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A Comparative Study of Flood Detection Models with Optimized Machine Learning Methods Using Sentinel-1 Data

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ABSTRACT

Floods are one of the most prevalent and devastating natural disasters, and their impact on various societies worldwide has always been significant. While preventing floods is nearly impossible, obtaining sufficient information about flood situations and timely detection can mitigate potential damages. With advancements in remote sensing satellite technology and progress in deep learning and machine learning, the capability to flood detection with higher precision and efficiency has been achieved. In this regard, this study aims to develop ensemble-optimized models for flood detection utilizing Sentinel-1 satellite data and compare the performance of these models. The first step involved feature extraction from the images using the pre-trained deep neural network model, VGG-16. Subsequently, machine learning algorithms including Random Forest (RF) and Gradient Boosting (GB) were employed as classifiers, and Genetic Algorithm (GA) and Harris Hawks Optimization (HHO) were utilized for hyperparameter optimization of these classifiers. The prediction accuracy of the four ensemble flood detection models RF-GA, RF-HHO, GB-GA, and GB-HHO were 90.97%, 90.37%, 91.45%, and 91.61%, respectively. Model GB-HHO exhibited the lowest error rate and the highest prediction accuracy. The findings of this study indicate that all four models offer acceptable performance and accuracy rates. Moreover, Gradient Boosting-based classifiers, GB-HHO and GB-GA, exhibit superior prediction accuracy compared to Random Forest and demand significantly lower computational resources for model training processes.

KEYWORDS

Flood Detection
Sentinel-1
VGG-16
Random Forest
Gradient Boosting

1. Introduction

Floods, among all water-related natural disasters, have the highest prevalence. Approximately 23% of the world's population, equivalent to 1.8 billion people, are directly affected by floods (Amitrano et al., 2024). Climate change, heavy rainfall, snowmelt, and dam failures are counted among the causes of floods (Jeyaseelan, 2004).

Preventing floods is a challenging task, but with proper management, it is possible to reduce the negative impacts of these natural disasters. Flood management involves assessing flood-affected areas' risks, damages, and vulnerabilities and planning to mitigate any potential

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damages (Rahman & Di, 2017). Hence, the timely and precise gathering of data regarding flood conditions is paramount. Sensors used in satellite and aerial platforms can provide the necessary data for mapping flood-affected areas and assessing the damages caused by them (Klemas, 2014).

Despite achieving suitable spatial resolution, collecting the required data utilizing aerial platforms is costly (Clement et al., 2017), while satellite platforms can provide valuable information about flood conditions in large and inaccessible areas over multiple time intervals (Bhatt & Rao, 2016). With the advancement and development of remote sensing satellites in recent years, active and passive satellite sensors, operating in various parts of the electromagnetic spectrum, including the visible, infrared, and microwave bands, provide diverse data at low cost and sometimes free of charge from flood-affected areas during and after flood events. Alos-Palsar, Terrasar-X, RadarSat-1, Envisat, and Sentinel-1 are considered active sensors, whereas Landsat, Sentinel-2, and MODIS are among the popular passive sensors (Anusha & Bharathi, 2020).

There are multiple methods for flood detection. Among these methods, flood detection utilizing optical satellite data is mainly based on spectral information through spectral indices such as NDWI and other simple image classification methods. flood detection utilizing radar data is complicated due to the complex characteristics of these data, with common image classification methods being very complex. Traditional methods of flood detection require a lot of time and depend on expertise in this field (Wu et al., 2023). In recent years, machine learning has significantly advanced in various fields (Hussain et al., 2019). Additionally, deep learning-based methods have gained more attention than before and have been utilized in many studies (Wu et al., 2023). Neural networks form the basis of deep learning methods (Ma et al., 2019), with Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) being among the most common (Astola et al., 2021). One of the key challenges in deep learning methods is training models with large volumes of data, consequently increasing the time and computational burden required to complete the training process. In this regard, using transfer learning methods such as pre-trained models can significantly overcome this challenge (Tulasi Krishna & Kalluri, 2019).

In this study, Sentinel-1 satellite data were utilized as training data for flood detection, using a combination of transfer learning methods and machine learning algorithms, optimized with metaheuristic algorithms. The innovation in this study lies in utilizing four ensemble models based on training with features extracted from the transfer learning method using the VGG-16 deep neural network model for flood detection, alongside comparing their performance. While the VGG-16 model has general applicability and is not specific to remote sensing data, our approach focuses on employing this model and evaluating its results in the context of remote sensing for flood detection. The implementation and analysis of the models were conducted in the Google Colab programming environment.

2. Methodology

The primary objective of this study is to develop ensemble flood detection models using Sentinel-1 data, which is a valuable resource for flood detection and monitoring, and then to evaluate and compare the performance of these models with each other. The pre-trained VGG-16 neural network model is employed for feature extraction to achieve this goal. Machine learning algorithms are then employed to train classifiers using the features extracted by the VGG-16 model. Additionally, metaheuristic algorithms are utilized to optimize and fine-tune the hyperparameters of the machine learning models.

Furthermore, to examine the impact of combining deep learning and machine learning methods proposed in this study as feature extractors and classifiers under identical and completely equal conditions, the VGG-16 model was entirely excluded from the process. This was done to evaluate the performance of models developed and implemented without any involvement of the VGG-16 model. A comparison was also made between these models and our proposed models, in which the VGG-16 model played the role of feature extractor. The following sections fully introduce and describe the algorithms and methods used.

2.1. Dataset

The dataset used in this study, titled "Cloud to Street – Microsoft Flood and Clouds Dataset," consists of a collection of georeferenced ground image patches with the size of 512×512 pixels from Sentinel-1 and Sentinel-2 satellites. It is utilized for training and evaluating machine learning and deep learning models for flood detection on a global scale. This dataset includes 900 Synthetic Aperture Radar (SAR) image patches from the Sentinel-1 with two polarizations (VV and VH), 900 optical image patches from the Sentinel-2 with 13 spectral bands, and ground truth labels for each image patch which covers various regions around the world, including the Mekong River Basin in Southeast Asia, India, Bolivia, Spain, the United States, and Ghana, during 18 flood events. Figure 1 shows the sample of the image patches utilized in the study.

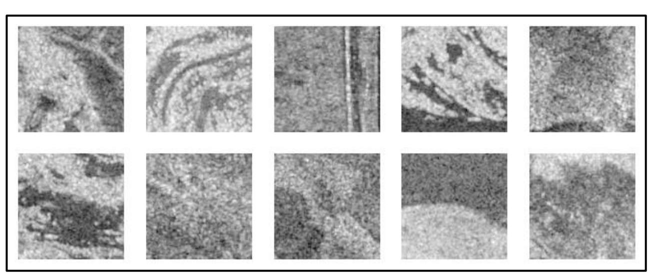

Figure 1. Sentinel-1 VV polarization image patches.

2.2. Data Preparation

In this study, only Sentinel-1 images have been used for training and evaluating flood detection models. All image patches underwent visual inspection to identify and exclude any with incorrect or unreliable labels, ensuring that they do not participate in the model training process.

For the ease of the process and to prevent potential issues due to the limitations of Google Colab service, each image patch with a size of 512×512 pixels was split into image patches with a size of 128×128 pixels along with their corresponding labels. Subsequently, to achieve a proper balance between background and flood pixels, image patches with the new size that lacked flood pixels or had an insignificant number of them compared to background pixels were removed from the dataset. Finally, this study's total number of image patches utilized for training and evaluating flood detection models was narrowed to 322. Table 1 shows the final number of image patches for each geographical region.

Table 1. Geographical dispersion of final data

ID	Region	Number of image patches
1	USA	34
2	Ghana	15
3	Pakistan	41
4	Sri Lanka	19
5	Somali	30
6	Nigeria	33
7	Spain	35
8	Paraguay	52
9	Mekong	22
10	Bolivia	24

2.3. Feature Extraction using Transfer Learning

Transfer learning is a machine learning method where a model is trained for a specific task or application and then reused for other similar purposes (Gao & Mosalam, 2018). This study utilizes the transfer learning method for automatic feature extraction without human intervention. For this purpose, the VGG-16 deep neural network model, which can extract diverse features from image data, is employed. The VGG-16 model is one of the Convolutional Neural Network models introduced in 2014 (Simonyan & Zisserman, 2015). This model is trained on the ImageNet dataset, which consists of approximately 15 million high-resolution images across 22,000 different classes.

Therefore, the VGG-16 model is pre-trained (Deng et al., 2009; Marmanis et al., 2016). This model exhibits satisfactory performance and prediction accuracy on both small and large and complex datasets (Theckedath & Sedamkar, 2020). The structure of this deep neural network model consists of 13 convolutional layers, 3 fully connected layers, and 5 pooling layers (Qu et al., 2020). Convolutional layers use 3×3 kernels with a stride of 1. The number of filters gradually increases from 64 in the first layer to 512 in deeper layers (Wang, 2020). In a study (Jain et al., 2020), a similar approach is used to automatically feature extraction from Sentinel-2 data with the aim of flood detection. Using the pre-trained VGG-16 model led to acceptable results and indicated the feasibility of automatic flood detection.

2.4. Classification Algorithms

After feature extraction, performed by the pre-trained VGG-16 model, classifiers need to be applied to classify the pixels of Sentinel-1 satellite images into two classes: flood and non-flood, to extract flood-affected areas from the background of the image. This study employs Random Forest (RF) and Gradient Boosting (GB) algorithms to train flood detection models.

2.4.1. Random Forest

Random Forest (Ho, 1995) is one of the most widely used and effective algorithms in machine learning, providing accurate and reliable precisions using an ensemble of decision trees. The final precision of a Random Forest is calculated based on the precisions of all decision trees created in the model (Breiman, 2001).

Therefore, Random Forest can control the problem of overfitting by averaging multiple precisions. Additionally, this algorithm can rank different features based on their importance and consider the feature with the highest importance as the differentiating factor in decision trees (Esfandiari et al., 2020). Compared to other machine learning algorithms such as Support Vector Machines (SVM), Random Forest has lower computational burden and less sensitivity to multicollinearity in multivariable linear methods (Feng et al., 2015). Over the past two decades, Random Forest has gained a prominent position among machine learning methods due to its outstanding performance in classification tasks and high processing speed (Belgiu & Drăguţ, 2016).

2.4.2. Gradient Boosting

Gradient Boosting with decision trees (Friedman, 2002) is one of the most common algorithms in the realm of machine learning (Guryanov, 2019). Gradient Boosting presents a predictive model as an ensemble of weak predictive models, for example, models that make very few assumptions about the data, such as simple decision trees. Its performance usually outperforms Random Forest.

Unlike Random Forest, in a Gradient Boosting with a decision trees model, trees are constructed sequentially and iteratively (Hastie et al., 2009; Piryonesi & El-Diraby, 2020).

The Gradient Boosting algorithm delivers exceptional performance, offering superior quality alongside relatively efficient training and inference times. One advanced base learner in this domain is the piecewise linear tree, which employs linear functions as precisions within its leaves. Compared with contemporary Gradient Boosting libraries using publicly accessible datasets, this algorithm demonstrated superior performance, achieving higher quality results while reducing the size of the ensemble and inference time (Guryanov, 2019).

2.5. Hyperparameter Optimization

Hyperparameter optimization is crucial in achieving the best prediction accuracy and performance for machine learning-based classification models. Nowadays, metaheuristic algorithms aimed at solving problems, especially in optimizing and tuning hyperparameters, have gained significant attention and have been accompanied by remarkable advancements compared to the past, as there has been the constant introduction of new algorithms (Morales-Hernández et al., 2023).

In this study, Genetic Algorithm (GA) and Harris Hawk Optimization (HHO) are used as representatives of traditional and modern generations of metaheuristic algorithms to optimize the hyperparameters of Random Forest and Gradient Boosting classifiers. Subsequently, the performance and prediction accuracy of the classifiers are evaluated for each combination of hyperparameters to determine the optimal values for each model. The hyperparameters considered for the Random Forest classifiers include the number of trees and maximum depth. In contrast, the hyperparameters considered include the maximum iterations, depth, and learning rate for Gradient Boosting classifiers. The task of optimizing and fine-tuning these hyperparameters in the models is undertaken by the metaheuristic as mentioned earlier algorithms.

2.5.1. Genetic Algorithm

The Genetic Algorithm (Holland, 1992) is inspired by fundamental theories of Darwinian evolution and natural selection, which explains the origin of species. In nature, weak and unfit species face extinction in their environment through natural selection. Strong individuals are more likely to pass their genes to future generations through reproduction. Over the long term, species carrying the right combination of genes become dominant within their population. Sometimes, during the time-consuming process of evolution, random changes in genes may occur. If these changes provide greater advantages in the survival challenge, new species will evolve from old ones. Unsuccessful changes are eliminated through natural selection (Konak et al., 2006).

Genetic Algorithms have received extra attention in recent years due to their potential as a new optimization method. The Genetic Algorithm, due to its simplicity, ease of use, minimal requirements, and parallel and global perspective, has been widely used in various problems (Sivanandam & Deepa, 2008).

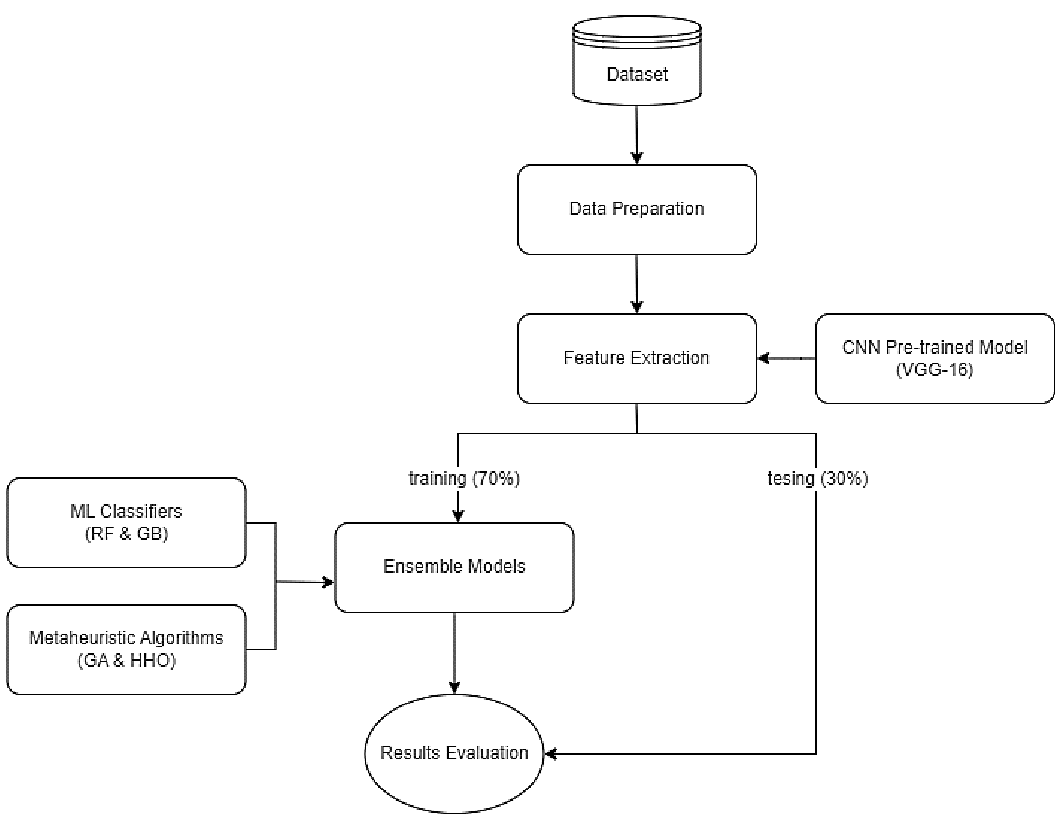

Figure 2. Procedure of methodology.

2.5.2. Harris Hawk Optimization

The Harris Hawk Optimization is a population-based optimization algorithm proposed by Ali Asghar Heidari for the first time in 2019 (Hussien et al., 2022). The main inspiration for the Harris Hawk Optimization derives from the cooperative behavior and collective pursuit and evasion tactics of Harris Hawks in nature, referred to as "startle-attack behavior." In this intelligent strategy, multiple Hawks collaborate to surprise prey from different directions. Harris Hawks can exhibit various tracking patterns based on the prey's evasion patterns.

The effectiveness of this algorithm has been investigated in solving and optimizing 29 fundamental problems and several engineering problems in the real world compared to other methods and algorithms inspired by nature. The Harris Hawk Optimization demonstrates promising results and performance compared to other common metaheuristic algorithms (Heidari et al., 2019).

3. Result

3.1. Pre-Trained VGG-16 Model

After loading the pre-trained VGG-16 model, a new model consisting of the first two layers of the loaded model was created to extract features from the Sentinel-1 data used in this study. Figure 3 shows a partial representation of feature extraction from sample training data. The purpose of selecting the first two layers of the pre-trained VGG-16 model was to extract general features with simpler patterns from the images and reduce the number of parameters. With the number of parameters reduced, the count decreased from 14,714,688 to 38,720. The parameter reduction significantly reduced the time, computational cost, and memory required for training and utilizing the models.

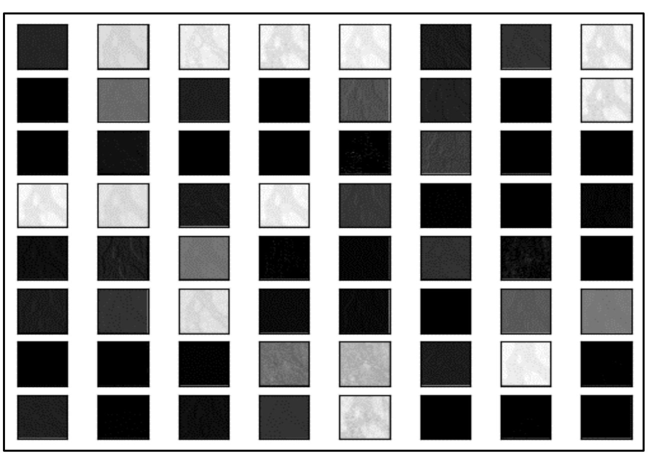

Figure 3. Sample data extracted features by VGG-16.

The features extracted by the VGG-16 model were used to train the flood detection models. Additionally, as mentioned at the beginning of the methodology section, the flood detection models are also trained once without using the features extracted by VGG-16. This approach examines the impact of using pre-trained models in implementing flood detection models. Specifically, in the first scenario, Random Forest and Gradient Boosting models are trained with the features extracted by VGG-16 to evaluate the impact of feature extraction by the deep neural network. In the second scenario, the same models are trained with the simple and raw features from the data to assess the models' performance without using the deep neural network.

3.2. Ensemble flood detection models

In this study, as mentioned earlier, Genetic and Harris Hawk algorithms were utilized to optimize and tune the hyperparameters of the machine learning classifiers. Table 2 shows the hyperparameter values for each flood detection model trained using features extracted from the VGG-16 model. Table 3 also shows the hyperparameter values for models trained solely on raw features from Sentinel-1 data without utilizing the VGG-16 model.

Table 2. Hyperparameters for models using VGG-16.

Model	Hyperparameters	
RF-GA	n of trees	54
	max depth	6
RF-HHO	n of trees	39
	max depth	6
GB-GA	n of trees	73
	max depth	4
	learning rate	0.048
GB-HHO	n of trees	76
	max depth	6
	learning rate	0.096

Table 3. Hyperparameters for models without using VGG-16.

Model	Hyperparameters	
RF-GA	n of trees	53
	max depth	6
RF-HHO	n of trees	57
	max depth	4
GB-GA	n of trees	77
	max depth	5
	learning rate	0.042
GB-HHO	n of trees	78
	max depth	6
	learning rate	0.023

Among the 322 images with ground truth labels, 300 were used as training and testing data with a 70% to 30% ratio. These data were used to implement flood detection models RF-GA, RF-HHO, GB-GA, and GB-HHO with two different approaches in the feature extraction stage. The remaining 22 image patches from the total available data were utilized to evaluate the performance of the flood detection models. Figure 4 shows the output classification of a sample image from these 22 images for each ensemble model with its corresponding ground truth label.

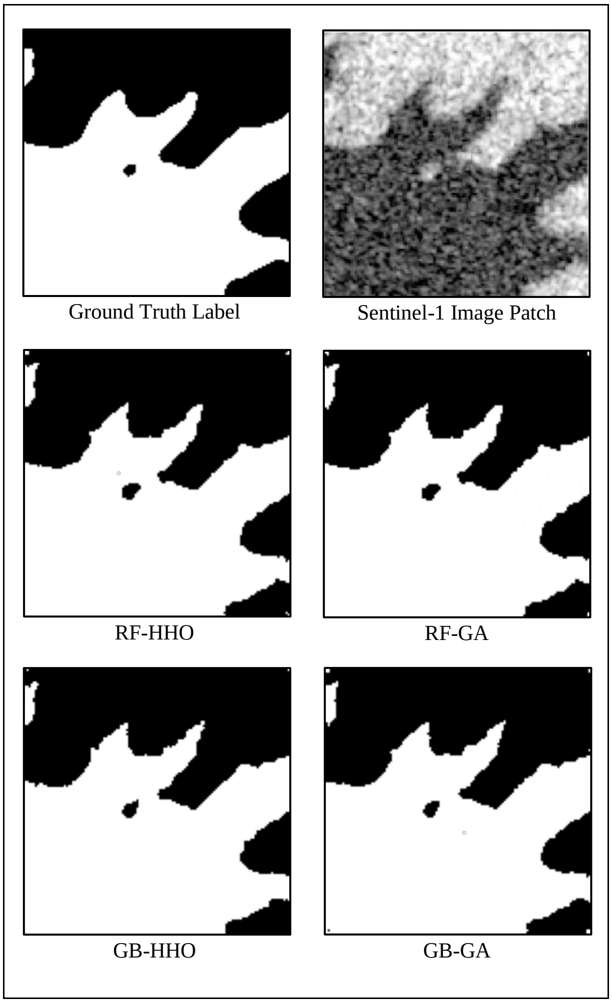

Figure 4. Flood detection with ensemble models.

3.3. Statistical Index Analysis

Table 4 shows the prediction accuracy, mean squared error (MSE), and root mean squared error (RMSE) of the ensemble models RF-GA, RF-HHO, GB-GA, and GB-HHO, which were trained based on features extracted by the VGG-16 model. The prediction accuracy indicates the models' correctness in identifying flood-affected samples, while the MSE and RMSE values show the overall error of the models in identifying flood-affected samples. The MSE values for the models are 0.090, 0.096, 0.086, and 0.084, respectively, and the RMSE values are 0.300, 0.310, 0.292, and 0.290, in order.

Table 4. Models' accuracy rate, MSE, and RMSE using VGG-16.

Model	MSE	RMSE	Accuracy (%)
RF-GA	0.090	0.300	90.97
RF-HHO	0.096	0.310	90.39
GB-GA	0.086	0.292	91.45
GB-HHO	0.084	0.290	91.61

According to the results, the GB-HHO model exhibited the lowest error rate and consequently achieved the highest prediction accuracy of 91.61% among the models. The GB-GA model secured the second position with 91.45% prediction rate, while the RF-HHO model had the lowest prediction of 90.39% among the four models. These results show that Gradient Boosting-based classifiers exhibited higher prediction accuracy than Random Forest-based classifiers.

Table 5 shows the prediction accuracy, mean squared error (MSE), and root mean squared error (RMSE) of the models trained on raw Sentinel-1 data features without using the VGG-16 model. All four models with this approach have had somewhat unsatisfactory performance, with very little difference between them. The prediction accuracy of the best model in this category did not exceed 52%. Therefore, it can be said that none of them achieved prediction accuracy similar to or close to the models where the VGG-16 model was responsible for feature extraction.

Table 5. Models' accuracy rate, MSE, and RMSE without using VGG-16.

Model	MSE	RMSE	Accuracy (%)
RF-GA	0.478	0.691	52.23
RF-HHO	0.478	0.691	52.21
GB-GA	0.478	0.691	52.22
GB-HHO	0.478	0.692	52.18

Considering the information provided in Tables 4 and 5, the first category of models, which resulted from a hybrid approach of deep learning and machine learning methods, demonstrated significant performance in achieving high prediction accuracy and low error rates. These models showed absolute superiority over the second category of models, which were trained solely on raw data features. Figure 5 shows the accuracy rates of flood detection models in this study using the VGG-16 model and without it for feature extraction.

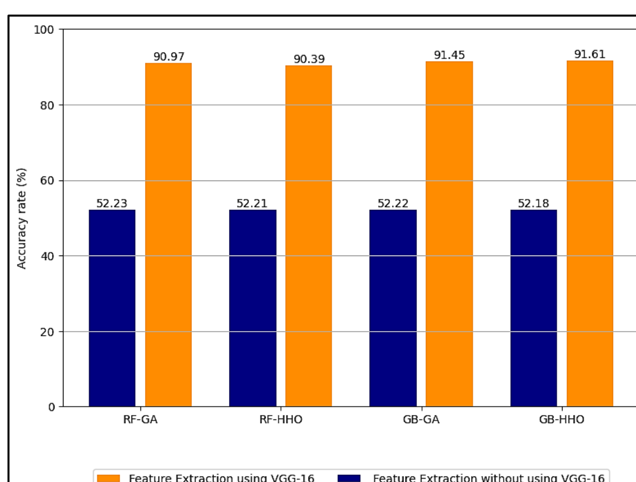

Figure 5. Comparison between models' accuracy rates.

3.4. ROC Curve Analysis

ROC curves have been utilized to assess the prediction accuracy of the models and compare them with each other. The ROC curve is a graphical representation of the balance between true Positive rate (TPR) and false positive rate (FPR) using training and testing data (Razavi Termeh et al., 2018). Figure 6 shows the GB-HHO models based on both feature extraction approaches considered in this study. The AUC values for the RF-GA, RF-HHO, GB-GA, and GB-HHO models trained on features extracted from the VGG-16 model are 0.9732, 0.9702, 0.9749, and 0.9780, respectively. These values for the mentioned models trained without utilizing the VGG-16 model were also 0.5102, 0.5098, 0.5099, and 0.5093, respectively.

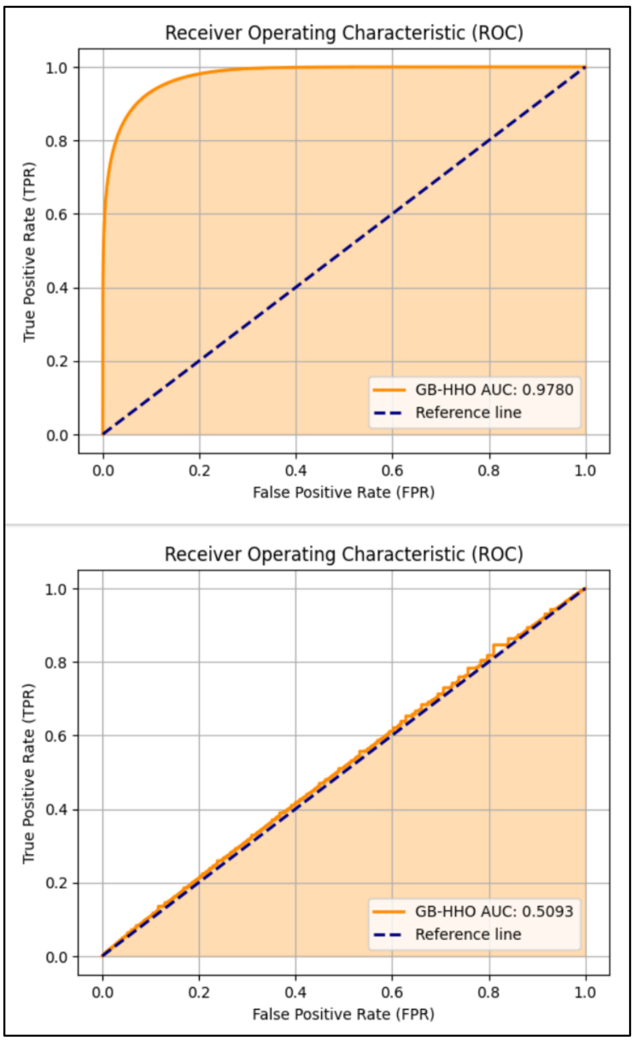

Figure 6. GB-HHO model ROC curve (top, feature extraction by VGG-16 and bottom simple feature extraction).

4. Discussion and Conclusions

This study employed ensemble flood detection models RF-GA, RF-HHO, GB-GA, and GB-HHO for flood detection through Sentinel-1 data. The transfer learning method was performed to achieve this goal, and the pre-trained VGG-16 model was employed to extract features required for training the models from Sentinel-1 data used in this study. Taking advantage of the VGG-16 model for feature extraction from images serves as a useful tool for image pattern recognition systems and other related image processing applications, potentially enhancing the training speed and efficiency of deep neural networks. Integrating deep neural network-based methods with machine learning techniques and metaheuristic algorithms for hyperparameter optimization has led to the development of models with remarkable accuracy and performance. However, these models failed to perform satisfactorily when the VGG-16 pre-trained model was not utilized for feature extraction.

One of the most significant outcomes of this study is the reduction of human intervention in supervised tuning and predefined feature extraction, achieved by leveraging the VGG-16 model as a feature extractor. Without human intervention, models trained solely on raw and simple features from Sentinel-1 data did not attain suitable accuracy and performance.

This issue becomes crucial when machine learning model developers cannot identify specific anomalies or complex patterns in images and cannot manually extract appropriate features to train the models. In this study, we utilized the capabilities of deep neural networks to perform this task, achieving notable results. This approach has not only improved the accuracy of flood detection but has also made the feature extraction process deeper and more efficient without the need for human intervention.

Furthermore, a comparison was made among models based on the proposed approach of this study, which integrates deep learning methods, machine learning techniques, and metaheuristic algorithms, serving respectively as feature extractors, classifiers, and optimizers. This comparison aimed to evaluate the performance of Random Forest classifiers and Gradient Boosting classifiers when combined with the two metaheuristic optimization algorithms: Genetic Algorithm and Harris Hawks Optimization. Many researchers have confirmed that ensemble machine learning models and metaheuristic optimization algorithms can improve prediction accuracy. For instance, in a study (Arabameri et al., 2022), Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) were employed to optimize Support Vector Machine models for flood susceptibility mapping, which demonstrated enhanced model performance and prediction accuracy. Similarly, in another study (Razavi Termeh et al., 2018), three ensemble models, ANFIS-GA, ANFIS-ACO, and ANFIS-PSO, were utilized for flood susceptibility mapping, showing highly satisfactory performance. In another study (Paryani et al., 2021), Harris Hawk Optimization and Bat Algorithm (BA) were employed to optimize support vector machine and ANFIS models for landslide susceptibility mapping in Lorestan province, which highlights the importance and effectiveness of metaheuristic algorithms in optimizing machine learning models. In yet another study (Rujan & Neagoe, 2022), a combination of Convolutional Neural Network and Ant Colony Optimization (ACO) algorithm was used for classifying hyperspectral images, with the CNN-ACO model outperforming support vector machine and pure convolutional neural network models in terms of performance and accuracy rate.

The results obtained in this study indicate that the ensemble flood detection models achieved approximately 90% accuracy rate, demonstrating excellent performance. Additionally, the training speed in the GB-GA and GB-HHO models was significantly higher than the RF-GA and RF-HHO models under the same conditions. This suggests that besides achieving an acceptable accuracy rate close to the Random Forest algorithm, the Gradient Boosting algorithm can also exhibit higher training speeds. Thereby, it potentially outperforms the Random Forest.

The proposed approach in this study is recommended for other research objectives, such as classifying and detecting various surface features including natural water resources, forests, agricultural lands, and other applications using remote sensing data. Additionally, it is suggested to develop more complex ensemble models using advanced transfer learning methods, such as the more contemporary and capable VGG-19. These models can examine and extract more diverse features with deeper layers and minimal human intervention.

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