

# Explainable social media disaster image classification using a lightweight attention-based deep learning approach

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## ABSTRACT

In recent years, the rapid dissemination of social media content during natural and man-made disasters has created a need for automated and accurate disaster image classification systems. This paper proposes lightweight explainable attention-based disaster network (LEAD-Net), a deep learning (DL) model designed for classifying disaster-related images with high accuracy and interpretability. The system integrates an EfficientNet-B0 backbone enhanced with squeeze-and-excitation (SE) attention modules and a lightweight neural architecture search (NAS-lite) strategy for tuning the classifier head and training hyperparameters. The model was evaluated on two benchmark datasets comprehensive disaster dataset (CDD) and damage multimodal dataset (DMD) achieving 96% and 87% accuracy, respectively, outperforming several established convolutional neural network (CNN) baselines. To ensure transparency, gradient-weighted class activation mapping (Grad-CAM) was employed to generate visual explanations of the model's decisions, confirming its focus on semantically relevant image regions.

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## 1. INTRODUCTION

Natural disasters such as earthquakes, floods, wildfires, and hurricanes bring distressing costs for human life, infrastructure, and the environment. The trend of past few decades shows that the frequency and intensity of natural disasters have increased due to climate change and urban expansion [1]. During disasters, getting timely and accurate information becomes very crucial for taking strategies for an effective emergency response, resource allocation and damage assessment [2]. However, in such situations, traditional communications systems often become overloaded or fail, severely delaying disaster response operations [3]. In recent years, social media channels such as Twitter, Facebook, and Instagram have proven to be useful sources of real-time information during disasters [4], [5]. People often share breaking news, photos, and videos of disaster-affected areas, which can serve as disaster warnings, ground references, and evidence. Among these, photos provide rich visual information that helps assess the severity and type of disasters [6]. However, manual analysis of photos is time-consuming, and it is not feasible to analyze thousands of photos daily, which delays immediate response. To address this challenge, researchers have begun to use data-driven and deep learning (DL) models that can identify types of disaster images and accelerate decision making [7]. Although these models are very effective, but several challenges still remain such as disaster images often containing complex and overlapping visual information, such that the same image may show multiple types of disasters or even look like other events; datasets are imbalanced; and social noise and unlabeled data pose

problems for model training [8]. Therefore, developing an effective solution requires a robust feature learning scheme and event-aware classification strategies to make correct predictions on natural disaster images from social media posts.

The recent research has explored different convolutional neural networks (CNNs) architectures [9] transfer and hybrid learning techniques [10] to classify disaster images. Ahmed *et al.* [11] adopted federated learning approach to reduce dependency of manual annotation and waste classification. This work shows their model enables local clients to automatically select informative unlabeled data, and achieve 3%–4% improvements in accuracy to fully labeled datasets, but it may face issues when subjected to heterogeneous sources. Ma *et al.* [12] addressed the scale variation problem in natural disaster imagery by developing a hybrid vision transformer model based on the joint approach of convolution operation with time series downsampling module. The result analysis shows benefits in prediction improvement but at cost of higher complexity that may hinder real-time deployment. Sheth *et al.* [13] introduced an ensemble model of InceptionV3 and a custom CNN to classify disaster images with accuracy of 92.79%. This approach lacks novelty and no significant contribution shown. Coopen and Pudaruth [14] developed a custom dataset combining existing dataset to increase the data diversity and classes, which is evaluated with pre-trained models like MobileNetV2, VGG16, and InceptionV3. Their results showed InceptionV3 and MobileNetV2 achieved 96.86% accuracy but under specific training conditions. Mustafa *et al.* [15] presented a DL framework, where they have explored different explainable AI methods such as gradient-weighted class activation mapping (Grad-CAM), Grad-CAM++, and local interpretable model-agnostic explanations (LIME) for disaster image classification. Bashir *et al.* [16] introduced a disaster monitoring scheme that uses aerial images and transmits them to a base station where a DL model with feature concatenation is used to classify disaster types. Yashi *et al.* [17] presented an ensemble framework based on the combination of eight CNN models for flood classification using FloodNet datasets, which shows training accuracy of 98.9% and test accuracy of 97.4%. However, they have not discussed the time complexity associated with ensemble prediction from 8 CNNs. Sathianarayanan *et al.* [18] addressed the lack of geolocation data in social media images for disaster response by suggesting a phone-number-based location extraction framework. The authors have used RetinaNet CNN model that detects digits, and used Google Maps API to retrieve locations, and the outcome shows an average precision of 82%. Though the authors have presented innovative approach but may be limited by the assumption that phone numbers are always visible and readable in disaster images. VanExel *et al.* [19] introduced a DL approach for detecting flooding and desertification from unmanned aerial vehicle (UAV) and satellite imagery using a climate change dataset, where DenseNet201 and ResNet50 achieved accuracies of 99.37% and 99.21%, respectively.

The work of Dubey and Katarya [20] designed a hybrid flood detection model based on the joint approach of transformer and adaptive firefly algorithm for feature optimization and achieved an accuracy of 97.85% over benchmarks. This work does not discuss much about the evolutionary parameters tuning as it may increase training and inference overhead. Wen *et al.* [21] suggested improvement over ResNet-50 CNN architecture to classify seven types of natural disasters on complex dataset and only achieved 87% accuracy. This shows addressed gradient vanishing issues, and improved training stability but left a scope for improvement on classification accuracy and model sensitivity. Shao and Xu [22] introduced a multimodal disaster recognition model based on pre-trained language models with visual backbones by integrating question-answering approach. They combined modalities and the Mamba mechanism, and obtained an accuracy of 97.82% against CNNs and vision transformers. However, it may lack scalability and associated with large computational costs due to the nature of model implementation. The study of Wang *et al.* [23] presented a multi-stage DL architecture based on the integration of U2Net model and swin transformer for damage assessment from satellite images. Their model showed significant performance improvements over existing methods on the xBD dataset. However, it has higher dependencies on accurate disaster-type input and pre-disaster segmentation performance, which may limit its adaptiveness to complex images obtained from social media posts.

Although many schemes have been presented in the literature, but most of them prioritized accuracy and neglect computational efficiency. Also, many works lack novelty as there are similar works by different researchers with slight changes in the adoption of standard CNNs, and ensemble methods which increases complexity, training time, and inference cost. Most DL models operate as black boxes, with limited focus on interpretability, that makes it difficult for first responders to understand and trust the system's predictions.

This paper introduces lightweight explainable attention-based disaster network (LEAD-Net) a DL architecture designed for efficient, interpretable, and high-accuracy disaster image classification. Unlike existing approaches that adopted standard but complex CNNs, the proposed LEAD-Net integrates a modified attention block with dual pooling, dynamic reduction, and Swish activation to enhance feature learning. The model also provides visual explanations via Grad-CAM, to ensure transparency in high-stakes decisions. The model is extensively validated on two diversified real-world disaster datasets to prove robustness and generalizability, something often missing in prior work.

## 2. METHOD

The prime aim of the proposed work is to develop a robust image classification model that can accurately identify disaster events from social media images, which are often visually complex and contains ambiguous nature of disaster scenes where a single image may illustrate multiple overlapping phenomena. This paper introduces LEAD-Net to effectively learn deep visual patterns, generalize across disaster categories, and provide interpretable predictions. The system design and methodology workflow of the proposed LEAD-Net is illustrated in Figure 1.

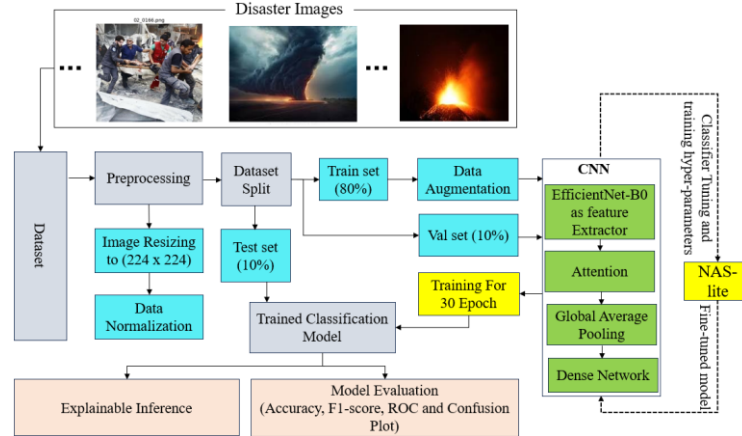


Figure 1. System design and methodology workflow of LEAD-Net

The input considered in the proposed system are the natural disaster image from the social media posts obtained from the comprehensive disaster dataset (CDD) [24] and damage multimodal dataset (DMD) obtained from MEDIC benchmark [25], [26]. The CDD dataset consists of total 13565 image samples distributed across 12 classes, whereas DMD has total 5878 images samples within 6 classes. Both datasets consist of visual scenes of natural disaster events which is not only contains visually ambiguous nature of disaster scenes but also subjected to multi-faceted content. The first computing module of the proposed system is the preprocessing which performs image resizing ( $224 \times 224$  pixels) and data normalization to standardize pixel values to match the input requirement of the LEAD-Net DL model. The datasets with preprocessed images are then subjected to train-test split operation where three different sub-sets are created such as train-set (80%), validation-set (10%), and test-set (10%). In order to provide better learning experience to LEAD-Net model, the diversity of train-set is enriched via data augmentation strategies such as horizontal and vertical flipping, zooming, rotating and random brightness variation. The data augmentation is not applied to validation and test sets to avoid any data leakage and model biasness.

The next computing module of the proposed system is LEAD-Net model, which is based on the integration of DL model i.e., EfficientNet-B0 CNN with transfer learning approach [27] and attention mechanism. The EfficientNet-B0 CNN is a lightweight and robust CNN architecture and in the proposed system it is implemented as a feature extractor module without using its original top classifier layer. After extracting features with EfficientNet-B0, a custom classifier head is developed which includes integration of attention layer, global average pooling (GAP) layer and dense layer for the multi-class classification layer. The attention layer used in the proposed LEAD-Net model is a modified version of the squeeze-and-excitation (SE) attention block to refine the channel-wise feature maps, which enables model to emphasize disaster-relevant features and ignore irrelevant ones. In the modified version of SE attention, the study has introduced dual-pooling in the squeeze phase, a deeper excitation network, Swish activation, and a dynamically determined reduction ratio. The attention layer considers the feature map  $F \in \mathbb{R}^{H \times W \times C}$ , where H and W represent the dimension of the feature map obtained from convolutional layers of EfficientNet-B0 and C presents the number of feature channel or depth. Afterwards, two global descriptors are computed via GAP and global max pooling (GMP) as in (1) and the final squeezed vector is obtained by concatenating both descriptors as given in (2).

$$z_{avg} = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W F(i, j), z_{max} = \max_{i, j} F(i, j) \quad (1)$$

$$z = [z_{avg}; z_{max}] \in \mathbb{R}^{2C} \quad (2)$$

After extracting a compact channel descriptor vector  $z$  from the above squeeze step, the next excitation operation transforms  $z$  to produce channel-wise attention weights followed by deep feedforward with Swish activation and dynamic reduction strategy as in (3) with  $k$  constant and the final excitation vector is computed as expressed in (4).

$$r = \max\left(1, \left\lfloor \frac{c}{k} \right\rfloor\right) \quad (3)$$

$$s = \sigma(W_3 \times f_s(W_2 \times f_s(W_1 \times z))) \quad (4)$$

Where  $W_i$  is weight matrices where  $W_1 \in \mathbb{R}^{d \times 2c}$  is weight of the first layer which reduces the dimensionality,  $W_2 \in \mathbb{R}^{d \times d}$  is the weights of the second layer that maintains the same size, and  $W_3 \in \mathbb{R}^{c \times d}$  denotes third layer weight which expands back to the original number of channels. Here  $d = C/r$ , which represents the number of units in each hidden layers and  $\sigma$  is a sigmoid function that scales values between 0 and 1. Finally, the output attention is applied channel-wise to the original feature map as given in (5), helps the model focus on disaster-specific features while suppressing noisy or irrelevant activations.

$$F'_c = s_c \times F_c \quad \forall c \in \{1, 2, \dots, C\} \quad (5)$$

To further optimize model performance, a lightweight neural architecture search (NAS-lite) strategy is used to fine-tune the classifier head and training hyperparameters proposed LEAD-Net model. A NAS refers to a technique of automatically searching for an optimal neural network architecture for a given task by exploring a large search space of possible architectural configurations and training hyperparameters. Figure 2 illustrates the workflow of proposed NAS driven efficient classification model setup with aim of achieving efficiency in training performance.

The proposed study considers a large search space of training hyperparameters as demonstrated on the left side of Figure 2, which includes various dense layer configurations, dropout rates, optimizers, and learning rates, without the overhead of exhaustive grid-based evaluation. The search process will continue and iteratively evaluates sampled architectures and update the strategy until the convergence criteria is met. The final selected architecture includes an optimal parameter as shown on right hand side of Figure 2 with fixed choice of batch normalization and GAP to enhance convergence stability and feature summarization. Additionally, a batch size of 16 was used during model training to prevent memory overhead, and class weighting was applied to address the imbalance present in the dataset. The model is trained for 30 epochs on the prepared dataset. After training, the model is evaluated using both quantitative and qualitative methods.

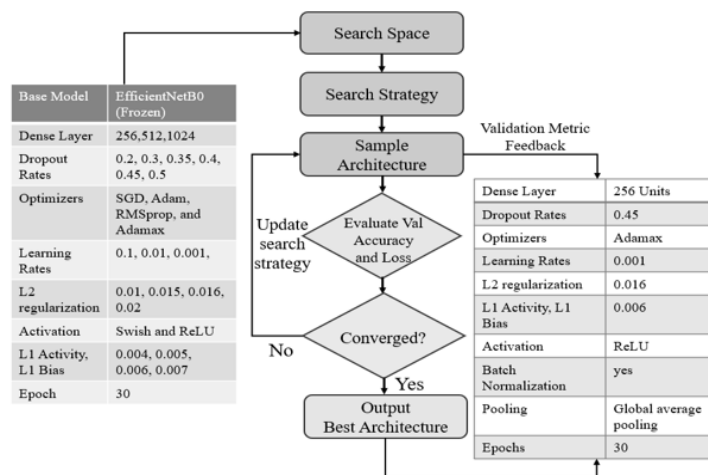


Figure 2. NAS workflow for EfficientNetB0 optimization

### 3. RESULTS AND DISCUSSION

This section discusses the experimental outcomes of the proposed LEAD-Net model, and validates its performance with two benchmarked publicly available datasets namely CDD and DMD. The development and performance assessment of the proposed LEAD-Net is carried out using python with GPU support on windows 11 64-bit machine. The validation of model is done considering classification accuracy, computational efficiency, model interpretability, and comparison with baseline approaches. Figure 3 provides

a comparative visualization of the training and validation loss curves for the LEAD-Net model on both CDD and DMD dataset. The loss curve illustrates the model’s learning dynamics over 30 training epochs, that shows the model is optimizing by minimizing error during its training phase. Base on the analysis of the Figure 3(a), it can be seen that the loss curve of the model on the CDD exhibits a stable trend that suggest effective convergence with good generalization on the validation set. On the other hand, Figure 3(b) shows slight divergence between the validation and training losses on DMD dataset, which may be due to the smaller data samples and class imbalance issues associated with DMD. However, both curves plateau by the final epochs, that demonstrates stable convergence achieved by the LEAD-Net model.

Figure 4 illustrates the confusion matrices of the proposed LEAD-Net model on the CDD and DMD datasets, respectively. The confusion matrix in Figure 4(a) provides class-wise prediction performance of the proposed model to the CDD dataset. It can be seen that the model has achieved high true positive counts for multiple classes such as non\_damage\_buildings\_street, non\_damage\_wildlife\_forest, and non\_damage\_sea, demonstrating the model’s ability to distinguish disaster types from similar visual contexts. On the DMD dataset in Figure 4(b), the confusion matrix shows relatively strong performance for the non\_damage and damaged\_infrastructure classes, both of which have high true positive rates (TPR). However, more confusion is observed among visually similar classes such as damaged\_nature, fires, and flood, likely due to overlapping features in real-world scenarios and due to lack of large data samples in DMD. However, LEAD-Net maintains a high level of accuracy across most categories, with particularly strong generalization in identifying non\_damage content, which is critical for filtering irrelevant data in emergency response pipelines. Table 1 provides quantitative analysis of the proposed LEAD-Net on CDD dataset considering precision, recall, and F1-score.

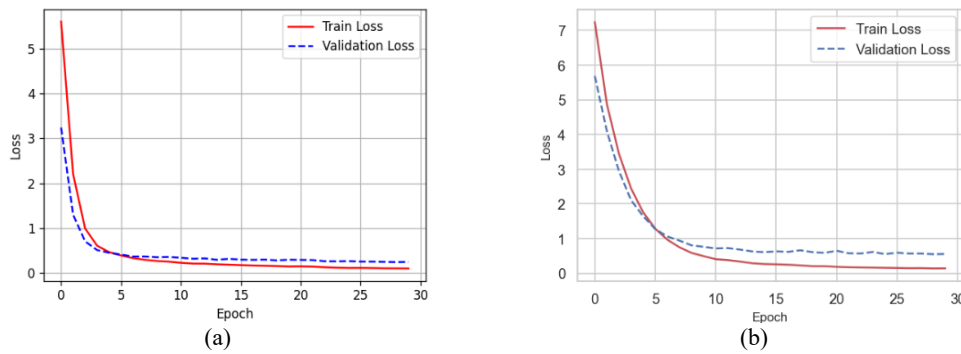


Figure 3. Training and validation loss curves of the proposed LEAD-Net model on (a) CDD dataset and (b) DMD datasets

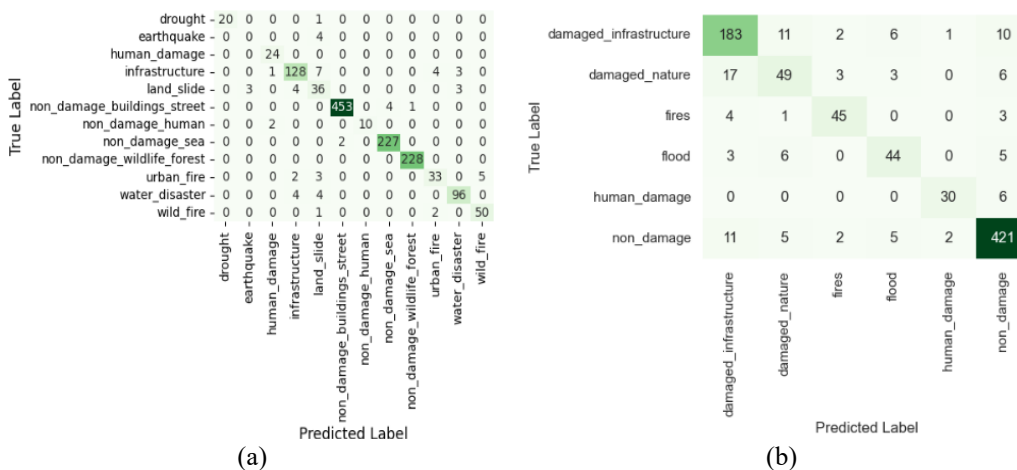


Figure 4. The confusion matrix of the proposed LEAD-Net model on (a) CDD datasets and (b) DMD datasets

The quantified outcome demonstrated in Table 1 reveals that the model has achieved an overall classification accuracy with 96%, that indicates strong performance across all the 12 classes. In terms of

precision and recall, a considerable performance is shown by the model for all most every class except earthquake due to very less instances in the test dataset. The class `human_damage` achieved F1-score of 0.94, and `water_disaster` and `wild_fire` both exceeded 0.93, thereby showing strong classification capability even for disaster categories. Overall outcome demonstrate that LEAD-Net performs reliably across most disaster classes in CDD dataset, with exceptional strength in high-support categories and non-damage detection.

Table 2 presents quantified outcome of the proposed model on DMD dataset which is considered to be more challenging due smaller sample size, class imbalance, and greater visual ambiguity among classes. The analysis of the numerical outcome in Table 2 shows that on DMD dataset the model has achieved an overall accuracy of 87%, with strong performance particularly in the `non_damage` (F1-score: 0.94), `human_damage` (F1-score: 0.87), and `fires` (F1-score: 0.86) classes, except `damaged_nature` class with F1-score 0.65, suggests the model faced difficulty distinguishing it from other damage-related classes, likely due to overlapping visual characteristics in disaster imagery. This level of performance is noteworthy given the nature of the dataset. In the existing literature, models trained on image-only disaster datasets typically report classification accuracies below 90%. Accuracy levels above 90% are usually achieved only when textual metadata (e.g., tweets or captions) is combined with images in a multimodal setup. Therefore, achieving 87% accuracy using image data alone highlights the robustness of the proposed LEAD-Net model, even under data constraints and real-world variability, which is further evident by receiver operating characteristic (ROC) curve in Figure 5.

Table 1. Classification report on CDD dataset

Class	Precision	Recall	F1-score	Support
drought	1.00	0.95	0.98	21
earthquake	0.1	0.1	0.1	4
human_damage	0.89	1.00	0.94	24
infrastructure	0.93	0.90	0.91	143
land_slide	0.64	0.78	0.71	46
non_damage_buildings_street	1.00	0.99	0.99	458
non_damage_human	1.00	0.83	0.91	12
non_damage_sea	0.98	0.99	0.99	229
non_damage_wildlife_forest	1.00	1.00	1.00	228
urban_fire	0.85	0.77	0.80	43
water_disaster	0.94	0.92	0.93	104
wild_fire	0.91	0.94	0.93	53
Overall test accuracy =96%				1,365

Table 2. Classification report on DMD dataset

Class	Precision	Recall	F1-score	Support
damaged_infrastructure	0.84	0.86	0.85	213
damaged_nature	0.68	0.63	0.65	78
fires	0.87	0.85	0.86	53
flood	0.76	0.76	0.76	58
human_damage	0.91	0.83	0.87	36
non_damage	0.93	0.94	0.94	446
Overall test accuracy =87%				884

The ROC curves are basically a threshold-independent assessment metric that plots the TPR against the false positive rate (FPR) at various classification thresholds. It offers a more complete view of a model's ability to distinguish between classes than a single-point metric like accuracy or F1-score. As it can be seen that the proposed model demonstrated discriminative capacity of its prediction by achieving area under the curve (AUC) scores above 0.97 for most of the classes on the both datasets.

On the CDD dataset in Figure 5(a), most classes achieved perfect or near-perfect AUCs of 1.00, and the other classes such as `earthquake` and `urban_fire` shows AUC of 0.97 and 0.98, respectively. Interestingly, while the classification accuracy on the DMD dataset is slightly lower, the ROC curves in Figure 5(b) reveal that LEAD-Net achieves strong AUC scores ranging from 0.93 to 0.99, which shows strong evidence that the LEAD-Net model effectively differentiates between disaster categories, reinforcing the validity of the classification results presented earlier. The next analysis in Table 3 is carried out for evaluating the explainability of the proposed LEAD-Net model.

Table 3 illustrates the explainability of LEAD-Net using Grad-CAM visualizations on selected samples from the CDD and DMD datasets. The activation maps clearly show that the model focuses on contextually relevant regions such as flames in wildfire scenes, damaged infrastructure, or affected individuals when making its predictions. This indicates that the model is learning semantically meaningful features rather than relying on irrelevant background noise.

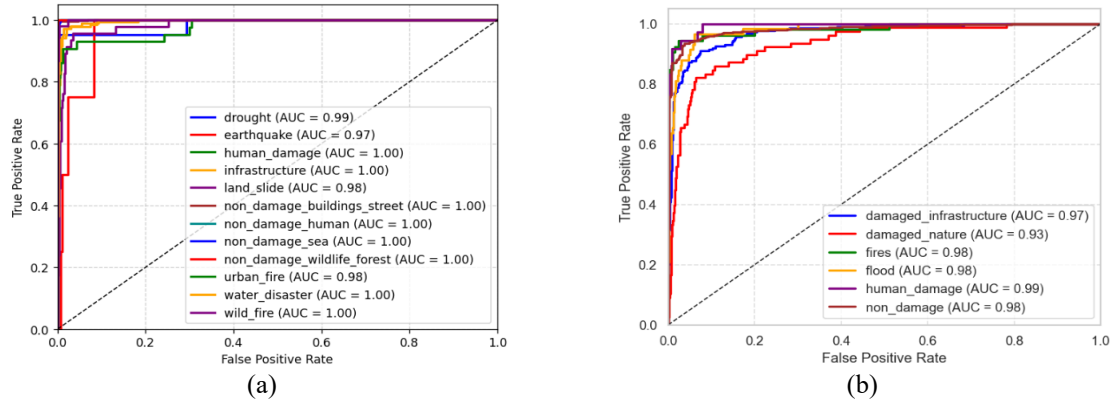


Figure 5. The ROC curve of the proposed LEAD-Net model on (a) CDD datasets and (b) DMD datasets

Table 3. Grad-CAM based model explainability on CDD and DMD datasets

CDD		DMD	
Test images	Activation map	Test images	Activation map

Table 4 provides a comparative analysis of the proposed LEAD-Net model against several well-established CNN architectures such as Inception, DenseNet121, ResNet-50, VGG-16, and AlexNet based on their performance on the CDD and DMD datasets, as well as their model complexity measured by the number of parameters. On the CDD dataset, LEAD-Net achieved the highest accuracy of 96%, outperforming all baseline models, including DenseNet (93%) and ResNet (91%). Similarly, on the more challenging DMD dataset, LEAD-Net maintained superior performance with an accuracy of 87%, compared to 84% for both DenseNet and ResNet, and significantly higher than VGG (73%) and AlexNet (72%). In addition to its strong predictive performance, LEAD-Net is also computationally efficient model, with approximately 6 million parameters than other models, thereby making it much lighter to be deployed in the real-world scenarios. The above outcome suggests that LEAD-Net successfully balances high classification performance with low model complexity for identifying disaster events from the social media posts.

Table 4. Comparative analysis with baseline DL models

Model	Complexity	Accuracy	
		CDD (%)	DFD (%)
Inception	~23 million	89	82
DenseNet-121	~8 million	93	84
ResNet-50	~25 million	91	84
VGG-16	~138 million	88	73
AlexNet	~60 million	84	72
Proposed (LEAD-Net)	~6 million	96	87

**4. CONCLUSION**

This paper proposed LEAD-Net, a DL model designed for effective and interpretable classification of disaster-related images from social media posts. The proposed LEAD-Net is developed based on the integration of EfficientNetB0 CNN architecture and modified SE attention mechanism to achieve a focused learning of complex features from disaster images. To make model training more robust, its hyperparameters are tuned and optimized via a NAS-lite, thereby enabling an optimal balance between accuracy and computational efficiency. The model was evaluated on two benchmark datasets, CDD and DMD, using accuracy, F1-score, ROC-AUC, and model complexity. The model achieved 96% accuracy on the CDD dataset and 87% on the more challenging DMD dataset, and outperforms several baseline CNNs in terms of both classification performance and model complexity. The integration of Grad-CAM further provided visual explanations of the model's decisions, confirming its attention to disaster-relevant regions in the images and enhancing model transparency. Future work may explore the incorporation of multimodal features, such as text and geolocation metadata to enhance the model's practical utility in emergency response applications.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

**CONFLICT OF INTEREST STATEMENT**

Authors state no conflict of interest.

**DATA AVAILABILITY**

The data that support the findings of this study are available on request from the corresponding author, [RKT].




**REFERENCES**

- [1] M. Krichen, M. S. Abdalzaher, M. Elwekeil, and M. M. Fouda, "Managing natural disasters: An analysis of technological advancements, opportunities, and challenges," *Internet of Things and Cyber-Physical Systems*, vol. 4, pp. 99–109, 2024, doi: 10.1016/j.iotcps.2023.09.002.
- [2] V. Jayawardene, T. J. Huggins, R. Prasanna, and B. Fakhruddin, "The role of data and information quality during disaster response decision-making," *Progress in Disaster Science*, vol. 12, 2021, doi: 10.1016/j.pdisas.2021.100202.
- [3] Z. E. L. Khaled and H. Mcheick, "Case studies of communications systems during harsh environments: A review of approaches, weaknesses, and limitations to improve quality of service," *International Journal of Distributed Sensor Networks*, vol. 15, no. 2, 2019, doi: 10.1177/1550147719829960.
- [4] K. Seneviratne, M. Nadeeshani, S. Senaratne, and S. Perera, "Use of social media in disaster management: challenges and strategies," *Sustainability*, vol. 16, no. 11, Jun. 2024, doi: 10.3390/su16114824.
- [5] L. Belcastro *et al.*, "Using social media for sub-event detection during disasters," *Journal of Big Data*, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00467-1.
- [6] A. S. Albahri *et al.*, "A systematic review of trustworthy artificial intelligence applications in natural disasters," *Computers and Electrical Engineering*, vol. 118, Sep. 2024, doi: 10.1016/j.compeleceng.2024.109409.
- [7] A. Akhyar *et al.*, "Deep artificial intelligence applications for natural disaster management systems: a methodological review," *Ecological Indicators*, vol. 163, Jun. 2024, doi: 10.1016/j.ecolind.2024.112067.
- [8] D. Yu and Z. He, "Digital twin-driven intelligence disaster prevention and mitigation for infrastructure: advances, challenges, and opportunities," *Natural Hazards*, vol. 112, no. 1, pp. 1–36, May 2022, doi: 10.1007/s11069-021-05190-x.
- [9] M. Haidarh, C. Mu, Y. Liu, and X. He, "Exploring traditional, deep learning and hybrid methods for hyperspectral image classification: a review," *Journal of Information and Intelligence*, Apr. 2025, doi: 10.1016/j.jiixd.2025.04.002.




- [10] K. Abraham, M. Abdelwahab, and M. A. -Zahhad, "Classification and detection of natural disasters using machine learning and deep learning techniques: a review," *Earth Science Informatics*, vol. 17, no. 2, pp. 869–891, 2024, doi: 10.1007/s12145-023-01205-2.
- [11] L. Ahmed, K. Ahmad, N. Said, B. Qolomany, J. Qadir, and A. A. -Fuqaha, "Active learning based federated learning for waste and natural disaster image classification," *IEEE Access*, vol. 8, pp. 208518–208531, 2020, doi: 10.1109/ACCESS.2020.3038676.
- [12] Z. Ma, W. Li, M. Zhang, W. Meng, S. Xu, and X. Zhang, "HTCViT: an effective network for image classification and segmentation based on natural disaster datasets," *The Visual Computer*, vol. 39, no. 8, pp. 3285–3297, Aug. 2023, doi: 10.1007/s00371-023-02954-3.
- [13] K. A. Sheth, R. P. Kulkarni, and G. K. Revathi, "Enhancing natural disaster image classification: an ensemble learning approach with inception and CNN models," *Geomatics, Natural Hazards and Risk*, vol. 15, no. 1, Dec. 2024, doi: 10.1080/19475705.2024.2407029.
- [14] A. Coopen and S. Pudaruth, "Image classification based on disaster type using deep learning," *International Journal of Computing and Digital Systems*, vol. 15, no. 1, pp. 1473–1483, Sep. 2024, doi: 10.12785/ijcds/1601109.
- [15] A. M. Mustafa, R. Agha, L. Ghazalat, and T. Sha'ban, "Natural disasters detection using explainable deep learning," *Intelligent Systems with Applications*, vol. 23, Sep. 2024, doi: 10.1016/j.iswa.2024.200430.
- [16] M. H. Bashir, M. Ahmad, D. R. Rizvi, and A. A. E. -Latif, "Efficient CNN-based disaster events classification using UAV-aided images for emergency response application," *Neural Computing and Applications*, vol. 36, no. 18, pp. 10599–10612, Jun. 2024, doi: 10.1007/s00521-024-09610-4.
- [17] E. Yasi, T. U. Shakib, N. Sharmin, and T. H. Rizu, "Flood and non-flood image classification using deep ensemble learning," *Water Resources Management*, vol. 38, no. 13, pp. 5161–5178, Oct. 2024, doi: 10.1007/s11269-024-03906-9.
- [18] M. Sathianarayanan, P. -H. Hsu, and C. -C. Chang, "Extracting disaster location identification from social media images using deep learning," *International Journal of Disaster Risk Reduction*, vol. 104, Apr. 2024, doi: 10.1016/j.ijdr.2024.104352.
- [19] K. VanExel, S. Sherchan, and S. Liu, "optimizing deep learning models for climate-related natural disaster detection from UAV images and remote sensing data," *Journal of Imaging*, vol. 11, no. 2, Jan. 2025, doi: 10.3390/jimaging11020032.
- [20] V. Dubey and R. Katarya, "Flood-FireNet: a novel flood image classification architecture using the adaptive firefly algorithm," *Signal, Image and Video Processing*, vol. 19, no. 8, Aug. 2025, doi: 10.1007/s11760-025-04235-z.
- [21] L. Wen, Z. Xiao, X. Xu, and B. Liu, "Disaster recognition and classification based on improved ResNet-50 neural network," *Applied Sciences*, vol. 15, no. 9, May 2025, doi: 10.3390/app15095143.
- [22] Y. Shao and L. Xu, "Multimodal natural disaster scene recognition with integrated large model and mamba," *Applied Sciences*, vol. 15, no. 3, Jan. 2025, doi: 10.3390/app15031149.
- [23] B. Wang, C. Zhao, J. Li, Q. Sheng, and X. Ling, "U2DDS-Net: A new architecture based on U2Net with disaster type for building damage assessment under natural disasters," *The Photogrammetric Record*, vol. 40, no. 189, Jan. 2025, doi: 10.1111/phor.12530.
- [24] A. Verma, "Disaster images dataset," *Kaggle*. [Online]. Available: <https://www.kaggle.com/datasets/varpit94/disaster-images-dataset>
- [25] F. Alam, F. Ofli, and M. Imran, "CrisisMMD: multimodal twitter datasets from natural disasters," in *12th International AAAI Conference on Web and Social Media, ICWSM 2018*, 2018, pp. 465–473, doi: 10.1609/icwsm.v12i1.14983.
- [26] H. Mouzannar, Y. Rizk, and M. Awad, "Damage identification in social media posts using multimodal deep learning," *Proceedings of the International ISCRAM Conference*, vol. 2018-May, pp. 529–543, 2018.
- [27] V. Nikolaou, S. Massaro, M. Fakhimi, L. Stergioulas, and W. Garn, "COVID-19 diagnosis from chest x-rays: developing a simple, fast, and accurate neural network," *Health Information Science and Systems*, vol. 9, no. 1, Dec. 2021, doi: 10.1007/s13755-021-00166-4.

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