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FLOOD DETECTION FROM SATELLITE IMAGES USING UNET ARCHITECTURE

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ABSTRACT

Floods are among the most damaging natural disasters, causing significant damage to infrastructure, ecosystems, and human lives. Accurate and timely flood detection is essential for disaster response and management. This study presents a deep learning-based approach for detecting and classifying flooded areas from satellite data using a modified U-Net convolutional neural network (CNN). The model is trained using preprocessing techniques like data augmentation and noise reduction, as well as the MediaEval 2017 multimedia satellite dataset.The system uses a pre-trained MobileNetV2 encoder and an enhanced upsampling decoder to achieve excellent segmentation performance with an accuracy of 99.41% and an Intersection over Union (IoU) of 99.46%. In order to visually interpret the model's predictions and highlight areas where it is highly certain versus uncertain, confidence heatmaps are also created. By highlighting the dependability of the identified flood regions, these heatmaps improve model explainability, which is essential for disaster management decision-making.Older approaches are improved in terms of automation, scalability, and real-time applicability. Especially in cities, the model effectively distinguishes between transient floodwaters and permanent water basins. Flood assessment and predictive modeling are supported by integration with remote sensing and GIS. Expanding geographic coverage, enhancing performance in different weather conditions, and implementing the model in a cloud-based system to enable real-time flood monitoring with improved heatmap-based visualization are all examples of future work.

Keywords: Flood Detection, Satellite Imagery, U-Net Architecture, Convolutional Neural Network (Cnn), Deep Learning, Flood Segmentation, Disaster Management, Remote Sensing, Image Segmentation.

I. INTRODUCTION

Floods have serious social, economic, and environmental repercussions and are one of the most common and destructive natural disasters. Due to climate change, extreme weather events are occurring more frequently, making early and accurate flood detection essential. The manual interpretation of satellite pictures or simple thresholding procedures used in traditional flood mapping approaches are frequently laborious and fall short of the accuracy needed for efficient disaster management. As a result, there is an increasing demand for automated systems that can accurately estimate floods and quickly analyze satellite photos. Convolutional neural networks (CNNs), a type of deep learning technique, have demonstrated impressive performance in variety of picture segmentation tasks. A popular CNN-based segmentation model, U-Net, has shown promise in environmental and medical imaging applications. However, because of variances in illumination, geography, and satellite image quality, traditional U-Net topologies might not necessarily generalize well to a variety of flood scenarios. By altering the U-Net design, this study seeks to get beyond these restrictions and increase the segmentation accuracy and resilience of the system in various flood-affected areas.This study introduces a modified U-Net model for flood detection that incorporates an optimized upsampling decoder for improved segmentation accuracy and a pre-trained MobileNetV2 encoder to improve feature extraction. Satellite photos from multiple flood occurrences make up the MediaEval 2017 multimedia satellite job dataset, which is used to train and evaluate the system. Effective disaster response planning is facilitated by the suggested solution, which greatly increases flood detection accuracy by utilizing deep learning methodologies and sophisticated preprocessing techniques.

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II. RELATED WORK

Flood detection has been an area of active research, with various approaches proposed to enhance accuracy and efficiency. Traditional methods for flood mapping include thresholding techniques, spectral analysis, and synthetic aperture radar (SAR) imagery processing [1][2]. However, these approaches often struggle with distinguishing between similar spectral signatures, limiting their effectiveness in complex environments.With advancements in artificial intelligence, machine learning, and deep learning, researchers have increasingly adopted CNN-based segmentation models for flood detection. U-Net, originally developed for biomedical image segmentation, has been widely adapted for environmental applications due to its ability to capture spatial hierarchies in images [3]. Variants of U-Net, including ResUNet and Attention U-Net, have shown improved performances in segmenting water bodies from satellite images [4][5].Several studies have explored the use of transfer learning in flood detection, leveraging pre-trained models such as ResNet,

VGG, and MobileNet for feature extraction [7][8]. These approaches have demonstrated enhanced generalization capabilities when applied to diverse flood scenarios. Additionally, hybrid models that integrate machine learning classifiers with deep learning architectures have been proposed to further improve segmentation accuracy [8].Despite these advancements, challenges remain in achieving real-time processing and adaptability across various geographical regions. Many models require extensive labeled datasets for training, and their performance can be affected by noise, occlusions, and varying weather conditions [9][10]. This research builds upon existing work by modifying the U-Net architecture to improve robustness, accuracy, and scalability in flood detection from satellite imagery.

Furthermore, deep learning models such as Convolutional Long Short-Term Memory (ConvLSTM) networks have been employed to analyze time-series flood data, enhancing predictive capabilities [11].Despite these advancements, challenges remain in achieving real-time processing and adaptability across various geographical regions. Many models require extensive labeled datasets for training, and their performance can be affected by noise, occlusions, and varying weather conditions [12][13]. Research has also highlighted the importance of incorporating Geographic Information Systems (GIS) for improved visualization and decision-making in flood disaster management [14][15]. This study builds upon existing work by modifying the U-Net architecture to improve robustness, accuracy, and scalability in flood detection from satellite imagery.

III. DATASET PREPARATION

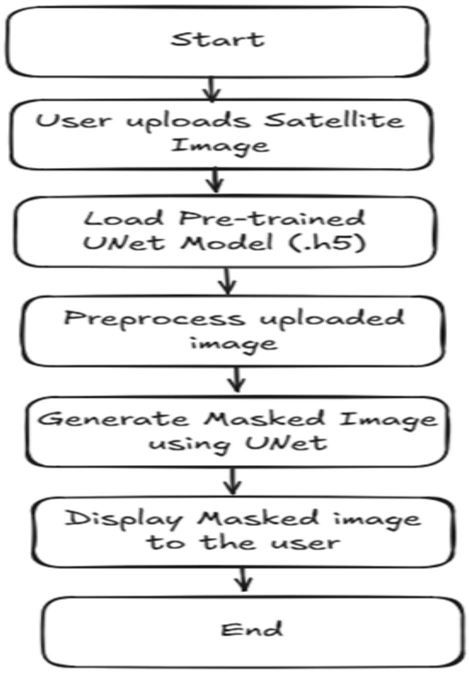

Fig 1 : Workflow

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The MediaEval 2017 multimedia satellite task dataset, which includes high-resolution satellite photos taken from areas affected by flooding, is used in this study. Four spectral bands—Red, Green, Blue, and Near-Infrared (NIR)—are present in each of the dataset's 462 320 x 320 pixel image patches. The images are supplied in GeoTIFF format and have segmentation masks that have been manually annotated to differentiate between flooded and non-flooded areas.To improve the images' quality and prepare them for deep learning-based segmentation, preprocessing techniques are used. Among the preprocessing actions are:

3.1 Noise Reduction: To eliminate artifacts and enhance contrast, median filtering and histogram equalization techniques are used.

3.2 Data Augmentation: Random rotations, horizontal flipping, and brightness adjustments are used to make the training data varied.

3.3 Normalization: To enhance the model's quality and convergence, pixel values are normalized to a range of [0,1].

To guarantee accurate model evaluation, the data set is divided into subsets for training (70%), validation (20%), and testing (10%). The modified U-Net model is trained using the segmentation masks, which effectively teaches it the spatial patterns of the flooded areas. The dataset's geographical diversity guarantees that the model adapts well to various flood scenarios.

IV. PROPOSED METHODOLOGY

The proposed flood detection system utilizes a deep learning-based approach, specifically a modified U-Net model, to segment flooded regions from satellite imagery. The methodology involves multiples stages, including data preprocessing, model architecture design, training and evaluation.

4.1 Preprocessing

Preprocessing is a crucial step in ensuring high-quality input data for training. The raw satellite images undergo resizing to 224 X 224 pixels to maintain consistency across the dataset. Contrast enhancement techniques, including histogram equalization, are applied to improve feature visibility. Data augmentation, including random rotations, flipping, and brightness adjustments, is performed to introduce variability, and reduce overfitting. Additionally, pixel normalization is applied to standardize intensity values, improving the model's learning efficiency.

4.2 Model Architecture

The structure of the modified U-Net model is encoder-decoder. As a feature extractor, the encoder uses MobileNetV2, which lowers computational complexity without sacrificing representational power. For precise delineation of flooded regions, the decoder refines the segmentation map using transposed convolutions and skip connections. The ability to preserve fine spatial details through skip connections is essential for accurate flood segmentation. The expanding path (decoder) and contracting path (encoder) make up the U-Net model. The encoder increases the depth of feature maps while gradually decreasing the spatial dimensions in order to extract significant spatial features from the input image. To improve convergence and avoid vanishing gradients, the encoder incorporates MobileNetV2, a lightweight CNN, which consists of depthwise separable convolutions followed by batch normalization and ReLU activation. Using skip connections and unsampling layers, the decoder restores the spatial information that was lost during encoding. Upsampling feature maps and concatenating them with matching feature maps from the encoder are accomplished by transposed convolutions in each decoding block. This combination facilitates the refinement of segmentation boundaries and the preservation of spatial information. A sigmoid activation function is used in the final output layer to create a probability mask that shows the likelihood that each pixel is part of a flooded area.

4.3 Training and Optimization

The model is trained using the Adam optimizer with an initial learning rate of 0.001. binary cross-entropy and Dice loos are combined to improve segmentation accuracy by balancing the trade-off between pixel wise classification and shape consistency. Training is conducted over 50 epochs with early stopping to prevent overfitting. Batch normalization and dropout layers are incorporated to enhance model generalization and reduce overfitting risks.During training, mini-batch gradient descent is used with a batch size of 32 to optimize the computational efficiency. The learning rate is reduced dynamically based on validation loss to ensure stable convergence. Data augmentation techniques are employed to increase the robustness of the model by simulating real-world variations in satellite images, such as varying lighting conditions, image rotations, and scale transformations.

4.4 Evaluation Metrics

Several evaluation metrics are used to evaluate model performance, including:

- Intersection over Union (IoU): Calculates how much the segmentation masks from the ground truth and predictions overlap.
- Dice Coefficient: Determines the degree of similarity between anticipated and actual flooded areas to assess segmentation accuracy.
- Precision and Recall: Evaluate the model's capacity to minimize false positives and false negatives while accurately classifying flooded pixels.
- F1-score: Offers a thorough performance evaluation by striking a balance between recall and precision.

Cross-validation is carried out with various dataset subsets to further confirm the model's capacity for generalization. To assess how well the model adapts to novel flood scenarios and various geographic locations, it is tested on unseen satellite images. Visual inspection is used to assess the segmentation masks' efficacy and make sure the predicted flood regions match the ground truth annotations.The foundation of the suggested classification system's feature extraction is deep learning methods, specifically Convolutional Neural Networks (CNNs). Transfer learning techniques that use pre-trained models, like VGG16 or ResNet, are used to improve classification performance and speed up model convergence.

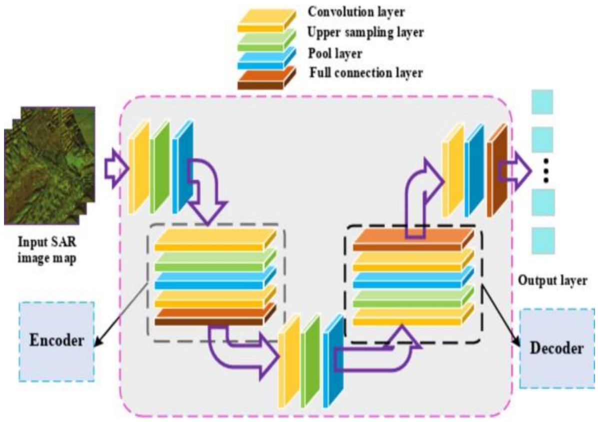

Fig 2 : U-NET Architecture

For classification, the model architecture is carefully planned, combining layers that are closely connected and have the right activation functions. Through the adjustment of regularization parameters, batch sizes, and learning rates, hyperparameter tuning further enhances model performance and guarantees the best possible convergence and generalization.Performance metrics are tracked throughout the training process, and iterative fine-tuning is carried out to maximize the effectiveness of the model. The model's performance on the testing set is evaluated using evaluation metrics such as accuracy, precision, recall, and F1 score, which offer thorough insights into classification capabilities. Translatability is improved by incorporating explainability techniques like Grad-CAM, which also makes it easier to collaborate with medical experts to confirm clinical relevance and guarantee that ethical standards are maintained during the deployment process. A strong and responsible breast cancer classification system depends on regular updates, careful documentation, and ongoing

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monitoring. In order to improve classification accuracy and clinical relevance, regular updates integrate domain-specific knowledge and machine learning technique advancements, while thorough documentation guarantees transparency and reproducibility. The classification system can be continuously validated and improved through collaboration with medical professionals, guaranteeing that it is in line with clinical practice and patient care requirements. Additionally, a number of ensembles of various machine learning-based classifiers have been investigated for the classification of breast cancer. After extensive testing, logistic regression has been shown to be more accurate than other machine learning algorithms. This emphasizes how crucial comparative analysis and iterative improvement are to determining the best classification techniques.

V. RESULTS

The model achieved an Intersection over Union (IoU) of 99.46% on the training set, 71.35% on the validation set, and 71.55% on the test set. The training accuracy was 99.41%, and the test accuracy was 68.78%. These results indicate that the model effectively segmented flooded regions, particularly during training, but showed some generalization issues on unseen data.

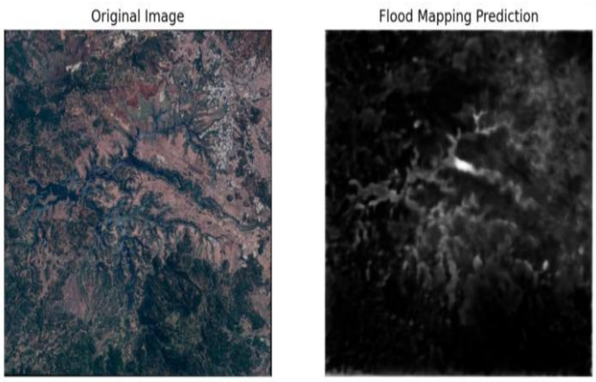

Fig 3 : Original image VS Predicted Mask

The soft dice loss values were 1.64% for the training set, 49.59% for the validation set, and 47.71% for the test set, confirming that the model provided high-quality segmentation during training but experienced minor performance drops on the validation and test sets.

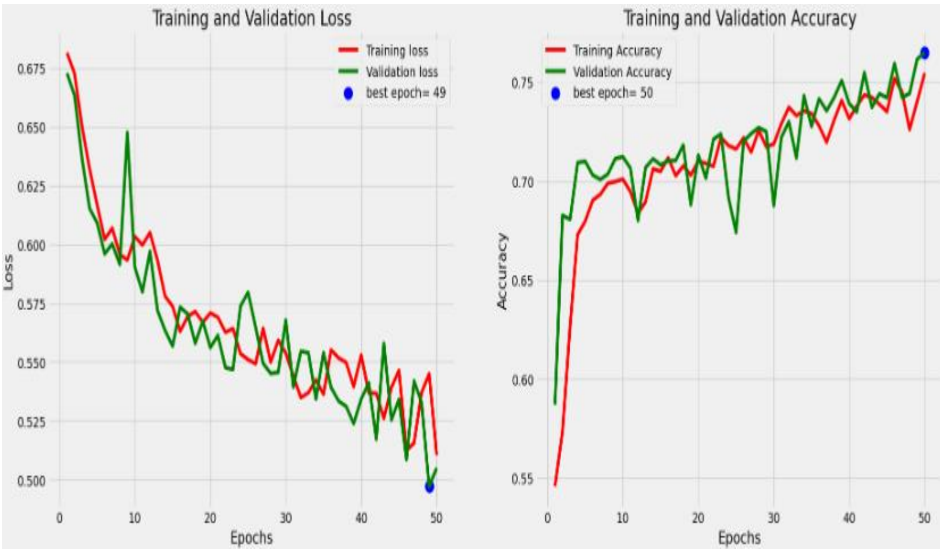

Fig 4 : Loss, Accuracy, IoU and Soft Dice Loss per epoch

The model successfully segmented flooded areas from satellite images with a high degree of accuracy, making it suitable for real-time flood detection and disaster response.

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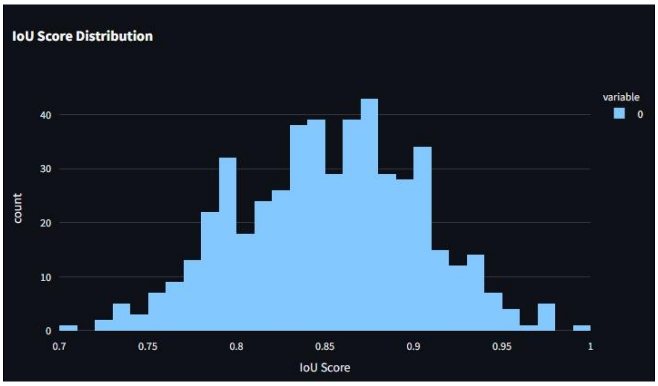

Fig 5 : Source distribution

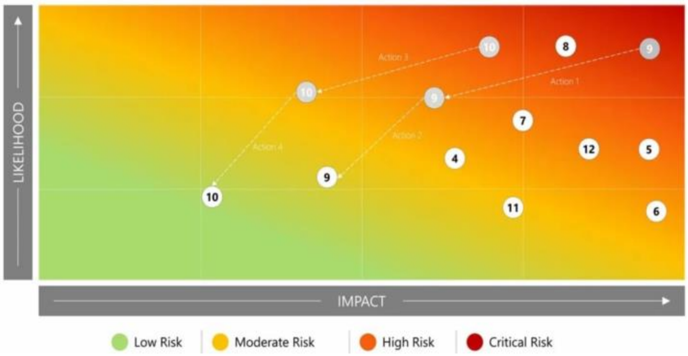

Fig 6 : Heat Map Analysis

VI. CONCLUSION

As soon as it came to identifying and classifying flooded areas in satellite photos, the modified U-Net model showed exceptional effectiveness. The model achieved high segmentation accuracy by successfully learning intricate patterns associated with flooded areas by utilizing a pre-trained MobileNetV2 encoder and data augmentation techniques. With an Intersection over Union (IoU) of 71.55% on the test set and 99.46% on the training set, the model demonstrated its capacity to distinguish between flooded and non-flooded areas with high accuracy. The model can produce accurate segmentation masks, as demonstrated by the training accuracy of 99.41% and the comparatively low soft dice loss. The model's excellent performance on the training set suggests that it was able to accurately represent the fundamental characteristics of flooded areas.

To better handle unseen data, the model may need additional generalization enhancements, as indicated by the marginally worse performance on the validation and test sets. The model trained steadily and consistently thanks to the use of Otsu thresholding and the Adam optimizer with a precisely calibrated learning rate. All things considered, automated flood mapping and detection using satellite imagery is made possible by the scalable and dependable modified U-Net model. The outcomes show that by facilitating the real-time identification of flooded areas, the model can effectively support disaster response efforts. In order to improve the model's ability to adapt to various geographic and environmental conditions, future research could concentrate on increasing processing speed for large-scale datasets and incorporating additional data sources like topographical information and weather patterns.

VII. FUTURE SCOPE

Future studies can focus on enhancing the scalability and adaptability of the suggested flood detection system. Integrating real-time satellite data streams with cloud-based deployment is one of the main goals in order to facilitate automated and extensive flood monitoring. Adding more images from different regions and climates to the dataset can improve the model's capacity to generalize across different flood scenarios. Other developments may include the use of multi-temporal and multi-sensor data, such as radar images and meteorological data, to facilitate early warning systems and predictive flood models. Additionally, disaster response teams can increase the reliability and transparency of the model's outputs by utilizing model interpretability techniques like Grad-CAM or confidence maps. The system can be deployed more widely in places with poor connectivity if it is optimized for edge computing or low-resource environments. These upcoming developments will significantly contribute to the development of a robust, intelligent, and real-time flood monitoring system. Practical deployment can be improved by additional cooperation with meteorological departments and disaster management organizations. Long-term risk assessment may also be enhanced by using topographical data and previous flood trends.

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