Predicting Natural Disasters Damages using Hybrid Convolutional Neural Networks Machine Learning Model

J. T. Thirukrishna
Department of Information Science and Engineering, Dayananda Sagar Academy of Technology and Management, Bangalore, India

***Abstract* – There are many natural disasters that have been occurring throughout the world wide. The damage caused during the disaster vital process to assess in the earlier days. Previously, there used to be traditional methods for assess the cause of damage and a few earlier researches were also made on processing the text data for damage assessment computation. To assess the disaster, there are advancements in later stages. The net sources serve as the dynamic facilitator in getting the data for the model to produce the desired output. The proposed work shown how the defect is identified, and also the assessment of defect calculations. The Proposed MobileNet V2 used to validate the accuracy, and identifying the type of the disaster. Also identify the processing of imagery data specifically, cost estimation of the disaster defect assessment with any objects precisely higher accuracy rate of 95%. Proposed method findings suggest that (a) Multiple disaster type identify together to find out the caused damages (b)Effectively mine and predicts the damage. (c) Support disaster management.**

***Keywords:* Machine Learning, Neural Networks, Proactive Detection, Pattern extraction and prediction, ,Data Science.**

1. INTRODUCTION

Millions of people worldwide cope with the long-lasting effects of both man-made and natural disasters each year which have a significant impact on their lives. Sadly, these occurrences frequently result in significant property and infrastructure damage as well as human casualties. Disaster management operations must be coordinated in the stages leading up to, during, and after disasters, with the main goals being the prevention of human casualties, the protection of people and property, the reduction of economic damage, and the return of the situation to normal. Resilient decision-making processes are required due to the complex nature of disasters and the crucial and complex features of disaster response operations. These processes are strengthened even more by the incorporation of information technology. The necessity of efficient and knowledgeable catastrophe management has grown more apparent, considering the scope and consequences [1].

Recent advances in machine learning (ML) have played a significant role in improving disaster management's capabilities. A variety of calamities require skilled management techniques, including landslides, hurricanes, earthquakes, floods, and wildfires. Moreover, the utilization of sophisticated technologies, namely in the field of artificial intelligence, has shown advantages in managing the intricacy and scope of these difficulties. The utilization of digital platforms as essential channels for real-time updates during catastrophes has drawn a lot of interest

in the past 10 years. These updates contain a variety of information, including information about fatalities, resource accessibility, and the urgent needs of those who have been impacted or injured [6].

After a calamity, user-generated content in online communities increases dramatically, offering insightful commentary on the state of affairs [7]. Essentially, discussion boards and online data are not only dynamic databases of current information during and after calamities, but they also act as worldwide conduits for the outpouring of human emotions and support from people all over the digital landscape. When there is a natural or man-made disaster, microblogging platforms receive a large volume of content in the form of text, photographs, audio, and videos. Notably, platforms like Social have emerged as prominent channels for the exchange of news and updates.

The World Wide Web has emerged as a vital channel for communication during crises, facilitating the rapid dissemination of information to a wide audience. Whether the content shared is informative or not, posts during emergencies consistently use disaster-related terminology. These posts provide valuable data that are essential for victims, humanitarian organizations, and responders, covering various aspects such as the needs of affected individuals, casualties, infrastructure damage, and resource availability. One unique feature of social media is its ability to allow users to follow others without mutual consent, thus enabling non-registered individuals to access updates as well. This inclusive approach empowers community members to monitor critical data in real time, making social media an unparalleled platform for aggregating and maintaining a substantial repository of potentially life-saving disaster-related information [8][9].

On the other hand, non-informative data are devoid of meaningful facts regarding the calamity, which makes it difficult to find relevant information during a crisis. This paper investigates the binary and multi-class classification problem of damage assessment tweets, covering damage to humans as well as infrastructure. Understanding the importance of different types of damage data in catastrophe situations, by present a novel method. With this method, weighted features are created for binary and multi-class classification by using linear regression and support vector reconstruction approaches. classification. The development of machine learning (ML) in recent years has transformed many fields by making it possible to extract useful insights from enormous volumes of data. Making use of machine learning techniques provides a viable way to improve defect management procedures by enabling real-time problem identification, root cause analysis, and decision-making [2][3].

To enable prompt and efficient reactions to new hazards, this study presents a complete architecture that combines real-time data streams with sophisticated algorithms to investigate the possibilities of machine learning in defect disaster management. Through the utilization of machine learning, industries can shift from reactive to proactive approaches to defect management, ultimately reducing the frequency and consequences of defect catastrophes [4].

The elements that make up our methodology are carefully crafted to capture a whole comprehension of textual material, including low-level lexical and grammatical aspects together with the words that are used the most [5]. By rigorously examine a variety of classifiers throughout a phase of intensive experimentation to choose the best one that is suited to our suggested features. The chosen classifier is then put through a thorough evaluation process utilizing a variety of disaster datasets to assess its performance using a range of criteria. The key contributions of this study can be outlined as follows.

1. By describe a novel approach that incorporates a unique algorithm, which is best suited for the processing of the imagery data, and also flexible to use the model through mobile, which makes it more responsive and gives better accuracy results when compared to the earlier proposed studies.
2. Different datasets for defective and non-defective identification are trained for the model to understand and excel in identifying the imagery data that is loaded, and with the training of this the desired output is obtained.

Expanding upon the methodological intricacies of our approach, bydelve into the nuances of feature engineering and classifier selection, highlighting the novel aspects that set our methodology apart. Our feature extraction process meticulously captures not only the surface-level lexical and syntactic structures but also delves into the semantic nuances embedded within the text data [10]. By incorporating the most frequently used words, by ensure that our feature set encapsulates the salient aspects of disaster-related discourse, enabling the classifier to discern patterns indicative of damage assessment and other critical aspects.

The data from the internet which by acquire could be either text or later it is advanced for getting image data, examples of text data could be in such a way: India and Nepal are devastated by a deadly monsoon: flooding in northern and eastern India has claimed dozens of lives. From the given text machine learning model identifies whether the disaster has occurred or not and the rate of percentage of the damage caused, if occurred could be identified through the text data that is found on the internet or any other social media resources (including tweets, posts, etc) [11].
Objectives are as followed by,
Rate of Damage Caused (in Percentage) -The amount of Damage caused by the image is assessed and will be displayed as a part of the output. Name of the disaster - The name of the Disaster caused will also be identified from the image loaded as input. Part of the image where the damage occurred gets highlighted - When the image gets loaded, then the image is processed and the part where damage occurred gets highlighted. Image comparison Model is trained with more than one natural disaster, hence to give accurate results about the name, there has to be a comparison of the images internally and it has to produce the results respectively, so internal image comparison also takes place.
Novelty of the proposed work is given by,

- Multiple disaster information can be used together to find out the caused damages
- Estimation of the disaster defect with any objects precisely will be measure the accuracy greater than 95%.
- It processes the estimation calculation less than 2 minutes.
- Also able to identify disaster happened specified part of the area

2. RELATED WORK

By outline the relevant research in two domains, including a) damage-related images that address various methods for categorizing images related to disaster, and b) particular damage assessment data that mention the damage assessment-related tasks, such as utility and infrastructure damage assessments.

2.1 DAMAGE-RELATED DATA

Many disasters involve the analysis of image and sensor data for damage assessment and situational awareness. Explore research on using machine learning for image classification, object detection, semantic segmentation, and anomaly detection in disaster-affected areas. This may include satellite imagery analysis, drone-based reconnaissance, or IoT sensor data processing [12][13][14]. The authors developed a system for reporting earthquakes. that identifies tweets related to an earthquake by looking at criteria including duration, the location of the phrase "earthquake," and context words in tweets. A method called Artificial Intelligence Disaster Response (AIDR) was created by the authors using n-gram characteristics to determine the user-specified category of tweets in the event of a crisis. The authors used textual-based and domain-expert random forest classifier. characteristics to automatically identify eyewitness reports.

The eyewitness reports are divided into three categories: vulnerable direct witnesses, indirect eyewitnesses, and direct eyewitnesses. They worked with datasets related to storms, floods, earthquakes, and forest fires. The authors employed transfer learning-based and low-supervision techniques to identify the urgency of tweets [15].

Whenever byare considering direct eyewitnesses, it includes much time consumption as the person has to physically observe and collect the data hence it results in a delay in the response time in getting the output, this is the area that is been identified as a gap till years, but later some authors come up with the beautiful solutions whereby can analyze the data without being physically present and still get the response, it was all started by experimenting the text data, and checked for the results whether the model could meet the expected outputs or not and later it was an accuracy test the model while testing for text processing, the accuracy was checked meeting expectations or not, if it is not meeting the expectation then the model is trained again till the output is given as expected. Later, the images came into pictures, the important part of this model is bycan get the data from the internet through which response time was reduced, and the output could take nowhere as much time as the previous models [16][17].

They have demonstrated the advantages of their approach, particularly in situations with a low amount of labelled data, and the superiority of their method over the current baseline approaches. All of these studies, however, concentrate on tweets about disasters rather than the subcategory of tweets such as harm to people, damage to infrastructure, demand for and availability of resources, etc. Few research concentrated on separating the various tweet categories that occurred during a calamity. To locate help requests during a crisis, the Novelist employed context and content features with a variety of classifiers, including decision trees, SVM, random forests, and Adaboost. Out of all the classifiers, the choice Compared to the others, CNN (convolutional neural networks) produces better results. Recently, the authors employed terminology about geography, communication, infrastructure damage, etc. to identify resources in the event of a disaster. As the type of data that is being considered is image data, it works efficiently for processing the image data. As a result, the authors concentrated particularly on identifying the need for and availability of resources.

2.2 PARTICULAR DAMAGE ASSESSMENT DATA

During training, bypass the images of categories water disaster, drought, and urban fire through the subnetworks. After the images are routed via the subnetworks, two feature vectors—one for each image—are obtained as the output. If the input pairings are comparable, by want these two vectors to be as close to each other as possible, and vice versa. The model is also trained with data, that is not defective that data will help the model to understand how the non-defective data looks like, that will help to produce the output as expected [18].

The data sent out after natural calamities like droughts, urban fires, and water disasters were examined by the writers. It covers classes like "affected individual," "damage to infrastructure and utilities," "caution and advice," and so on. They demonstrated that the disaster's image provided supplementary data. When it comes to evaluating damage assessment data, machine learning models are essential. Convolutional neural networks (CNNs) is example of supervised learning approaches that are used to detect particular forms of damage or classify damage severity. The effective management of disaster defects through machine learning necessitates a comprehensive understanding and utilization of damage assessment data, encompassing various types, collection methods, Preprocessing techniques, annotated datasets, machine learning models, and evaluation strategies. Developing strong solutions to lessen the effects of disasters on impacted communities and infrastructure requires an all-encompassing approach [19].

The effectiveness and constraints of current catastrophe defect management techniques, especially when including damage assessment data, point to a number of important areas in need of development. First off, a lot of the current research mainly divides data connected to disasters into general categories like informative and non-informative, which might not fully meet the requirement of locating particular damage assessment photos during emergencies. As a result, these techniques could be imprecise in identifying important details about the scope and gravity of the harm done. Second, although damage assessment using data from social media photos has been the focus of certain study efforts, their attention frequently fails to appropriately analyze the real harm caused by catastrophic situations. Such methods' inability to offer useful information for disaster response and recovery operations is hampered by this shortcoming [20][21].

This research presents a unique framework that uses advanced features that are weighted using the CNS method to address these drawbacks. The suggested system intends to improve the accuracy and reliability of automatically detecting and assessing damage assessment data during disasters by utilizing a sophisticated weighting scheme and new features. An important factor in improving the effectiveness of the suggested framework is the CNS algorithm, which is renowned for its capacity to efficiently balance features according to their importance. The framework can enhance the overall efficacy of disaster defect management systems by prioritizing pertinent information related to damage assessment through the intelligent assignment of weights to features. Through enhanced accuracy and precision in detecting and assessing damage assessment data during disasters, the framework holds promise for improving disaster response, recovery, and mitigation efforts[22][23].

3.PROPOSED WORK

This section outlines the suggested method for determining damage assessment—image by 90% and greater accuracy during a disaster.

3.1. DATA COLLECTION

In this module, by are collecting the disaster image data from the kaggle.com. Our Dataset contains four classes Drought, Non-Damage SEA, Urban Fire, and Water Disaster. Each class contains a minimum of 250 images.

3.2 DATA PREPROCESS

Data preprocessing is the next step after data collection. It is a procedure for converting unusable data into information that can be used to make decisions. Another name for this procedure is data cleaning.

Here applying ImageGenerator functions to preprocess the data.

Figure 1 depicts that proposed system architecture. In a training phase, fed dataset to begin the preprocess, once preprocess over then extract the required features from the dataset using MobileNet V2 model which applied KERAS to process the trained and featured images to provide accurate defect detection and estimation of the defect area in precise manner.

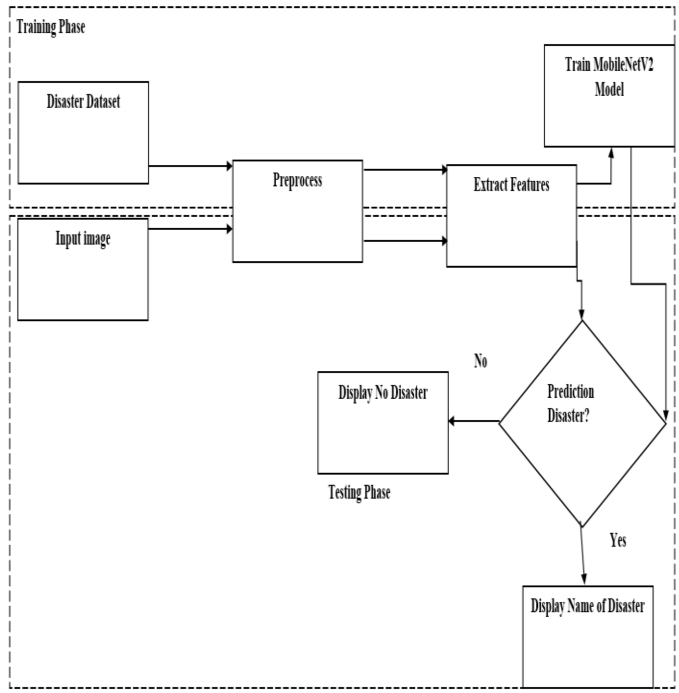

Figure 1. System architecture of the proposed method

3.3 MOBILENET V2

MobileNetV2 is a convolutional neural network architecture designed for mobile and edge devices. It is an improvement over the original MobileNet V2, aiming to be faster and more efficient while maintaining similar accuracy. MobileNetV2 uses a combination of depth wise separable convolutions and inverted residuals with linear bottlenecks to achieve this efficiency. It also introduces a new feature called "linear bottlenecks" to increase representational capacity while keeping the model lightweight. Overall, MobileNetV2 is well-suited for applications where computational resources are limited, such as mobile phones, IoT devices, and embedded systems.

The MobileNetV2 algorithm is a convolutional neural network (CNN) architecture that is used for various computer vision tasks, including image classification, object detection, and semantic segmentation. In the context of disaster defect management, here’s a general overview of how the MobileNetV2 algorithm could be used in a disaster defect management project:

Data Collection: Images or video feeds of the disaster-affected area are collected using drones, satellites, or other imaging devices.

Preprocessing: The images or video frames are pre-processed to enhance features that will help in identifying defects or damage.

Model Input: The pre-processed images or video frames are fed into the MobileNetV2 algorithm.

Feature Extraction: MobileNetV2 extracts features from the input images or frames at various levels of abstraction.

Defect Detection: The extracted features are used to detect defects or damage in the images or frames. This could involve identifying collapsed buildings, damaged roads, or other infrastructure issues.

Classification or Segmentation: Depending on the requirements, the algorithm may classify defects into different categories (e.g., minor damage, major damage) or perform segmentation to outline the extent of damage in each area.

There are 5 layers in this which are utilized in disaster defect management, they are:

- Average pooling2D
- Flatten
- Dense
- Dropout
- BaseModel

Work plans are devised into

- Collection of Multiple Datasets.
- Survey on Disaster Management.
- Identifying the right Algorithms.
- Understanding the software libraries needed for implementation.
- Preprocessing, feature selection and extraction of the datasets.
- Training the Datasets.
- Implement MobileNetv2, with the help of KERAS and TENSORFLOW libraries.
- Identifying defect analysis and cost damage.

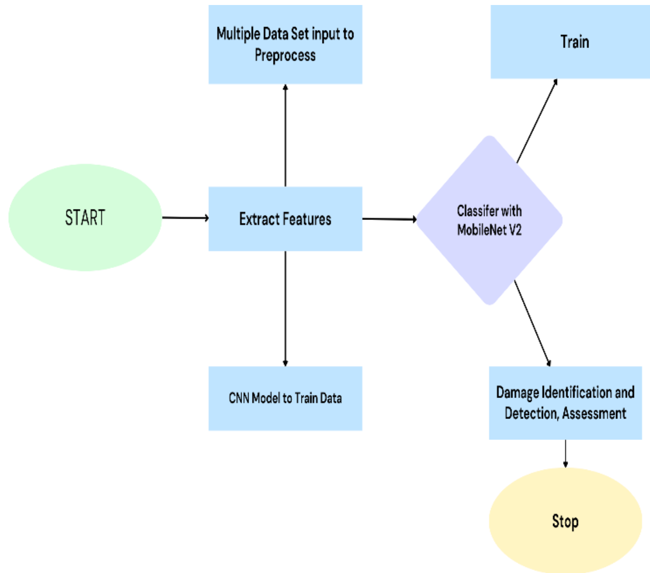

Figure 2. Schematic view of flow

Figure 2 denotes the process flow using the flowchart. Here the classifier keeps on training and extract the features until get the proper assessment results.

3.4 Convolutional Neural Network Algorithm

Step 1: *start the process.*

Step 2: *Define the input shape.*

//Considering the number of disaster types training samples up/down pass with height, weight and depth as an input.

Step 3: *Define output shape.*

//Considering the number of disaster types training samples up/down pass with height, weight and depth as an output.

Step 4: *Extract features through filter.*

//Disaster data set convolved with filter and extract the features. Here the matrix used to perform the dot product operation based on the image region also output the value with matrix form.

Step 5: *Calculate the greater number of parameters filters, kernel size in matrix form and input shape with matrix.*

Step 6: *Calculate the parameters in CNN with Bias, Weight values.*

Step 7: *Result of predictive and descriptive values.*

Step 8: *stop the process.*

To calculate the shape followed by using equation,

$$Shape = \frac{I-F+2*P}{S} + 1 \qquad \text{----------------} \ (1)$$

Here the representation defined by,

F-> Filter Size, P-> Padding, I-> Input, S->Stride

If the Padding value is not defined then,

$$Shape = I - F + 1 \quad \text{-----------------} \; (2)$$

NOW, ASSUME SPLIT THE INPUT IMAGE INTO M*M GRID,

FOR EACH GRID MAY USE THE CONVOLUTIONAL NEURAL NETWORK TO PREDICT THE DEFECT IN MULTIPLE DISASTER INPUT THE PREDICTS THE VALUE P WITH GIVEN IN THE EQUATION,

$$P = [Probability\ P_K, OBJ_x, OBJ_y, OBJ_h, OBJ_w, b1, b2, \ldots., b_p]^T \in RR^{G*G*K*(6+P)} \quad \text{-----------------} \; (3)$$

WHERE PK IS THE PROBABILITY OF OBJECT DETECTION, PROPERTIES OF BOX BOUND $\boldsymbol{OBJ_x}, \boldsymbol{OBJ_y}, \boldsymbol{OBJ_h}, \boldsymbol{OBJ_w}$ AND $\boldsymbol{b1}, \boldsymbol{b2}, \ldots., \boldsymbol{b_p}$ CLASSES ARE IDENTIFIED K DENOTES THE BOX WITH ANCHOR.

HERE, WHEN THE INITIAL VALUE OF PROBABILITY OF OBJECT DETECTION IS ZERO THEN IGNORE THE VALUES OF $\boldsymbol{b1}, \boldsymbol{b2}, \ldots., \boldsymbol{b_p}$.

4. RESULTS AND DISCUSSIONS

Natural disasters are a primary cause of fatalities as well as destruction to property and infrastructure. Man-made practices such as industrialization and deforestation are aggravating most of the repercussions of natural disasters. The increase in factory demand negatively impacted millions of families. Reducing the impact of nature requires controlling these activities. Because disasters are so complex, developments in machine learning (ML) are being applied more and more. In order to allocate resources for disaster management in accordance with specific needs, the taxonomy provides a helpful way to classify impending seismic events. The results of a review study that examined the ways in which machine learning techniques have been used to support and improve many facets of disaster management are presented in this paper. The fact that certain studies on disasters have been produced in languages other than English may be important to this field of research. The reaction dynamics and coordination of people communicating through platforms can vary.

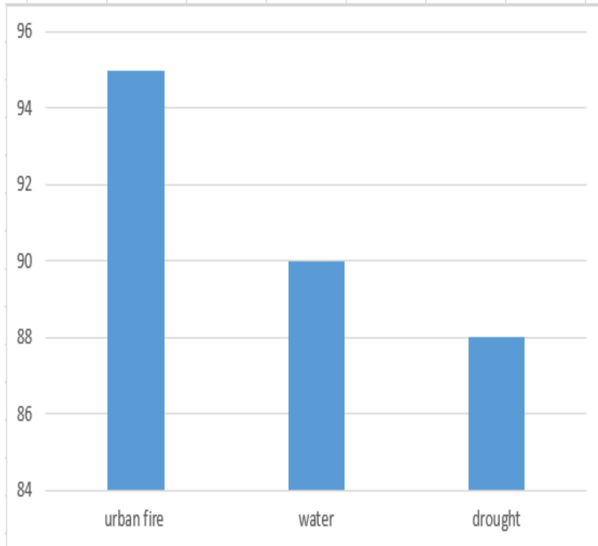

Figure 3. Disaster defect prediction accuracy

Figure 3 represents about x axis with type of Disaster and Y-axis with accuracy levels. There are three types of natural disaster considered for accuracy calculation those are Urban fire, water and drought disasters.

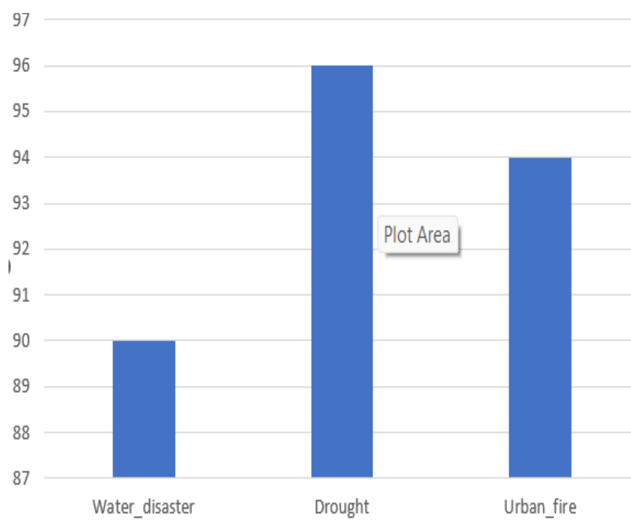

Figure 4. Disaster image datasets average of pdi(pixel density)

Figure 4 portrays based on the pixel density assessment carried out and displayed in the chart.

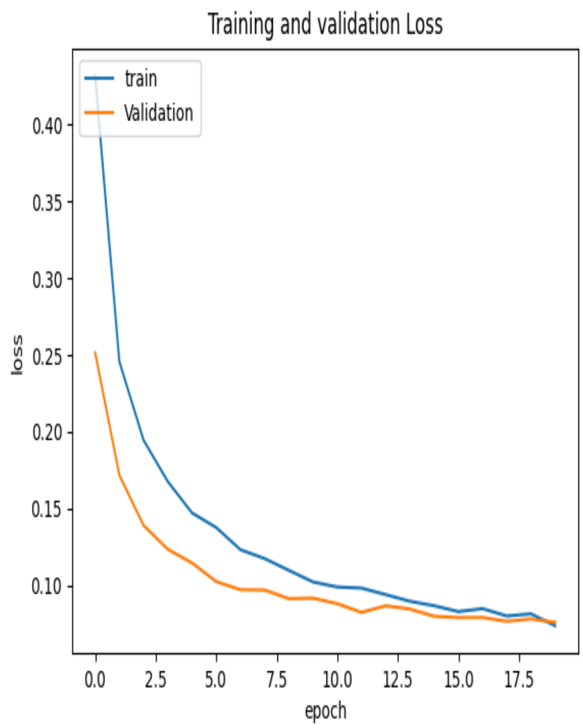

Figure 5. Training and Validation Loss

Figure 5 describes the training and validation loss of the given data set with a greater number of epoch iterations to reduce the loss during the classifier usage.

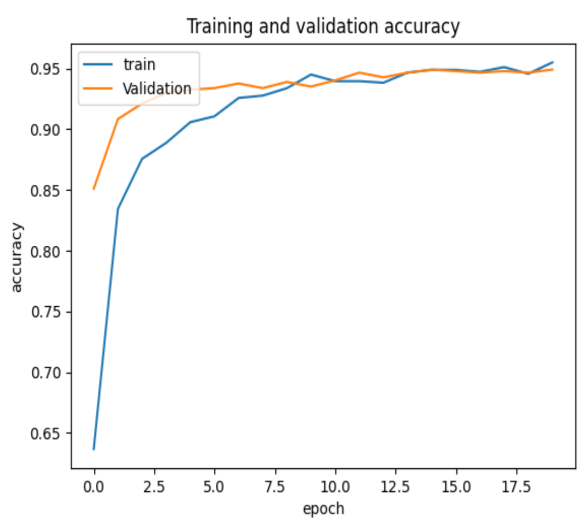

Figure 6. Training and Validation Accuracy

Figure 6 shows the training and validation accuracy while performing the feature classification. Here training takes more times while comparing with validation process.

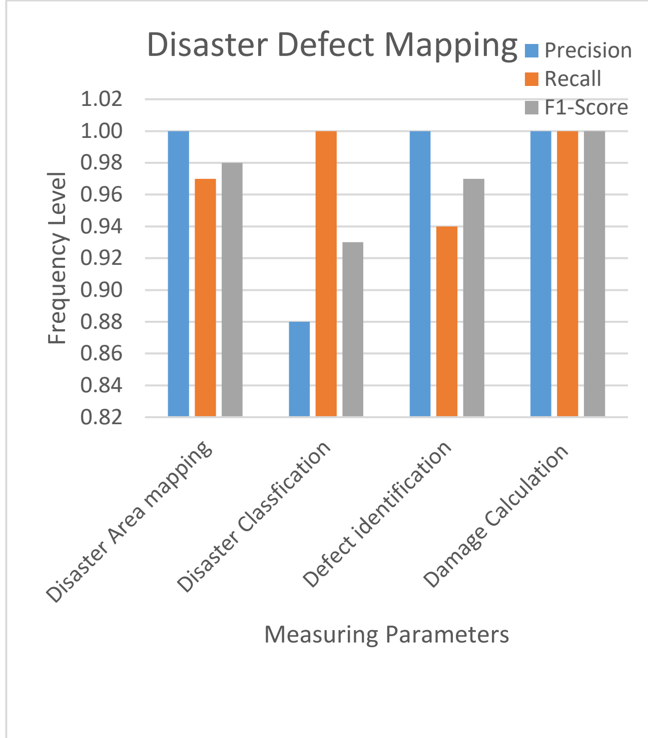

Figure 7. Precision, Recall and F1 Score

Figure 7 labels the computing the accuracy by using the Precision, Recall and F1 Score. Here more parameters are defined such as disaster area mapping, Disaster classification, Defect identification and damage calculations.

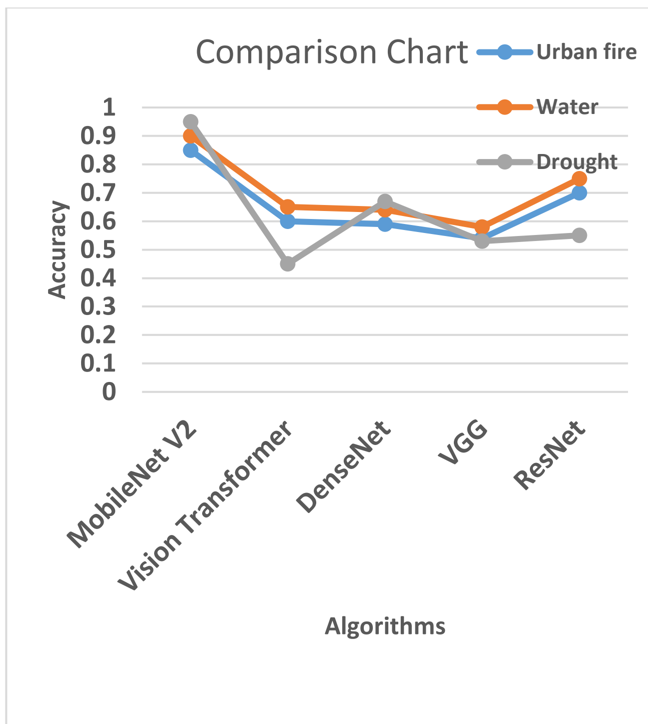

Figure 8. Comparison Chart

Figure 8 marks the comparison chart for accuracy assessment based on the Urban fire, Water and drought disasters. Here different kind of algorithms are used for comparison chart. The proposed MobileNetV2 algorithm is providing the better accuracy while compared with Vision Transformer, DenseNet, VGG and ResNet.

Further research on these newest Internet community platforms won't be possible until data extraction API functionality is established. A wide range of subjects were covered in the other examined research, such as risk and vulnerability assessment, applications, case studies, and early warning systems. Additional themes covered in this review study include hazard prediction, damage assessment, and quicker post-disaster action. Future research should focus on using machine learning to increase the efficacy of disaster recovery operations.

Given the need for long-term disaster recovery operations, The application of machine learning to improve mitigation techniques and lower vulnerabilities should be the main focus of research.

Because catastrophe operations are so complicated and crucial, robust and tested machine learning solutions are required. The generated models have implications for human life as catastrophe operations do. It should also make sense to decision-makers and subject-matter specialists. Furthermore, studies should focus on improving data quality, developing novel approaches to data collection, and employing crowdsourcing to boost the effectiveness of machine learning-based disaster management plans. The Siamese network algorithm is used in the pictures in this article to compare the input images and show the differences. Locating impacted individuals, finding internet data makes it possible to find out about their current situation and learn about the different rescue efforts carried out during natural and man-made disasters.

In this research, by aimed to develop a machine-learning approach to catastrophe assessment data management. This paper's main flaw is that it only offers a limited amount of results. Natural disasters can range widely in scope and severity, from isolated occurrences to massive catastrophes. Certain disasters can be so large that local, regional, and even national response capabilities are overwhelmed. The primary tools used to handle the issues related to flood management include systems that use machine learning models, such as CNN, in addition to systems that use image processing techniques, such as edge detection, segmentation, and pixel analysis.

The three primary techniques utilized to handle the issues related to flood control are detection, segmentation, and pixel analysis. The three most popular techniques for taking pictures are SAR, remote sensing, and UAV imaging. The current methods in the machine learning and image processing fields typically concentrate on the pre- and post-disaster eras. When it comes to identifying photographs on the Internet, photos are essential. The reality is that using Mobilenetv2 by can assess the damage rate caused and it is designed to improve the accuracy. It is a part of a convolutional neural network that is 53 layers deep you can load a pre-trained version of the network trained on more than a million images from the image net database. MobileNet V2 algorithm is applied, model will get trained with certain ample of images, and the model is trained with the basic formulas, and each prediction is considered as one neuron. The model is trained to give the parameters such as accuracy, name of the disaster, and damage rate caused.

5. CONCLUSION

Disaster assessment is a tedious process once it was happened. It is essential to identify and understand the importance of cost estimation based on the defect happened during disaster also to identify disaster happened specified part of the area. The proposed MobileNet V2 model helps in multiple disaster information can be used together to find out the caused damages. Model provide quick estimation calculation less than 2 minutes. Estimation of the disaster defect with any objects precisely will be measure the accuracy greater than 85% to 95%. In future, Internet of Things helps to capture disaster in real-time and further identifying causes and damage estimation with minimum spanning time.

Author Contributions: J.T. Thirukrishna designed the study and wrote the manuscript also implemented the methods and performed experiments.

REFERENCES

[1] H. S. Munawar, A. W. A. Hammad, and S. T. Waller, "A review on flood management technologies related to image processing and machine learning," in *IEEE Transactions on Geoscience and Remote Sensing*, 2021.

[2] D. D. Atsa'am, T. Gbaden, and R. Wario, "A machine learning approach to formation of earthquake categories using hierarchies of magnitude and consequence to guide emergency management," in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 2023. [3] M. A. Islam, S. I. Rashid, N. U. I. Hossain, R. Fleming, and A. Sokolov, "An integrated convolutional neural network and sorting algorithm for image classification for efficient flood disaster management," in *IEEE Transactions on Image Processing*, 2023.

[4] A. Kurkcu, F. Zuo, J. Gao, E. F. Morgul, and K. Ozbay, "Crowdsourcing Incident Information for Disaster Response using Twitter," in *IEEE Transactions on Intelligent Transportation Systems*, 2017.

[5] R. R. Arinta and A. W. R. Emanuel, "Natural Disaster Application on Big Data and Machine Learning," in *IEEE Access*, 2019.

[6] A. Alshehri, "A Machine Learning Approach to Predicting Community Engagement on Social Media During

Disasters," in *IEEE Transactions on Computational Social Systems*, 2019.

[7] L. Dwarakanath, A. Kamsin, R. A. Rasheed, A. Anandhan, and L. Suhib, "Automated Machine Learning Approaches for Emergency Response and Coordination via Social Media in the Aftermath of a Disaster," in *IEEE Access*, 2021.

[8] Xing, R., Ju, W. & Lu, H (2024). A comprehensive evaluation model for forest fires based on MCDA and machine learning: A case study of Zhenjiang City, China. Environ Dev Sustain. https://doi.org/10.1007/s10668-024-05125-z.

[9] M. Drakaki, "Machine learning to analyze social media data for disaster management," in *IEEE Transactions on Computational Social Systems*, 2022.

[10] S. Madichetty and S. M. Sridevi, "A Novel Method for Identifying the Damage Assessment Tweets during Disaster," in *IEEE Access*, 2020.

[11] A. Kruspe, J. Kersten, and F. Klan, "Review article: Detection of informative tweets in crisis events," in *IEEE Transactions on Computational Social Systems*, 2020.

[12] D. D. Atsa'am, T. Gbaden, and R. Wario, "A machine learning approach to the formation of earthquake categories using hierarchies of magnitude and consequence to guide emergency management," in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 2020.

[13] C. Reuter, A. L. Hughes, and M.-A. Kaufhold, ''Social media in crisis management: An evaluation and analysis of crisis informatics research,'' Int. J. Hum.–Comput. Interact., vol. 34, no. 4, pp. 280–294, Apr. 2018.

[14] J.T.Thirukrishna, Certain Investigation on Healthcare Monitoring for Enhancing Data Transmission in WSN, International Journal of Wireless Information Networks (Q2 Journal), 30, 103–110 (2023), ISSN: 1572-8129, Web of Science Indexed, https://doi.org/10.1007/s10776-021-00530-x

[15] A Novel Approach for QoS Enhancement with Revision Scheme Using SeDSR Protocol in Wireless Sensor Networks, Wireless Personal Communication (Q2 Journal), ISSN: 09296212, SCI Indexed, Springer, Vol. 120, pp.401–417, 2021. https://doi.org/10.1007/s11277-021-08466-4

[16] An Efficient QoS Based Data Packet Transmission in Wireless Sensor Networks Using OREA, Wireless Personal Communications (Q2 Journal), ISSN: 09296212, Vol. 113, 1839-1850 (2020), Springer, SCI Indexed Journal. https://doi.org/10.1007/s11277-020-07295-1

[17] OREA for improving data packet transmission in Wireless Sensor Networks with Cloud Security Mechanism, International Journal of Cloud Computing (Q4 Journal), ISSN: 20439997 Inder science, Scopus, Vol. 9. Issue No. 2/3, pp. 245-257, 2020. https://doi.org/10.1504/IJCC.2020.109379

[18] An Extensive Study and Evaluation of Tribological Properties of FSW Plates Using Linear Reciprocating Tribometer (LRT), Journal of Mines, Metals and Fuels (Q4 Journal), Scopus, 2023. https://doi.org/10.18311/jmmf/2023/36054

[19] V-Shaped Binary Version of Whale Optimization Algorithm for Feature Selection Problem, In: Saini, H.S., Sayal, R., Govardhan, A., Buyya, R, (eds) Innovations in Computer Science and Engineering, ICICSE 2022, Lecture Notes in Networks and Systems (Q4 Journal), Scopus Indexed, Vol. 565. Springer, Singapore, 2023. https://doi.org/10.1007/978-981-19-7455-7_23

[20] An Enhanced Information Broadcast in WSN Using Optimized Energy Algorithm for Healthcare, Innovations in Computer Science and Engineering, Lecture Notes in Networks and Systems, (Q4 Journal), Scopus Indexed, Vol. 385, Springer, Singapore, 2022. https://doi.org/10.1007/978-981-16-8987-1_16

[21] Enhancing Accuracy Performance in Novel Drug Delivery System for Composite Microbeads Using Hadoop Ecosystem Over Conventional Drug Delivery Systems, In: Saini H.S., Sayal R., Govardhan A., Buyya R, (eds) Innovations in Computer Science and Engineering, Lecture Notes in Networks and Systems (Q4 Journal), Scopus Indexed, Vol. 385, Springer, Singapore, 2022. https://doi.org/10.1007/978-981-16-8987-1_33

[22] Implementation of Smart Parking Application Using IoT and Machine Learning Algorithms, In: Smys S., Bestak R., Palanisamy R., Kotuliak I. (eds) Computer Networks and Inventive Communication Technologies, Lecture Notes on Data Engineering and Communications Technologies (Q3 Journal), Scopus Indexed, Vol. 75, Springer, Singapore, 2022. https://doi.org/10.1007/978-981-16-3728-5_18

[23] Fuzzy Interference System based Link Failure prediction in MANET, Journal of Physics: Conference Series (Q4 Journal), Scopus Indexed, Vol.1964, 2021, ISSN: 1742-6596. https://doi.org/10.1088/1742-6596/1964/7/072020

[24] Survey on Diagnosing CORONA VIRUS from Radiography Chest X-ray Images Using Convolutional Neural Networks, Wireless Personal Communication (Q2 Journal), Vol. 124, 2261–2270, 2022 Springer, SCI Indexed Journal. https://doi.org/10.1007/s11277-022-09463-x

Dr. J.T. Thirukrishna working as an Associate Professor in the Department of Information Science and Engineering, Dayananda Sagar Academy of Technology and Management, Dayananda Sagar Institutions, Bangalore, India, since 2019. He is a Senior IEEE member. Author of more than 50+ Research Articles, Patents (U.K and Indian), Books and Book Chapters. Focused research areas include Cyber Security, Data Science and Wireless Sensor Networks. Recognized Research Supervisor and Research Scholars are guiding under his supervision. Delivered technical talk and invited as a resource person for FDP etc. at reputed Institution's. Journal Reviewer of SCI/Web of Science/Scopus indexed Journals. Applied many funding proposals to ATAL, DST, CSIR and AICTE etc. Dr. J.T.Thirukrishna was a

recipient of "Award of Excellence in Research Award 2020-2021" from Novel Research Academy and Global Teacher Award 2019 for Excellence, and Member of the various professional bodies such as Life member of **Cryptology Research Society of India and** Life Member of Indian Society for Technical Education (ISTE).