## Ideation Phase Literature Survey

Date	13 October 2022	
Team ID	PNT2022TMID45554	
Project Name	Project – Natural Disaster Intensity Analysis and Classification Using Artificial Intelligence	
Maximum Marks	2 Marks	

Literature Survey for the project "Natural Disaster Intensity Analysis and Classification Using Artificial Intelligence"

## 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 developed a multilayered deep convolutional neural network model that classifies the natural disaster and tells the intensity of disaster of natural The model uses an integrated webcam to capture the video frame and the video frame is compared with the Pre-trained model and the type of disaster is identified and showcased on the OpenCV window.

Keywords: Natural Disaster, Losses, Ecosystems, CNN, OpenCV

## LITERATURE SURVEY

S. No	Paper Title	Idea	Advantages	Disadvantages
1.	Natural Disasters	Block-I convolutional	Easier and	Takes time since it
	Intensity Analysis	neural network (B-I	accurate	deals with a lot of
	and Classification	CNN), for detection	calculation of	images.
	Based on	and occurrence of	Multispectral	
	Multispectral	disasters Block-II	images	

2.	Images Using Multi- Layered Deep Convolutional Neural Network	convolutional neural network (B-II CNN), for classification of natural disaster intensity types with different filters and parameters Deep learning model	Accurate	Since
2.	Intensity Estimation Using Multidimensional Convolutional Neural Network From Multichannel Satellite Imagery	called 3DAttentionTCNet is created, which is inspired by AlexNet. The pooling layer compresses some important information resulting in the loss of some intensity features, we remove the pooling layers	estimation of TC intensity is important to theoretical research studies and practical applications when compared to models like CNN.	3DAttentionTCNet is a deep learning model, the amount of data needed to train the model is huge.
3.	Designing Deep- Based Learning Flood Forecast Model With ConvLSTM Hybrid Algorithm	A robust mathematical tool used to determine the flood state at a particular time for a given area is the Flood Index (IF) A model is developed using ConvLSTM, as an objective model, with alternative methods of LSTM, CNN-LSTM and SVR that can also determine the flood state	Early detection of natural disasters such as floods can greatly assist humans in reducing the extent of the damage caused by such events. The accuracy is high when compared to other models.	Since model developed using ConvLSTM is a deep learning model, the amount of data needed to train the model is huge and also time and processor consuming.
4.	A Conformal Regressor With Random Forests for Tropical Cyclone Intensity Estimation	A multiple linear regression (MLR) model was constructed based on the extraction of the most significant	It is considered an excellent way to extract features from satellite images to estimate TC	The MLR regression technique is exactly not suitable for all the scenarios of images.

		signals and	intensity. The	
		parameters from	Dvorak technique	
		satellite infrared	tried to estimate	
		images.	the TC intensity	
		imageo.	using visible or	
			infrared images	
			based on the	
			cloud structure	
5.	Rainformer:	Framework:		The Rainformer
J 5.			It can extract	
	Features Extraction	Rainformer	global and local	model is processor
	Balanced Network	Rainformer consists of	features from	complex and also the
	for Radar-Based	an encoder (green box)	radar echo maps	encoding may not be
	Precipitation	and decoder (blue	separately, and	very efficient.
	Nowcasting	box). They both have	fuses balanced	
		four stages.	these two	
		When the stage goes	features to	
		deeper, the feature size	enhance the	
		becomes smaller. Both	model's ability to	
		encoder and decoder	predict heavy rain	
		include FEBM.	or rainstorm.	
		FEBM enhances the		
		low to medium and		
		highintensity rainfall		
		features at every		
		stage.		
6.	Quantifying change	It indicates that how	We analyzed the	The mobile phone
	after natural	mobility patterns are	relationship	data is sometimes
	disasters to	changing, in the post	between the	not sufficient for
	estimate	disaster timeframe, is	reach score	better quantification.
	infrastructure	crucial in order to	changes and the	
	damage with mobile	settle rescue centers	damage index of	
	phone data	and send help to the	the earthquake in	
		most affected areas.	urban areas, and	
		We describe the	it showed that	
		approach taken to	the correlation	
		work with aggregated	was negative on	
		CDR data	the day after the	
			natural disaster.	
		l		L

## **REFERENCES:**

- 1. Tonini M., D'Andrea M., Biondi G., Degli Esposti S., Trucchia A., Fiorucci P. A Machine Learning-Based Approach forWildfire Susceptibility Mapping. The Case Study of the Liguria Region in Italy.
- 2. Amit S.N.K.B., Aoki Y. Disaster detection from aerial imagery with convolutional neural network; Proceedings of the 2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC); Surabaya, Indonesia.
- 3. Padmawar P.M., Shinde A.S., Sayyed T.Z., Shinde S.K., Moholkar K. Disaster Prediction System using Convolution NeuralNetwork; Proceedings of the 2019 International Conference on Communication and Electronics Systems (ICCES); Coimbatore, India.
- 4. Nguyen D.T., Ofli F., Imran M., Mitra P. Damage assessment from social media imagery data during disasters; Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining; Sydney, NSW, Australia.
- 5. D. Han, L. Chan, and N. Zhu, "Flood forecasting using support vector machines"
- 6. X. H. Le, H. V. Ho, G. Lee, and S. Jung, "Application of long short-term memory (LSTM) neural network for flood forecasting"
- 7. M. F. Piñeros, E. A. Ritchie, and J. S. Tyo, "Estimating tropical cyclone intensity from infrared image data"
- 8. T. L. Olander and C. S. Velden, "Tropical cyclone convection and intensity analysis using differenced infrared and water vapor imagery".
- 9. X. Shi et al., "Deep learning for precipitation nowcasting: A benchmark and a new model"