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An Intelligent Deep Learning Framework for Flood Risk Mapping from Aerial Imagery

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Abstract
Flood detection and damage assessment from aerial imagery play a critical role in effective disaster response and management. However, accurately identifying flooded roads and damaged areas from large-scale aerial and satellite imagery remains challenging due to variations in illumination, occlusions, water reflections, and complex environmental conditions. To address these challenges, a U-Net-based segmentation model was developed to accurately delineate road regions and distinguish between flooded and non-flooded road segments in aerial imagery. The proposed model employs an encoder–decoder architecture with skip connections to retain fine-grained spatial information while effectively learning high-level semantic features, thereby enabling robust segmentation under diverse environmental conditions.

Keywords: Flood Impact Assessment; Aerial Image Analysis; Deep Neural Networks; Semantic Segmentation; Roadway Extraction; Flood-Affected Infrastructure; Convolutional Neural Networks; EfficientNet-B0; Xception; Disaster Response

1.Introduction

Flooding is a major hydro-meteorological hazard that frequently results in severe disruption to transportation systems, public infrastructure, and populated areas. Rapid and reliable assessment of flood-affected regions is therefore essential for emergency response, resource allocation, and post-disaster recovery. The widespread availability of high-resolution aerial and remote-sensing imagery provides an efficient means of acquiring detailed information over extensive geographic areas. Nevertheless, extracting meaningful information from such imagery remains challenging when performed manually, particularly during large-scale disasters where the volume of image data increases substantially. Differences in illumination, surface appearance, shadows, reflections, and environmental conditions further complicate the identification of inundated areas. These limitations have encouraged the adoption of deep learning and computer vision techniques capable of learning complex visual patterns directly from image data.

In addition to identifying inundated road networks, evaluating the physical condition of infrastructure is essential for determining the severity of flood impacts. Image-based damage classification can assist authorities in identifying areas requiring inspection, repair, or immediate intervention. To perform this assessment, aerial imagery is divided into standardized 128 × 128-pixel patches and analyzed using two established deep convolutional neural network architectures, Xception and EfficientNet-B0. The models are trained to perform binary classification by assigning each image patch to either a damaged or non-damaged category. Xception employs depthwise separable convolution operations to achieve efficient extraction of representative visual features while limiting computational requirements. EfficientNet-B0 adopts a systematic network-scaling strategy that balances model complexity with predictive performance. The complementary characteristics of these architectures provide a basis for evaluating their suitability for automated infrastructure damage recognition.

The combination of road-level semantic segmentation and image-patch-based damage classification establishes an integrated framework for automated flood impact analysis. Such a framework can transform large volumes of aerial imagery into actionable information concerning inundated transportation corridors and potentially damaged infrastructure. By minimizing dependence on time-intensive manual inspection, the proposed approach can contribute to faster situational awareness and more informed decision-making during emergency response and recovery activities. Furthermore, the integration of segmentation and classification capabilities provides a foundation for scalable, data-driven flood assessment that can support infrastructure resilience and disaster management planning.

1.1 Motivation

The proposed framework is intended to convert complex aerial imagery into structured information that can assist emergency management authorities and response teams. Automated identification of affected road sections can help determine potentially inaccessible routes, whereas damage classification can provide additional evidence for prioritizing inspection and restoration activities. By minimizing the dependence on manual image interpretation, the approach has the potential to improve the speed, consistency, and scalability of post-flood assessment.

1.2 Objectives:

The research further aims to establish a comprehensive analytical framework by integrating flood segmentation and infrastructure damage classification into a unified workflow. Such integration is expected to enable the generation of both spatial flood maps and quantitative information regarding affected infrastructure, providing a more complete representation of post-flood conditions. The study also focuses on evaluating model robustness under challenging image conditions, including variations in illumination, background complexity, image noise, occlusions, and water-surface reflections. Model performance will be assessed using appropriate evaluation measures to examine segmentation quality, classification reliability, and computational efficiency.

2.Related work

Flood-related disasters frequently cause extensive disruption to transportation systems and built infrastructure, creating a need for rapid methods to determine the location and severity of affected areas. Remote sensing platforms have become valuable sources of post-disaster information because they can capture large geographic regions without requiring direct access to hazardous locations. The increasing use of high-resolution aerial, UAV, and satellite imagery has consequently encouraged researchers to develop automated approaches for extracting flood-related information. Deep learning has emerged as an effective solution in this context because its ability to learn hierarchical representations directly from image data reduces the dependence on manually designed image-processing rules. Recent investigations have shown that deep neural networks can provide reliable flood delineation and assist in converting remotely sensed observations into useful information for emergency assessment [1].A major challenge in flood-image interpretation is the accurate separation of inundated surfaces from visually similar objects and unaffected regions. Water bodies may exhibit substantially different appearances depending on illumination, viewing conditions, surrounding land cover, and surface reflections. Conventional pixel-based and threshold-driven techniques can therefore produce inconsistent results when applied to heterogeneous aerial scenes. Semantic segmentation approaches address this limitation by assigning a meaningful class to individual pixels while simultaneously considering their surrounding context. Among the available architectures, U-Net has been widely investigated because its contracting and expanding paths allow the network to combine semantic representations with detailed spatial information. Several studies have reported that U-Net-based networks can effectively identify flood extent and preserve boundary information in remotely sensed imagery [2]. The characteristics of aerial imagery also make model architecture an important consideration. Unlike low-resolution satellite observations, aerial images may contain roads, buildings, vegetation, vehicles, shadows, and other objects within the same scene. Consequently, a segmentation model must be capable of distinguishing floodwater from visually complex backgrounds while maintaining accurate object boundaries. Researchers have addressed this issue through modified encoder–decoder architectures, attention mechanisms, multiscale feature extraction, and alternative backbone networks. These developments have demonstrated that improving feature representation can enhance the identification of irregular and partially obscured flood regions [3]. Such findings are particularly relevant to road-level flood analysis, where narrow road segments may be surrounded by water, vegetation, or built structures. Flood mapping alone, however, does not provide sufficient information about the condition of infrastructure after a disaster. Two locations may experience similar levels of inundation while exhibiting substantially different levels of physical damage. Consequently, automated damage recognition has become an additional research direction in post-disaster image analysis. Convolutional neural networks are particularly suitable for this task because they can learn discriminative patterns associated with changes in texture, shape, edges, and structural appearance. Research using aerial and remotely sensed imagery has demonstrated that CNN-based approaches can assist in identifying damaged buildings, roads, and other infrastructure components with considerably less manual intervention [4].

Transfer learning has further expanded the applicability of deep CNNs to disaster-related datasets. Pre-trained architectures can utilize visual representations learned from large-scale image collections and subsequently adapt these features to specialized disaster-classification tasks. This strategy is beneficial when labeled post-disaster imagery is limited, which is a common issue in emergency-response applications. Xception is one such architecture that employs depthwise separable convolutions to improve feature-learning efficiency, while EfficientNet introduces systematic scaling of network dimensions to achieve a favorable relationship between predictive capability and computational demand. Comparative studies of lightweight and pre-trained CNN architectures have indicated that these models can provide competitive results for image classification while reducing the resources required for model training and deployment [5]. Another emerging direction involves combining different deep learning tasks rather than treating flood mapping and infrastructure assessment as independent problems. A segmentation model can establish the geographical distribution of floodwater, whereas a classification model can provide additional information concerning the condition of infrastructure within the affected region. This complementary relationship creates an opportunity to construct a multi-stage disaster assessment pipeline in which the output of spatial analysis provides contextual information for subsequent infrastructure evaluation. Recent multimodal and multitask studies have demonstrated the value of integrating flood extent, object detection, and damage-related information to obtain a more comprehensive representation of disaster consequences [6]. Despite these developments, reliable automated flood assessment remains affected by several unresolved issues. Variations in weather and illumination can alter the visual characteristics of water surfaces, while shadows and occlusions may conceal important portions of roads and infrastructure. In addition, models trained on a particular geographic region may experience reduced performance when applied to imagery acquired under different environmental or geographical conditions. The computational requirements of complex deep learning architectures also need to be considered when rapid analysis is required during emergency situations. Therefore, there is a continuing need for frameworks that combine accurate spatial segmentation with efficient infrastructure classification while maintaining practical computational requirements [7]. Based on the limitations identified in existing research, an integrated approach that addresses both flood-affected road identification and infrastructure damage recognition can provide more useful information for post-disaster decision-making. The present study therefore investigates a combined deep learning framework in which U-Net-based semantic segmentation is used to identify flood-affected road regions, followed by CNN-based classification using Xception and EfficientNet-B0 to distinguish damaged and non-damaged aerial image patches. Rather than relying solely on flood extent, the proposed framework considers both the spatial distribution of flooding and the visual condition of affected infrastructure. This integrated perspective is intended to support faster flood-impact assessment and provide a scalable foundation for intelligent emergency response, infrastructure monitoring, and post-disaster recovery planning. models provide improved performance; their high complexity often limits deployment on low-resource hardware commonly used in field operations. Therefore, designing efficient yet accurate architectures is critical for practical applications. Techniques like depthwise separable convolutions, used in Xception, and compound scaling.

2.1 Types of Learning models for Deep Learning:

2.1.1 U-Net:

U-Net is an encoder–decoder-based deep neural network specifically designed to perform pixel-wise image segmentation. The architecture consists of three principal components: an encoder, a bottleneck, and a decoder. For binary flood segmentation, the final decoder output is passed through a imes convolutional layer followed by a sigmoid activation function. The sigmoid operation converts the extracted features into pixel-level probabilities representing the likelihood that each pixel belongs to the target class. The probability of a pixel being classified as flood-affected can be expressed as:

$$Z_{i,j,k} = \sum_{m}\sum_{n}\sum_{c} W_{m,n,c,k} X_{i+m,j+n,c} + b_k$$

where z is the output of the network for each pixel.

2.1.2 Autoencoder:

An Autoencoder (AE) is a type of neural network that learns to represent input data in a compact form and then reconstruct the original input. It consists mainly of two parts: Encoder: Converts the input into a smaller, meaningful representation called the latent representation. Decoder: Uses this latent representation to reconstruct the original input. The basic process can be represented as:

$$X \rightarrow \text{Encoder} \rightarrow Z \rightarrow \text{Decoder} \rightarrow \hat{X}$$

where (X) is the original input, (Z) is the compressed representation, and ({X}) is the reconstructed output.

2.1.3 CNN

A conventional CNN consists of convolutional, activation, pooling, and fully connected layers. The convolutional layers apply learnable filters to generate feature maps, while activation functions such as ReLU introduce non-linearity into the network. Pooling operations reduce the spatial dimensions of feature maps and help retain the most informative characteristics. The extracted features are subsequently used by the classification layers to determine the appropriate class.The fundamental convolution operation can be represented as:

$$Z_{i,j,k} = \sum_{m} \sum_{n} \sum_{c} W_{m,n,c,k} X_{i+m,j+n,c} + b_k$$

where X represents the input feature map, W denotes the convolutional kernel, bk_ is the bias associated with the kth filter, and Zi,j,k represents the resulting feature map.

3.Proposed Methodology

The proposed study introduces a multi-stage deep learning framework for analyzing flood-affected transportation infrastructure from aerial imagery. Instead of relying on a single prediction model, the framework separates the problem into complementary stages involving image preparation, representation learning, flood-region segmentation, and infrastructure-condition classification. This arrangement allows the system to first understand the visual characteristics of the input scene and subsequently determine the spatial extent and condition of the affected road infrastructure.

The methodology begins with the preparation of the aerial image dataset. Images acquired from aerial or UAV sources are organized according to the requirements of the segmentation and classification tasks. Image dimensions are standardized, pixel values are normalized, and unsuitable or corrupted samples are removed. To improve the diversity of training data, controlled transformations such as rotation, horizontal and vertical flipping, scaling, cropping, and brightness variation can be introduced. These operations help the models learn representations that are less sensitive to changes in viewpoint and environmental conditions. The prepared images are then divided into training, validation, and testing subsets to enable unbiased evaluation of the developed models.

The training strategy is designed to improve the reliability of both segmentation and classification models. Appropriate loss functions are selected according to the respective learning tasks. Binary cross-entropy can be used for the damaged/non-damaged classification task, while segmentation can be optimized using Dice loss, binary cross-entropy, or a combination of these losses. The Dice coefficient is particularly useful when the flood-affected region occupies a relatively small proportion of the complete image. Model parameters are optimized using the Adam optimization algorithm, and validation performance is monitored during training to reduce overfitting. Early stopping and learning-rate adjustment can additionally be applied when required.

After independent model training, the outputs are analyzed jointly to produce a more informative representation of flood impact. The U-Net output provides the geographical location of flood-affected road segments, whereas the CNN models provide an indication of the damage condition associated with image patches. Autoencoder-derived representations can further be used to examine the underlying visual characteristics of the aerial data and identify reconstruction-based anomalies. The combined outputs can subsequently be projected onto the original aerial imagery to generate an interpretable flood-impact visualization.

The overall framework therefore combines Autoencoder-based representation learning, U-Net-based semantic segmentation, and CNN-based damage classification to obtain complementary information from aerial flood imagery. The methodology is designed not only to determine the spatial distribution of flood-affected roads but also to characterize their apparent damage condition. Such an integrated approach can provide more meaningful information for emergency route assessment, infrastructure inspection, flood-impact visualization, and post-disaster recovery planning.

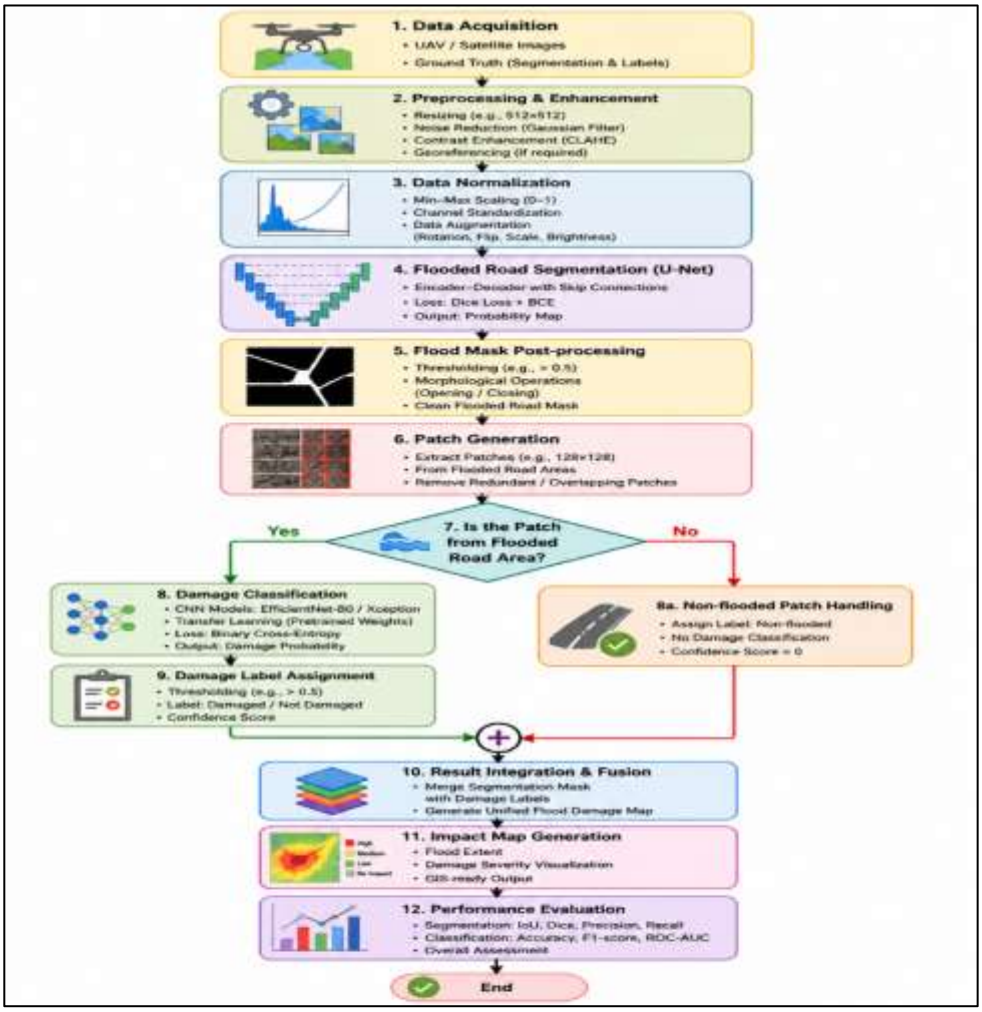

Figure 1. Proposal Model

This multi-model strategy provides a foundation for developing scalable and intelligent disaster-analysis systems capable of assisting rapid assessment, infrastructure monitoring, emergency planning, and data-supported decision-making.

3.1 Dataset:

The two datasets serve complementary purposes within the proposed methodology. FloodNet provides the basis for learning the spatial characteristics of flood-affected regions, whereas the Hurricane Damage Detection dataset supports the learning of visual patterns associated with infrastructure damage. Their use enables the proposed framework to address both flood-region delineation and damage recognition rather than treating flood detection as an isolated image-classification problem.

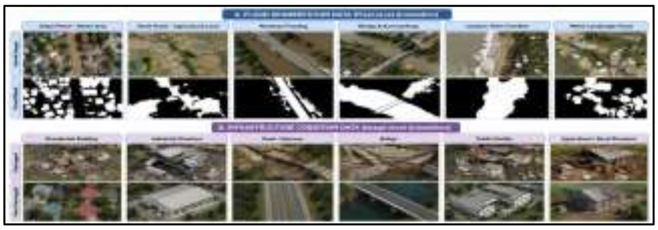

Figure 2: Dataset for Classification

3.2 Data Processing:

To increase the diversity of training samples and improve model robustness, controlled image augmentation is applied to the training data. Transformations such as rotation, horizontal and vertical flipping, zooming, cropping, and brightness variation are used to simulate differences commonly observed in aerial imagery. The augmented samples are supplied to the U-Net and CNN models in batches during training, while validation and testing data remain separated from the augmentation process. This preparation strategy helps reduce overfitting and enables the models to learn more generalizable visual features for flood segmentation and infrastructure damage classification.

3.3 Model Training:

The proposed framework employs U-Net as the primary network for extracting flood-affected road regions from aerial images. The model follows an encoder–decoder design in which the encoder learns progressively deeper representations of the input scene, while the decoder restores the spatial resolution required for pixel-level prediction. Information from corresponding encoder stages is transferred to the decoder through skip connections, helping preserve important road boundaries and fine spatial details.

For the flood-mapping task, the network produces a binary segmentation output that identifies pixels associated with inundated and non-inundated regions. The combination of contextual feature extraction and spatial-detail recovery enables the model to distinguish flooded road surfaces from surrounding objects such as vegetation, buildings, and other background structures. This makes the approach suitable for aerial scenes containing variations in illumination, shadows, water reflections, and partial obstructions.

4. S/W Requirement:

The implementation and evaluation of the proposed deep learning framework were carried out using a Python-based computational environment. Python 3.10 was used as the primary programming platform, with TensorFlow 2.12 and Keras supporting the development and training of the neural network models. Standard libraries, including NumPy, Pandas, OpenCV, and Matplotlib, were utilized for image handling, dataset organization, preprocessing, augmentation, and result visualization. Jupyter Notebook was used to manage the experimental workflow and facilitate model development and analysis.

5.Results

5.1 Evaluation and Metrics

To evaluate the performance of our deep learning models, we used metrics that measure how accurately and reliably the models identify flooded roads and classify damaged areas. This included accuracy, which shows the overall correctness of predictions; precision, which measures how many predicted flooded or damaged regions are actually correct; recall, which indicates how many actual flooded or damaged areas are correctly identified; and F1-score, which balances precision and recall. Confusion matrices were also used to visualize misclassifications across classes. These metrics help identify strengths and weaknesses of each model, guide improvements, and ensure the system can reliably support automated flood impact assessment and disaster management.

Model	IoU (%)	Dice Coefficient (%)	Precision (%)	Recall (%)	Overall Accuracy (%)	AUC-ROC (%)
EfficientNet-B0	87.45	91.23	88.91	89.67	92.18	94.32
Xception	80.34	85.71	81.26	82.19	86.73	88.91
U-Net (Segmentation)	83.62	89.04	86.48	87.35	90.11	92.07

Table 1: Performance Parameter with accuracy

The comparative performance of the three deep learning models is presented in the figure using IoU, Dice coefficient, Precision, Recall, Overall Accuracy, and AUC-ROC. EfficientNet-B0 achieves the strongest overall performance, with an IoU of 87.45%, Dice coefficient of 91.23%, Precision of 88.91%, Recall of 89.67%, Overall Accuracy of 92.18%, and AUC-ROC of 94.32%. U-Net also demonstrates good segmentation performance, particularly with a Dice coefficient of 89.04% and recall of 87.35%, confirming its effectiveness for identifying flood-affected regions. Xception records comparatively lower values across the evaluated metrics, with an overall accuracy of 86.73% and AUC-ROC of 88.91%. Overall, the results indicate that EfficientNet-B0 provides the most consistent and effective performance among the evaluated models, while U-Net is well suited for spatial lood-region segmentation.

Figure 3: Loss curves

The training and validation plots indicate a classic case of overfitting. The training loss steadily decreases and stabilizes around 0.3, while the training accuracy approaches ~96%, showing the model is learning the training data very well.

Figure 4: Model Accuracy

However, the validation loss plateaus around 0.32, and validation accuracy stagnates near 91%, suggesting the model's performance on unseen data is lower. The gap between training and validation metrics after epoch 10 highlights overfitting, where the model captures training-specific patterns rather than generalizable features. Early stopping or regularization techniques like dropout could help improve generalization.

The confusion matrix illustrates the classification performance of the model across four classes: glioma, meningioma, notumor, and pituitary. The diagonal elements show correctly predicted instances, with glioma at 137, meningioma at 169, notumor at 205, and pituitary at 138, indicating high accuracy in identifying each class. Off-diagonal elements represent misclassifications, which are minimal—for example, 3 glioma cases were misclassified as meningioma, and 1 meningioma case was misclassified as glioma or pituitary. Overall, the matrix demonstrates that the model reliably distinguishes between tumor types, with very few errors, highlighting its strong diagnostic performance and practical applicability.

7. Conclusion

The findings of this research indicate that deep learning can provide a practical computational framework for analyzing flood-affected infrastructure from aerial imagery. Rather than relying on a single prediction model, the proposed approach separates the problem into spatial identification and infrastructure-condition analysis, allowing each stage to address a specific aspect of post-disaster interpretation. Despite these advantages, the performance of such systems remains dependent on the quality, diversity, and representativeness of the training imagery. Differences in weather, image resolution, viewing angle, water reflections, shadows, occlusions, and structural characteristics may influence prediction reliability. Future research should therefore investigate larger and geographically diverse datasets, advanced attention- and transformer-based architectures, multimodal remote-sensing data, and lightweight models suitable for near-real-time deployment. Overall, the study establishes a foundation for automated aerial-image-based flood impact analysis by combining spatial segmentation with deep visual assessment. The proposed methodology demonstrates the feasibility of converting disaster imagery into structured information that can contribute to faster assessment, improved infrastructure monitoring, and more informed post-flood recovery planning.

References

[1] D. Hernández, J. M. Cecilia, J.-C. Cano, and C. T. Calafate, "Flood detection using real-time image segmentation from unmanned aerial vehicles on edge-computing platform," *Remote Sensing*, vol. 14, no. 1, Art. no. 223, 2022, doi: 10.3390/rs14010223.

[2] F. Safavi and M. Rahnemoonfar, "Comparative study of real-time semantic segmentation networks in aerial images during flooding events," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 16, pp. 15–31, 2023, doi: 10.1109/JSTARS.2022.3219724.

[3] S. D. Khan and S. Basalamah, "Multi-scale and context-aware framework for flood segmentation in post-disaster high resolution aerial images," *Remote Sensing*, vol. 15, no. 8, Art. no. 2208, 2023, doi: 10.3390/rs15082208.

[4] A. Jamali, S. K. Roy, L. Hashemi Beni, B. Pradhan, J. Li, and P. Ghamisi, "Residual wave vision U-Net for flood mapping using dual polarization Sentinel-1 SAR imagery," *International Journal of Applied Earth Observation and Geoinformation*, vol. 127, Art. no. 103662, 2024, doi: 10.1016/j.jag.2024.103662.

[5] Y. Jiang, "Road damage detection and classification using deep neural networks," *Discover Applied Sciences*, vol. 6, Art. no. 421, 2024, doi: 10.1007/s42452-024-06129-0.

[6] S. Preetha, S. Priya M. S., and P. Manikandan, "Optimized flood scene segmentation with Swin Transformer-based architecture," *Scientific Reports*, vol. 16, Art. no. 20532, 2026, doi: 10.1038/s41598-026-39188-x.

[7] J. Ranjbar, H. Ebrahimnezhad, and M. H. Sedaaghi, "SWUFlood: Segmentation of flood-affected regions in UAV imagery using an enhanced hybrid approach integrating shifted window transformers with U-Net," *Remote Sensing Applications: Society and Environment*, vol. 42, Art. no. 102018, 2026, doi: 10.1016/j.rsase.2026.102018.

[8] H. Shokati, K. D. Seufferheld, P. Fiener, and T. Scholten, "Rapid flood mapping from aerial imagery using fine-tuned SAM and ResNet-backboned U-Net," *Hydrology and Earth System Sciences*, vol. 30, pp. 743–765, 2026.

[9] M. U. Danish, M. Buwaneswaran, T. Fonseka, and K. Grolinger, "Graph attention convolutional U-Net: A semantic segmentation model for identifying flooded areas," arXiv preprint arXiv:2502.15907, 2025.

[10] B. V. Kumar, M. K. Goel, and G. Singh, "Flood area segmentation using U-Net: A deep learning approach with UAV and satellite imagery," in *Proc. 2025 6th International Conference for Emerging Technology (INCET)*, 2025, doi: 10.1109/INCET64471.2025.11140089.

[11] A. Andriany and N. Sulistianingsih, "Pemanfaatan model U-Net berbasis deep learning untuk segmentasi citra dalam identifikasi area genangan banjir," *Prosiding Seminar Nasional Sains Teknologi dan Inovasi Indonesia*, vol. 7, 2025, doi: 10.54706/senastindo.v7.2025.419.

[12] "Semantic segmentation of aerial images using pixel-wise segmentation," *Procedia Computer Science*, vol. 259, pp. 463–472, 2025, doi: 10.1016/j.procs.2025.03.348.

[13] "Hurricane damage detection from satellite imagery using convolutional neural networks," *International Journal of Information Systems and Management*, 2022, doi: 10.4018/IJISMD.306637.

[14] Y. Srinivas, V. K. Lakshmi, N. R., V. S., and S. S. G., "Autonomous road damage detection using unmanned aerial vehicle images and YOLO V8 methods," *Turkish Journal of Computer and Mathematics Education*, vol. 15, no. 3, 2024, doi: 10.61841/turcomat. v15i3.14782.

[15] R. S. Kumar, "Automated Road damage detection using UAV images and deep learning techniques," *American Journal of AI Cyber Computing Management*, 2026.

[16] P. Aishwarya, S. Geethika, L. V. Prasad, P. C. S. Naidu, and B. K. Kumari, "Deep learning-powered automated road damage detection using UAV images," *International Journal of Engineering Research and Science & Technology*, 2026.

[17] "Flood scene understanding using U-Net and DeepLabV3+: Semantic segmentation on FloodNet," in *Proc. 2025 International Conference on Intelligent Computer Systems, Data Science and Applications (IC2SDA)*, 2025, doi: 10.1109/IC2SDA68097.2025.11331401.

[18] "A hybrid deep learning approach using Vision Transformer and U-Net for flood segmentation," *Computers, Materials & Continua*, vol. 86, no. 2, 2025.
[19] D. H. M. Patel, D. P. K. Shah, D. A. A. Sutariya, P. A. M. Patel, and D. A. V. Shah, "Intelligent crop disease prediction using IoT sensors and deep learning," *International Journal of Artificial Intelligence and Machine Learning*, vol. 6, no. 2, pp. 151–161, 2026, doi: 10.51483/IJAIML.6.2.2026.151-161.