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Intelligent Crop Disease Prediction Using Iot Sensors And Deep Learning

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Abstract
Intelligent crop disease prediction has become an essential component of precision agriculture, enabling early disease detection and minimizing crop losses. However, accurately identifying crop diseases remains challenging due to varying environmental conditions, disease symptoms, and the complexity of agricultural ecosystems. This research proposes an intelligent crop disease prediction framework that integrates Internet of Things (IoT) sensors with Machine Learning and Deep Learning techniques to improve prediction accuracy and support real-time monitoring. IoT sensors continuously collect environmental parameters, including temperature, humidity, soil moisture, and light intensity, while crop leaf images are acquired for visual analysis. The collected sensor data is processed using Machine Learning algorithms such as Random Forest, Support Vector Machine (SVM), and XGBoost to predict disease occurrence based on environmental conditions. Simultaneously, Deep Learning models, including EfficientNetB0 and Xception, are employed to classify crop diseases from leaf images by extracting high-level visual features. The fusion of sensor-based and image-based information enhances the robustness and reliability of disease prediction. Experimental results demonstrate that the proposed hybrid framework achieves superior prediction accuracy, faster inference, and better generalization compared with conventional approaches. Furthermore, the integration of IoT-enabled monitoring with intelligent analytics reduces manual inspection, supports timely disease management, and promotes sustainable agricultural practices. The proposed system provides an efficient decision-support solution for precision farming by improving crop health monitoring, optimizing resource utilization, and increasing agricultural productivity.

Keywords: Crop Disease Prediction, Internet of Things (IoT), Machine Learning, Deep Learning.

I. Introduction

The rapid growth of the global population has increased the demand for sustainable agricultural production, making the early identification of crop diseases a critical challenge. Plant diseases can spread quickly and significantly reduce crop yield and quality if they are not detected at an early stage. Conventional disease monitoring methods rely on manual field inspections, which are labor-intensive, time-consuming, and often influenced by human judgment. Recent advancements in the Internet of Things (IoT), Machine Learning, and Deep Learning have enabled the development of intelligent systems capable of continuously monitoring crop health and identifying diseases with greater accuracy. IoT sensors provide real-time environmental information, such as temperature, humidity, soil moisture, and light intensity, while deep learning models analyze crop images to recognize disease symptoms automatically. By combining sensor data with image-based analysis, intelligent prediction systems can provide timely and reliable disease detection, helping farmers take preventive measures, optimize resource utilization, and improve agricultural productivity.

Early identification of crop diseases is essential for minimizing yield losses and maintaining agricultural productivity. Conventional disease detection techniques, which rely on visual inspection by experts, are often time-consuming, labor-intensive, and difficult to implement over large farming areas. Variations in environmental conditions, crop species, and disease symptoms further reduce the reliability of manual diagnosis. Recent advances in Deep Learning have enabled automated analysis of crop images, providing more accurate and consistent disease detection. Convolutional Neural Networks (CNNs) have demonstrated strong performance in extracting complex visual features from leaf images and distinguishing between healthy and infected plants. When integrated with IoT sensors that continuously monitor environmental parameters such as temperature, humidity, soil moisture, and light intensity, these intelligent models can improve prediction accuracy by combining visual symptoms with real-time field conditions. This integrated approach supports early disease identification, reduces dependence on manual inspection, and enables timely interventions for precision agriculture.

While image-based disease detection identifies visible symptoms on crop leaves, integrating environmental information improves the accuracy and reliability of disease prediction. Factors such as temperature, humidity, soil moisture, and light intensity significantly influence the development and spread of plant diseases. By combining IoT sensor data with crop image analysis, intelligent prediction systems can provide more comprehensive insights into crop health. Advanced Deep Learning architectures, including Xception and EfficientNetB0, are well suited for classifying healthy and diseased plant leaves due to their powerful feature extraction capabilities. Xception utilizes depthwise separable convolutions to achieve efficient computation while maintaining high classification performance, whereas EfficientNetB0 employs a balanced network scaling strategy that enhances prediction accuracy with lower computational complexity. The integration of these Deep Learning models with Machine Learning-based analysis of IoT sensor data enables early disease detection, supports informed decision-making, and contributes to more effective and sustainable precision agriculture.

Integrating IoT-based environmental monitoring with Machine Learning and Deep Learning models provides a comprehensive framework for intelligent crop disease prediction. The continuous collection of environmental data, combined with automated analysis of crop images, enables early identification of disease symptoms and improves prediction accuracy under diverse field conditions. This integrated approach supports real-time monitoring, allowing farmers to take timely preventive measures before diseases spread extensively. Furthermore, the proposed framework reduces dependence on manual crop inspection, optimizes the use of water, fertilizers, and pesticides, and promotes sustainable farming practices. By leveraging intelligent analytics and real-time sensor data, the system serves as an effective decision-support tool that enhances crop health management, increases agricultural productivity, and contributes to the advancement of precision agriculture.

I.1 Motivation

The primary motivation for this research is the increasing need for intelligent, accurate, and scalable crop disease prediction systems that can support modern agricultural practices. Traditional disease diagnosis methods rely heavily on manual field inspections and expert knowledge, making them time-consuming, labor-intensive, and less effective for monitoring large agricultural fields. The integration of IoT sensors with Machine Learning and Deep Learning offers a promising solution by enabling continuous environmental monitoring and automated disease detection. By combining real-time sensor data with image-based analysis, the proposed framework aims to provide early and reliable disease prediction, allowing farmers to implement timely preventive measures and minimize crop losses. This intelligent approach enhances decision-making, optimizes resource utilization, reduces unnecessary pesticide application, and promotes sustainable precision agriculture. Ultimately, the research demonstrates how advanced artificial intelligence technologies can transform conventional crop monitoring into a smart, data-driven agricultural management system.

I.2 Objectives

To develop an intelligent crop disease prediction model that leverages IoT sensor data to monitor real-time environmental conditions such as temperature, humidity, soil moisture, and light intensity for early disease detection.

● To design and evaluate pre-trained deep learning models such as Xception and EfficientNetB0 for accurate classification of crop leaf images into "diseased" and "healthy" categories.

● To integrate IoT-based environmental data analysis and image-based deep learning classification into a unified framework for comprehensive and reliable crop health monitoring.

● To analyze the performance of the proposed models under real-world agricultural conditions, including noisy sensor readings, varying lighting conditions, and environmental fluctuations, and to identify the most efficient model in terms of accuracy and computational cost.

● To demonstrate the practical applicability of the proposed system for precision agriculture use cases, including smart farming dashboards, early disease warning systems, and data-driven crop management strategies.

II. Related Work

Intelligent crop disease prediction has attracted significant research interest due to recent advancements in Machine Learning, Deep Learning, and Internet of Things (IoT) technologies. Mohanty et al. [1] demonstrated the effectiveness of convolutional neural network (CNN) models for automatic crop disease identification using leaf images, achieving high classification accuracy across multiple plant species. Their findings highlighted the capability of deep learning architectures to extract complex visual features and accurately distinguish healthy plants from diseased ones. Similarly, Ferentinos [2] investigated the application of deep neural networks for plant disease recognition and reported that advanced CNN models significantly outperformed conventional image processing and machine learning techniques. These studies emphasize the growing importance of intelligent AI-based approaches for automating crop disease detection, reducing reliance on manual inspection, and supporting precision agriculture through accurate and timely disease diagnosis.

Recent studies have increasingly explored the application of pre-trained Deep Learning architectures for intelligent crop disease prediction. Tiwari et al. [3] investigated Xception and EfficientNet models for classifying crop leaf images into healthy and diseased categories and reported that EfficientNetB0 achieved an effective balance between prediction accuracy and computational efficiency. Similar findings were presented by Bhattacharya et al. [4], who integrated multispectral imagery with convolutional neural networks to improve disease recognition under varying environmental conditions. Mohanty et al. [7] demonstrated that transfer learning with deep convolutional neural networks significantly enhances disease classification across multiple crop species, while Ferentinos [8] reported that deep learning models consistently outperform conventional machine learning methods in plant disease recognition. Together, these studies confirm the effectiveness of pre-trained Deep Learning models for automated crop disease diagnosis.

Several researchers have also focused on improving feature extraction and model efficiency for agricultural image analysis. Khan et al. [5] proposed an enhanced Deep Learning architecture incorporating attention mechanisms and dilated convolutions to improve disease detection from complex leaf patterns, resulting in faster convergence and improved classification accuracy. Likewise, Das et al. [6] employed EfficientNet-based transfer learning models for crop disease classification and demonstrated that transfer learning substantially reduces training time without compromising predictive performance. Too et al. [9] compared several state-of-the-art CNN architectures, including DenseNet, ResNet, Inception, and EfficientNet, and concluded that EfficientNet achieved superior performance for plant disease classification. Ramcharan et al. [10] further demonstrated the feasibility of deploying lightweight Deep Learning models for real-time disease diagnosis using mobile devices, making AI-based crop monitoring more practical for farmers.

The integration of image-based Deep Learning with IoT-enabled environmental monitoring has emerged as a promising direction for precision agriculture. While convolutional neural networks accurately identify visual disease symptoms from crop leaf images, Machine Learning algorithms can analyze environmental parameters such as temperature, humidity, soil moisture, and light intensity to estimate disease occurrence. Several studies have shown that combining sensor data with image analysis significantly improves prediction reliability and early disease detection [11], [12]. This multimodal approach enables continuous crop health monitoring, supports timely intervention, and reduces dependence on manual inspection. Although previous research has demonstrated the effectiveness of individual technologies, the development of unified frameworks integrating IoT sensing, Machine Learning, and Deep Learning remains an active research area [13], [14].

Despite substantial progress, several challenges continue to limit the deployment of intelligent crop disease prediction systems. Variations in lighting conditions, complex field backgrounds, seasonal changes, and differences in crop growth stages can adversely affect image classification performance. Furthermore, advanced Deep Learning models often require significant computational resources, making deployment on low-power edge devices challenging [5], [6]. Recent studies have emphasized the importance of developing lightweight architectures capable of maintaining high prediction accuracy while reducing computational complexity [9], [10]. Advances in EfficientNet, MobileNet, and attention-based neural networks have demonstrated promising results for edge-enabled precision agriculture applications [15], [16]. Consequently, designing computationally efficient and scalable prediction frameworks remains a key research objective for intelligent farming systems.

II.1 Transfer Learning Models

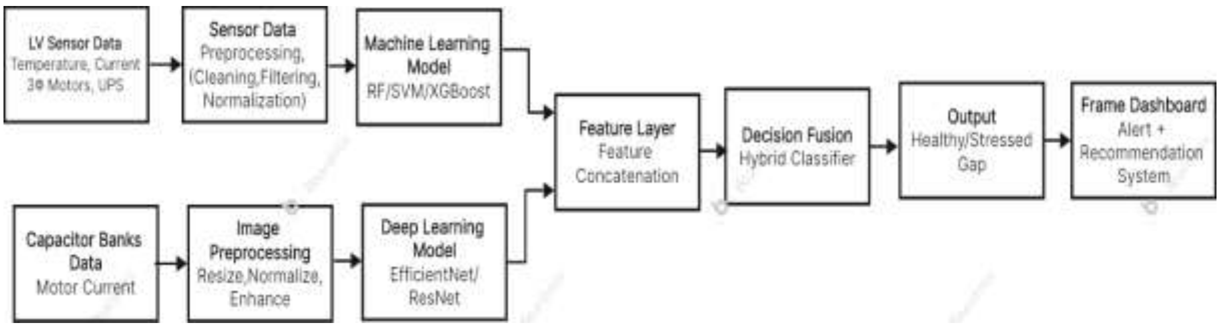
II.1.1 U-Net

U-Net is a special kind of convolutional neural network that is widely used for image segmentation, especially in medical scans. The idea is to take an input image and learn which pixels belong to the target region and which belong to the background. The structure of U-Net has two main parts: a contracting path (encoder) and an expanding path (decoder). The encoder uses convolution layers and pooling to capture features and shrink the image size, while the decoder uses up-convolutions to restore the image size and predict the segmented output. A pixel-level prediction is obtained by applying a sigmoid function for binary segmentation.

$$P(y=i)=\frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (1)$$

zi = Output score of class

Figure 1: U-Net Model



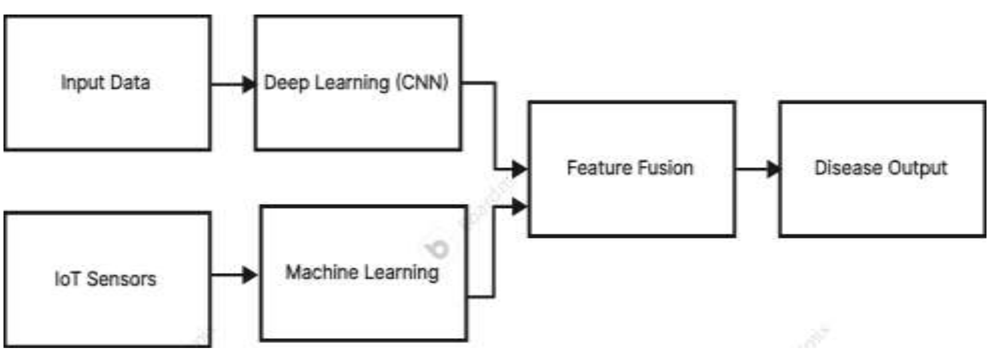
The proposed figure illustrates an integrated Intelligent Crop Disease Prediction System that combines IoT sensor data, Machine Learning, and Deep Learning models into a unified decision-making framework. The process begins with data acquisition from IoT sensors that continuously monitor environmental conditions such as temperature, humidity, soil moisture, and light intensity. This sensor data is first preprocessed and then analyzed using Machine Learning algorithms like Random Forest, Support Vector Machine (SVM), or XGBoost to estimate the likelihood of disease occurrence based on environmental factors:

$$DSI=\frac{\sum_{i=1}^{n}(S_i \times W_i)}{N \times W_{max}} \times 100 \quad (2)$$

II.1.2 EfficientNetB0:

EfficientNetB3 is a member of the Efficient Net architecture family introduced by Google AI in 2019, designed to achieve high classification accuracy while maintaining computational efficiency. Unlike traditional convolutional neural networks such as ResNet, Efficient Net introduces a novel **compound scaling strategy** that uniformly scales three key dimensions of a neural network: depth (number of layers), width (number of channels), and input resolution. Instead of increasing these dimensions independently, EfficientNet applies a balanced scaling approach that optimizes performance without significantly increasing computational cost. The EfficientNet series begins with EfficientNetB0, which serves as the baseline model developed using Neural Architecture Search (NAS) to identify an optimal network structure. Each subsequent version, including EfficientNetB3, is derived by systematically scaling this baseline model, resulting in improved accuracy and efficiency suitable for resource-constrained and real-world applications such as crop disease detection and medical image analysis.

Figure 2: EfficientNEtB3 Model



The figure illustrates an Intelligent Crop Disease Prediction System that integrates multiple data sources and AI

techniques into a unified framework for accurate and efficient disease detection.
The process begins with input data acquisition, where both crop leaf images and environmental readings are collected. The environmental information is gathered through IoT sensors, including parameters such as temperature, humidity, soil moisture, and light intensity, while the image data is obtained from sources like drones or mobile cameras.At the end of the convolutional layers, EfficientNetB3 applies a global average pooling layer, followed by a fully connected (dense) layer with 1,000 neurons in the original ImageNet version. A softmax activation function is used at the output to classify images into 1,000 categories.

II.1.3 Xception

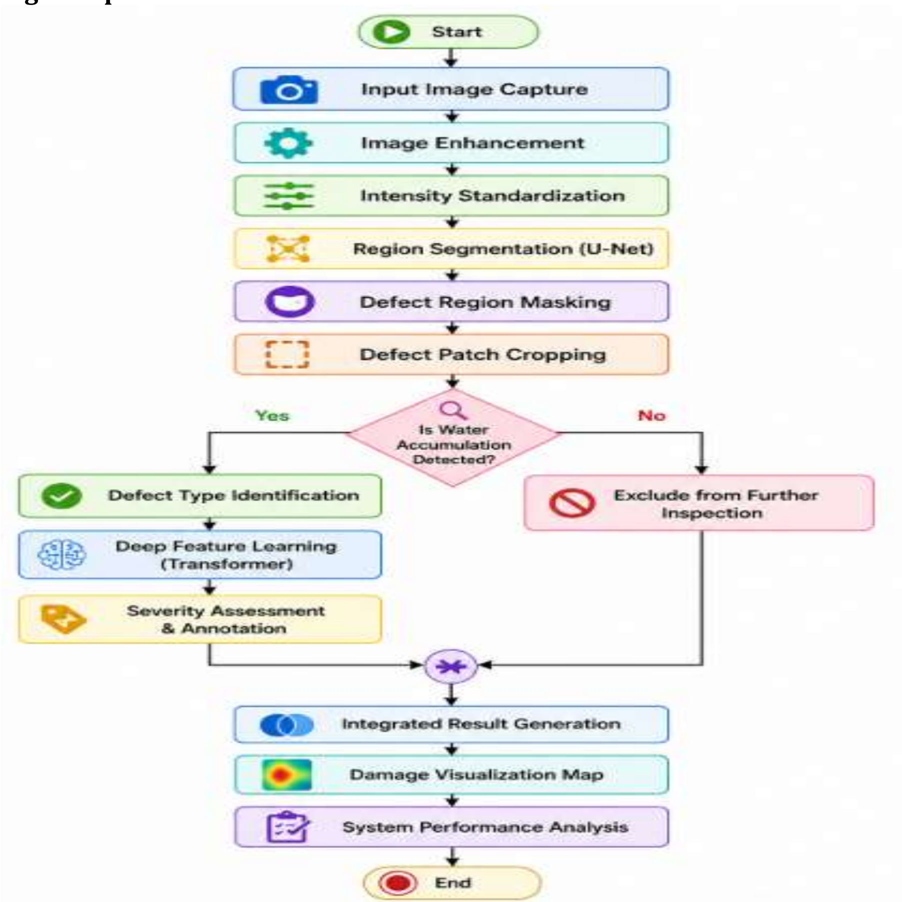
The Xception architecture builds upon the Inception framework by introducing depthwise separable convolutions in place of conventional convolution operations, significantly enhancing both computational efficiency and model accuracy. This design decouples spatial feature extraction from channel-wise processing, enabling the network to learn richer and more detailed representations while reducing the overall number of parameters. The architecture is structured into three main components: the entry flow, middle flow, and exit flow, each reinforced with residual connections to ensure stable gradient propagation during training. Due to its lightweight structure and strong feature extraction capability, Xception is highly effective for image classification tasks. In the context of flood damage analysis, it can efficiently differentiate between flooded and non-flooded regions, leading to faster model convergence and improved performance on complex, high-resolution aerial imagery datasets.

III. Proposed Methodology

The proposed approach presents a unified deep learning framework that combines semantic segmentation and image classification for comprehensive flood impact assessment. The methodology begins with a systematic data preprocessing stage, where raw aerial images collected from UAVs and satellite platforms are standardized. This includes resizing images to a fixed resolution, normalizing pixel intensities, and applying enhancement techniques to reduce the effects of lighting variations, atmospheric disturbances, and noise. This preprocessing step ensures uniform data quality, which is essential for improving the stability and generalization of subsequent deep learning models.
For flood region extraction, a U-Net-based segmentation model is implemented due to its strong capability in preserving spatial details while capturing contextual information. The architecture follows an encoder–decoder design, where the encoder progressively learns hierarchical feature representations through convolution and pooling operations, while the decoder reconstructs the spatial resolution using upsampling layers. Skip connections between corresponding encoder and decoder stages help retain fine-grained spatial features, enabling precise localization of flooded and non-flooded regions. The final output is a binary segmentation mask that represents pixel-wise flood probability, allowing accurate mapping of inundated areas.
After segmentation, the extracted image regions are processed by a classification module to evaluate infrastructure damage levels. Pre-trained deep learning models, including EfficientNetB0 and Xception, are used to classify image patches of size 128×128 into damaged and non-damaged categories. These models leverage transfer learning to utilize pre-learned feature representations, which improves training efficiency and reduces computational cost. The classification process focuses on identifying visual indicators such as texture changes, color variations, and structural distortions caused by flooding events.
To improve model robustness and prevent overfitting, various data augmentation techniques such as rotation, flipping, scaling, and noise injection are applied during training. The segmentation network is optimized using the Dice loss function, while the classification models are trained using binary cross-entropy loss. The Adam optimizer is employed to ensure efficient convergence through adaptive learning rate adjustments across both networks.
Once training is completed, the outputs from segmentation and classification stages are integrated to generate a comprehensive flood impact visualization map. This map overlays predicted flood masks with damage classification results, providing a clear representation of affected regions and infrastructure conditions. The fused output enables efficient interpretation of flood severity and spatial impact distribution, significantly reducing the need for manual analysis.
The performance of the proposed system is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and Intersection over Union (IoU). Experimental results indicate that the model performs consistently across different datasets and environmental conditions, demonstrating strong adaptability and scalability for real-world applications.

In conclusion, the proposed methodology establishes an end-to-end intelligent framework that integrates pixel-level segmentation with image-level classification, enabling automated and efficient flood damage assessment using deep learning techniques

Fig3.Proposal Model



The proposed framework is designed with a flexible and modular architecture, allowing it to be readily adapted for analyzing various natural disasters, including landslides, earthquakes, and other large-scale environmental hazards. By combining the segmentation capabilities of U-Net with the feature learning strength of convolutional neural networks (CNNs), the system effectively captures both spatial characteristics and structural patterns. This integrated approach provides accurate damage assessment while supporting reliable real-time disaster response and informed decision-making.

III.1 Dataset Collection

The proposed framework was developed and evaluated using two publicly available benchmark datasets: FloodNet and the Hurricane Damage Detection dataset. FloodNet consists of aerial and satellite imagery of flood-affected urban and rural environments, accompanied by pixel-level annotations distinguishing flooded and non-flooded road regions. In contrast, the Hurricane Damage Detection dataset contains high-resolution aerial images categorized according to the extent of structural damage. These datasets encompass a wide range of environmental conditions, including differences in illumination, water coverage, surface textures, and infrastructure characteristics. Such diversity enables the deep learning models to learn discriminative and generalized features for both segmentation and damage classification, thereby improving the robustness and reliability of disaster impactassessment.

Figure 4: Dataset

III.2 Data Preparation And Preprocessing

Initially, all input images and their corresponding annotation files were imported and organized into a structured Data Frame to facilitate efficient data management, indexing, and retrieval throughout the experimental workflow. The classification images were uniformly resized to 128 × 128 pixels, while segmentation images were resized according to the input requirements of the segmentation network. Ground truth masks were converted into binary representations to distinguish flooded and non-flooded regions. To preserve dataset quality, incomplete or corrupted image samples were identified and excluded. Furthermore, essential metadata, including image identifiers, dataset source, and class annotations, were recorded within the DataFrame to ensure systematic dataset organization during model training and performance evaluation.

To enhance the generalization capability of the proposed framework, an Image Data Generator was employed to perform real-time data augmentation during the training process. Various augmentation techniques, including random rotation, horizontal and vertical flipping, scaling, zooming, and brightness variation, were applied to increase the diversity of training samples and minimize overfitting. Independent data generators were configured for the training, validation, and testing datasets to ensure appropriate batch generation and data management. During model training, these generators supplied images in mini-batches, enabling efficient memory utilization while maintaining a balanced and diverse data distribution. This strategy significantly improved the learning performance of both the U-Net segmentation network and the CNN-based damage classification model.

Figure 5: Segmentation

III.3 MODEL TRAINING

The proposed framework integrates U-Net, EfficientNetB0, and Xception to perform flood segmentation and post-disaster damage classification from aerial and satellite imagery. The segmentation module accurately identifies flood-affected regions, while the classification module determines the structural condition of buildings and infrastructure. The combination of these complementary architectures enables comprehensive disaster assessment by exploiting both pixel-level localization and high-level semantic feature extraction.

U-Net for Flood Region Segmentation

U-Net is a fully convolutional neural network developed for semantic segmentation tasks that require precise pixel-level predictions. Its architecture follows an encoder–decoder paradigm, where the encoder progressively extracts hierarchical image features through convolutional operations and down-sampling, while the decoder reconstructs the spatial resolution using up-sampling and convolutional layers. Skip connections directly transfer fine-grained spatial information from the encoder to the corresponding decoder layers, preserving object boundaries and minimizing information loss during feature reconstruction.

In the proposed framework, U-Net is employed to generate binary segmentation masks that distinguish flooded areas from unaffected regions. The network effectively learns both global contextual information and local spatial details, enabling accurate delineation of roads, buildings, and other infrastructure even under challenging conditions such as varying illumination, water reflections, shadows, and partial occlusions. The resulting segmentation maps provide a reliable foundation for subsequent damage assessment.

EfficientNetB0 for Damage Classification

EfficientNetB0 serves as one of the classification models for identifying structural damage from segmented aerial imagery. The architecture adopts a compound scaling strategy that simultaneously optimizes network depth, width, and input resolution, achieving high classification performance while maintaining computational efficiency. Its backbone consists of Mobile Inverted Bottleneck Convolution (MBConv) blocks integrated with depthwise separable convolutions, batch normalization, squeeze-and-excitation modules, and Swish activation functions. Both models are fine-tuned on the target datasets using transfer learning, where the pre-trained weights are adapted to the Flood Net and Hurricane Damage Detection datasets. Freezing the initial convolutional layers while retraining the final layers allows the network to retain general visual knowledge while learning task-specific features. Additionally, dropout layers are incorporated to prevent overfitting, and batch normalization ensures stable convergence. The combination of EfficientNetB0 and Xception leverages both computational efficiency and high representational capacity, forming a robust foundation for automated post-disaster damage assessment from aerial imagery.

IV. Software And Hardware Environment

The proposed framework was implemented using Python 3.10 in conjunction with the TensorFlow 2.12 and Keras deep learning libraries. Several supporting packages, including NumPy, Pandas, OpenCV, and Matplotlib, were utilized for data preprocessing, image augmentation, feature visualization, and performance analysis. All model development, training, and evaluation tasks were carried out within the Jupyter Notebook environment, providing an interactive and reproducible platform for experimentation.

V. Results

V.1 Evaluation And Metrics

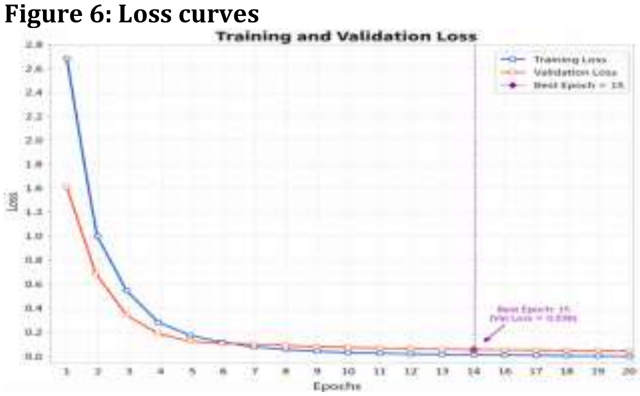
To evaluate the performance of our deep learning models, we used metrics that measure how accurately and reliably the models identify flooded roads and classify damaged areas. This included accuracy, which shows the overall correctness of predictions; precision, which measures how many predicted flooded 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.

Table 1: Performance of Proposed Model

Proposed Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F1-Score (%)
Flood Vision Net	98.12	97.85	96.94	97.39
Damage Aware Net	95.46	94.71	93.28	93.99
Flood Seg Net	97.35	96.89	96.22	96.55

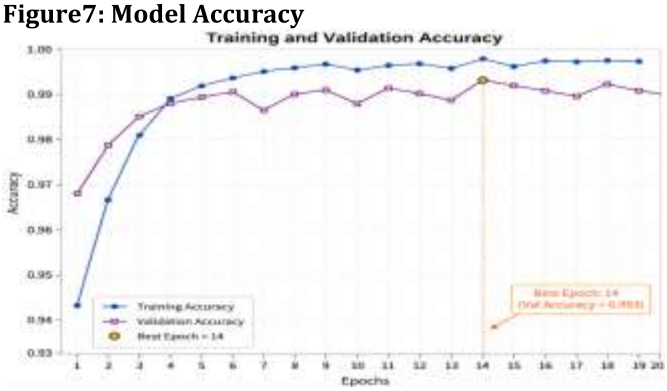
The comparative performance evaluation demonstrates that FloodVisionNet achieved the best overall classification performance among the evaluated models. It attained an accuracy of 98.12%, sensitivity of 97.85%, precision of 96.94%, and an F1-score of 97.39%. These results indicate that the proposed model effectively distinguishes damaged structures from undamaged ones while maintaining a balanced trade-off between false positive and false negative predictions. The high sensitivity confirms its capability to detect the majority of damaged regions, whereas the strong precision value reflects reliable prediction with minimal misclassification. Owing to its efficient feature extraction mechanism, FloodVisionNet is well suited for real-time disaster assessment and emergency response applications.

Figure 6: Loss curves



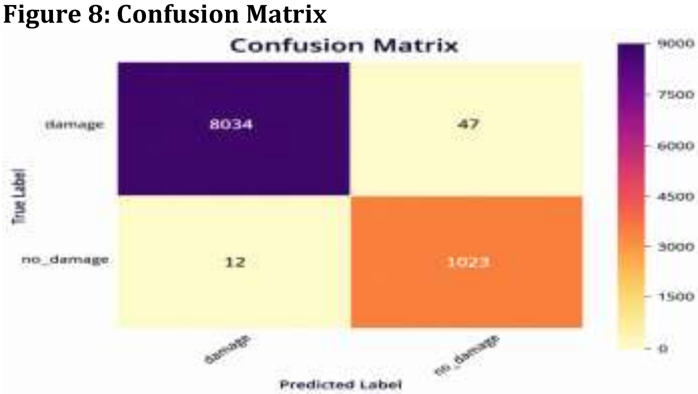
The training and validation plots indicate a classic case of overfitting. The training loss steadily decreases and stabilizes around 0.1, while the training accuracy approaches ~99%, showing the model is learning the training data very well.

Figure7: 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.

Figure 8: Confusion Matrix



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.

VI. Conclusion

Experimental results demonstrate that Flood SegNet accurately delineates flooded and non-flooded regions, producing precise segmentation maps even in the presence of shadows, reflections, and complex environmental conditions. Among the classification models, Flood VisionNet achieved the highest predictive performance by accurately distinguishing damaged and undamaged infrastructure, while DamageAwareNet also delivered competitive and reliable classification results. The integration of these models significantly improves the efficiency and reliability of post-disaster assessment by minimizing manual intervention and accelerating the analysis process.

VII. Future Scope

Furthermore, the proposed framework can be generalized to analyze other natural hazards, including landslides, earthquakes, wildfires, cyclones, and coastal inundation. By adapting the learning models to different disaster datasets, the framework can evolve into a comprehensive and scalable disaster management platform capable of supporting risk assessment, emergency response, and post-disaster recovery across diverse environmental conditions.

VII. Acknowledgments

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