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Calamity Sensing With Artificial Intelligence

Maurya Vijayaramachandran[1], Vishnusai R[2]
[1]*(Department of ECE, Sri Venkateswara College of Engineering,Sriperumbudur, India)*
[2]*(Department of ECE, Sri Venkateswara College of Engineering,Sriperumbudur, India)*

Abstract:*Natural disasters like hurricanes, wildfire, earthquake, flood, tsunamis, and volcanic eruption often have catastrophic effects on human lives and cause significant infrastructure harm. It is challenging to detect these disasters as quickly as possible before it can largely affect human and animal lives. Remote sensing applications are used for this purpose. Images captured from the satellite are assessed to identify any abnormal change in the atmosphere, which may lead to a natural disaster. However, these systems are still not fully automatic and require human effort to analyze satellite images properly. Use of human resources for this purpose makes this process time-taking and also human error-prone. Recently, a wildfire in Amazon rainforest got the attention of the world when NASA released a satellite image of the burning forest. The forest could be saved if we can detect wildfire at an early stage and take appropriate action to minimize losses.Current advances in remote sensing applications yield significant success in the management of natural disasters. It still requires human effort and time to analyze satellite images, which causes a delay in prediction. This challenge leads to a substantial loss of infrastructure and lives. Therefore, a fully automated system is the need of the hour, which can identify these natural disasters with minimum time delay. This system can prevent the loss of precious human lives and other resources.In this study, we developed an automated calamity detection system using deep learning, which can predict disasters in real-time and send an alert message. For this purpose, we trained ResNet50 CNN model, and performance is measured by calculating the confusion matrix. Model is also tested with pre-recorded videos acquired from satellites and drones. Experimental results yield 91% accuracy and perform well when tested with videos collected from YouTube.*

Background*: Existing scales for natural calamities define severity in terms of intensity. Intensity scales are not highly connected with impact factors such as fatalities, injuries, homelessness, affected population, and cost of damage. The descriptive words for disasters are also not sufficient to clearly understand the real magnitude of severity as there is no consistent method to distinguish one terminology from another. Further, data collection standards vary among countries and, therefore, comparisons across space and time are difficult to make. Several discrepancies between various sources of information complicate the interpretation of trends in disaster data. Moreover, comparing different events and obtaining a sense of scale are problematic due to the deficiencies that reduce the quality of the data set. There is no scale currently that is supported with data that can rate the severity of any natural calamity. An initial severity scale based on fatalities is used to compare and rate disasters such as earthquake, tsunami, volcano and tornado. This concept can be applied to any type of disaster including windstorms, snowstorms, and wildfires.*

Conclusion: *To conclude, the proposed calamity detection method will be helpful to detect calamity and generate alert message well before in hand. The proposed method shall process satellite images to predict and warn cyclone and forest fire. It shall process satellite images to detect natural calamities like flood, rapidly and can generate alert swiftly to take necessary steps against such calamities.*

Key Word*:* ***Machine Learning , Calamity Detection , AI , Image processing*** *.*

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I. Introduction

Calamity is an incident that brings loss, damage or a disaster. Calamity is the suffering that results from a major disaster. Every year natural calamities kill nearly 90,000 people and affect close to 160 million people worldwide. Natural calamities include earthquakes, tsunamis, volcanic eruptions, landslides, hurricanes, floods, wildfires, heat waves and droughts. They have an immediate impact on human lives and often result in the destruction of the physical, biological and social environment of the affected people, thereby having a longer-term impact on their health, well-being and survival.

1.1.1 SCALES OF NATURAL CALAMITY:Existing scales for natural calamities define severity in terms of intensity. Intensity scales are not highly connected with impact factors such as fatalities, injuries, homelessness, affected population, and cost of damage. The descriptive words for disasters are also not sufficient to clearly understand the real magnitude of severity as there is no consistent method to distinguish one terminology from another. Further, data collection standards vary among countries and, therefore, comparisons across space and time are difficult to make. Several discrepancies between various sources of information complicate the interpretation of trends in disaster data. Moreover, comparing different events and obtaining a sense of scale are problematic due to the deficiencies that reduce the quality of the data set. There is no scale currently that is supported with data that can rate the severity of any natural calamity. An initial severity scale based on fatalities is used to compare and rate disasters such as earthquake, tsunami, volcano and tornado. This concept can be applied to any type of disaster including windstorms, snowstorms, and wildfires.

1.1.2 DESTRUCTIONS CAUSED BY NATURAL CALAMITIES : The largest natural calamities have slowed down the regional economic growth for decades together. Roads, bridges and many other public utilities are destroyed during calamities. Individual property owners who doesn’t have proper insurance coverage go bankrupt and are forced to move elsewhere since they are not able to rebuild the destroyed property.

1.1.3 INDIAN OCEAN TSUNAMI OF 2004 : The Tsunami hit the coasts of several countries of south and southeast Asia in December 2004. The tsunami and its aftermath were responsible for immense destruction and loss on the rim of the Indian Ocean. The total official death toll of the disaster (including unaccounted people) was over 226 thousand, Over 2.4 million people were displaced The total economic cost of damage was estimated at US$ 9.4 billion

1.1.4 HURRICANE KATRINA: the tropical cyclone struck the south eastern United States in 2005. The hurricane claimed around 1800 lives. The National Hurricane Center estimated Hurricane Katrina’s damage at $125 billion, with $80 billion in insured losses.

1.1.5 HAITI EARTHQUAKE - . At least 200,000 people were killed by the 7.0 magnitude earthquake that attacked Haiti in January 2010.[23] The Inter-American Development Bank estimated that it cost $8.5 billion in damage to Haiti's economy. The earthquake made the country's GDP shrink by 5.1%

1.1.6 JAPAN’S EARTHQUAKE AND TSUNAMI - , Japan’s economy faced a devastating blow by the 9.0 magnitude earthquake and tsunami that thrashed the country on March 11, 2011. As a result the Fukushima Nuclear Power Plant was damaged. It leaked radiation into the Pacific Ocean. The effect of radiation showed up in the local milk and vegetables. There was a human fatality of around 20,000 and close to 5,00,000 went missing.

1.1.7 TORNADO OUTBREAK IN US – cost $5 Billion The largest tornado outbreak in U.S. history occurred April 25-27, 2011. In that week, 305 twisters damaged several different regions, breaking the 1974 record of 148 tornadoes. The outbreak caused $11 billion in damage.

1.1.8 ICELAND VOLCANO - . The ice-covered Grímsvötn volcano in Iceland created an unusually large and powerful eruption in 2011, sending ash to around 20km into the atmosphere. This caused the cancellation of about 900 passenger flights. The much smaller 2010 eruption of Eyjafjallajökull caused the cancellation of about 1,00,flights. Slow down in Europe’s air traffic affected more than just passengers. Drug companies, time sensitive high-tech imports and many premium products faced a huge impact.

1.1.9 U.S. WILDFIRES – In 2018 more than 58,083,000 wildfires burned 8.8 million acres. The U.S Forest service spent a record $3.1 billion fighting the 2018 fires

II. Use Of Ai To Predict Natural Calamities

We understand artificial intelligence has made its significance in various areas like customer service, business process improvement and healthcare. In the recent years, many researchers have discovered AI can predict natural calamities. With huge amount of good quality data, AI will be able to predict the occurrence of natural calamities. For this study purpose, we hereby cite few natural calamities that can be predicted by AI as mentioned in referred Forbes article

2.1.1 EARTHQUAKES: Artificial Intelligence can use seismic data to analyse the magnitude and patterns of earthquakes. [Seismic surveys are used to investigate locations for landfills and characterize how an area will tremble during an earthquake. They were primarily used for oil and gas exploration]. Seismic data can be helpful to predict the occurrence of earthquakes. In this relevance, Google and Harvard teamed up to develop an AI system that can predict the aftershocks of an earthquake. Scientists studied more than 131,000 earthquakes and aftershocks to build a neural network. The researchers tested the neural network on 30,000 events, and the system predicted the aftershock locations more precisely when compared to traditional methods. At present Japan is using satellites to analyse images of the earth to predict natural calamities such as earthquakes and tsunamis

2.1.2 FLOODS: Google has teamed up with Central Water Commission of India and uses artificial intelligence tools to alert people in India about impending floods. As mentioned by Tim Sandlein his article published in digitaljournal.com, Mr.YossiMatias, Google’s engineering Vice President mentions, “A variety of elements – from historical events, to river level readings, to the terrain and elevation of a specific area – feed into our models. With this information, we have created river flood forecasting models that can more accurately predict not only when and where a flood might occur , but the severity of the events as well” The data used in the AI system is collected from the rainfall records and flood simulations.

2.1.3 VOLCANIC ERUPTIONS: Scientists are developing AI systems to recognise tiny ash particles from volcanoes. The shape of ash participles may be applied to identify the type of volcano. IBM is also developing Watson to predict volcanic eruptions with location and intensity using seismic sensors and geological data as cited in the Forbes article

2.1.4 HURRICANES: A huge grouping and mixture of satellite images and machine learning technique can effectively predict hurricanes. For example, when Hurricane Harvey hit southern Texas in 2017, NASA and Development Seed tracked the hurricane's intensity and path using satellite images and machine learning which "proved to be six times better than the usual techniques, as the hurricane can be tracked every hour instead of every six hours with the traditional methods" according to Forbes article

III. Literature Survey

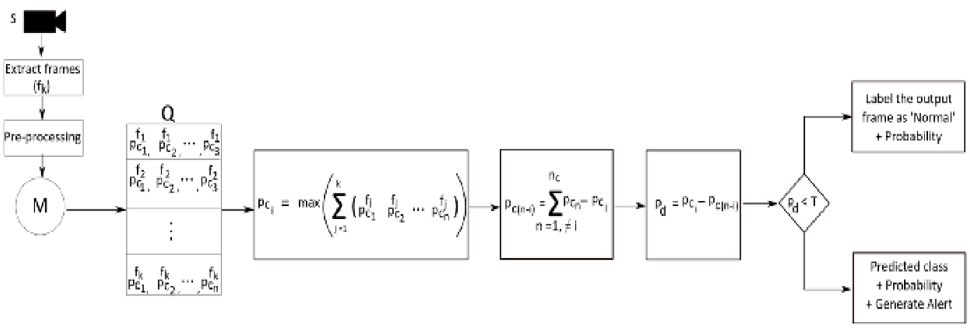
In a Google AI Blog, published on June 16, 2020, posted by Joseph Xu, Senior Software Engineer and PranavKhaitan, Engineering Lead, Google Research, they have mentioned the use of very high resolution (VHR) satellite imagery, with up to 0.3 meter resolution, is becoming an increasingly important tool for crisis response, giving responders an unprecedented breadth of visual information about how terrain, infrastructure, and populations are changed by disasters Mr.JosephXu and Mr.PranavKhaitan further states in their blog that to help mitigate mitigate the impact of such disasters, we present "Building Damage Detection in Satellite Imagery using Convolutional Neural Networks", which details a machine learning (ML) approach to automatically process satellite data to generate building damage assessments. Developed in partnership with the United Nations World Food Program(WFP) Innovation Accelerator, we believe this work has the potential to drastically reduce the time and effort required for crisis workers to produce damage assessment reports. In turn, this would reduce the turnaround times needed to deliver timely disaster aid to the most severely affected areas, while increasing the overall coverage of such critical services. Their approach is that the Automatic damage assessment process is split into two steps: building detection and damage classification. In building detection step, their approach uses an object detection model to draw bounding boxes around each building in the image. They then extract pre-disaster and post disaster images cantered on each detected building and use a classification model to determine whether the building is damaged. The classification model as mentioned by them, consists of a convolutional neural network to which is input two 161 pixel x 161 pixel RGB images, corresponding to a 50 m x 50 m ground footprint, centred on a given building. One image is from before the disaster event, and the other image is from after the disaster event. The model analyses differences in the two images and outputs a score from 0.0 to 1.0, where 0.0 means the building was not damaged, and 1.0 means the building was damaged. Since the before and after images are taken on different dates, at different times of day, and in some cases by different satellites altogether, there can be a host of different problems that arise. For example, the brightness, contrast, colour saturation, and lighting conditions of the images may differ significantly, and the pixels in the image may be misaligned. To correct for differences in colour and illumination, they have used histogram equalization to normalize the colors in the before and after images. We also make the model more robust to insignificant colour differences by using standard data augmentation techniques, such as randomly perturbing the contrast and saturation of the images, during training. They mentioned that assembling a training data set is one of the main challenges in their work model. Since Data availability is limited because there are only a handful of disasters that have high resolution satellite images. They obtained the original satellite images on which the manual assessments are performed and then used Google Earth Engine to spatially join the damage assessment labels with the satellite images to produce the final training examples. All images used to train the model were sourced from commercially available sources

Mr.JosephXu and Mr.PranavKhaitan mentioned in their blog that they evaluated 3 major past earthquakes : the 2010 earthquake in Haiti (magnitude 7.0), the 2017 event in Mexico City (magnitude 7.1), and the series of earthquakes occuring in Indonesia in 2018 (magnitudes 5.9 - 7.5). For each event, they trained the model on buildings in one part of the region affected by the quake and tested it on buildings in another part of the region. They used human expert damage assessments performed by UNOSAT and REACH as the ground truth for evaluation. They measured the model's quality using both true accuracy (compared to expert assessment) and the area under the Receiver Operating Characteristic Curve (AUROC), which captures the trade-off between the model's true positive and false positive rates of detection, and is a common way to measure quality when the number of positive and negative examples in the test dataset is imbalanced. An AUROC value of 0.5 means that the model's predictions are random, while a value of 1.0 means the model is perfectly accurate. According to crisis responder feedback, 70% accuracy is the threshold needed for making high-level decisions in the first 72 hours after the disaster

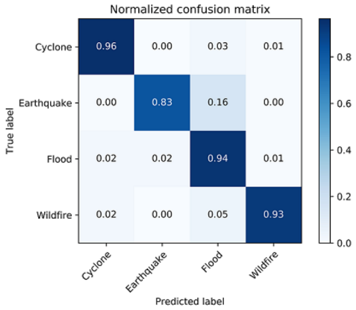
In his work cited in reference ,Mr.Gautam Kumar, PhD, National Institute of Technology, Rourkela, India, used sample test image dataset to evaluate its performance. His work used ROC curve to show trade-off between false positive rate and true positive rate. He analysed the performance of the model by plotting precision-recall and area under curve. He mentioned that he provided real-time videos as input and from the live video stream source, a frame is extracted and pre-processed by resizing it. Each extracted and pre-processed frame from the live video is fed to model to predict its class label. The algorithm calculates the probability of each class and returns a label for each class for which probability is more. The process is repeated for each frame from a video stream. He got output video as a series of the annotated frame showing class label and the probability of predicted class. However, as there is 'prediction flickering' problem with this method. Due to this, label in the output video frequently changes among classes. To reduce the flickering effect, he applied the principle of rolling averaging. The mean of last 'k' prediction is calculated and label is selected with corresponding high probability. If the difference between probabilities of the predicted class label and a sum of the probabilities of rest of the classes label is > 80%, annotate the output frame with predicted label as well as corresponding probability. An alert message whenever change in label occurs else "Normal" alert message is sent.

IV. Machine Learning Model For Calamity Sensing

Machine learning is the use of artificial intelligence (AI). Machine learning focuses on the development of computer programs that can access data. Machine learning helps to analyse massive quantities of data. Machine learning is a data analytics technique that shows computers to do what comes naturally at humans who learn from experience. With the available big resource of data, machine learning models can solve problems in Computational Finance for algorithmic trading, Image processing and computer vision for face recognition, motion detection and object detection, Computational biology for detecting tumour and DNA sequencing, Natural language processing for voice recognition applications. In machine learning model, the process of learning starts with the observation of data. Machine learning algorithms use computational methods to "learn" information directly from data without relying on a predetermined equation as a model. The algorithms improve performance as the number of samples available for learning increases. Deep learning is a specialised form of machine learning. Combining machine learning with AI and cognition technologies can make it even more effective in processing large volumes of information.Machine learning technologies can help detect natural calamities and its scale of destruction. In cases of earthquakes, it can help predict the type of building that will be vulnerable to damage. Machine learning models can analyse and predict the area that is going to be affected by a calamity and the volume of people live around the area. It helps to send warning message to the concerned area and help in evacuation of people before hand. It can estimate the damage cost caused due to the calamity. To sum up, the machine learning model can analyse large amount of data from past disasters to create new awareness on upcoming similar events. The model is trained to process the data information and evaluate results through the learning experience. we propose to create a dataset on the many natural calamities happened in the past. The collected data is sorted and stored model wise. Live video sources shall be extracted in frames. The extracted frames shall be fed into trained CNN model. While capturing frames from video, there is a problem of flickering of images. To decrease the flickering effect, we propose to use principle of rolling averaging here. It is commonly known as running average or moving mean or rolling mean. Each output frame is marked and sorted as per the type of calamity with its probability rate. As a result, when an calamity is detected, the output frame is marked with the type of predicted calamity and sends an alert message. If not calamity is detected, then the output frame will be marked as "Regular". For output frames that are marked as "Regular", no alert message is generated.



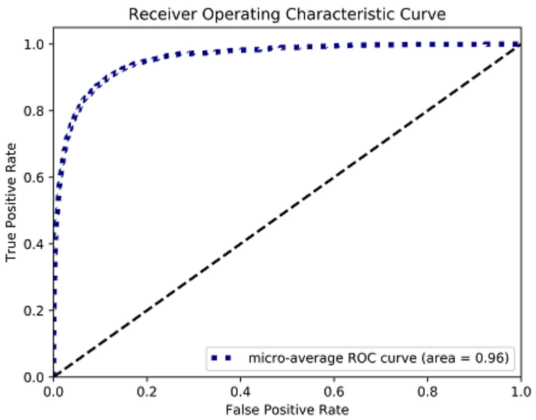
4.1.1 DATABASE COLLECTION: Here, we propose to use images of various natural disasters as the dataset for the model and using this we intend to train a calamity detector with keras and deep learning. The images of the natural disasters/calamity are collected using google images. These images are given as input to a Convolutional Neural Network which shall be trained to take a photo and identify what type of calamity it is. After the identification, the photos are segregate in respect to the type of calamity.



4.1.2 SATELLITE IMAGES: Images captured from the satellite are assessed to identify any abnormal change in the atmosphere, which may lead to a natural disaster.We can get satellite images of different calamities such as cyclone, wildfires, earthquake and flood after passing through the Convolutional Neural Network trained for segregating the input images. Before using any of the detectors, it is standard procedure to convert the images to grayscale. A dedicated function executes the classifier stored and takes the grayscale image as a parameter.

4.1.3. PATTERN RECOGNITION: Patterns are recognized by the help of algorithms used in Machine Learning. The pattern recognition algorithms considered are models like Statistical Algorithm Model, Structural Algorithm Model, Template matching algorithm model.

4.1.4 MODEL TRAINING: The model can be created and trained in two ways: Either by building a CNN from scratch or by using transfer learning to create a CNN that can identify the type of calamities from images. Your CNN must attain at least 70% accuracy on the test set.



4.1.5.BEST CASE APPROACH: The CNN built using transfer learning can return an accuracy of above 70% whereas the CNN built form scratches gives a maximum accuracy of 10-15% even after 15 epochs

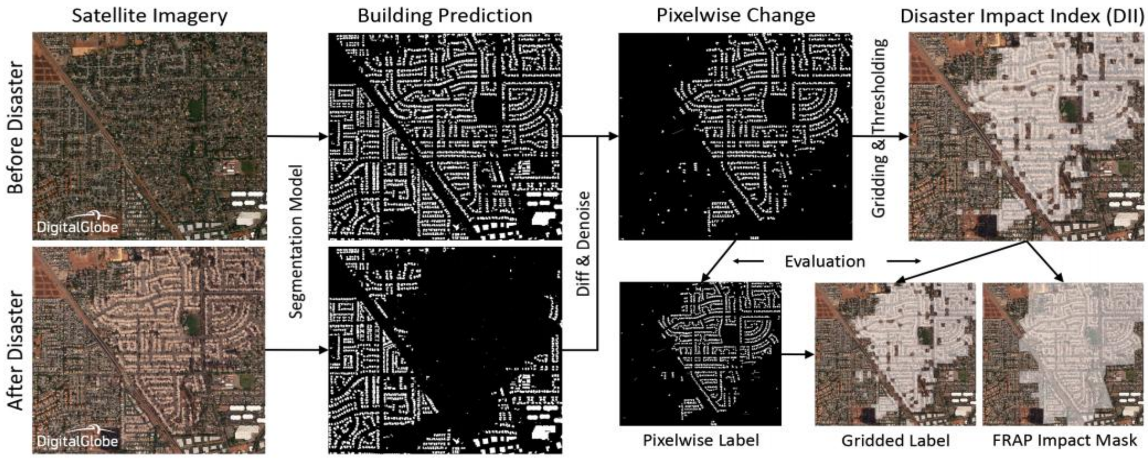
4.1.6.TIME FOR DETECTION: The flickering effect in the output video, can be reduced by selecting a proper subset of frames in the queue, but in reality, this process would delay the calamity detection time. In fact, this is the main challenge faced due to this process.

4.1.7.EARLY SIGN DETECTION : With the image captured from the satellite Is analysed for any abnormality and detected at a early stage. This will help to take proper steps to reduce loss and damage.

4.1.8.ML MODEL ACCURACY : The machine learning model experimental results normally has yielded around 90% accuracy and has showed high performance in detection of calamity, before in hand

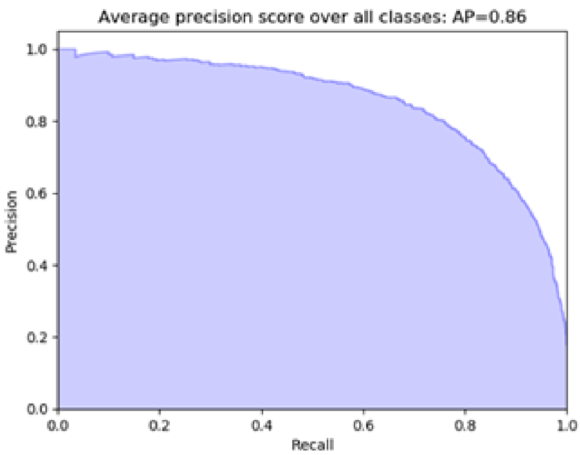
4.1.9.TRAINING AND TESTING : Satellite images downloaded from google are varied. They consist of noise, blur, low-resolution. The performance of a model can be enhanced by training the CNN with good quality images. The CNN is trained by 80% of database image while tested with 20% and we can plot confusion matrix for the test set. We should calculate True Positive(TP), False Positive(FP), True Negative (TN), False Negative (FN). From the above parameters, accuracy of the system shall be calculated. We shall plot Receiver Operating

Characteristics (ROC) curve to illustrate between false positive rate and true positive rate. Finally, we shall examine the performance of the model with the plotting precision-recall and area under curve.



V. Conclusion

To conclude, the proposed calamity detection method will be helpful to detect calamity and generate alert message well before in hand. The proposed method shall process satellite images to predict and warn cyclone and forest fire. It shall process satellite images to detect natural calamities like flood, rapidly and can generate alert swiftly to take necessary steps against such calamities.



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