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Hybrid Forest Fires Prediction (HF^{2}P) Strategy Based on Ensemble Classification of Convolutional Neural Networks (CNN) and Decision Tree (DT) Models

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Abstract

Forest fires have become an increasingly pressing global issue, causing severe environmental, economic, and social consequences. Factors such as climate change, deforestation, and extreme weather conditions have contributed to the growing frequency and intensity of these fires, underscoring the importance of early detection and prevention. Traditional forest fire prediction methods, which primarily rely on meteorological data and historical fire patterns, often fall short in terms of accuracy and response speed, limiting their effectiveness in disaster management. Deep Learning (DL), a subset of artificial intelligence, has emerged as a powerful approach for accurately predicting forest fires. In this paper, DL is integrated with Decision Trees (DT) to harness the complementary strengths of both techniques. Convolutional Neural Networks (CNNs) are employed to analyze satellite imagery and identify high-risk areas, while DTs assist in generating accurate fire outbreak predictions. By leveraging large volumes of real-time data, the proposed method can detect subtle patterns that traditional approaches may overlook, enabling more precise and timely forecasts. The main contribution of this study is the introduction of a Hybrid Forest Fire Forecasting Strategy (HF^{2}S), which combines the predictive capabilities of CNN and DT models. Specifically, the VGG16 architecture is used for feature extraction from satellite images, followed by Gray Wolf Optimization (GWO) to select the most relevant features. These selected features are then input into two separate binary classifiers: (i) a Deep Learning Classifier (DLC) based on transfer learning with VGG16, and (ii) a Decision Tree Classifier (DTC). The outputs of both classifiers are combined to generate the final prediction. A comprehensive dataset, compiled from various publicly available sources, was used to evaluate the proposed model. Experimental results demonstrate that the HF^{2}S approach outperforms other state-of-the-art models in terms of accuracy, precision, F-measure, recall, error rate, and processing time. The highest achieved accuracy is approximately 88%, based on a training set of 12,000 images.

Keywords: Prediction, Fire, ANN, feature extraction, feature selection, classification.

1. Introduction

Forest fires possess immense destructive potential, often causing long-term ecological damage that is difficult to reverse. The regeneration of forest ecosystems after such disturbances is a slow and complex process. Therefore, effective prevention strategies are essential to reduce both the frequency and severity of these events [1]. Forests play a crucial role in maintaining environmental stability through various ecological functions, including oxygen production, climate regulation, water conservation, soil stabilization, wind erosion control, air purification, noise reduction, and public health enhancement. They also serve as critical sources of timber and other forest products that support national development and human livelihoods [2]. Furthermore, forests underpin sustainable agricultural practices and livestock production, underscoring their indispensable ecological, social, and economic significance to human survival [3,4]. The persistent and escalating threat of forest fires driven by climate change, land-use changes, and the expansion of human settlements into forested areas demands the development of high-precision fire prediction technologies. As a result, designing robust forecasting models and conducting comprehensive wildfire hazard assessments have become urgent research priorities [5,6].

Traditional fire detection methods primarily rely on satellite-based remote sensing, aerial surveillance, and ground-based monitoring systems, such as lookout towers, wireless sensor networks, and remote video systems [5]. Satellite systems typically use data from visible and near-infrared spectral bands, along with other multispectral inputs, to detect fire activity by analyzing temporal changes in landscape features [6,7]. Recent advances in artificial intelligence have enabled real-time data processing using deep learning models, leading to faster fire detection and response. This capability is critical for emergency management and firefighting operations, as it significantly reduces fire-related damage [3]. Machine learning techniques are increasingly employed for data analysis and knowledge discovery due to their ability to process large and complex datasets. These techniques reveal hidden patterns and extract key features, thereby improving fire prediction accuracy [7–9]. Consequently, forest fire susceptibility mapping has become a vital tool for risk management. Various software platforms such as ENVI 6.0, Global Mapper 25.1, eCognition 10.4, ERDAS IMAGINE 16.8, and particularly Google Earth Engine (GEE) 7.3 are widely used for such analyses, with GEE being especially suitable for large-scale applications [10]. The application of deep learning to wildfire prediction has gained significant momentum, demonstrating strong performance across numerous tasks [11–14]. Analyses of remote sensing data show that image-based data is the most frequently used and particularly well-suited for deep learning algorithms [15].

Artificial intelligence-based approaches have proven effective for both predicting and monitoring forest fire events [16]. A variety of machine learning and deep learning models including neural networks, classification and regression trees, Random Forest, Support Vector Machine, Deep Neural Networks, and XGBoost have been developed for forest fire prediction under diverse environmental conditions. These models have been applied across regions in Asia [17], Europe [18], North America [19], and Brazil, especially in the southeastern and central-western regions [20]. Despite these advancements, there remains a pressing need for targeted research in highly vulnerable areas, such as the Triunfo do Xingu Environmental Protection Area (EPA) in Pará, Brazil. According to the National Institute for Space Research (INPE), this region is the most deforested and fire-prone conservation unit in the Legal Amazon (INPE, 2023). This study aims to propose an effective forest fire prediction model that integrates the strengths of the Decision Tree (DT) and VGG16 models through an ensemble approach, thereby enhancing classification and prediction accuracy. Features extracted using the VGG16 architecture are optimized via the Binary Gray Wolf Optimizer. These optimized features are then processed by individual classifiers, whose outputs are combined through a voting mechanism to produce the final prediction.

The proposed Hybrid Forest Fire Prediction (HF^{2}P) strategy is applied to develop a susceptibility model for forest fires in South Carolina, USA, with the objective of forecasting the spatial expansion of high-risk fire zones. The remainder of this paper is structured as follows: Section 2 outlines the problem and proposed methodology, Section 3 reviews related literature on forest fire prediction techniques, Section 4 presents the HF^{2}P methodology, Section 5 presents the experimental results, followed by a discussion of their significance in Section 6. Section 7 offers concluding remarks, while Section 8 outlines directions for future research.

2. Problem Definition of wildfire and Suggested Solution

Wildfires have become an increasingly prevalent and destructive force, posing serious threats to ecosystems, human lives, and economies across the globe. In recent years, both the frequency and severity of wildfire events have escalated, leading to substantial and, in many cases, unprecedented losses. Figure 1 illustrates the distribution of major wildfires by continent and decade since 1950 [16], revealing a significant rise in fire incidents—particularly within major industrialized nations. Figure 2 presents projected global changes in wildfire activity under two climate scenarios: RCP 2.6 and RCP 6.0, where RCP (Representative Concentration Pathway) denotes greenhouse gas concentration trajectories used to model future climate conditions. The projections indicate that, by the end of the 21st century, the likelihood of large-scale wildfires may increase by a factor ranging from 1.31 to 1.57 [16]. Notably, even under the lowest emissions scenario (RCP 2.6), a substantial increase in the frequency and intensity of catastrophic wildfires is anticipated. Figure 3 shows the global annual average fire density per square kilometer for the period 2000–2020 [16]. The data suggests that nearly every vegetated region around the world experiences free-burning fires at some point during the year, underscoring the widespread and persistent nature of the wildfire threat.

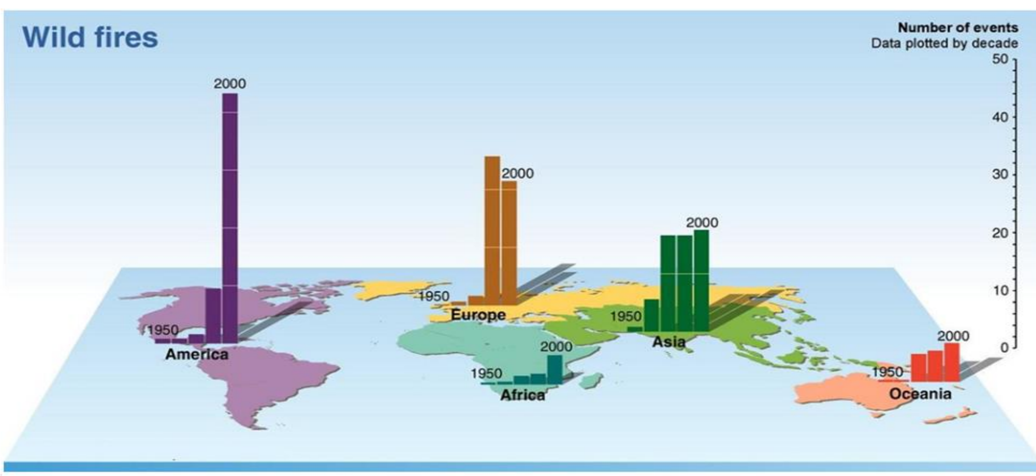


Figure 1, The number of major wildfires by continent and decade since 1950

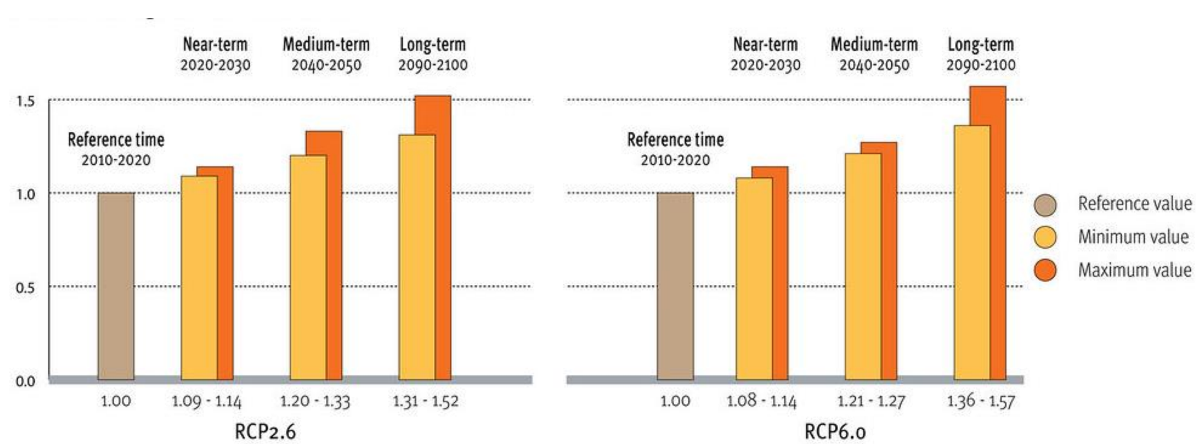


Figure 2, The global change in wildfire events under RCP=2.6 and RCP=6.0

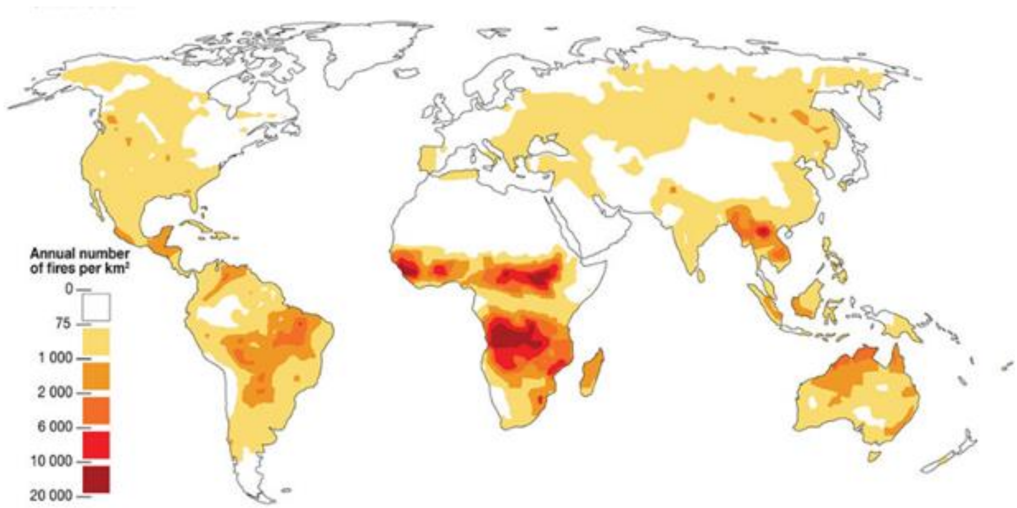


Figure 3, Annual average fire density observed per Km^2 for the period 2000–2020

Wildfires are among the most devastating natural disasters, causing extensive ecological degradation, significant economic losses, and posing serious risks to human life. Accurate wildfire prediction is essential for enabling early intervention and implementing effective firefighting strategies. However, traditional wildfire prediction methods are hindered by several limitations that compromise their reliability. These limitations stem from factors such as insufficient data availability, reliance on outdated modeling techniques, limited adaptability to changing climate conditions, and inefficiencies in real-time forecasting. Conventional wildfire prediction models typically depend on empirical formulas, statistical analyses, and historical fire records. While these methods have yielded useful insights, they often fail to capture the complex, dynamic, and nonlinear behavior of wildfire events. Moreover, the escalating influence of climate change has altered fire behavior patterns, rendering many historical models inadequate for predicting extreme or atypical fire events. This paper examines the key limitations of traditional wildfire prediction techniques and evaluates their implications for disaster preparedness and response efforts. By critically analyzing the weaknesses of these conventional approaches, the study lays the groundwork for advancing wildfire forecasting methods. It emphasizes the potential of integrating deep learning and machine learning techniques with satellite imagery to enhance prediction accuracy and responsiveness in the face of evolving wildfire risks.

3. Related Works

A substantial body of research has investigated the application of advanced machine learning (ML) and artificial intelligence (AI) techniques in enhancing wildfire prediction and risk assessment, thereby contributing to the development of more effective wildfire management strategies [21–23]. Numerous algorithms and predictive models have been proposed for forest fire risk evaluation, reflecting a dynamic and rapidly growing area of study. These methodologies can generally be grouped into three primary categories. The first category consists of physically based models**,** which employ mathematical formulations to simulate wildfire ignition, spread, and propagation by modeling the spatial distribution of combustible materials [24–26]. While these models can produce highly accurate fire spread maps, they require precise, location-specific input data—such as fuel characteristics and terrain information—that can be challenging and costly to obtain, especially across large or remote areas [19],[22]. The second category includes bivariate statistical methods such as Weight of Evidence (WoE), Evidential Belief Function (EBF), and Frequency Ratio (FR) models [27]. These approaches evaluate the statistical relationships between individual environmental variables and historical fire occurrences to produce weighted susceptibility maps. The weighted layers are then integrated to generate a final wildfire susceptibility map. However, the predictive

accuracy of these models is often limited, particularly in regions with complex or heterogeneous environmental conditions. The third category comprises machine learning techniques**,** which fundamentally differ from bivariate approaches by incorporating both fire-affected and unaffected areas into the modeling process [17],[28]. This group includes a wide range of advanced algorithms, supported by developments in remote sensing, geographic information systems (GIS), and data science. Algorithms such as logistic regression, support vector machines (SVM), random forests, decision trees, and neuro-fuzzy systems have enabled the creation of more flexible and accurate predictive models [28]. The growing availability of open-source platforms has also accelerated the use of deep learning for environmental modeling and natural hazard assessment [29]. Deep learning models are particularly beneficial due to their ability to detect complex spatial patterns, which can enhance prediction accuracy. However, their application in wildfire susceptibility modeling is still in the early stages, and further empirical research is needed to assess their generalizability and performance across different environmental contexts.
Among emerging techniques, ensemble methods show significant promise for improving wildfire prediction performance [30–32]. For instance, a recent study in [1] proposed a transformer-based time series forecasting model to enhance wildfire prediction accuracy at local scales. To identify relevant literature, an initial keyword search was conducted using terms such as *"Fire Detection," "Computer Vision," "Machine Learning," "Image Processing,"* and *"Deep Learning."* A secondary search focused on fire suppression technologies, combining terms like *"Fire Extinguishing"* with *"UAV"* (Unmanned Aerial Vehicle) and *"UGV"* (Unmanned Ground Vehicle). Figure 4 offers a visual overview of the selected research domains and their distribution, while table 1 provides a summary of key studies related to fire detection.

A recent study proposed a novel method integrating explainable AI with feature engineering to enhance wildfire prediction models [62]. This research evaluated a variety of machine learning algorithms for both classification and regression tasks, finding that XGBoost was particularly effective in classifying wildfire types, while the Random Forest regression model excelled in estimating the extent of burned areas. The incorporation of explainable AI techniques facilitated greater model interpretability, allowing for the identification of key predictive features and enhancing transparency in the process. Moreover, an innovative approach using Graph Neural Networks (GNNs) has been developed for global wildfire prediction [63]. This method tackled common challenges such as incomplete oceanic data and long-range temporal dependencies in meteorological variables by transforming global wildfire and climate data into a graph-based structure. The hybrid model, which combined Graph Convolutional Networks (GCNs) with Long Short-Term Memory (LSTM) networks, achieved superior predictive performance while also enhancing interpretability by uncovering spatial clusters linked to wildfire occurrences and highlighting critical contributing factors.

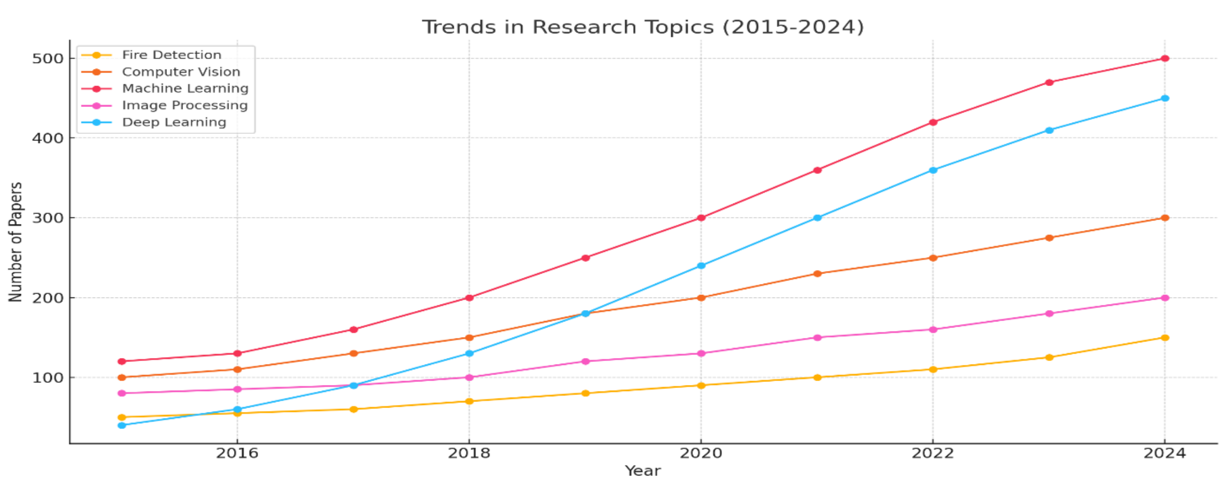


Figure 4, Research Selected Areas

Table 1, Previous fire detection studies

Paper	Published year	Methodology	Dataset	Accuracy	Advantages	Disadvantages
[33]	2022	Transfer learning	47,992 images	Recognition accuracy of 79.48% through using ResNet50 model.	Preventing and controlling large-scale forest fires early	Low accuracy
[34]	2022	YOLOv5 and Efficient Det	2976 images	The average accuracy of the suggested model for forest fire exploration reached 87%.	Using weighted fusion to get around the problems with hand feature extraction and improve the accuracy of detecting forest fires	Limited dataset
[35]	2022	YCbCr and correlation coefficient	11 videos	Achieved precision of 95.87% and accuracy of 97.89 on fire detection.	use a correlation coefficient and a rule-based multi-color space to identify forest fires effectively.	Unsatisfactory Regional Generalization
[36]	2021	Squeeze Net	11,456 images	obtained 93% accuracy.	determining whether a fire is present by first dividing up all regions that resemble fires, and then going through the classification module.	Impact of Climate Change
[37]	2021	CNN	2100 images	Achieved a classification accuracy of 95%.	attempting to use CNN to extract and categorize picture information for fire detection.	Despite its effectiveness, the approach presented in this paper was evaluated using a relatively small, manually curated dataset.
[38]	2021	SVM	data obtained from USGS website	99.21% of accuracy on fire detection and value precision about 98.41%.	use SVM to detect forest fires on LANDSAT pictures.	High Computational Requirements
[39]	2020	Automatic gain control algorithm	12,000 frames	The proposed approach achieved better situation awareness when compared to existing methods.	Using data-driven, near-real-time fire monitoring and detection using thermal infrared sensing.	Low accuracy
[40]	2020	Simple linear iterative clustering	37 images	attained an overall accuracy of over 99% on fire damage assessments.	constructing an unsupervised change detection framework to aid in the evaluation of wildfire damage by combining prefire PS data with post-fire VHR images.	Limited manually creates dataset

[41]	2022	Deep CNN	22 tiles of Landsat-8 images	97.35% overall accuracy	identifying the fire's origin in order to detect forest fires early.	Excessive computational demands
[42]	2022	FCOS	11,681 images	Attained 89.34% accuracy	identifying forest fires instantly and provide firefighting support.	Inadequate Consideration of Human Factors
[43]	2022	MTL	6595 images	Achieved 98.3% accuracy	addressing issues with weak small-target recognition and numerous missed and erroneous detections in intricate forest settings.	Poor Generalization Across Different Regions
[44]	2022	R-CNN	8000 images	accuracy of 93.65% and a precision of 91.85%	dividing video frames into two groups (fire and no-fire) based on whether a fire is present or not, as well as the segmentation technique applied to the detection and segmentation of forest fires that are just beginning.	High Requirements for Computing
[45]	2021	Non-sub-sampling contourlet transform and visual saliency	NA	It was asserted that the fusion results of the proposed method demonstrated enhanced clarity and contrast, while preserving a greater number of image features.	constructing a network monitoring system for solar-blind UV signals using machine vision.	Difficulty in Real-Time Adaptation
[46]	2021	R-CNN, Bayesian network, and LSTM	81,810 images	accuracy of 97.68%	increasing the accuracy of fire detection in comparison to previous video-based techniques.	High Processing Power Needs
[47]	2021	Vision transformer	500 images	97.7% F1-score	Detecting and segmenting them early to anticipate their spread and aid in battling fires	Limited dataset
[48]	2020	Artificial bee colony algorithm-based color space	2000 images	The evaluation yielded a mean Jaccard index of 0.76 and a mean Dice index of 0.85.	using color space for forest fire detection.	High Requirements for Computing
[49]	2020	Deep CNN	4000 images	94.6% F-score	Identifying fire as soon as feasible	High Processing Power Needs
[50]	2022	CNN and vision transformers	48,010 images	Accuracy about 85.12% on wildfire classification and F1-Score of 99.9%	identifying wildfire early on.	Inability to Accurately Model Complex Fire Behavior

[51]	2021	CNN	37,016 images	average IoU higher than 70%	Sentinel-2 imagery was used to build an automated framework for active fire detection.	Limited Predictive Accuracy
[52]	2023	DCNN and BPNN	7690 images	84.37% accuracy	creating a better DCNN model to predict the risk of forest fires. putting the BPNN fire algorithm into practice to determine the delay rate and processing speed of video images.	Challenges with Integrating Human and Environmental Factors
[53]	2023	DeepLabV3+	NA	94.26% accuracy, 94.04% recall, and 89.51% mIoU.	Introducing Defog DeepLabV3+ for accurate flame segmentation and cooperative defogging. suggesting DARA to improve the extraction of features connected to flames.	Poor Generalization to Different Regions
[54]	2023	Transfer learning	1452 images	99.32% accuracy.	A forest fire dataset was used to test and evaluate various convolutional neural network (CNN) models, incorporating transfer learning. Support Vector Machines (SVM) and Random Forest (RF) classifiers were applied for detection, while networks were trained and tested using both random and ImageNet-pretrained weights.	High Requirements for Computing
[55]	2023	FuF-Det (encoder–decoder transformer)	14,094 images	a fire spot detection rate of 78.69%.	AAFRM was designed with positional features in mind. RECAB construction to preserve fine-grained firing point information. Adding CA to the detection head to increase the precision of localization.	Limited Predictive Accuracy
[56]	2023	YOLOv5	3000 images	an mAP@0.5 of 84.56%.	The transformer module is integrated into the feature extraction network of YOLOv5, with the Channel Attention (CA) mechanism positioned before the YOLOv5 head. To enhance multi-scale feature fusion, the model's head incorporates the Adaptive Spatial Feature Fusion (ASFF) technique.	Computational Limitations

[57]	2023	Ensemble learning	1900 images	95.79% accuracy	An ensemble model is proposed for stacking, utilizing pre-trained models as base learners for feature extraction and initial classification. A Bi-LSTM network is employed as a meta-learner for the final classification step.	Limited Real-Time Adaptability
[58]	2023	YOLOv5s	5250 infrareds images	an mAP@0.5 of 0.907.	YOLOv5s-seg-based FFDSM is being proposed, with ECA and SPPFCSPC modules added to improve feature extraction and fire detection precision.	Inconsistent Model Validation
[59]	2023	Deep ensemble learning	204,300 images	NA	introducing a deep ensemble neural network model that makes use of RetinaNet, YOLOv2, YOLOv3, and Faster R-CNN.	Inadequate Fire Spread Modeling
[60]	2023	CNN	1900 images	accuracy of 97.63% and an F1-score of 98.00%.	putting forward a CNN architecture-based forest fire detection technique. utilizing separable convolution layers to enable real-time applications, minimize computational resources, and detect fires instantly.	Lack of Multi-Scale Integration
[61]	2023	Ensemble learning	51,906 images	accuracy rates of 99.62%	Introducing CT-Fire, a method for detecting forest fires in aerial and ground photos that combines the vision transformer Efficient Former v2 with deep CNN RegNetY.	High Computational Requirements

The proposed forest fire prediction strategy (HF^{2}P) aims to address or mitigate the challenges outlined above. This is achieved by incorporating evidence from both deep learning (DL) and machine learning (ML) models, thus leveraging the advantages of both methodologies. In HF^{2}P, VGG16, an efficient DL model, is employed for feature extraction, while a modified VGG16 and Decision Tree (DT) are combined as effective ML and DL techniques to enhance prediction accuracy. HF^{2}P utilizes a sufficient number of training images and applies a feature selection methodology (BGWO) to identify the most informative features. This approach facilitates faster training and testing of the model, while also reducing the risk of overfitting. A binary instance of the Gray Wolf Optimizer (GWO) is selected as the feature selector, and the final prediction is determined using a voting technique, thereby improving the accuracy of the final decision.

4. The Proposed Forest Fire Prediction Strategy (HF^{2}P)

This section presents a detailed overview of the proposed Hybrid Forest Fire Prediction Strategy (HF^{2}P). The HF^{2}P framework is structured into two primary sequential phases: (i) the *Pre-Processing Phase (PP)* and (ii) the *Ensemble Classification Phase (ECP)*, as illustrated in Figure 5. In the Pre-Processing Phase, the input dataset is first assessed for class imbalance and, if necessary, subjected to data augmentation or balancing techniques. This phase begins with the removal of noisy or inconsistent entries to ensure data integrity and facilitate accurate subsequent analyses. Following this data cleaning step, feature extraction is performed based on fire incidence location data. Relevant environmental and topographical attributes at the fire sites are systematically extracted to capture the conditions associated with fire occurrences. These extracted features are then analyzed using comprehensive data mining techniques to uncover patterns, correlations, and trends that provide insights into wildfire behavior and the factors influencing fire ignition and spread. For image-based data, the VGG16 deep learning model, a pre-trained convolutional neural network, is utilized to extract high-level spatial features from satellite or aerial imagery [41].

In the subsequent *feature selection* stage, the study applies a bio-inspired optimization algorithm, specifically the Gray Wolf Optimization (GWO) technique, to identify and retain only the most influential and informative variables related to forest fire occurrence. The final prediction is conducted in the Ensemble Classification Phase, where both machine learning and deep learning models are integrated. An ensemble voting mechanism is utilized, combining the outputs of a Deep Learning Classifier (DLC) and a Decision Tree Classifier (DTC) to enhance predictive accuracy and model robustness. A comprehensive workflow of the HF^{2}P framework is elaborated in the following subsections. This includes the initial risk analysis, feature extraction for both fire and non-fire (random) points, and the selection of key predictive variables for effective forest fire occurrence forecasting.

4.1. Utilizing Deep Learning Pre-Trained VGG16 Model for Feature Extraction

The feature extraction process aims to transform raw data into new features that enhance the performance of the machine learning system. The model employed is Visual Geometry Group 16 (VGG16), a convolutional neural network architecture first introduced in [30]. The VGG16-based CNN model utilizes input images of 224x224 pixels and consists of 16 weight layers, including three fully connected layers and 13 convolutional layers. The convolutional layers employ a 3x3 kernel size, 1-pixel padding, and use the Rectified Linear Unit (ReLU) activation function. Five max-pooling layers with a 2x2 pixel filter and two strides come after spatial pooling. Before sending output to layers that were fully connected, one flattened layer was added. Additionally, the last fully connected layer employed 1,000 output classes and the softmax activation function. A sizable dataset was used to train VGG16 on ImageNet. This model had 138,357,544 trainable parameters in total. Using the VGG-16 model, we eliminate the output layer—which is used for classification—in order to extract characteristics from an image. After that, a representation of the image is created using the remaining layers, which includes details about its characteristics including shape, color, and texture.

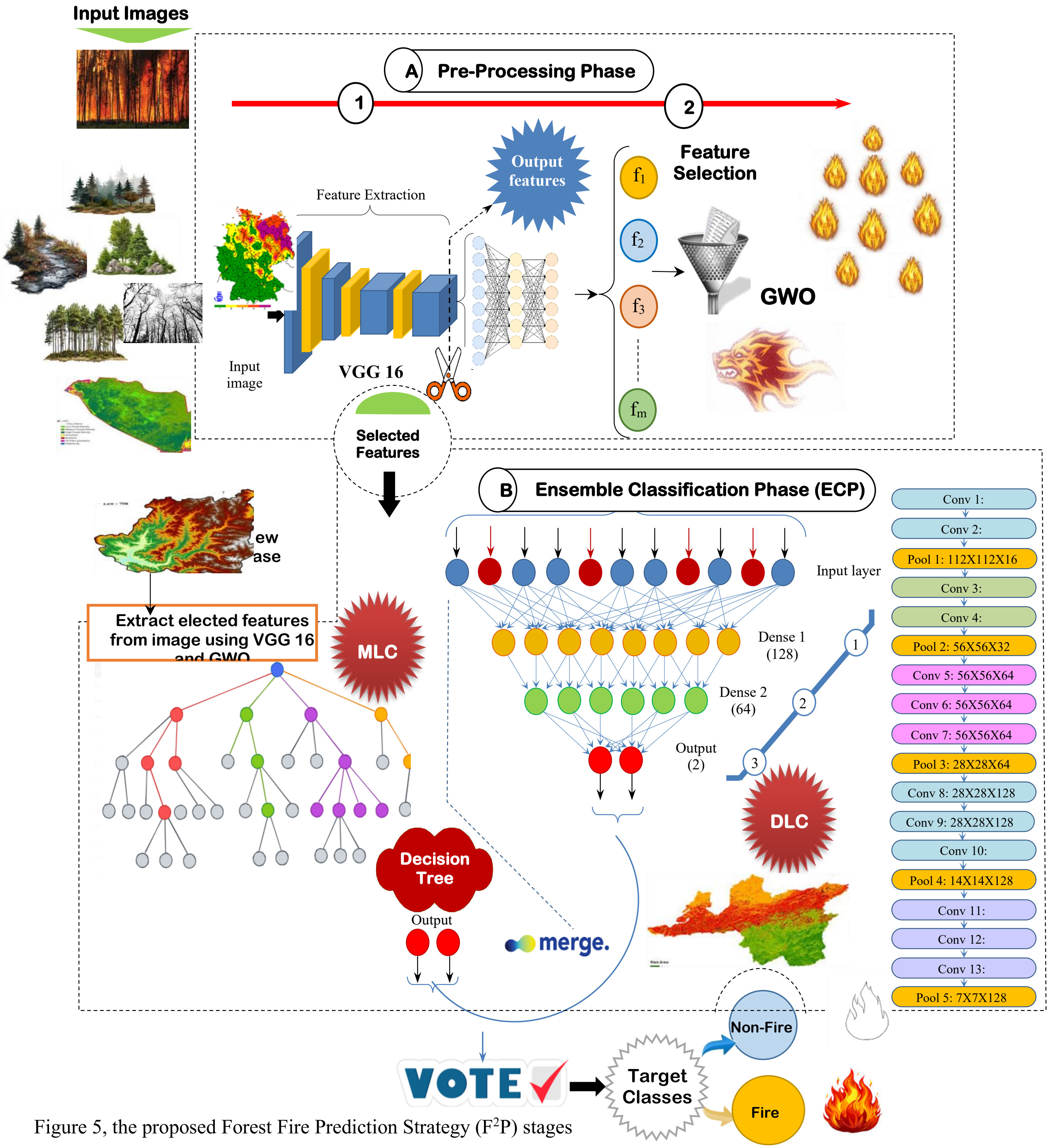


Figure 5, the proposed Forest Fire Prediction Strategy (F^2P) stages

4.2.Feature Selection based on Bio-Inspired Gray Wolf Optimization (GWO)

Feature selection aims to identify the most relevant characteristics in a dataset that contribute effectively to classification tasks, based on criteria such as consistency, originality, and significance. This step is crucial in feature engineering, as it determines which features will be used to optimize model performance. By selecting only the most informative features, it reduces the dimensionality of the data and enhances the efficiency of the deep learning model. In this study, the Gray Wolf Optimization (GWO) algorithm, a bio-inspired optimizer, is employed for feature selection [31]. The binary values (0 and 1) are used to define the search space, determining which features to include in the model. Consequently, meta-heuristic optimizers that typically operate with continuous values must be adapted to handle binary outputs corresponding to selected features. Each feature in the n-feature set is assigned a value of 0 or 1, indicating whether it will be used in the classification process.

4.3.Classification Phase using Deep Learning and Machine Learning

HF^{2}P classification phase consists of a pre-trained deep learning network that was used as the first classifier and, in the second instance, a decision tree classifier is used to form a combination which forms an ensemble classification procedure. The established hybrid deep learning and machine learning ensemble method is well known for its ability to increase accuracy by pooling predictions from several models [32].

4.3.1. The modified VGG16 Deep Learning Model

In this section VGG 16 CNN model serves as the first classifier to assist the machine learning classifier. Reusing models that have already been pre-trained on benchmark datasets, such ImageNet and image recognition tasks, is known as transfer learning. These models have been trained on over a million images and can classify images into 1000 classes and it is reusable as a starting point for similar problems [64].
The first classifier is the VGG16 Deep Learning Model which achieved high accuracy with the best five tests using ImageNet which contains more than 14 million image datasets with 1000 classes [65]. In addition to that VGG16 gives a lower error rate than all other VGG models. The VGG16 architecture, which consists of six blocks and 16 layers overall. The first five blocks carry out pooling and convolution operations. Three dense or fully connected layers, comprising two layers of neurons and a final layer of classes, make up the final block. ImageNet weights are used to train VGG16 on 14 million images from 1000 classes.
Two convolution layers with 64 channels of 3 × 3 kernels with padding of the same make up the first convolution block, which is followed by a pooling layer. There are two values for the padding parameter: same and valid. While the same does not permit modifications in the spatial domain, the valid does. The pooling layer chooses a maximum pool size of 2 × 2 and a stride of 2 × 2. The next two convolution layers have a 3 × 3 kernel with max pool operation and 112 × 112 of 128 channels. Then the next three layers of the architecture are 28 × 28 with 512 channels of 3 × 3 kernel and the same padding, followed by three convolution layers of 56 × 56 having 256 channels of 3 × 3 kernel and the same padding. The next three layers are 14 × 14 with 512 channels and the same padding. The following two layers are 7 × 7 with 512 channels, the same padding, and max pool functionality. The final three layers are dense or fully connected layers after all of the convolution layers have been learned. In order to classify the input images, the first dense layer has 4096 neurons with activation function, the second dense layer functions similarly, and the final dense layer has 1000 channels. Some modifications have been applied on the standard VGG 16 model by utilizing the feature selection beside modifying the dense layer by replacing the output layer of 1000 class with the two-class output layer to fit the binary application. As illustrated in figure 6, it can be said that the trained VGG 16 model has been reused by freezing the first layers and removing the top fully connection layers and the output layer. Anew five fully connected layers are then added. The redesigned VGG 16 can be divided into two sections: the trainable section, which displays the final five layers that need to be trained,

and the frozen section, which displays the initial layers and weights. Only the features that have been selected by the BLSO are embedded into the VGG 16 network which reduces the network size and therefore reduces the complexity and processing time. The rectified linear function (relu) was employed as an activation function in each fully connected layer. Since there are two classes for the prediction process, the output layer consists of two neurons.

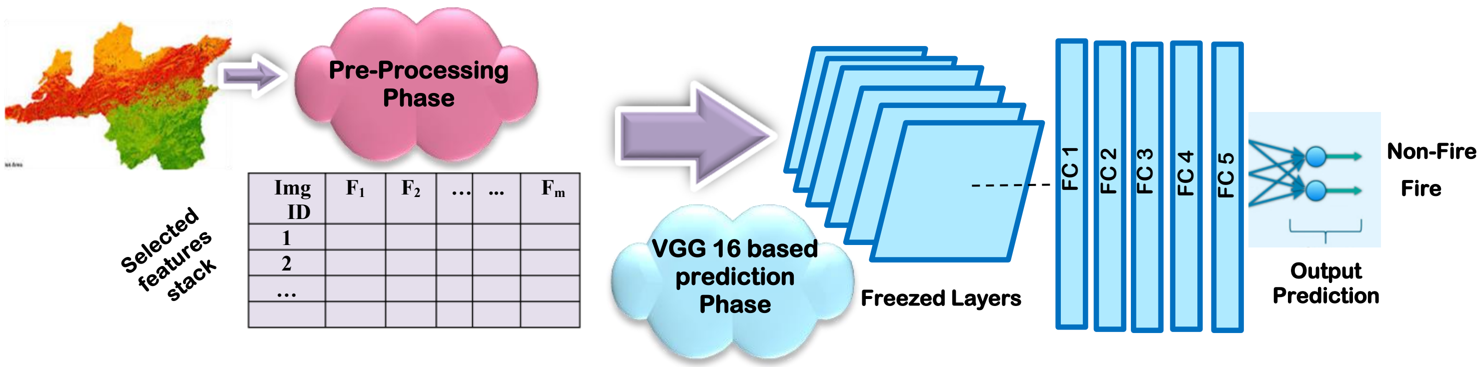


Figure 6, The modified VGG 16 Structure

4.3.2. Decision Tree Machine Learning Classifier

In this section Decision Tree ML model serves as the second classifier. The following factors make decision tree (DT) a popular choice for predictive modeling. DT is a non-parametric approach to supervised learning that is employed in regression and classification which make it easy to interpret and comprehend. It is feasible to use statistical tests to validate a model. This enables the model's dependability to be taken into consideration. DT capable of managing category and numerical data [66]. DT tends to require little to no adjustments which makes it quite simple to use. Assuming that DT learned in a roughly balanced manner, which is what most heuristics aim to guarantee, it can be learned very quickly. Usually, learning rises as O (mn log n) where, n the number of rows and m the number of columns in the data table. Prediction implies O (log n) tests under the same assumption, which usually translates to a few dozen CPU operations per instance [32]. Through the prediction procedure using DT the selected features using GWO after extracted them using the VGG16 feature extractor are embedded into the tree structure. To classify data according to a set of criteria derived from the features or attributes of the data as shown in figure 7. Then the final decision will be embedded into the voting stage to determine the final prediction from both the VGG16 model and the DT model.

4.3.3. Voting Technique

In this subsection the output classification decisions from the two considered classifiers DT and the deep neural network modified VGG 16 model will be merged to get the final decision of the monkeypox diagnosing process. The final decision will rely on the DT Classifier decision D_{DT} multiplied by its weight $\xi_1$and the Deep neural network decision D_{DNN} multiplied by its weight ξ_2 as explained in (1).

$$\text{Decision} = \xi_1\ D_{DT} + \xi_2\ D_{DNN} \quad (1)$$

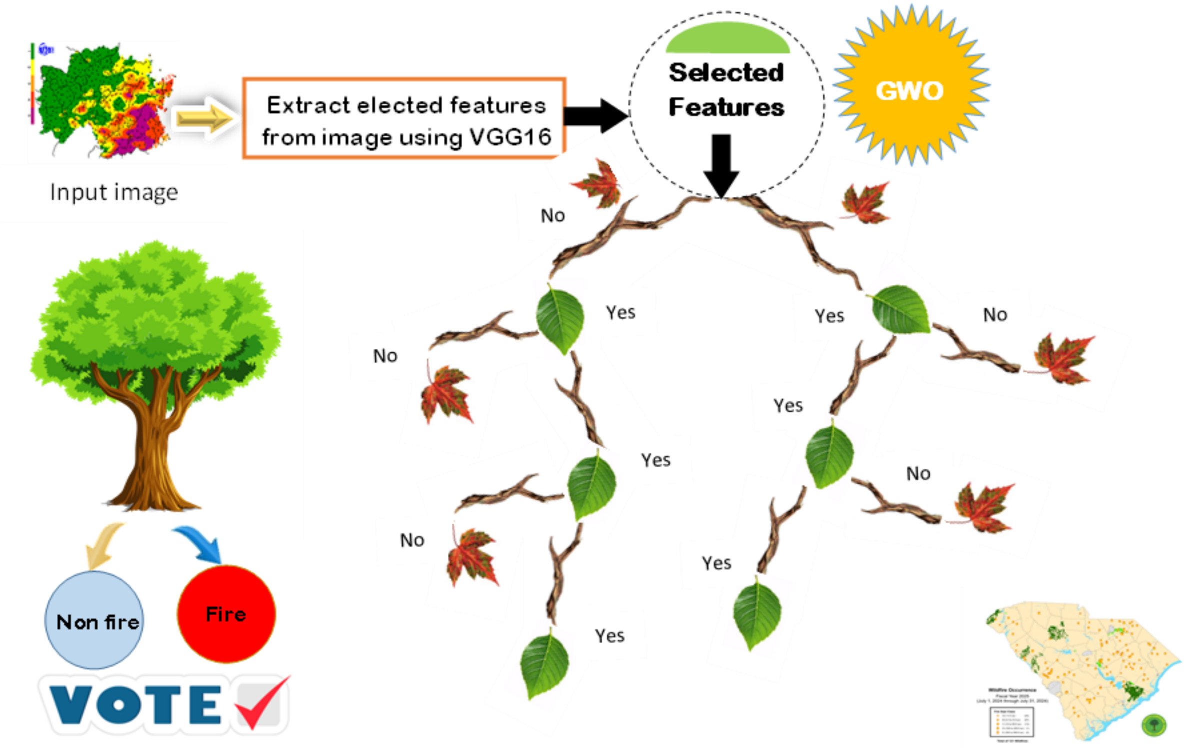


Figure 7, The Decision Tree Classifier Structure

5. Testing the proposed Accurate Forest Fire Prediction (HF^2P) Strategy

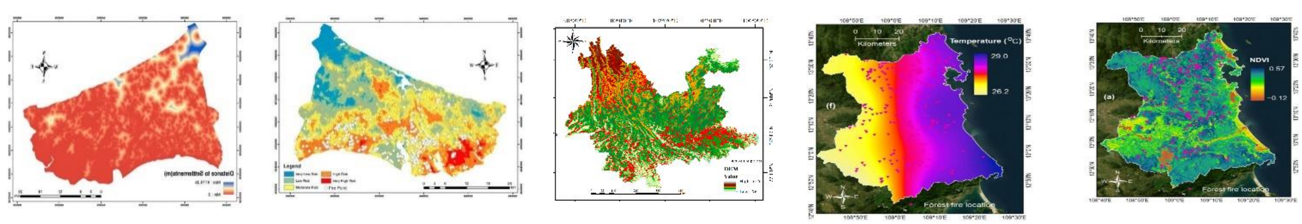
In this section the proposed methodology will be evaluated through different metrics. The preprocessing phase (PP) and the Ensemble Classification Phase (ECP), as described in the preceding section, are the two fundamental stages of the HF^2P strategy. The preprocessing phase applied in two stages; in order to achieve the best performance, features are first retrieved using the VGG16. The feature selection phase, which uses the BGWO to choose the most significant characteristics. The suggested ensemble classification process is used to accurately anticipate forest fires during the second phase, known as ECP. A training set is used to carry out the learning process. The testing set is then used to evaluate the proposed model's efficacy. Table 2 displays the tuning parameters that the feature selector (BGWO) uses and their values.

Table 2, Tuning parameters used by the proposed IBGWO

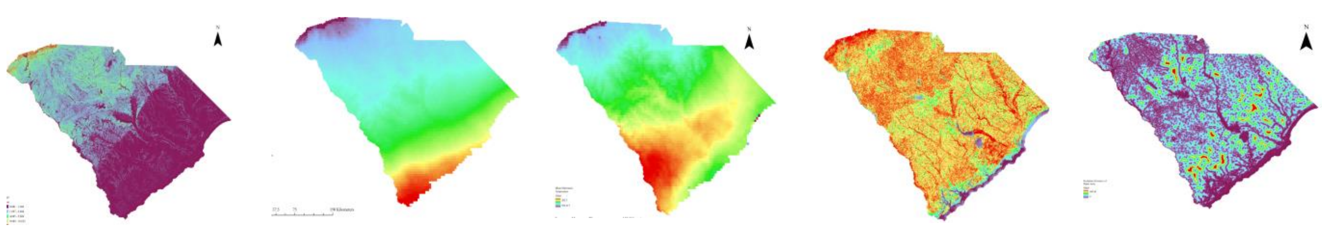
Parameter	Description	Used value
μ_1	weighting factor for the diagnosis accuracy	0.9
μ_2	weighting factor for the chromosome weight	0.1
n	Number of wolves	5
t	Number of iterations	100
Used Ensemble classification techniques		VGG16 and DT

5.1.Dataset Description

This study integrates a diverse range of geographic and environmental data sources to enhance the analysis of wildfire susceptibility across various locations in South Carolina (SC). Key environmental features—such as state boundaries, roads, rivers, and water bodies (e.g., ponds or lakes)—were obtained from publicly available datasets as cited in [67]. The National Land Cover Dataset (NLCD) [68] was also utilized, providing accurate and georeferenced land cover classifications and land cover change data for the region. To ensure spatial precision and contextual relevance, these raster layers were carefully clipped using the SC state shapefile. Additionally, the Normalized Difference Vegetation Index (NDVI) was integrated to assess vegetation health and density, serving as a critical factor for wildfire risk analysis [69]. A visual sample of the compiled dataset is shown in Figure 8(a). Wildfire incident point data for the year 2023 was provided by the South Carolina Forestry Commission and was processed within Google Earth Engine (GEE). To ensure a balanced dataset, an equal number of randomly generated non-fire points were created within GEE across the SC region. Elevation data were sourced from the Shuttle Radar Topography Mission (SRTM), a global-scale digital elevation initiative. The SRTM V3 (SRTM Plus) product, distributed by NASA's Jet Propulsion Laboratory (JPL), offers a spatial resolution of approximately 30 meters (1 arc-second) [70]. Relevant raster layers were further retrieved using GEE, as illustrated in Figure 8(b) [71]. GEE has been widely used for various geospatial applications, including agriculture monitoring, forest and vegetation studies, ecosystem assessments, and land cover classification, underscoring its versatility and reliability as a data processing platform [72], [73]. After data acquisition, an exploratory data analysis (EDA) phase was conducted as part of the preprocessing workflow. This phase involved noise reduction, handling missing data, and transforming categorical variables into numerical formats suitable for machine learning models. Feature extraction was performed using wildfire incident locations to derive key environmental and topographical attributes. These features were then analyzed to identify patterns, trends, and correlations that influence wildfire behavior and the underlying drivers of fire occurrence. The dataset was split into training (70%) and testing/validation (30%) subsets.



(a) Samples of Normalized Difference Vegetative Index (NDVI)



(b) Raster layers created in GEE (https://earthengine.google.com, accessed on 24 January 2025)

Figure 8, Samples of collected dataset

5.2.Evaluation Metrics

The following experiments will evaluate four key metrics: error, precision, accuracy, and sensitivity. The results of the application will be further assessed by measuring recall, F-measure, precision, accuracy, error, and runtime. A confusion matrix, as presented in Table 3, is utilized to derive the values for these metrics. Various distinct formulas are applied to summarize the confusion matrix, as outlined in Table 4 [74, 75].

Table 3, Confusion matrix.

		Predicted label	
		Positive	Negative
Known label	Positive	True positive (XP)	False Negative (YN)
	Negative	False positive (YP)	True Negative (XN)

Table 4, Confusion matrix formulas.

Measure	Formula	intuitive interpretation
Accuracy (A)	$\frac{(XP + XN)}{XP + XN + YN + XN}$	The proportion of correctly predicted cases
Error (E)	1-Accuracy	The proportion of predictions that are found to be inaccurate.
Precision (P)	$\frac{XP}{XP + YP}$	The proportion of true positive predictions.
Recall / Sensitivity (R)	$\frac{XP}{XP + YN}$	the proportion of positively tagged cases that were expected to be positively labeled.
F-measure	2*PR/(P+R)	Weighted harmonic mean of recall and precision

5.3.K-fold cross-validation

K-fold cross-validation enhances model reliability, mitigates overfitting, and ensures the model's generalizability [76]. In this method, the dataset is divided into k subsets, with k-1 subsets used for training and the remaining subset used for validation. This process is repeated k times, with each subset serving as the validation set once. In this study, 5-fold cross-validation was applied, and the average of the results from the five folds was computed. The representation of the k-fold cross-validation procedure is provided in equation (2).

$$\text{k-fold cross validation} = \frac{1}{k}\sum_{i=1}^{k} performane\ metric\ _i \qquad (2)$$

5.4.Testing the proposed HF^{2}P Strategy

In this subsection, the proposed HF^{2}P strategy will be evaluated using a voting ensemble prediction method, which combines the modified VGG16 model with the Decision Tree (DT). Initially, features are extracted from the images in the dataset using the VGG16 model. These features are then reduced using Binary Gray Wolf Optimization (BGWO) to select the most significant features, thereby simplifying calculations and improving classification accuracy. To assess the effectiveness of the HF^{2}P strategy, it will be compared with state-of-the-art ensemble methods, and the DT classifier will also be evaluated independently against HF^{2}P. A summary of recent ensemble prediction methods used for evaluation is provided in Table 5.

Table 5, The most contemporary methods for evaluating HF^{2}P.

Ensemble prediction technique	Description
GWO-XGBoost model [31]	A fire growth rate warning map for Liangshan Prefecture in Sichuan Province, China, generated using the ensemble model (GWO-XGBoost).
Ensemble Transfer Learning [32]	An Ensemble Transfer Learning method is presented which includes a fusion of ResNet-50 and VGG-19.
Time Series Prediction [77]	This study forecasts power consumption using a novel ensemble method that integrates three time series models: RNN, LSTM, and GRU.
Ensemble two DL models [78]	This method incorporates VGG16 and ResNet50 architectures.
Ensemble three DL models [79]	The authors employed the AlexNet, ResNet-50, and VGG-16 models.

Voting between DT and modified VGG16 processed according to (8). To explain how the classifiers' weights are calculated a test sample is presented below:

VGG 16 (DL):	DT (ML)
Fire Probability = 0.6	Fire Probability = 0.3
Non fire Probability = 0.4	Non fire Probability = 0.7

By applying (8):
As $\xi_1 + \xi_2 = 1$ & from a previous test sample infection probability: $D_{VGG\ 16} = 0.89$, $D_{DT} = 0.92$
then to calculate the weights: 0.89 x + 0.92 x = 1 → ∴ x= $\frac{1}{1.81}$ =0.55

$$weight\ of\ VGG\ 16: \xi_1 = \frac{0.89}{1.81} = 0.49$$

$$weight\ of\ \ DT : \xi_2 = \frac{0.92}{1.81} = 0.51$$

The final Fire Probability = 0.6 * 0.49 + 0.3 * 0.51= 0.447
The final Non fire Probability = 0.4 * 0.49 + 0.7 * 0.51= 0.553
∴Final decision is → Non Fire case

To evaluate the proposed HF^{2}P strategy, the comparative study performed under the same conditions using the same feature extractor (VGG16) and the same feature selector (BGWO) using the prementioned dataset. Different ensemble prediction methods compared in terms of accuracy, error, precision, runtime, f-measure and recall. The evaluation for training results are shown in figures (9-14). It is clear that all the model's ability to predict the right label is improving progressively with increasing the number of epochs.
According to the accuracy and error measurements in figures 9&10, the ensemble HF^{2}P model outperformed innovative algorithms with the average of 4-fold cross-validation. As noticed in figures 11&12 despite of precision and recall, the proposed HF^{2}P strategy demonstrates the best performance. Figure 13 illustrates the performance in terms of f-measure and it is clear that the proposed HF^{2}P strategy presents superiority against other competitors.
Despite the time-varying complexity of other rivals, the suggested HF^{2}P strategy produces fast prediction

results consequently after the DT algorithm, as seen in figure 14. This is due to the fact that other approaches rely solely on deep learning models, which are known for being computationally expensive, requiring significant memory and resources, and imposing substantial time penalties. In contrast, the HF^{2}P method is more user-friendly, time-efficient, and capable of handling various types of data. From the evaluation results shown in Figures (9-14), it is evident that the Decision Tree (DT) algorithm, when used independently, has limited predictive accuracy, despite its fast processing time. Furthermore, the ensemble time series algorithm in [77] fails to predict accurately, achieving a low accuracy of approximately 0.72. On the other hand, the ensemble of three deep learning models in [79] delivers good accuracy (around 0.8) when trained on 12,000 images but is a time-consuming algorithm due to its complexity. The model complexity and computational time were improved in the GWO-XGBoost model [31]. As illustrated in Figures (9-14), the proposed HF^{2}P strategy outperforms all other methods, demonstrating superior performance.

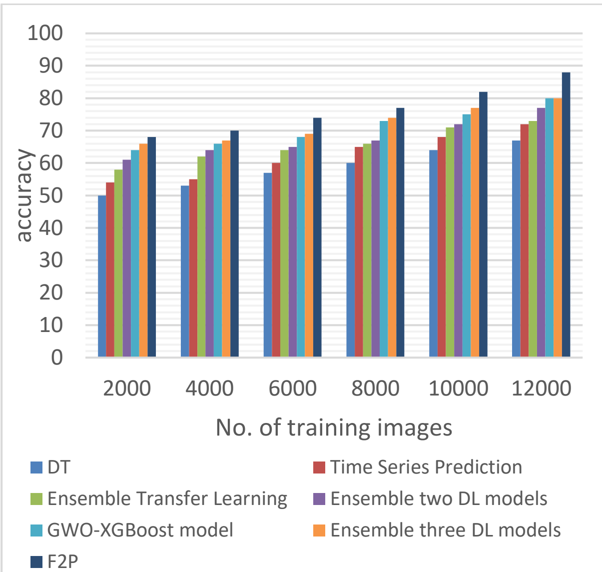


Figure 9, the proposed HF^{2}P Strategy compared with other approaches based on the average accuracy of 5-fold cross-validation.

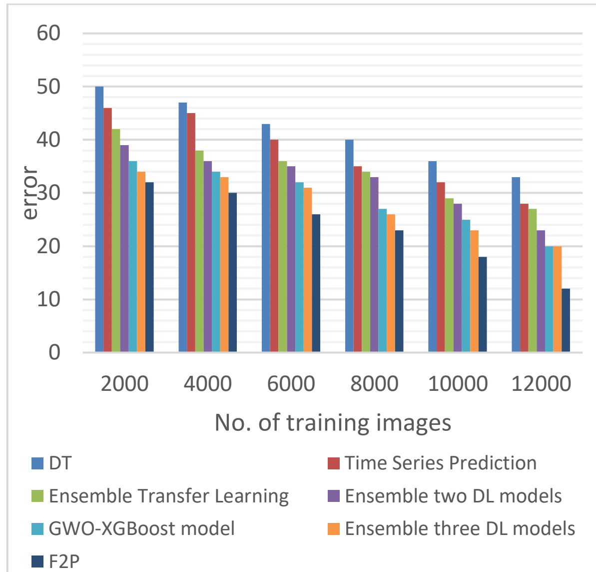


Figure 10, the proposed HF^{2}P Strategy compared with other approaches based on the average error of 5-fold cross-validation.

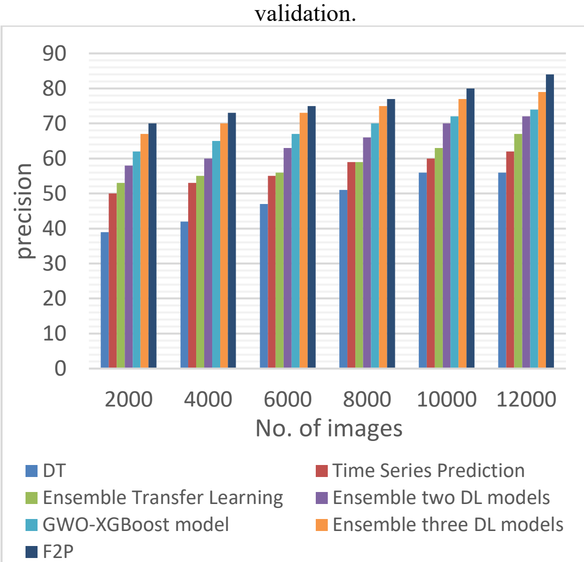


Figure 11, the proposed HF^{2}P Strategy compared with other approaches based on the average precision of 5-fold cross-validation.

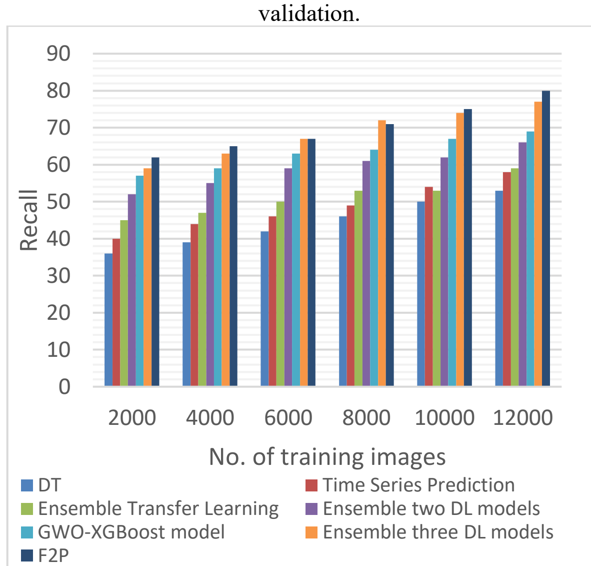


Figure 12, the proposed HF^{2}P Strategy compared with other approaches based on the average Recall of 5-fold cross-validation.

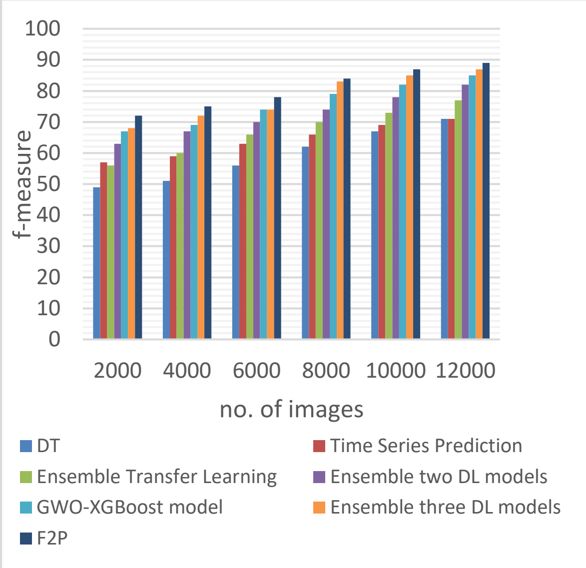


Figure 13, the proposed HF^{2}P Strategy compared with other approaches based on the f- measure of 5-fold cross-validation.

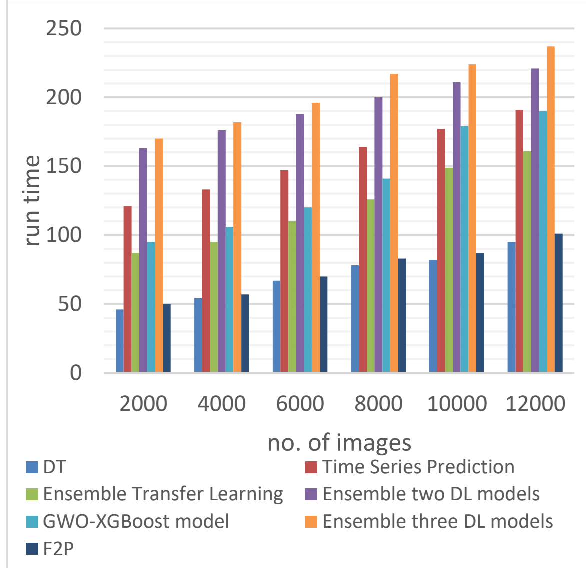


Figure 14, the proposed HF^{2}P Strategy compared with other approaches based on the processing time of 5-fold cross-validation.

6. The significance of the work presented in this study

Furthermore, the proposed HF^{2}P strategy demonstrates strong generalizability, making it suitable for a wide range of forecasting applications across diverse domains. The dataset employed in this study captures the fundamental principles underlying the model's utility and scalability. The approach can be effectively adapted for tasks such as variable prediction or item classification within specific fields. For instance, in business, the classification capability of the model can be applied to quality control processes, such as identifying defective products by categorizing items into "acceptable" and "defective" classes. In the energy sector, the strategy can support electrical load forecasting by classifying future energy demands into categories such as low, medium, and high. In biogas production, the model can be utilized to predict biogas yield based on key operational parameters like temperature and pH levels. The HF^{2}P approach also holds promise in the field of economics, where it can be employed to forecast crude oil prices, evaluate business profits and losses at the end of a fiscal year, or estimate potential risks associated with specific economic policies. In agriculture, the model can assist in predicting crop yields, enabling better planning and resource allocation. Finally, the approach can be applied to weather forecasting, where it may be used to classify and predict meteorological parameters such as temperature, wind speed, or precipitation levels.

7. Conclusion

Forest Fires have become an increasingly prevalent and destructive force, posing significant threats to ecosystems, human lives, and economies worldwide. In recent years, the frequency and severity of these fires have increased, resulting in unprecedented losses. Artificial Intelligence (AI) has emerged as a promising tool in addressing this challenge. By leveraging data analysis and machine learning techniques, AI enables the identification of high-risk areas, the prediction of fire behavior, and the provision of early warnings. However, despite these advancements, wildfire prediction remains a complex and challenging task. While AI models, particularly deep learning and machine learning techniques, have shown great potential in forecasting forest fires, several obstacles hinder their effectiveness. The unpredictable nature of forest fires, influenced by a wide range of environmental factors such as temperature, humidity, wind speed, and vegetation type, makes it difficult to create highly accurate predictive models. In this paper, an attempt to promote the prediction of forest fires by combining evidence from deep learning and machine learning techniques. A Hybrid Forest Fires Prediction (HF^{2}P) Strategy was introduced, which is based on an Ensemble Classification of Convolutional Neural Networks and Decision Tree Models. The proposed HF^{2}P employs VGG16 for feature extraction after removing the final dense layers form the model. Then, the most effective features are selected using GWO. The selected feature are then passed to two different predictors, namely; Deep Learning Classifier (DLC) and Decision Tree Classifier (DTC). The decisions provided by both predictors are then combined to provide the final forecast. An extensive set of images have been gathered and merged from multiple available online datasets. Experimental results have shown that the proposed HF^2P outperformed recent prediction methods in terms of accuracy, precision, f-measure, recall, error and processing time. Its accuracy reached 88% using 12000 training images.

8. Future work

The use of artificial intelligence (AI) for forest fire prediction is an evolving area of research, with numerous promising avenues that can be explored to improve upon the methodology proposed in this paper. For illustration, (i) improve Data Collection and Integration, which can be accomplished by three aspects: multi-modal data fusion, employing IoT and Remote Sensing, or providing better satellite coverage. The first aspect can be held by combining satellite imagery, weather data, social media feeds, sensor networks, and historical forest fires data to enhance predictive accuracy, the second can be done by deploying AI-powered drones and ground-based sensors to collect real-time environmental data, while the third can be satisfied by leveraging new satellite constellations such as hyperspectral imaging, for high-resolution wildfire monitoring. (ii) Employing advanced ML and AI techniques, which can be held by; employing transformers for more precise fire spread modeling as well as using Explainable AI (XAI) for making AI predictions more interpretable to help emergency responders understand risk factors. Reinforcement learning can also be applied by training AI models to simulate fire behavior and optimize firefighting strategies. (iii) Real-Time forest fires forecasting, which can be done by using AI-driven early warning systems. Hence, different models for fire prediction before ignition can be investigated using climate and vegetation conditions. Moreover, AI models can be implemented on local edge devices for instant risk assessment in fire-prone areas.

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