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Detecting Natural Disasters Using Deep Learning

B. Keshav[1], M. Cherryl[1], P. Naveen Kumar[3], Dr. G. Murugan[4]
[1, 2, 3]Student, [4]Professor, Computer Science and Engineering, Vardhaman College of Engineering, Hyderabad, India

Abstract: Natural disasters cannot be stopped, but they can be spotted, allowing people valuable time to flee to safety, as is often noted. One strategy is to utilize computer vision to supplement current sensors, which improves the accuracy of natural catastrophe detectors and, more significantly, enables people to take preparations, stay safe, and prevent/reduce the number of fatalities and injuries caused by these disasters. As a result, responding to natural disasters like earthquakes, floods, and wildfires requires extensive work by emergency responders and analysts who are on the ground. A low-latency data source for understanding crisis conditions has arisen in social media. While the majority of social media research just uses text, photos provide additional insight into accident and disaster situations.
Keywords: VGG16, CNN, CLR, Learning rate finder, Overfitting

I. INTRODUCTION

For response organizations, unexpected onset events like earthquakes, flash floods, and car accidents must be quickly identified. However, gathering information in an emergency is time-consuming and expensive because it frequently calls for manual data processing and professional evaluation.

There have been attempts to use computer vision algorithms on synthetic aperture radar, satellite photography, and other remote sensing data to reduce these laborious efforts. Unfortunately, these methods are still expensive to use and insufficiently reliable to gather pertinent data in emergencies.

Additionally, satellite imagery only offers an above perspective of the disaster-affected area and is subject to noise like clouds and smoke (i.e., common images during storms and wildfires).

According to studies, social media posts in the form of text messages, pictures, and videos can be accessible right away when a disaster strikes and can provide crucial information for disaster response, including reports of infrastructure damage and the immediate needs of those who have been affected. Social media imaging is still underutilized, nonetheless, in contrast to other data sources (such as satellites), mostly due to two significant difficulties.

First off, social media picture streams are notoriously noisy, and disasters are no exception. Sizable chunks of social media photographs are irrelevant to particular disaster categories even after applying a text-based filter. Second, although deep learning models, the industry standard for image classification, are data-hungry, there is currently no large-scale ground-level picture dataset available for the development of robust computational models.

In this work, we address these issues and look into the detection of accidents, damage, and natural disasters in photos. The large-scale Incidents Dataset, which comprises 4,428 scene-centric photos and is classified into four classes—cyclones, earthquakes, floods, and wildfires—is presented first. Our model uses these pictures as the training and testing datasets.

II. ABOUT NATURAL DISASTERS

Natural disasters are tragic occurrences brought on by global natural or natural processes. The number of lives lost, the amount of money lost, and the population's capacity to recover gauges disaster intensity. Natural catastrophes in general bring harm and loss to the local population as well as the environment. Floods, earthquakes, tsunamis, landslides, volcanic eruptions, and storms are examples of natural catastrophes.

Three categories further distinguish the severity and scope of the harm.

Minor disasters are those that cover more than 50 km or up to 100 km., Fires are considered minor catastrophes.

1) *Disasters of Medium Size:* These catastrophes have a radius of 100 to 500 kilometers. These cause greater harm than minor disasters. Medium-scale disasters include landslides, tornadoes, erosion, and more.
2) *Disasters:* These calamities affect a region larger than 1000 km. These produce the most catastrophic environmental impact. At a high level, these catastrophes may potentially affect the entire nation. Large-scale disasters include earthquakes, floods, tsunamis, and other natural calamities.

A. How to Detect Natural Disasters

We employ sensors to keep an eye out for natural disasters all over the world.

Seismic sensors (seismometers) and vibration sensors (seismoscopes) are used to keep an eye out for earthquakes (and downstream tsunamis). To identify a tornado's distinctive "hook echo," Radar maps are used (i.e., a hook that extends from the radar echo).

Water level sensors track the height of water along a river, stream, etc. While Flood sensors gauge moisture levels.

Although wildfire sensors are still developing, it is expected that they will eventually be able to identify minute amounts of smoke and fire. The purpose of each of these sensors is to early detect a natural disaster, warn people, and enable them to flee to safety.

By combining existing sensors with computer vision, we can improve the accuracy of natural disaster detectors and, most importantly, enable people to take protective measures, stay safe, and prevent/reduce the number of fatalities and injuries caused by these disasters.

B. Objective

The primary goal of this project is to create a cutting-edge Convolutional Neural Network (CNN) model for classifying natural disaster images and videos into different disaster kinds. On the dataset, the model is trained and tested. The system should accept images and input and provide output on the probability of natural disasters occurring, the goal is to predict them at an early stage.

Abbreviation and Acronyms

1) *CNN:* Convolution Neural Network
2) *CV:* Computer Vision
3) *NN:* Neural Networks
4) *VGG:* Visual Geometry Group
5) *CLR:* Cyclical Learning rate
6) *LRF:* Learning Rate Finder

III.RESEARCH METHODOLOGY

It is well said, "Natural disasters cannot be prevented — but they can be detected, giving people precious time to get to safety. One strategy is to utilize computer vision to supplement current sensors, which improves the accuracy of natural catastrophe detectors and, more significantly, enables people to take preparations, stay safe, and prevent/reduce the number of

Fatalities and injuries caused by these disasters. In our research, we demonstrate the automatic detection of natural disasters in photos and video feeds using computer vision and deep learning techniques. We have thought after that, we will go over our dataset of four classes related to natural disasters.

Then, we created a series of tests that will:

1) Aid us in optimizing our database's VGG16 (which was trained on ImageNet).
2) Discover the ideal learning rates like cyclical learning rates.

In the work of Ethan Weber and Ferda Ofl, they provided the Incidences Dataset in this study, which consists of 446,684 human-annotated photos covering 43 incidents across various scenes.

On millions of social media photos from Flickr and Twitter, they do image filtering tests and use a baseline classification model that reduces false-positive errors. With the help of these tests, they demonstrate how the Incidents Dataset may be used to find pictures of incidents in the field. [1]

Considering Albertus Joko Santoso; Findra Kartika Sari Dewi; Thomas Adi Purnomo Sidhi[2].The technology can analyze sequences of satellite imagery taken before and during a natural catastrophe to identify patterns. The goal of this project is to select the best wavelet to compress the satellite image sequences and to use an artificial neural network to recognize natural disaster patterns. Satellite imagery sequences of tornadoes and hurricanes are used in this investigation. [2]

A. Population and Sample

The data is collected from different sources; some are social media platforms like Twitter, Facebook, etc. 428 images are collected through google images, and these images are sampled according to their respective classes of natural disasters (cyclones, Floods, Earthquakes, and Wildfires).

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B. Data and Sources of Data

We have utilized Google Photos' capabilities to quickly collect training images and so reduce the amount of time it takes to create a dataset**.** The dataset includes images belonging to four classes of natural disasters (cyclones, Earthquakes, floods, and wildfires). The distribution of image count is as below: **-**

Table 1: Images Count

Category	No.of images
Cyclone	928
Earthquake	1350
Flood	1073
Wildfire	1077

Here is the link for accessing the dataset, the dataset is stored in google drive and accessed when required for execution: - https://drive.google.com/drive/folders/139H6Nmf9gBbP15BXSRCD6MLHTAwem1mt?usp=sharing

C. Theoretical Framework

This section includes the pre-processing of data.

1) *Data Cleaning and Feature Extraction:* Data pre-processing, often known as data cleansing, is the first step in data extraction. The goal of data cleaning is to simplify the dataset so that it is easier to deal with. One observation per row and one variable per column are two traits of a clean/tidy dataset.
2) *Model:* The machine learning process is carried out using a deep learning artificial neural network that has a hierarchy of levels. The model is built on deep networks, in which the information flow starts at the initial level. The model learns something simple and transmits its output to layer two of the network while merging its input into something slightly more difficult and passing it on to layer three of the network. This process continues as each level of the network draws on the knowledge it received from the preceding level.

D. Statistical Tools and Econometric Models

This section elaborates on the proper statistical/econometric/financial models, which are being used to forward the study from data toward inferences. The details of the methodology are given as follows.

1) *Convolutional Neural Network (CNN):* Deep neural networks that have been specially designed to analyze data with input forms resembling a 2D matrix are known as convolutional neural networks. Images could be represented by a straightforward 2D matrix. CNN is crucial while using images. It accepts an image as input, assigns weights and biases to various parts and objects within the image, and then separates them based on significance. The CNN uses filters(sometimes referred to as kernels) to aid in feature learning and detect abstract ideas such as blurring, edge detection, sharpening, etc., like how the human brain detects objects in time and space. Because the weights can be reused and there are fewer parameters (2048 to 256), the architecture fits the picture dataset more effectively.

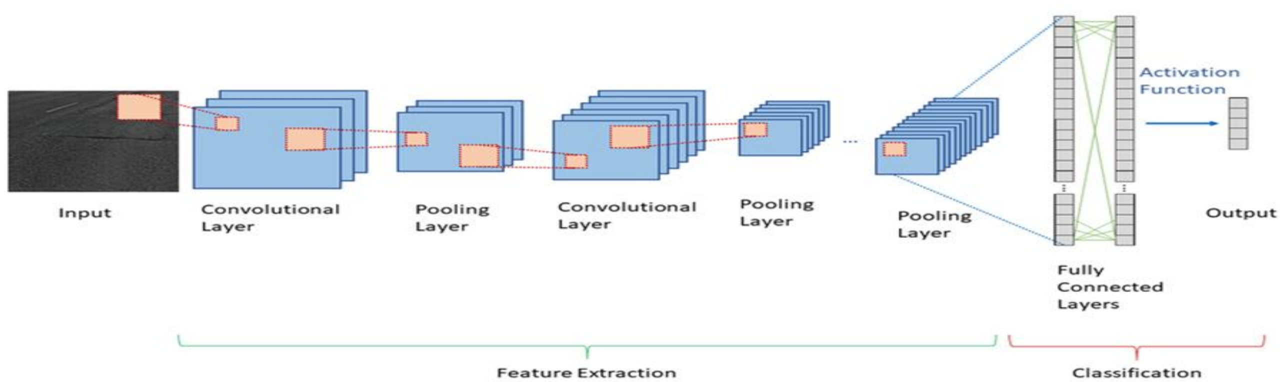


Fig 1: CNN Process Model

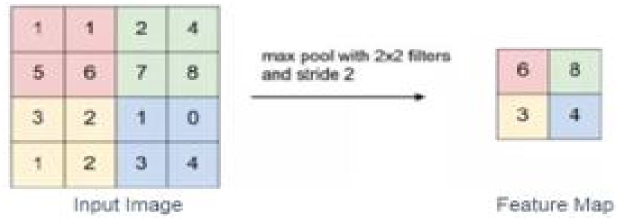


Fig. 2 Max pooling operation

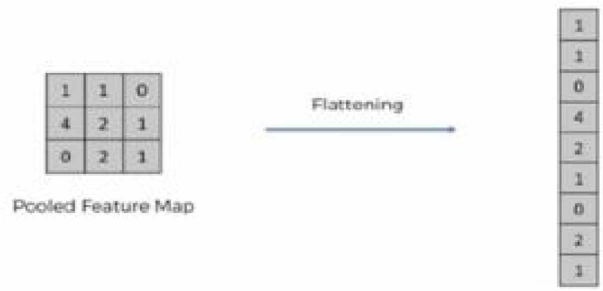
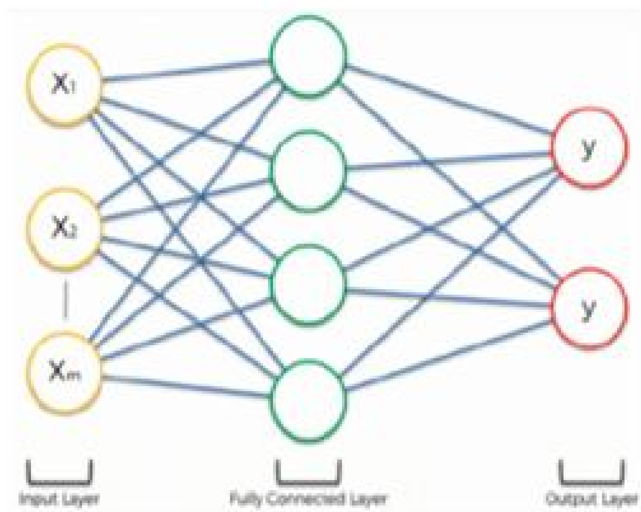


Fig 2: Max Pooling operation



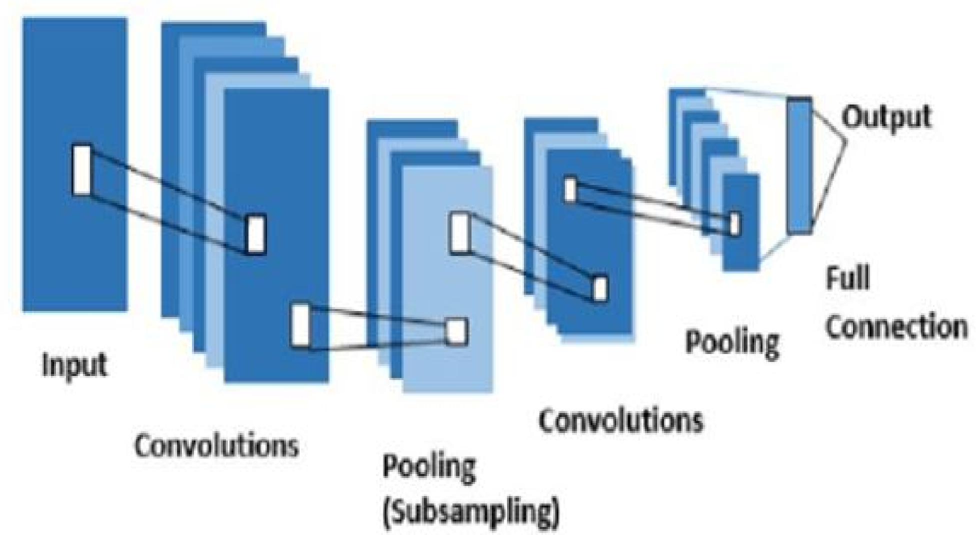
5	3	2	1	7	4
3	5	8	9	1	3
2	5	6	0	1	4
1	6	7	1	0	2
6	2	4	0	8	2
2	5	4	2	3	9

*

1	0	-1
1	0	-1
1	0	-1

Figure 3. 6 × 6 image with 3 × 3 filter.

-6	3	7	-1
-15	6	10	1
-8	12	8	-7
-6	10	4	-10



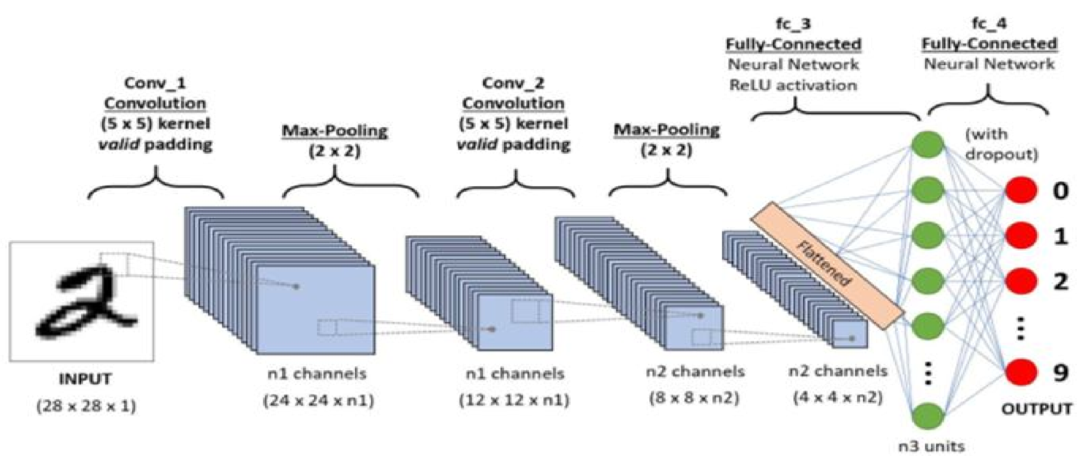


Fig 4: CNN Architecture for classifying objects.

In this study, a convolutional neural network (CNN) is employed to convert an RGB image into a visual feature vector. The three most often used CNN layers are convolution, pooling, and fully connected. Additionally, ReLU f(x) = max (0, x), a nonlinear active function, is used. ReLU is faster than the common equation f(x) = tanh (x). The use of a dropout layer prevents overfitting. The dropout sets the output of each hidden neuron to zero with a probability of 0.5. The "dropped out" neurons are a part neither of the backpropagation nor the forward pass.

Due to the millions of parameters that both the CNN and the RNN include, there are specific convergence concerns when they are merged. For instance, Vinyals et al. found that fixing the convolutional layer's parameters to those trained from ImageNet is optimal. The only CNN parameters that are learned from caption instances are the RNN parameters and the non-convolution layer parameters.

Table 2: Architectures of CNN:

YEAR	CNN	DEVELOPED BY	FEATURES	IMPORTANCE	NO. OF LAYERS	NO. OF PARAMETERS
1998	LeNet	Yann LeCun	1. Average pooling layer with subsampling. 2. Activation of the tanh. 3. MLP is used as the final classifier. 4. Sparse layer connections will simplify calculations.	1. Character Recognition. 2. Classify handwritten numbers on banks and other financial institutions.	7 layers	60 thousand
2012	AlexNet	Geoffrey Hinton, Ilya Sutskever, Alex KriZhevsky	1. ReLU Activation function. 2. Batch size is 128. 3. Ensembling models to achieve the greatest outcomes.	1. Object detection task.	8 layers	60 million
2014	GoogleNet	Google	1.1x1 convolution. 2. Inception module. 3. Auxiliary Classifier for training.	1. Image classification 2. Object recognition 3. Quantization	27 layers	4 million
2014	VGG Net	Zisserman, Simonyan	1. Has 2 networks i.e., VGG-16, VGG-19	1. Large-scale Image Recognition	16 layers 19 layers	138 million
2015	ResNet	Kaiming He	1. The skip Connection technique is used 2. Residual mapping	1. efficient backbone model	34 layers	25 million
2020	Xception	Francois Chollet	1. Depth Wise separable Convolutions 2. Takes the tenets of Inception for a logical conclusion.	1. Image recognition	71 layers	22 million

2) *VGG16:* A convolution neural network (CNN) architecture called VGG16 was utilized to win the 2014 ILSVR (ImageNet) competition. It is regarded as having one of the best vision model architectures to date. The distinctive feature of VGG16 is that it prioritized having convolution layers of 3x3 filters with a stride 1 and always utilized the same padding and max pool layer of 2x2 filters with a stride 2. Throughout the entire architecture, convolution and max pool layers are arranged in the same manner. Two FC (completely connected layers) are present at the very end, followed by a softmax for output. The 16 in VGG16 indicates that there are 16 weighted layers. This network has over 138 million parameters, making it a sizable network.

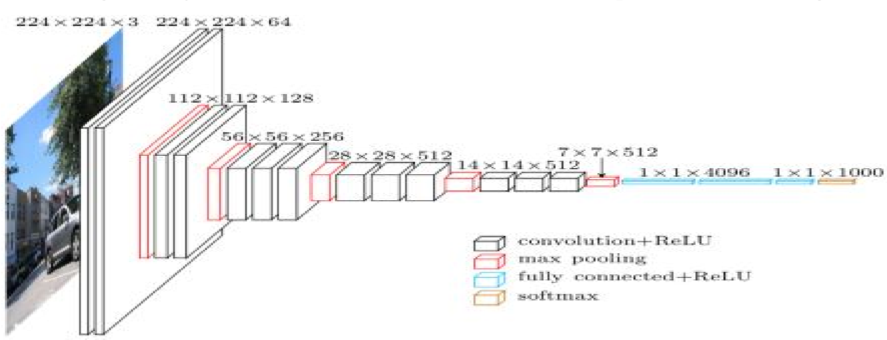


Fig 5: Architecture of VGG16

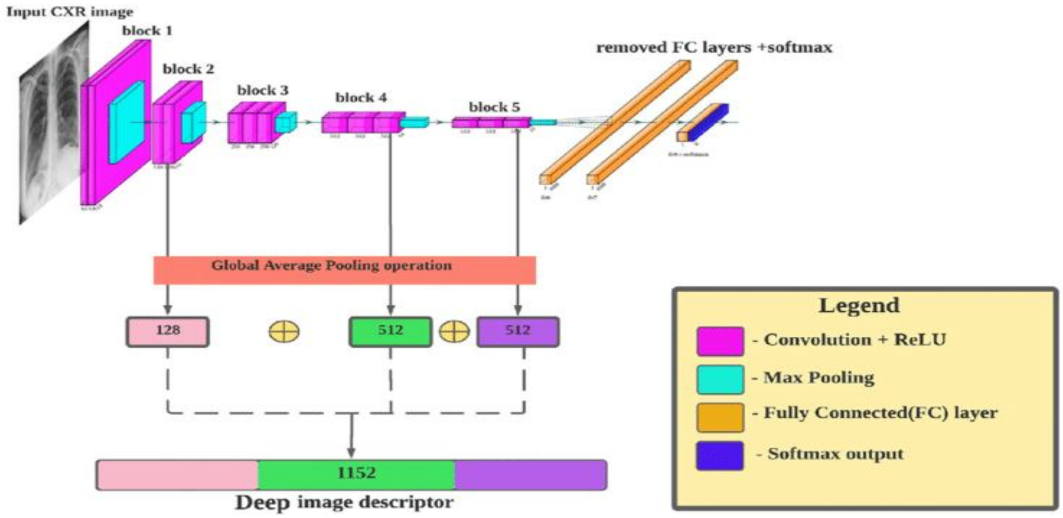


Fig 6: Process Diagram of VGG16

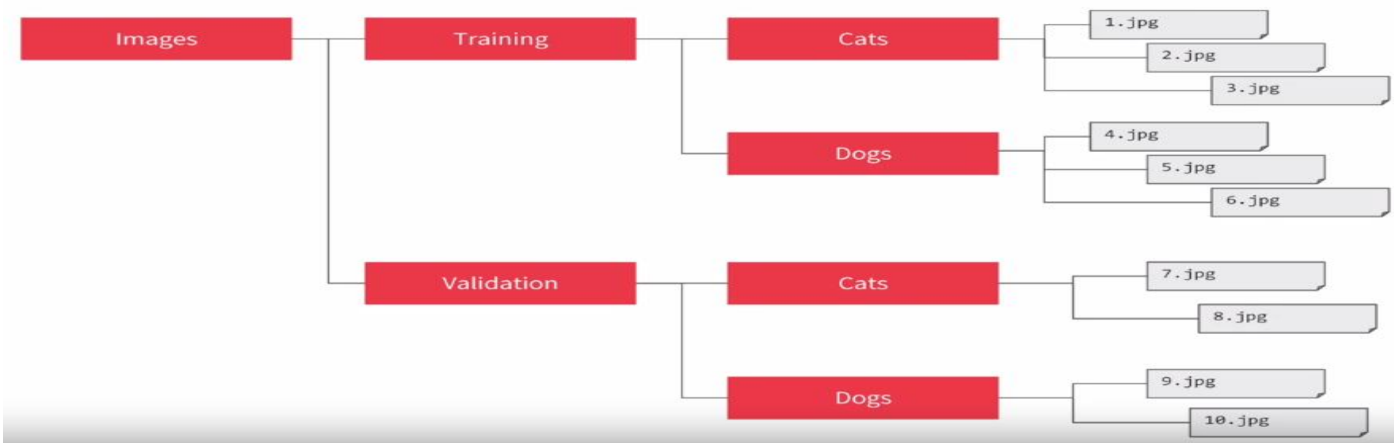


Fig 7: Flow Chart of VGG16

IV. RESULTS AND DISCUSSION

A. Results of the Training Model

Performance Metrics used: Accuracy

Accuracy is defined as the ratio of the number of accurately predicted image classes to the total number of images. It is the most straightforward performance metric. However, accuracy is only valid when the class distribution is symmetric, or when there are nearly equal numbers of images (or observations) in each class. We also plot the Confusion Matrix (4*4) to check how well our model performs in every class.

Table 3: Training values comparison

S.No	Epochs	Accuracy	ValAccuracy	Loss
1	5	83.5	0.9309	1.1671
2	15	88.5	0.952	0.3553
3	20	89.85	0.9309	0.319
4	48	97	0.94	0.223

Table 3 displayed the accuracy obtained after running some set of epochs at each interval. It is observed that as the set of epochs running increases from interval to interval, the accuracy is increased. Finally, after running 48 epochs at a time it is noted that the accuracy obtained is **97%.**

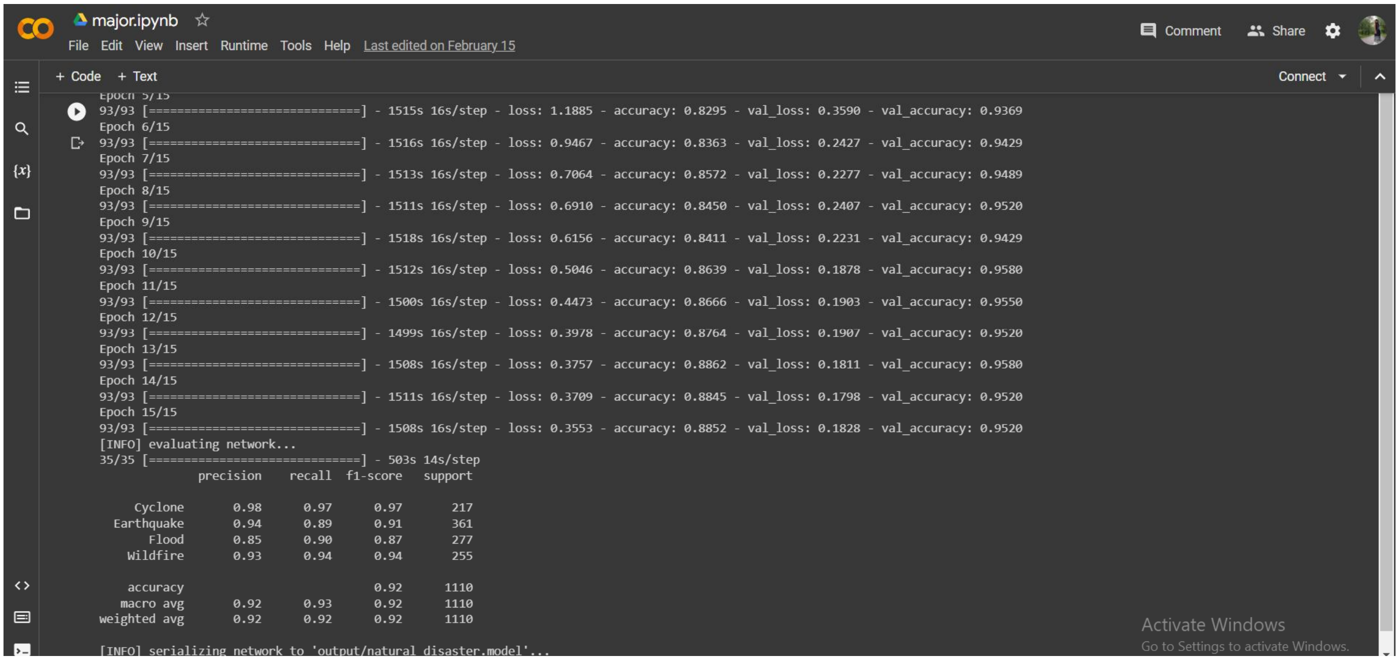


Fig 8: Accuracy at 15/15 epochs

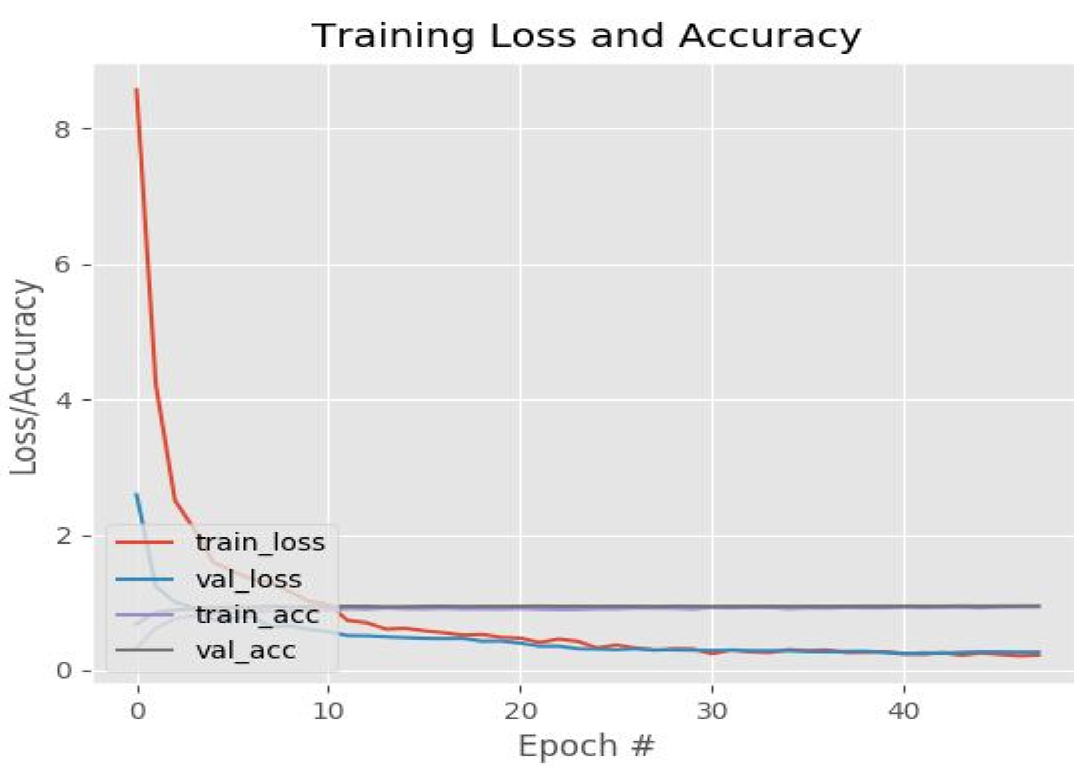


Fig 9: Graph showing training loss vs Accuracy

B. Observation

1) Finally, the learning rate plot demonstrates how the learning rate oscillates between the MIN_LR and MAX_LR values in our CLR callback:

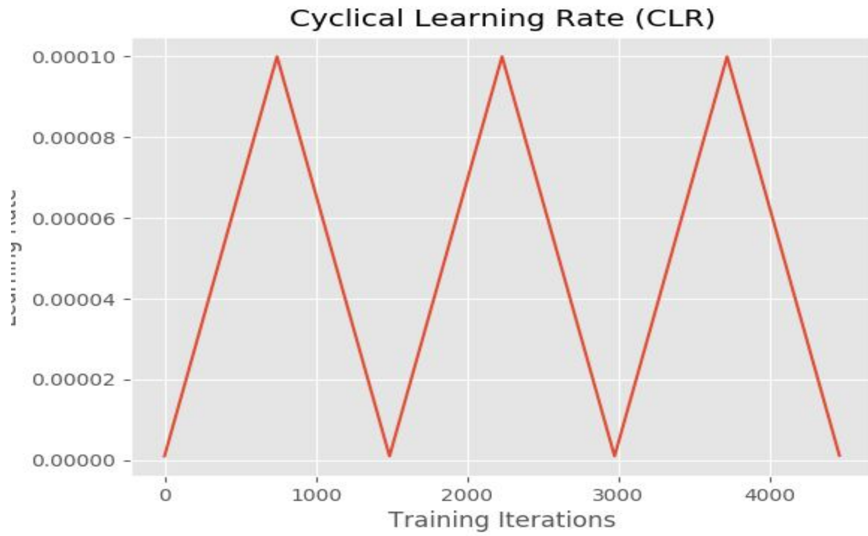


Fig 10: CLR graph

Cyclical Learning Rate: We trained our neural networks using Keras and Cyclical Learning Rates (CLR). Cyclical Learning Rates can significantly cut down on the number of tests needed to fine-tune and identify the best learning rate for your model.

2) Finding the best learning rates for our Network on our natural catastrophe dataset using a Keras Learning Rate Finder. With the Keras deep learning framework, we will use the dataset to train a model for identifying natural disasters.

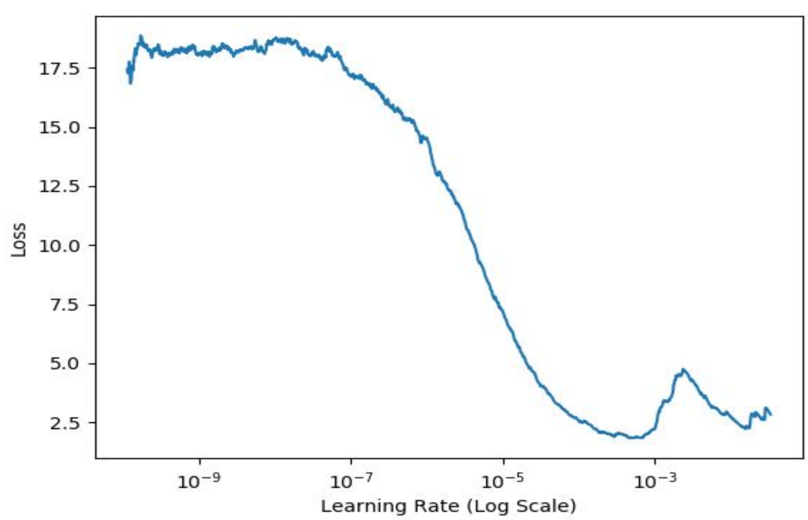


Fig 11: Learning rate finder

If you look at the plot, you can see that our model immediately picks up speed and learns around 1e-6.
Our loss keeps decreasing until it reaches about 1e-4, at which point it starts to increase once more, indicating overfitting.
Hence, the range of our ideal learning rate is 1e-6 to 1e-4.

C. Output

Fig 12: Output displaying over Video

Above fig.12 shows, the output displayed over a video. After the successful completion of training, we uploaded a video as input and checked its activity. As a result, we obtained good accuracy in detecting video as Flood.

V. ACKNOWLEDGMENT

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REFERENCES

[1] In Proceedings of Journal of arXiv ISSN: 2008.09188v1, August 2021, Ethan Weber, Nuria Marzo, Dim P. Papadopoulos, Aritro Biswas, Agata Lapedriza, Ferda Ofli, Muhammad Imran, and Antonio Torralba published "Detecting natural disasters, damage, and occurrences in the wild."

[2] Multimodal classification of crisis occurrences in social media by M. Abavisani, L. Wu, S. Hu, J. Tetreault, and A. Jaimes. In: Computer Vision and Pattern Recognition Conference Proceedings, IEEE/CVF (2020).

[3] Deep landscape features for enhancing vector-borne disease prediction, N. Abdur Rehman, U. Saif, and R. Chunara. Workshops from the IEEE Symposium on Computer Vision and Pattern Recognition (2019).

[4] A real-time decision support system for earthquake crisis management, called Ears (earthquake alert and report system), was developed by M. Avvenuti, S. Cresci, A. Marchetti, C. Meletti, and M. Tesconi. pp. 1749–1758 in SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD). ACM (2014). (2014).

[5] Inundation modeling in areas with a lack of data: Ben-Haim, Z., Anisimov, V., Yonas, A., Gulshan, V., Shafi, Y., Hoyer, S., Nevo, S. NeurIPS Workshop on Artificial Intelligence for Disaster Response and Humanitarian Aid (2019).

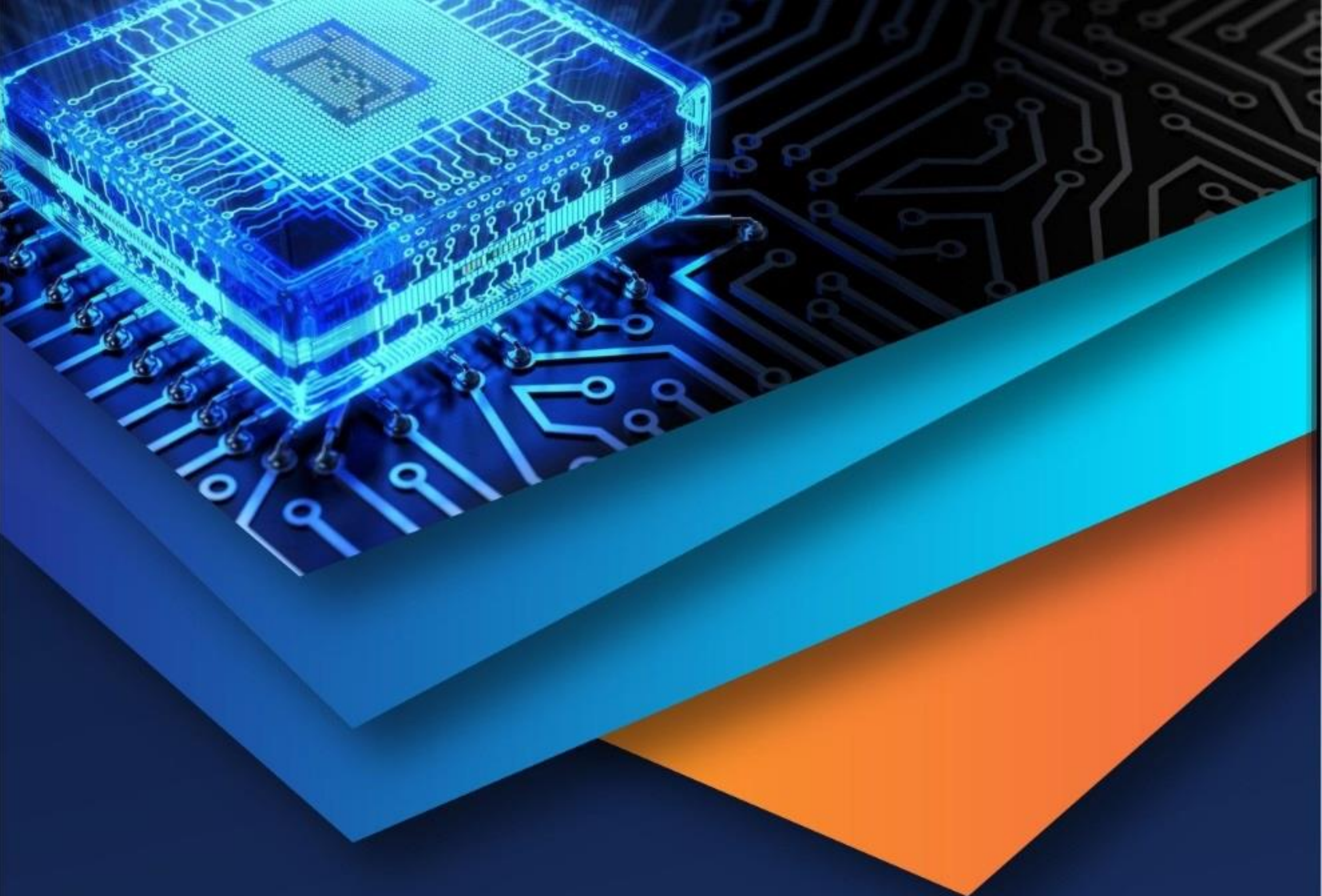
[6] The multimedia satellite challenge at Medieval 2017: Emergency response for flooding occurrences. Bischke, B., Helber, P., Schulze, C., Venkat, S., Dengel, A., Borth, D. MediaEval 2017 Workshop Proceedings, pp. 1–3. (2017).

[7] Daly, S., Thom, J.: Exploiting and categorizing social media image posts to assess fires. Pages 1–14 in 13th International Conference on Information Systems for Crisis Response and Management (ISCRAM) (2016).

[8] Fernandez UAV-based urban structural damage assessment utilizing object-based picture processing and semantic reasoning. Galarreta, J., Kerle, N., Gerke, M. Earth System Science and Natural Hazards, 15(6), 1087-1101 (2015)

[9] https://ieeexplore.ieee.org/document/7237228

[10] https://www.itm-conferences.org/articles/itmconf/pdf/2022/04/itmconf_icacc2022_03010.pdf



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