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CHENNAI

Detecting Natural Disasters with PyTorch

CSE4019 : Image Processing

PROJECT REPORT

SLOT : B2 + TB2

FALL SEMESTER 2021-22

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Date : 25-Dec-2021

DECLARATION

I hereby declare that the project entitled "Detecting Natural Disasters" submitted by us to the School of Computer Science and Engineering, Vellore Institute of Technology, Chennai Campus, Chennai 600127 in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology – Computer Science and Engineering is a record of bonafide work carried out by me. I further declare that the work reported in this report has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma of this institute or of any other institute or university.

Signature

Souhardya Datta (19BCE1330)

Manav Jaiswal (19BCE1037)

CERTIFICATE

The project report entitled "Detecting Natural Disasters" is prepared and submitted by us. It has been found satisfactory in terms of scope, quality and presentation as partial fulfilment of the requirements for the award of the degree of Bachelor of Technology – Computer Science and Engineering in Vellore Institute of Technology, Chennai, India.

Examined by:

Examiner

ACKNOWLEDGEMENT

We wish to express our sincere thanks and deep sense of gratitude to our project guide, Dr. Ayesha SK, Assistant Professor, School of Computer Science Engineering, for her consistent encouragement and valuable guidance offered to us in a pleasant manner throughout the course of the project work.

We express our thanks to our Head of the Department Dr. NITHYANANDAM P for his support throughout the course of this project.

We also take this opportunity to thank all the faculty of the School for their support and their wisdom imparted to us throughout the course.

We thank our parents, family, and friends for bearing with us throughout the course of the project and for the opportunity they provided us in undergoing this course in such a prestigious institution.

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ABSTRACT

Cataclysmic events are wild peculiarities happening yearly which make broad harm lives, property and cause extremely durable harm to the climate. Anyway by, utilizing Deep Learning, ongoing acknowledgment of these fiascos can help the people in question and crisis reaction offices during the beginning of these ruinous occasions. As of now, there are still holes in the writing in regards to continuous cataclysmic event acknowledgment. In this paper, we present a model for the classification of disasters and labelling them. Along these lines, the demonstrated that precise acknowledgment of catastrophic events is conceivable utilizing a lightweight model and move learning. We trust that this report would prompt advancement of checking or observation frameworks that can perform exact, on-the-ground, and ongoing acknowledgment of cataclysmic events taking into consideration fast crisis reactions moderating the deficiency of lives and harms to properties.

INTRODUCTION

Disaster detection has been one of the most active research areas in remote sensing today because saving human lives is our priority once a disaster occurred. Because preserving human lives is our top concern after a disaster, disaster detection has become one of the most active research fields in remote sensing today. It is critical in the coordination of rapid response measures following a devastating disaster such as a landslide or flood. Previous research has mostly focused on detecting changes caused by disasters, relying solely on sensors and manually adjusting image processing techniques such as image algebra (band differencing and band rationing), post-classification comparison, and an object-based change detection method in. Machine learning is used to improve the efficiency of feature extraction in order to improve detection accuracy. A substantial quantity of literature has been written on machine learning-based detection. In the bags-of-visual-words setting, recommended hierarchical form attributes for detecting large-scale damage. The use of artificial neural networks to anticipate cyclone tracks is shown in the year 2010, assesses the efficacy of multilayer systems.

Prior catastrophe detection systems were primarily focused on sensors and were underdeveloped. As a result, they face a number of severe issues. For example, due to a lack of sensors, the range for inspecting the existence of a disaster is limited, and the accuracy of information transmission is low due to verbally conveyed information. Aside from that, the operators engaged are unable to process a large volume of satellite imagery and discover disasters in a timely manner. As a result, information may be misinterpreted or the onset of a tragedy may be overlooked. Based on prior studies, it is difficult to obtain instant performance improvement in disaster identification and management, as demonstrated by this case. As a result, the goal of this work is to develop a catastrophe detection *model using CNN.*

MOTIVATION

Studies examining the power of cataclysmic events have acquired huge consideration in the current decade. used a video hotspot for fire location; handling video sources is a practical assignment due to convolutional neural organizations (CNNs), which require superior execution computational assets including illustrations equipment, and accordingly a shrewd and financially savvy fire identification network is proposed dependent on engineering of convolutional neural organizations.

Convolutional Neural Networks (CNN) are everywhere. It is arguably the most popular deep learning architecture. The recent surge of interest in deep learning is due to the immense popularity and effectiveness of convnets. Using CNNs for classification has seen an amazing rise in recent times. And linking this with one of the most important human's enemy 'Disaster' can be a great opportunity for learning.

PROBLEM STATEMENT

Disaster Classification Model using CNN, for classification and labelling of different disaster categories with high accuracy is the sole purpose that we want to work on. Also, while learning and experiencing we tried to provide a novelty in the project with a multiclass(12) classification.

LITERATURE SURVEY

The examination of past writing has shown different characterization plans to get logical data from catastrophe related information—be that as it may, each study centres around a particular occasion covering a couple of calamity classes. For instance, centred around recognizing pictures applicable to a specific kind of catastrophe like fire, flood, storm, and so on Essentially, others centre around a piece of explicit data need, for example, seriousness levels of harm ,salvage, chipping in, or gift, alert, cautioning, guidance , food and fundamental need supplies, impacted people (individuals) , and influences.

Francalanci etal. (17) proposed a system to prize the geo-located images from tweets to support the exigency response. They've offered the birth system of geo-located images comprised of tweet selection, tweet cleaning, geo-localization, selection of tweets with media, image analysis, and fine-granulated localization. The authors have developed the system caled Image Birth from tweets (IMEXT) to validate the proposed system. The IMEXT tool redounded in14.18 of useful images with position information in the available tweets dataset. This study is limited to one disaster type, and the tweets with position and damage- related keywords filtered manually. Murthy etal. (7) conducted a study on geo-located images taken from the Instagram's app druggies and posted on Twitter accounts during Hurricane Sandy. The images were posted in three phases of the Hurricane Sandy disaster, i.e.,pre-USpre-storm, when Sandy made US landfall, and Sandy's fate. The results showed that utmost prints were about inventories during the time Hurricane Sandy made US landfall, and the most common content was'Sandy parties'.

Daly & Thom (9) named Flickr as a social media data source to probe the visual characteristics and the geospatial characteristics distribution of major fire prints and metadata. The'Bag of Features model'is used for image bracket. The authors have compared the four different approaches to train the SVM SIFT, SURF, ColorSURF, and ColorSIFT. ColorSIFT was plant to be the stylish, with 91 recall and 93 perfection. The study is limited to the Flickr platform, and the images were just classified as fire andnon-fire events. Nguyen etal. (10) delved images posted on social media during a natural disaster to determine the position of damage. To achieve that, they employed state-of-the- art machine literacy ways. The authors explored the performance of several image bracket ways, i.e., the traditional fashion of Bag-of-Visual- Words (BoVW) and CNN for assessing the position of damage inflexibility of social media images. Different trial settings were set for assessing the performance of machine literacy classifiers of BoVW model, VGG16 network, and VGG16 transfer literacy approach where the last subcaste ofpre-trained VGG16 was initialized using the new dataset of three damage orders. (1) severe, (2) mild, and (3) little or no damage. The results showed that VGG16 forfeiture-tuned outperformed other ways. In this study geo- position information wasn't explored.

Name	**Algorithm**	**Disaster type**
Experimentally defined convolutional neural network architecture variants for non-temporal real-time fire detection	AlexNet, Inception V1, VGG13, Inception V1-OnFire, FireCNN	Fire
Disaster image Detection model	Bag-of-Visual-Words (BoVW), SVM, VGG16, VGG15fine-tuned, VGG16fine-tuned	Earthquake, Hurricane, Flood
CNN and GAN Based Satellite and Social Media Data Fusion for Disaster Detection	AlexNet (4096), GoogleNet, VGGNet 19 (4096), ResNet (with 50, 101 and 152 layers)	Flood
. Enhancing Flood Impact Analysis using Interactive Retrieval of Social Media Images	SVM, Sequential CNN	Flood

PROPOSED WORK

Algorithm

CNN model can be thought as a combination of two components: feature extraction part and the classification part. The convolution + pooling layers perform feature extraction. For example given an image, the convolution layer detects features such as two eyes, long ears, four legs, a short tail and so on. The fully connected layers then act as a classifier on top of these features, and assign a probability for the input image being a dog.

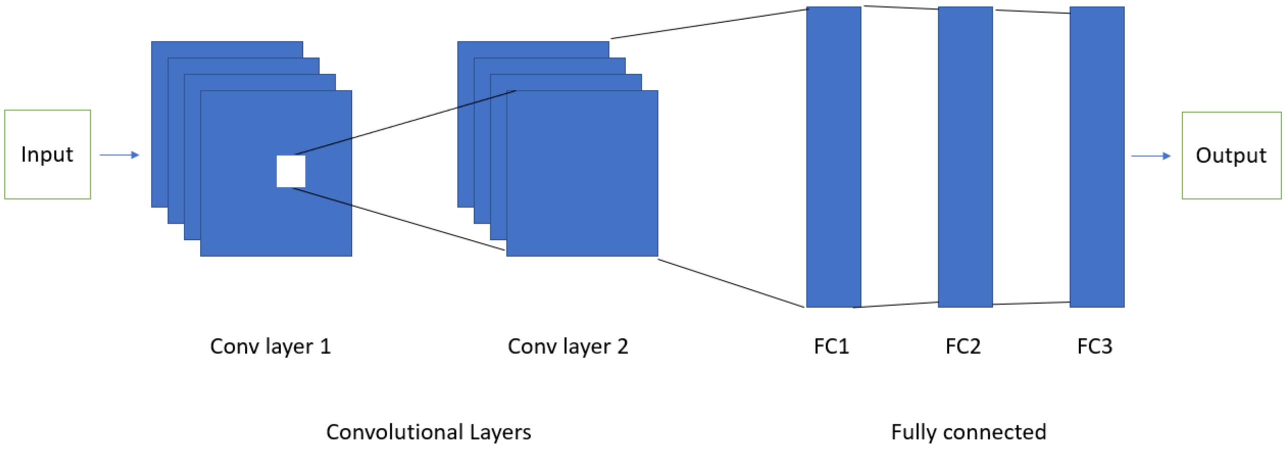
The convolution layers are the main powerhouse of a CNN model. Automatically detecting meaningful features given only an image and a label is not an easy task. The convolution layers learn such complex features by building on top of each other. The first layers detect edges, the next layers combine them to detect shapes, to following layers merge this information to infer that this is a nose. To be clear, the CNN doesn't know what a nose is. By seeing a lot of them in images, it learns to detect that as a feature. The fully connected layers learn how to use these features produced by convolutions in order to correctly classify the images.

Conv2D: this method creates a convolutional layer. The first parameter is the filter count, and the second one is the filter size. For example in the first convolution layer we create 32 filters of size 3x3. We use relu non-linearity as activation. We also enable padding. In Keras there are two options for padding: same or valid. Same means we pad with the number on the edge and valid means no padding. Stride is 1 for convolution layers by default so we don't change that. This layer can be customized further with additional parameters, you can check the documentation here.

MaxPooling2D: creates a maxpooling layer, the only argument is the window size. We use a 2x2 window as it's the most common. By default stride length is equal to the window size, which is 2 in our case, so we don't change that.

Architecture

A total of 5 layers have been used for the CNN in this project. Two convolutional layers and three fully connected layers to get the final classification of 12 classes.



Respective 12 classes are-

'Drought', 'Earthquake', 'Human_Damage', 'Infrastructure', 'Land_Slide', 'Non_Damage_Buildings_Street', 'Non_Damage_Wildlife_Forest', 'Urban_Fire', 'Water_Disaster', 'Wild_Fire', 'human', 'sea'

EXPERIMENTAL SETUP

Dataset-

The dataset contains images of different disasters collected from different sources and stored category wise. A total of twelve classes disaster images are available and are as follows:

Damaged Infrastructure

- Earthquake
- Infrastructure

Fire Disaster

- Urban Fire
- Wild Fire

Human Damage

Land Disaster

- Drought
- Land Slide

Water Disaster

Non-Damage

- Human
- Non-Damage Buildings
- Non-Damage Wildlife Forest
- Sea

Details of Hardware & Software
Hardware Requirements:
Laptop (32-bit or 64-bit architecture, 2+ GHz CPU, 8 GB

RAM.)

Software Requirements:

● Operating System: Windows 7/8/8.1/10, Linux

●Tools and Framework: Deep learning, PyTorch

● Language Requirement: Python

● Server: Locally hosted

Technology Used: Image pre-processing, PyTorch, Google Collab, Deep Learning, Image Processing.

RESULTS

We have trained our CNN for a total of 20 epochs and used Adam optimization with cross entropy loss criteria. Varying loss for the respective epochs are:

EPOCH: 0 LOSS: 1.59404826

EPOCH: 1 LOSS: 1.24864268

EPOCH: 2 LOSS: 1.02186406

EPOCH: 3 LOSS: 1.04771984

EPOCH: 4 LOSS: 1.00388062

EPOCH: 5 LOSS: 0.74705756

EPOCH: 6 LOSS: 0.82798064

EPOCH: 7 LOSS: 0.66204590

EPOCH: 8 LOSS: 0.47108760

EPOCH: 9 LOSS: 0.45658061

EPOCH: 10 LOSS: 0.50887066

EPOCH: 11 LOSS: 0.27159068

EPOCH: 12 LOSS: 0.54561436

EPOCH: 13 LOSS: 0.45605493

EPOCH: 14 LOSS: 0.61639780

EPOCH: 15 LOSS: 0.43443215

EPOCH: 16 LOSS: 0.64382869

EPOCH: 17 LOSS: 0.28061903

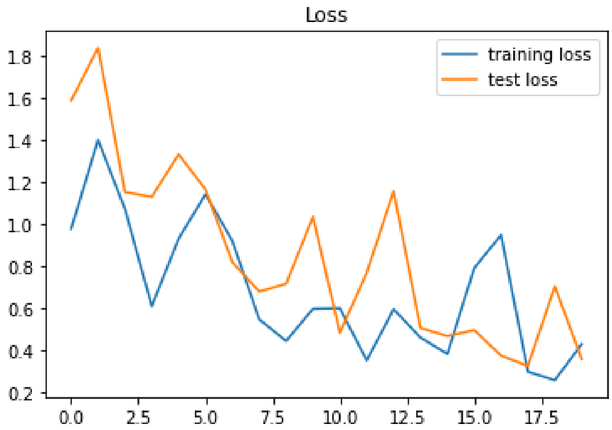
EPOCH: 18 LOSS: 0.67545241

EPOCH: 19 LOSS: 0.44038191

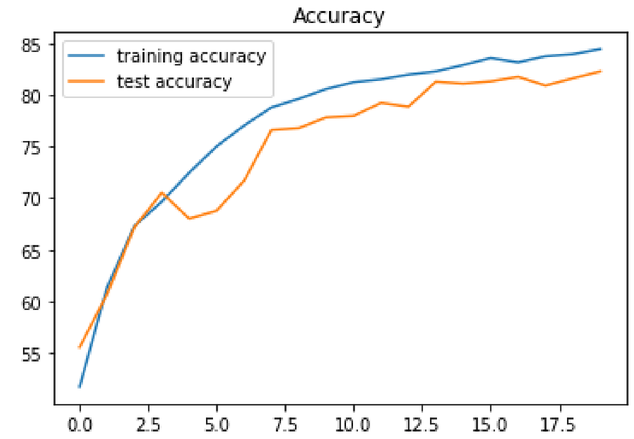
Training of our model took a total of 71.47 minutes.

Duration: 71.47224881649018 minutes

Loss- Epoch graph



Accuracy- Epoch graph



Our model achieved an accuracy of 81.83%

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Predicted value: 0 Drought
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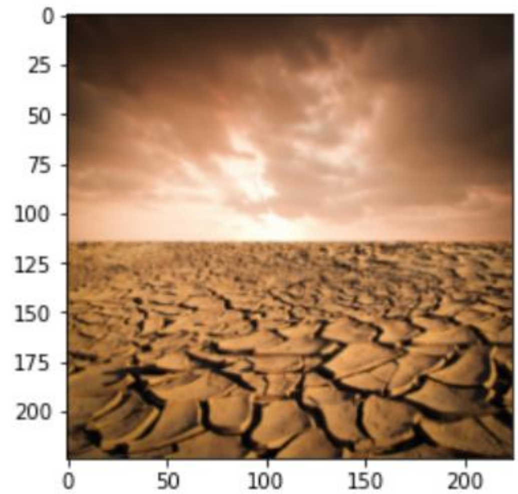

CONCLUSION

Many academics have attempted to detect natural disasters using various deep learning algorithms. However, utilizing deep learning techniques to detect natural disasters still has a number of drawbacks, including noise and major class imbalance issues. We suggested a multilayered deep convolutional neural network for natural disaster identification and intensity classification to overcome these issues. We achieved an accuracy of 81.83%. Due to its multilayered structure, the suggested model earned the maximum accuracy when compared to other state-of-the-art approaches.

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