Flood Detection in Satellite Images using Deep Learning

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***Abstract*—Flood detection is crucial for effective disaster response and management, enabling early warning systems and targeted relief efforts. This paper proposes a deep learning-based approach for flood detection in satellite images using convolutional neural networks (CNNs) and transfer learning techniques. Satellite imagery provides wide coverage and high spatial resolution, making it a valuable resource for flood monitoring. However, the complexity of flood patterns requires advanced computational techniques for accurate analysis. CNNs have shown remarkable success in image classification tasks and can automatically learn meaningful features from imagery. The proposed methodology aims to train a robust flood detection model capable of discerning flooded and non-flooded regions within satellite images. Transfer learning enhances the model's performance by adapting pre-trained models to the flood detection domain, even in regions with limited historical flood data. The outcomes of this research have the potential to revolutionize flood detection systems and improve disaster management strategies, leading to reduced vulnerability in flood-prone areas. By leveraging deep learning methodologies, we can advance our understanding of floods and build more resilient communities to confront this escalating threat. The paper introduces a novel approach combining CNNs and transfer learning for flood detection, with the goal of developing an accurate and robust flood detection model. The work's outcomes contribute to the advancement of flood monitoring systems, improving disaster response and reducing vulnerability in flood-prone areas.**

***Index Terms*—Flood detection, Deep learning, Satellite imagery, Convolutional neural networks (CNNs), Transfer learning, Computer Vision & AI**

I. Introduction

Floods represent a significant global challenge, posing a substantial threat to communities worldwide and imposing severe socio-economic and environmental consequences. On time and accurate detection and monitoring of floods are paramount for effective disaster response, enabling early warning systems, evacuation planning, resource allocation, and targeted relief efforts [1]. To address this critical need, this paper proposes a state-of-the-art deep learning-based approach for flood detection in satellite images, taking advantage of the power of convolutional neural networks (CNNs) and transfer learning techniques.

Satellite imagery has emerged as a valuable resource for flood monitoring due to its wide coverage, high spatial resolution, and frequent updates [2]. However, the vast amount of data and the intricate nature of flood patterns necessitate advanced computational techniques for accurate and efficient analysis [3].

CNNs, renowned for their prowess in image classification tasks, have exhibited remarkable success in various domains, including computer vision and remote sensing [4]. By harnessing the inherent capability of CNNs to automatically learn and extract meaningful features from imagery, our proposed methodology aims to train a robust flood detection model capable of discerning subtle differences between flooded and non-flooded regions within satellite images.

Transfer learning, a powerful technique in deep learning, allows the adaptation of pre-trained models to specific domains with limited training data [5]. By leveraging knowledge acquired from extensive image datasets, transfer learning accelerates the training process and enhances the performance of our flood detection model [6]. This approach enables effective flood detection even in regions with limited historical flood data, improving the generalization capability of the model.

The outcomes of this research hold significant potential for revolutionizing flood detection systems and enhancing disaster management strategies worldwide. Accurate and timely identification of flooded areas can significantly contribute to reducing the loss of life, protecting infrastructure, and facilitating targeted response efforts [7].

By advancing our understanding of floods through advanced deep learning methodologies, we can build more resilient communities better equipped to confront the escalating threat of floods.

This paper introduces a novel deep learning-based approach for flood detection in satellite images, combining the power of CNNs and transfer learning techniques. Taking advantages of the strengths of these technologies, our methodology aims to develop an accurate and robust flood detection model.

II. Related Works

In [8], the critical importance of near-real-time flood detection and mapping is highlighted, with a focus on leveraging deep learning techniques to gather data from 16 flood events within the Yangtze River Basin. This research introduces efficient methods for creating datasets tailored for training, testing, and application purposes. Notably, the study reveals that convolutional neural networks (CNNs) outperform traditional flood detection methods, underscoring the robustness of convolutional neural networks in the context of near-real-time.

In [9], present a novel and robust real-time flood detection system based on Machine Learning and Deep Learning techniques, including Random Forest, Naive Bayes J48, and Convolutional Neural Networks. This system aims to detect rising water levels and predict potential floods with humanitarian consequences before they occur. This research contributes to the fields of Artificial Intelligence, data mining, and Deep Learning by introducing an innovative approach to flood prevention using Arduino with GSM modems.

The work in [10], centers on the precise identification of flooded areas through the utilization of a dual patch-based Fully Convolutional Network (FCN) that leverages deep learning-based feature fusion. The FCNs are independently trained on Synthetic Aperture Radar (SAR) and Multispectral (MS) images, allowing them to capture distinct features that are subsequently combined to enhance flood detection capabilities.

[11]presents a flooding detection within time-based satellite image sequences, they leverage a combination of classical computer vision and machine learning approaches. Their results underscore the effectiveness of their methods in addressing the challenges posed by the MediaEval task and contribute to the broader field of disaster event analysis and satellite data utilization.

III. Methodology

The approach combining CNNs and transfer learning for flood detection Takes advantage of the strengths of both techniques to develop an accurate and robust flood detection model.

Convolutional Neural Networks (CNNs) [12]are a type of deep learning model specifically designed for image analysis tasks. CNNs excel at learning and extracting meaningful features from images, allowing them to recognize patterns and structures that are essential for flood detection. CNNs consist of multiple convolutional and pooling layers, which help capture spatial information and hierarchical representations of the input images. By leveraging the power of CNNs, the flood detection model can effectively analyze satellite images and identify regions impacted by floods.

Transfer learning, known as Deep Transfer Learning (DTL) [13], is a powerful technique in deep learning that allows the adaptation of pre-trained models to new tasks with limited training data. In the context of flood detection, transfer learning involves utilizing a pre-trained CNN model that has already learned rich features from a large-scale image classification task, such as the ResNet50 model pretrained on the ImageNet dataset. By starting with a pre-trained model, the flood detection model benefits from the knowledge and representations already acquired from extensive image datasets. This accelerates the training process and enhances the performance of the flood detection model, even when dealing with limited flood-specific training data.

By analyzing satellite images, our model can identify regions that have been impacted by floods, aiding in disaster response and resource allocation. We collected a comprehensive dataset consisting of satellite images that encompass both flood and non-flood areas. The dataset is organized into separate folders, flood_images and non_flood_images. These images serve as the foundation for training and evaluating our flood detection model.

To enhance the model's performance and improve generalization, we apply preprocessing techniques to the dataset. This involves resizing the images to a consistent size and applying appropriate normalization techniques. Additionally, data augmentation methods such as random flipping and rotation are employed to increase the diversity of the training samples and reduce overfitting.

In addition to mitigating overfitting, we employed a technique to calculate the learning rate that allowed us to stop the training process before reaching the maximum number of epochs, specifically 50 epochs. This approach helps prevent unnecessary training iterations and aids in optimizing the model's performance.

A. *Model Architecture*

Many valuable papers used different CNN models such as ResNet50 VGG16, InceptionV3 etc, [14]–[16], and performed very interesting results on different area. We adopt a transfer learning approach by utilizing these models as a choice to be applied in our work and we discuss there validities on the area of flood detection. All of the choosen models are pretrained on the ImageNet dataset [17]. The pretrained model has already learned rich features from a large-scale image classification task, making it a suitable base for our flood detection model. We modify the architecture by adding a global average pooling layer to capture essential features, followed by a dropout layer for regularization. The final layer utilizes the sigmoid activation function to classify flood and non-flood areas see Figure 1.

B. *Model Training and Evaluation*

The model on Figure 2 is trained using the compiled dataset, employing the Adam optimizer with binary cross-entropy loss as the objective function. The training process involves iterating through multiple epochs, continuously updating the model's weights to minimize the loss and improve accuracy. The model's performance is evaluated on a validation dataset, measuring metrics such as accuracy and loss.

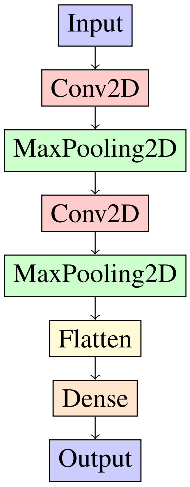

Fig. 1: CNN Architecture

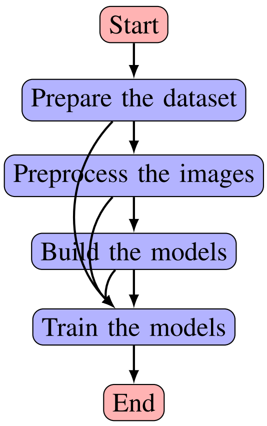

Fig. 2: Workflow Diagram of the trained model

IV. Implementation

We implemented our deep learning model using TensorFlow with the Keras API, a widely used framework for developing deep neural networks (DNN) [18], [19]. TensorFlow provided the underlying infrastructure and computational capabilities, while Keras facilitated the design and training of our model architecture.

To implement the approach, the pre-trained CNN model, such as ResNet50, is used as a base for the flood detection model. The architecture is modified by adding additional layers to adapt it to the flood detection task. For example, a global average pooling layer is added to capture essential features from the pre-trained model's output. This is followed by a dropout layer, which helps prevent overfitting by randomly deactivating a fraction of neurons during training. The final layer utilizes the sigmoid activation function to classify flood and non-flood areas Figure 3

Once the flood detection model is trained, it can be applied to predict flood areas in test images. The model outputs predicted probabilities for each image, indicating the likelihood of it being a flood or non-flood area. By applying a threshold (typically 0.5), the predicted probabilities are converted into class labels, such as "flood" or "non-flood." The confidence of the prediction is calculated as the predicted probability itself if the label is "flood," or as 1 minus the predicted probability if the label is "non_flood". The predicted label and confidence are drawn on the resized image. Finally, the output image with the predicted label and confidence is saved to disk.

V. Experimentation Results

A. Dataset

Some works, as in [2] for their experiments, used the images of China High-resolution Earth Observation System (CHEOS). In [3], used the SEN12-FLOOD dataset [20], [21], available at IEEE data port, was used to evaluate the efficacy of their proposed DeepFlood models.

In contrast, for our experiment evaluation, we utilized high-definition satellite images collected from the Internet. These images were organized into two folders: "flood_images" and "non_flood_images." This approach differs from previous works but allows for the examination of a distinct set of data.

A total of 102 images were divided into two groups: 82 images were allocated for training purposes, while the remaining 20 images were reserved for validation.

B. Evaluation and Performance

Our DeepFlood architecture was developed using the TensorFlow-Keras library in Python. The implementation was executed on a workstation equipped with 8 GB of RAM, an Intel Core i7-7700HQ CPU, and an NVIDIA GTX-1060 GPU.

The proposed DeepFlood architecture is evaluated for its classification performance using commonly utilized metrics, including Precision (Equation 1), Recall (Equation 2), F1-score (Equation 3), and classification accuracy (Equation 4). These metrics are derived from the confusion matrix and provide insights into the model's effectiveness.

Specifically, True Positives (TP), False Positives (FP), and False Negatives (FN) are calculated for both the Flood and No Flood classes. For the Flood class, TP represents the accurate classification of Flood images, FN denotes Flood images misclassified as No Flood, and FP indicates No Flood images mistakenly classified as Flood.

Precision (Producer Accuracy-PA) measures the proportion of correctly identified positives within the identified positives, focusing on the accuracy of Flood classification.

Recall (User Accuracy-UA) quantifies the proportion of correctly identified positives relative to all actual positives, highlighting the model's ability to recognize Flood patches.

F1-score considers both PA and UA, providing a balanced assessment of the model's performance. These metrics rely on TP, FN, FP, and TN values in their computation.

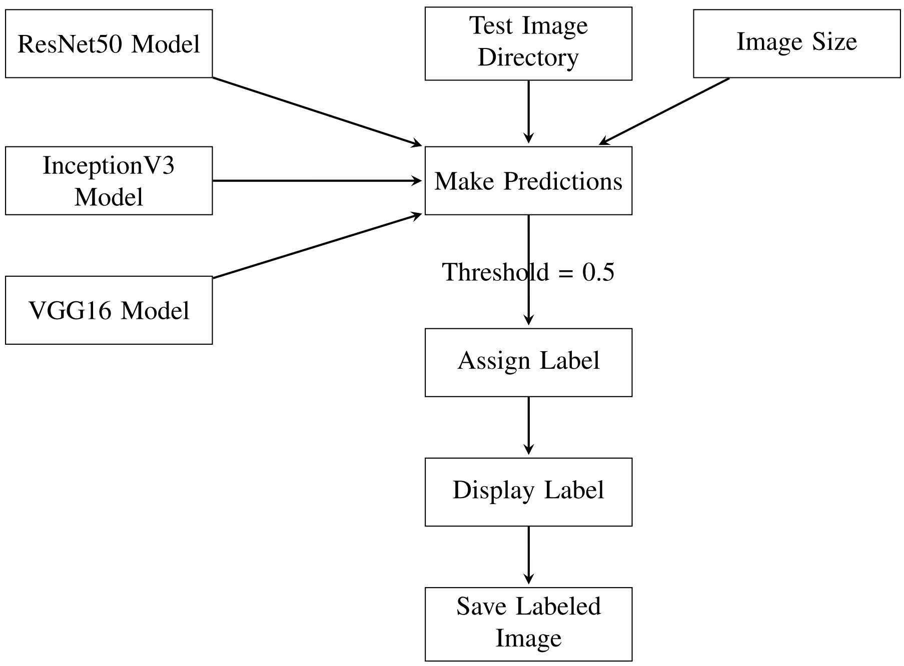

Fig. 3: Modified CNN Architecture for Prediction

For flood prediction, we utilize a composite model comprising ResNet, VGG, and Iceptron to generate predictions on images and overlay the labels ”flood” or ”no flood” accordingly.

$$\text{Precision (PA)} = \frac{TP}{TP + FP} \quad (1)$$

$$\text{Recall (UA)} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{F1-score} = \frac{2}{\left(\frac{1}{UA}\right) + \left(\frac{1}{PA}\right)} \quad (3)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

The performance of the VGG16 (Table I) model can be considered moderate, as it achieves an accuracy of 0.60. However, there is room for improvement, particularly in terms of precision and recall for both the ’flood_images’ and ’non_flood_images’ classes. Figure 4, 5.

In contrast, the InceptionV3 (Table II) model exhibits lower performance for the ’flood_images’ class, with no instances correctly predicted. Nevertheless, it demonstrates better performance for the ’non_flood_images’ class, achieving a precision of 0.65 and recall of 1.00. The overall accuracy of 0.65 indicates that the model correctly predicts 65% of the instances.

However, there is a clear need for improvement, especially in terms of the ’flood_images’ class, which advised us to modify (just for Iception model) the trainable that will transfer knowledg from weights trained on ImagNet and update them during trainable (Table III). Figure 6, 7.

On the other hand, the ResNet50 (Table IV) model demonstrates reasonably good performance, with higher precision, recall, and F1-score for the ’non_flood_images’ class compared to the ’flood_images’ class. This suggests that the model is more accurate in identifying non_flood_images. Figure 8, 9.

TABLE I: VGG16 Classification Report

Class	Precision	Recall	F1-Score	Support
flood_images	0.45	0.71	0.56	7
non_flood_images	0.78	0.54	0.64	13
Accuracy		0.60		
macro avg	0.62	0.63	0.60	20
weighted avg	0.66	0.60	0.61	20

TABLE II: IceptionV3 Classification Report

Class	Precision	Recall	F1-Score	Support
flood_images	0.00	0.00	0.00	7
non_flood_images	0.65	1.00	0.79	13
Accuracy		0.65		
Macro avg	0.33	0.50	0.39	20
Weighted avg	0.42	0.65	0.51	20

TABLE III: Enhanced IceptronV3Classification Report

Class	Precision	Recall	F1-score	Support
flood_images	0.44	0.57	0.50	7
non_flood_images	0.73	0.62	0.67	13
Accuracy		0.60		
Macro Avg	0.59	0.59	0.58	20
Weighted Avg	0.63	0.60	0.61	20

TABLE IV: ResNet50 Classification Report

Class	**Precision**	**Recall**	**F1-score**	**Support**
flood_images	0.75	0.43	0.55	7
non_flood_images	0.75	0.92	0.83	13
Accuracy			0.75	
Macro avg	0.75	0.68	0.69	20
Weighted avg	0.75	0.75	0.73	20

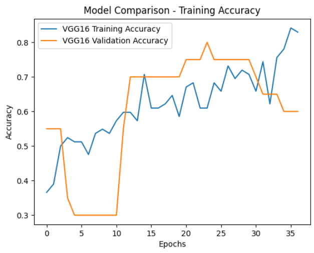

Fig. 4: Vgg-Training Accuracy Comparison.

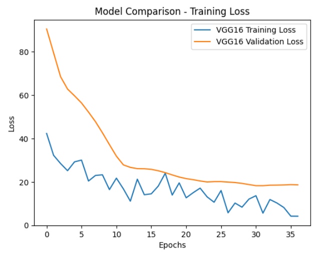

Fig. 5: Vgg-Training Loss Comparison.

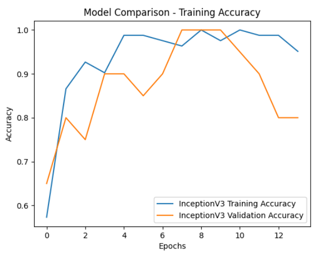

Fig. 6: Iceptron-Training Accuracy Comparison.

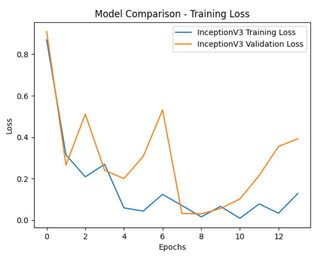

Fig. 7: Iceptron-Training Loss Comparison.

Fig. 8: ResNet-Training Accuracy Comparison.

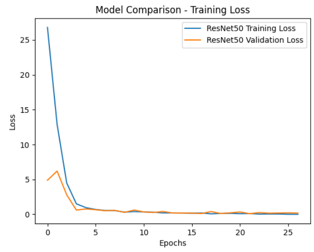

Fig. 9: ResNet-Training Loss Comparison.

We utilize a composite model comprising ResNet, VGG, and Iceptron to generate predictions on images and overlay the labels ”flood” or ”no flood” accordingly.

The proposed approach was devised during the training process of the three models, ensuring a balanced prediction by taking the advantages of the combined capabilities of ResNet, VGG, and Iceptron. This enhanced approach allows us to accurately annotate the labels ”flood” or ”no flood” on the predicted images. Figures: 10, 11, 12 and 13

Fig. 10: Sample1 of image predicted no_flood.

Fig. 11: Sample2 of image predicted flood.

VI. Conclusion

In this paper, we introduce a deep learning-based approach for flood detection in satellite images. By

Fig. 12: Sample3 of image predicted no_flood.

Fig. 13: Sample4 of image predicted no_flood.

taking advantages of convolutional neural networks (CNNs) and transfer learning techniques, the proposed methodology aims to develop a robust model capable of accurately identifying flooded and non-flooded regions. The approach combines the power of CNNs and transfer learning to enhance the model's accuracy and generalization capabilities. The model architecture is modified by adding extra layers, such as global average pooling and dropout layers, to adapt it to the flood detection task. Training is performed using a comprehensive dataset of satellite images, and the model's performance is evaluated using metrics like accuracy and loss. The proposed approach has significant potential for revolutionizing flood detection systems and improving disaster management strategies, contributing to reduced loss of life and infrastructure damage.

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