and made it more optimized for models by adding a total of approximately 800 more data to both classes.

	Toplam
Drought	452
Earthquake	1339
Fire	514
Flood	1035
Normal	2271

Table 1 Dataset statistics

III. Experimental Results

Training and testing phases for classification natural disasters were performed on Google Colab PC with a Tesla P100-PCIE-16GB GPU and 25GB RAM. No any transfer learning method is used. All hyperparameters used in the model are given in Table 2.

Parameters	**Model**
Batch Size	4
Learning Rate	0.001
Momentum Value	0.9

Table 2 Hyperparameters used in our model

A. Evaluation Criteria

In order to evaluate the success of our natural disaster classification algorithm, we initially use 4 different performance metrics that are widely used in the literature. These metrics are basically based on two measures as shown in the following two equations. These Precision and Sensitivity (Recall) values are:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Figure 2 Precision and Recall Formulas

There is a trade-off between recall and precision metrics. To express this with an example, if the precision value increases too much, the recall value decreases, and if the recall value increases too much, the precision value decreases.

These metrics are used for binary classifiers but since our model has more than one class, we will treat each class as if it was the only class in our model and collect the results. In these equations 'True Positive' stands for the ones, hypothetically speaking for the class 'Drought', that our algorithm predicted as 'Drought' and the correct result was also 'Drought'. 'False Positive' specifies that our algorithm predicted a non-drought image as if it was 'Drought'. 'True Negative' values are for the ones that our algorithm predicted truly other classes than 'Drought'. Lastly, 'False Negative' clarifies the situation where our algorithm predicts a 'Drought' image as if it was not.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

Figure 3 Accuracy Formula

For the calculation of our algorithm's achievement other than precision and recall metrics, we have used accuracy and f1-score also. Here in Figure 3 and Figure 4 the formulas for these values are shown. Accuracy alone is not an enough metric for the evaluation process for the classification algorithms. Therefore we also calculated F1-Score which is basically harmonic mean of precision and recall. The results for there metrics are shown in Table 5.

$$F1\ score = 2 * \frac{Precision\ * Recall}{Precision + Recall}$$

Figure 4 F1-Score Formula

	precision	recall	f1-score	support
Drought	0.802083	0.687500	0.740385	112.000000
Earthquake	0.697605	0.714724	0.706061	326.000000
Fire	0.877193	0.781250	0.826446	128.000000
Flood	0.633700	0.667954	0.650376	259.000000
Normal	0.921875	0.934859	0.928322	568.000000
accuracy	0.799713	0.799713	0.799713	0.799713
macro avg	0.786491	0.757257	0.770318	1393.000000
weighted avg	0.802072	0.799713	0.800157	1393.000000

Figure 5 Classification Report

For the evaluation of the success of the proposed model, confusion matrix is calculated. With the confusion matrix it is possible to both visualize and summarize the performance of a classification algorithm. For our proposed model, the results are shown in Figure 6.

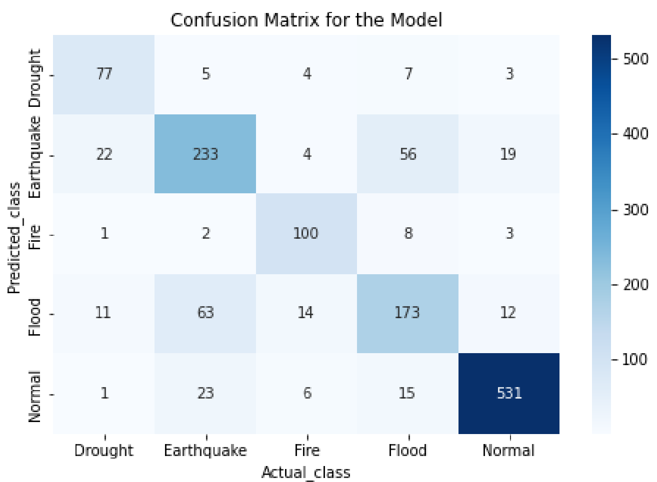

Figure 6 Confusion Matrix

IV. Performance Analysis

In this section, the results of the model used in the classification study on disaster images will be evaluated. According to the results of the classification report given in Figure 5, the accuracy of our model was measured as approximately 80 percent. Since the accuracy value alone is not a sufficient metric to evaluate the model, other metrics were examined and reported.

The Precision metric measures how many of the images tagged as belonging to a class in the entire dataset actually belong to that class. Precision value is above 60 percent for all 5 classes in our data set. In terms of this metric, the most unsuccessful class is 'Flood', while the most successful class is 'Normal'. From this perspective, images not included in the 'Flood' class are labeled as if they belong to the 'Flood' class.

The Recall metric measures how many of the images belonging to a class are correctly detected and labeled in the entire data set. The recall value is above 65 percent for all 5 classes in our data set. In terms of this metric, the most unsuccessful classes are 'Flood' and 'Drought', while the most successful class is 'Normal'. In other words, there are images that belong to the 'Fire' and 'Drought' class but cannot be labeled correctly.

The F1-Score metric is created by the harmonic mean of precision and recall values. F1-Score values for our model are 65 percent and above. While the 'Flood' class had the lowest F1-Score value, the most successful class in terms of this metric was again the 'Normal' class.

Confusion matrix of the model used in our project is given in Figure 7.2. According to the matrix, it seems that the 'Earthquake' class and the 'Flood' class are mostly confused with each other. According to the evaluation metrics given in Figure 5 and Figure 5, it is understood that the performance of the model used in our project in classifying natural disaster images is at a good level.

V. Demonstration

Parameters are weights that are learned by the model throughout the application and change with the back-propogation stage. In order for the parameters to exist in a layer, back-propogation must exist in that layer. In Table 3, the parameter values of the layers implemented throughout our application are calculated using the relevant formulas.

In our application, the estimation results for four randomly selected natural disasters seen in Figure 7, Figure 8, Figure 9 and Figure 10 are shown.

	Layer Number	Activation Shape	Activation Size	Parameters
1	Input Layer	(256, 256, 3)	196608	0
2	CONV1(f=5, s=1)	(256, 256, 3)	381024	456
3	POOL1	(126, 126, 6)	95256	0
4	CONV2(f=5, s=1)	(126, 126, 6)	238144	2416
5	POOL2	(61, 61, 16)	59536	0
6	FC1	(59536, 120)	59536	7203856
7	FC2	(120, 84)	120	7144440
8	FC3	(84, 5)	84	10164

Table 3 Parameter Statistics

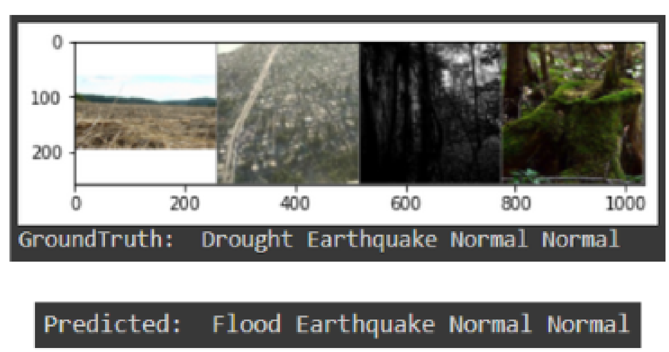

Figure 7 Actual and Detection Results

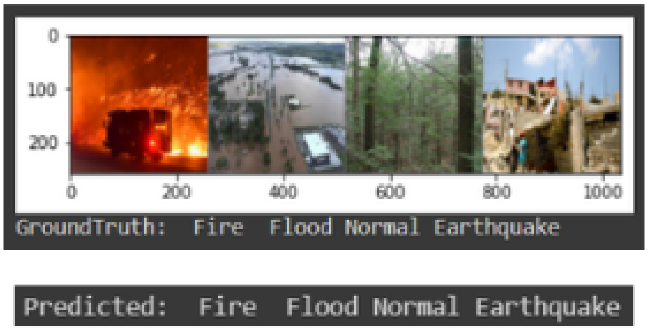

Figure 8 Actual and Detection Results

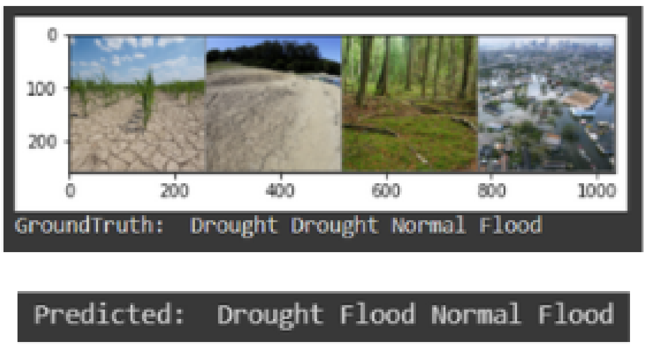

Figure 9 Actual and Detection Results

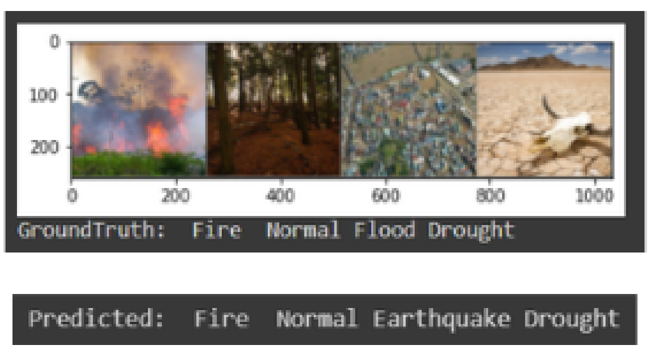

Figure 10 Actual and Detection Results

VI. Conclusion

In this study, CNN-based model training on classification in the data set consisting of natural disaster images was performed and its results were evaluated. After trying different 'batch size' and number of kernels in the training process of the model, the most optimum result was chosen as the main model and it was deemed appropriate to be used in the project. The application of the model, its experimental results and performance analysis were made, and also deep learning and CNN were examined and explained in detail within the scope of the report.

In the implementation of the code of the project, the PyTorch library of the Python programming language was used due to the reasons examined in the Software Feasibility section. The environment chosen to run the code has been Google Colab Pro, as it provides the GPU support required for deep learning algorithms to work.

With the realization of this project, it is possible to reduce the destructive consequences of natural disasters, which are a major economic, human and social problem in today's world. After a natural disaster, the images to be obtained from the cameras and satellites in the region can be automatically detected and labeled, thereby accelerating the delivery of relevant aid to the region, and thus our project can be presented for the benefit of humanity.

References

[1] R. Nijhawan, M. Rishi, A. Tiwari, and R. Dua, "A novel deep learning framework approach for natural calamities detection," in *Information and Communication Technology for Competitive Strategies*. Springer, 2019, pp. 561–569.