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Hybrid Grasshopper Optimization Algorithm (GOA)-Swin Transformer Model for Satellite Image Based Wildfire Prediction

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ABSTRACT: Wildfire prediction plays a major role in quickly identifying fire incidents to prevent losses due to environmental hazards, property damage, and the loss of human lives. However, existing image-based wildfire prediction methods cannot reliably distinguish wildfire image from a non-wildfire image as the quality of fire-affected images varies with respect to the natural environment. To overcome these existing issues, a Hybrid Grasshopper Optimization Algorithm (GOA)-based Swin Transformer for Satellite Image-based Wildfire Prediction is proposed. The proposed model is evaluated using wildfire prediction dataset. The input images are enhanced using an Unsharp Mask Filter, and relevant image areas are segmented based on thresholding. The edge features of the image are extracted using Histogram of Oriented Gradients (HOG), and the features are optimized through Swin Transformer using GOA for better classification. Implemented in Python, the proposed model attains 98.38%, 98.41%, 98.38%, and 99.92% of accuracy, precision, recall, and AUC-ROC, respectively, over CNN, VGG-16, and CNN-LSTM-based models. The final Wildfire and Non-Wildfire predictions are visualized through a Flask-based application.

Keywords: Wildfire Detection, Unsharp Mask Filter, threshold, HOG, Swin Transformer, GOA.

1. Introduction

Wildfires rank as one of the most destructive disasters in terms of their effects on human life and property, forests, plants, and animals. Moreover, wildfires have a negative influence on soil composition and natural processes. With rising frequency and magnitude of wildfires, the demand for valid detection systems and continuous monitoring increases [1-2]. Current approaches to monitoring wildfires include ground, aerial, and satellite monitoring. These techniques allow for detecting incidence of incidents and monitoring the affected regions. Satellite monitoring, unlike traditional approaches, provides large coverage, high quality of information received, and prompt detection of fire incidents [3-4].

In recent years, the technology of remote sensing has been advanced to detect wildfires and follow their activities by means of thermal, optical, and radar devices. All given tools and technologies give useful information about the fire, its location, intensity, and the areas being impacted [5]. This is also supported by the information obtained from satellite imagery that is widely adopted in various areas, such as the assessment of fire hazards, fuel moisture estimation, identification of active fires, analysis of fire spreading, as well as post-fire damage assessment. Nonetheless, differences in the environmental conditions and parameters of images create difficulties in the correct identification of the fire [6-7]. Therefore the creation of an intelligent image-based wildfire detection system with the application of latest techniques of image processing and DL is necessary for the enhancement of classification quality and making early wildfire monitoring possible.

Various techniques in DL have been designed to detect and classify wildfires based on satellite

imagery. Among these, CNN, VGG16, CNN-LSTM, and BiLSTM are most commonly utilized for feature extraction and classification. CNN identifies spatial features, such as edges, textures, and wildfire patterns, via convolutional and pooling layers. VGG16 uses a stack of 13 convolutional and 3 fully connected layers for hierarchical feature extraction. CNN-LSTM combines spatial feature learning with temporal analysis to characterize wildfire variations across consecutive satellite images. With BiLSTM, temporal relations are captured accordingly as information flows forward and backward through the architecture. Nevertheless, these methods provide for automatic feature extraction and pattern recognition with high degrees of effectiveness. CNNs and VGG16 are unable to completely capture global context information, and VGG16 is computationally costly. CNN-LSTM and BiLSTM require sequential observations, more memory, and prolonged training time. Moreover, BiLSTM's operation depends on future observations, thus rendering it less applicable for real-time applications [8-11].

To overcome these issues, a Hybrid GOA-based Swin Transformer model is proposed for enhancement in feature representation, classification performance, and satellite image-based wildfire prediction.

1.1 Research gap

A major research issue in satellite wildfires detection is the challenge of accurately differentiating regions affected by fires from normal areas under diverse conditions. Variations in image quality, background features, and environmental conditions may influence the identification of wildfires and compromise the accuracy of classification. While traditional deep learning models like CNN and VGG-16 are effective in extracting spatial features, they fail to capture global contextual information. Likewise, CNN-LSTM and BiLSTM models require sequential data, considerable memory, and extensive training. Therefore, there is a need for a good classification system that extract relevant features from the images

2. Recent Works

S. No	Tittle/ author name/year	Methodology used	Advantages	Disadvantages
1.	Bouteraa et al (2025) [12]	Satellite images are pre-processed for the image quality improvement, and then fractal analysis is applied to extract texture features related to fire. Chaotic maps improve Gray Wolf Optimization (GWO) optimizing DCNN parameters for accurate classification of Wildfire and Non-Wildfire.	Enhances feature extraction, diversity of optimization, and classification accuracy. The improved GWO provides better exploration and exploitation. DCNN detect patterns of wildfires in the satellite images.	This increases the computational complexity and training time. Performance depends on optimization parameters, quality of training data, and conditions of satellite images such as cloud cover, smoke and illumination variations.
2.	Xylomenos et al (2026) [13]	Satellite fire data are processed by Cellular Automata (CA) to simulate wildfire spread. Ant Colony Optimization (ACO) is used to optimize fire perimeter geometry through iterative search operations.	Enhances fire perimeter estimation, spatial modelling, and wildfire spread prediction. It offers better optimization of fire boundary geometry and supports accurate spread analysis.	Computationally intensive and complex environmental conditions. If satellite data are incomplete or environmental factors change rapidly, its performance may decrease.
3.	Salaria et al (2025) [14]	Wireless sensor networks are used for collecting forest environmental data and ABC algorithm is used to optimize the placement of the sensors and network topology for early wildfire detection.	Enhances sensor deployment, energy efficiency, network coverage and early wildfire detection. It enables ongoing surveillance of forests.	Must install and maintain sensors. Communication failures and limited battery capacity may affect detection reliability.

4.	Istinabiyah et al (2026) [15]	CubeSats use thermal sensors to create heat maps of satellite images.The Bat Optimization Algorithm (BA) is used to optimize the heat mapping parameters to identify abnormal temperature regions and detect possible forest fires.	Enhanced accuracy of heat maps, efficiency of optimization and early fire identification. Supports satellite observations for wide-area forest monitoring.	It requires a lot of computing power and is dependent on the quality of the satellite images. Detection accuracy may be affected by cloud interference, limited spatial resolution, and analyse time.

2.1 Objectives

- To improve quality of input images by Unsharp Mask Filtering, image sharpening and edge enhancement.
- To detect wildfire regions by thresholding based segmentation and intensity separation.
- To extract important shape and edge features using HOG.
- To enhance the classification performance by using a Hybrid GOA based Swin Transformer model.
- To accurately categorize images into Wildfire and Non-Wildfire classes and show results using a Flask application.

3. Proposed Work Explanation

The proposed system consists of image pre-processing, segmentation, feature extraction, and an optimized Swin Transformer model. The input images are first processed with Unsharp Mask Filter, image sharpening and edge enhancement to improve image quality. Then the thresholding based segmentation separates the intensities and extracts the areas to find out the significant areas. The extracted regions are passed through HOG feature extraction for shape and edge information. These features are then fed to the Hybrid GOA based Swin Transformer model for optimized classification. Finally, the output images are classified into two classes namely Wildfire and Non-Wildfire and the results are displayed through the Flask application is denoted in Figure 1.

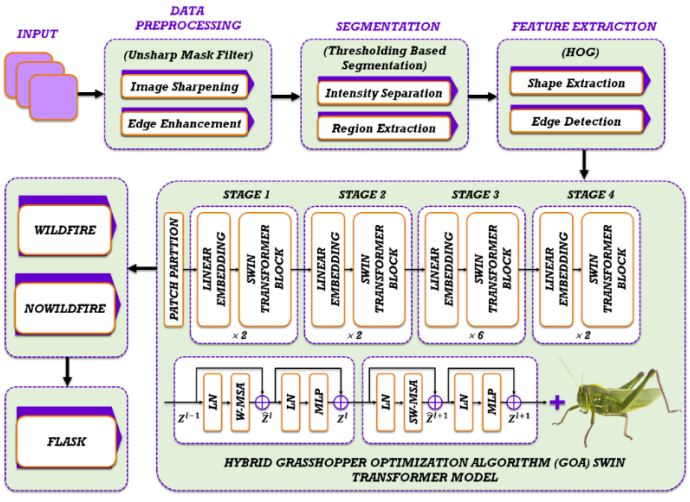


Figure 1: *Proposed System Architecture*

4. Proposed system modelling

4.1 Unsharp Masking Filter

The Unsharp Mask Filter enhances the sharpness of satellite images and improves the visibility of wildfire-related details by subtracting a Gaussian-blurred image from original image and adding the resulting details back.

$$U(x,y) = p(x,y) + \lambda(x,y)[p(x,y) - G(x,y)] \quad (1)$$

Where $p(x,y)$ is original image, $G(x,y)$ is the Gaussian blurred image and $U(x,y)$ is sharpened image.

The adaptive sharpening parameter is computed as:

$$T_{diff} = |N_d + S_d + E_d + W_d| \quad (2)$$

$$\lambda(x,y) = \frac{exp(-\sigma^2)}{0.18+T_{diff}} \quad (3)$$

WhereN_d, S_d, E_d and W_d are differences between neighboring pixels and σ^2 is image variance. This process improves edge clarity and improves wildfire-related image features.

4.2 Threshold

Thresholding is an effective segmentation technique which uses pixel intensity values to distinguish potential wildfire regions from the background. The grayscale satellite images are converted to binary images to simplify the image analysis and to help identify the relevant fire regions.

The thresholding process is described as follows:

$$T = T[x,y,p(x,y),f(x,y)] \quad (4)$$

The segmented image is given by:

$$g(x,y) = \begin{cases} 1, & f(x,y) \geq T \\ 0, & f(x,y) < T \end{cases} \quad (5)$$

Where T is threshold value, $f(x,y)$is input image intensity and $g(x,y)$is segmented binary image. The intensity variations are used to separate fire related regions and provide regions of interest for the next feature extraction.

4.3 HOG

HOG extracts the shape and edge information by computing the gradient magnitudes and orientations in local regions of the satellite image.

The horizontal and vertical gradients are computed as:

$$G_x = \frac{\partial I}{\partial x} \quad (6)$$

$$G_y = \frac{\partial I}{\partial y} \quad (7)$$

The gradient magnitude is given as:

$$G = \sqrt{G_x^2 + G_y^2} \quad (8)$$

HOG descriptors are formed by collecting gradient values into orientation bins and weighting them by their magnitudes. These features capture the wildfire-related shapes and edges, and are forwarded to the classification model for further analysis.

4.4 Hybrid GOA-based Swin Transformer

The Swin Transformer extracts multi-scale features and captures important image patterns by using shifted-window self-attention. The extracted HOG features are passed through the model and the GOA optimizes its parameters through iterative updates for better feature learning and improved accuracy of wildfire classification.

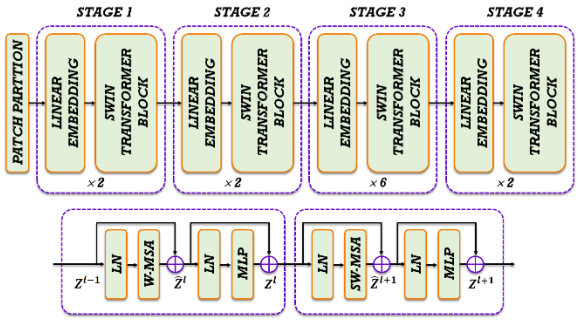


Figure 2: *Swin transformer*

The Swin Transformer block expressed as:

$$\hat{Z}^l = W - MSA\left(LN(Z^{l-1})\right) + Z^{l-1} \quad (9)$$

$$Z^l = MLP\left(LN(\hat{Z}^l)\right) + \hat{Z}^l \quad (10)$$

GOA mimics the behaviour of the grasshopper swarm and optimizes the parameters of Swin Transformer by searching for the optimal solutions to enhance the classification performance. The grasshopper position is:

$$P_i = S_i + G_i + A_i \quad (11)$$

Where P_i is the position of grasshopper, S_i is the social interaction, G_i is the gravity force and A_i is the wind advection.

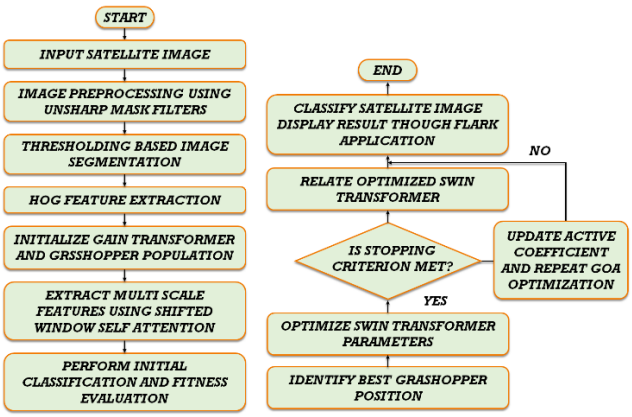


Figure 3: *Flow chart of GOA*

The social interaction is computed as:

$$S_i = \sum_{\substack{j=1 \\ j\neq 1}}^{N} s(d_{ij})\hat{d}_{ij} \quad (12)$$

The grasshopper position is updated as:

$$P_i^d = c\left(\sum_{\substack{j=1 \\ j\neq 1}}^{N} c\,\frac{ub_d - lb_d}{2}\, s\left(\left|P_j^d - P_i^d\right|\right)\frac{P_j - P_i}{d_{ij}}\right)\hat{T}^d \quad (13)$$

The adaptive coefficient is defined by:

$$c = c_{max} - t\,\frac{c_{max} - c_{min}}{t_{max}} \quad (14)$$

Where N is number of grasshoppers, d_{ij} is distance between two grasshoppers, c is the adaptive coefficient, and $\hat{T}^d$ is the best solution. The hybrid GOA optimizes the parameters of the Swin Transformer by iteratively updating the position and evaluating the fitness. This process improves the feature learning and helps to classify the satellite images accurately into Wildfire and Non-Wildfire categories.

5. Results and Discussion

The proposed GOA-based Swin Transformer is implemented in Python and tested on the satellite wildfire dataset. In this section, the performance and classification results are discussed.

Table 2: *Distribution of training validation and testing datasets*

Dataset	
Train	"nowildfire", "wildfire"
nowildfire	14499
wildfire	15750
Valid	
nowildfire	2820
wildfire	3480
Test	
nowildfire	2820
wildfire	3479

Table 2 Shows the training set consists of 14,499 non-wildfire and 15,750 wildfire images. The validation and testing sets include 2,820 and 3,480 images, respectively

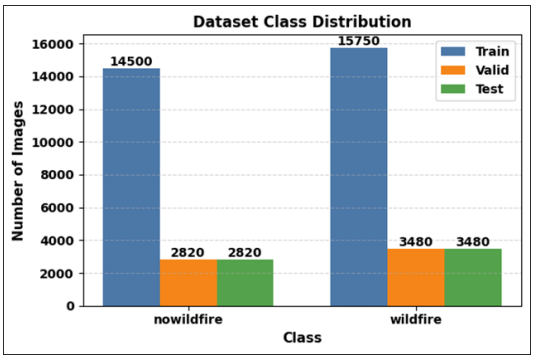


Figure 4: *Dataset Distribution*

Figure 4 shows the distribution of wildfire and non-wildfire images in training, validation and testing datasets. The number of training images is 14500 and 15750 respectively and the corresponding validation and testing samples

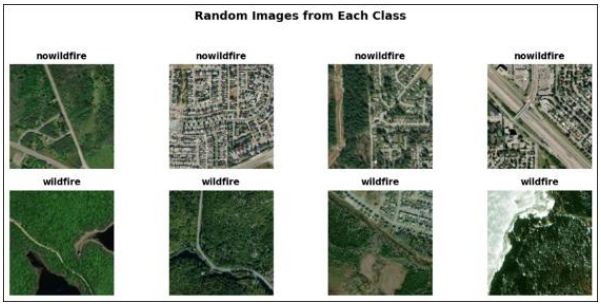


Figure 5: *Satellite Image Samples*

Figure 5 shows sample satellite images from both classes, with differences in vegetation, land cover and visible wildfire-related areas

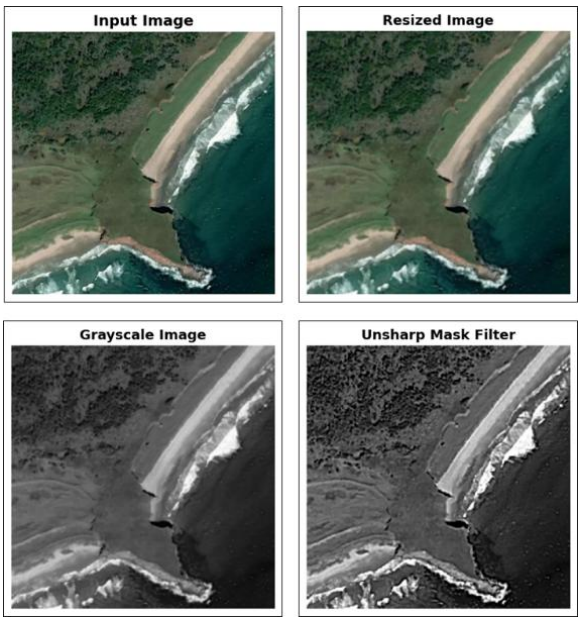


Figure 6: *Image pre-processing using unsharp mask filter*

Figure 6 shows image resizing, grayscale conversion and filtering with Unsharp Mask to enhance the sharpness and edges details of an image. This process improves image clarity and emphasizes salient features for later segmentation.

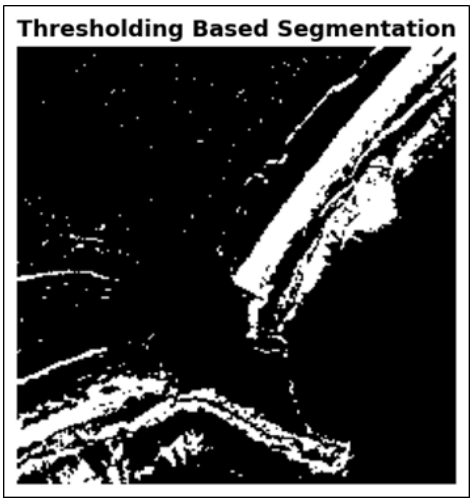


Figure 7: *Thresholding Based Image Segmentation*

Figure 7 Binary segmentation of the satellite image on the basis of pixel intensity thresholds. It segments the relevant regions from the background, highlighting important wildfire-related features of the image.



Figure 8: *HOG Feature extraction*

Figure 8 shows the extraction of gradient based features from the segmented image of satellite, it stresses the important edge orientations and shape patterns for fire classification

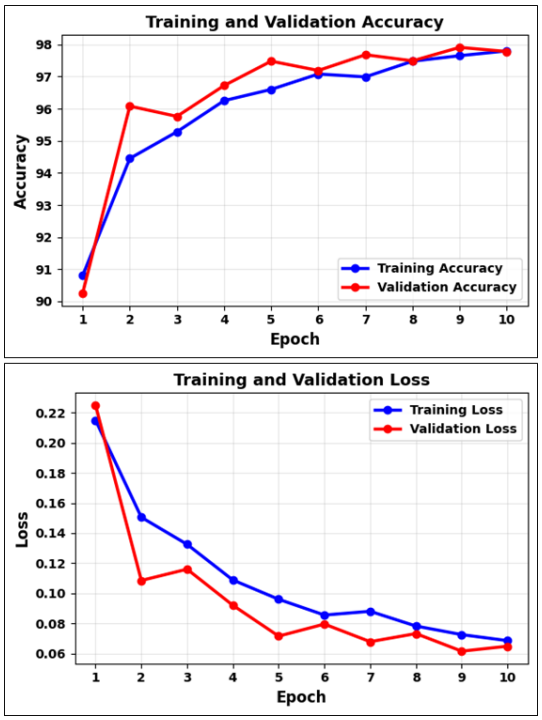


Figure 9: *Training and Validation Accuracy and Loss*

Figure 9 shows the accuracy and loss variation for 10 epochs. The model is learning and converging well during training, as evidenced by increasing accuracy and decreasing loss

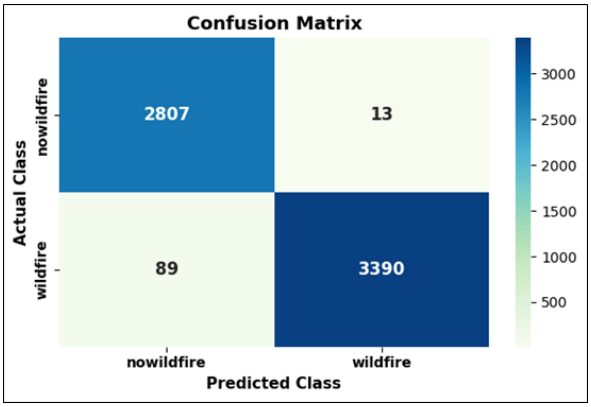


Figure 10: *Confusion matrix for wildfire*

The effective classification performance is shown in the figure 10. 2,807 images of non-wildfires and 3,390 wildfire images are correctly classified, only 102 misclassifications.

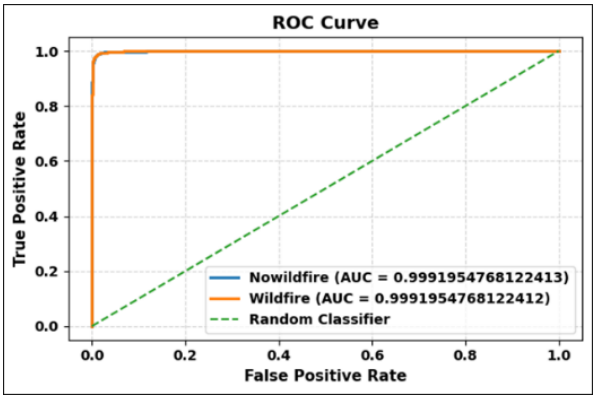


Figure 11: *ROC curve*

Figure 11 shows the classification performance for wildfire and non-wildfire classes. The AUC values are about 0.999 for both classes, which indicates excellent classification capability.

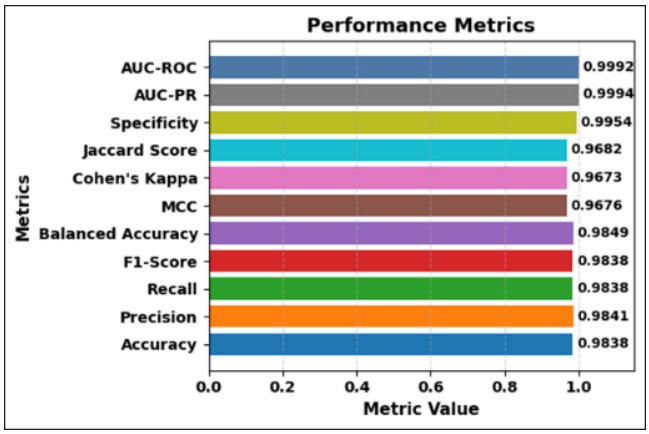


Figure 12: *Performance metrics*

Figure12 shows the classification performance on different evaluation metrics with 98.38% accuracy, 98.41% precision, 98.38% recall and 99.92% AUC-ROC, which indicates reliable wildfire detection.

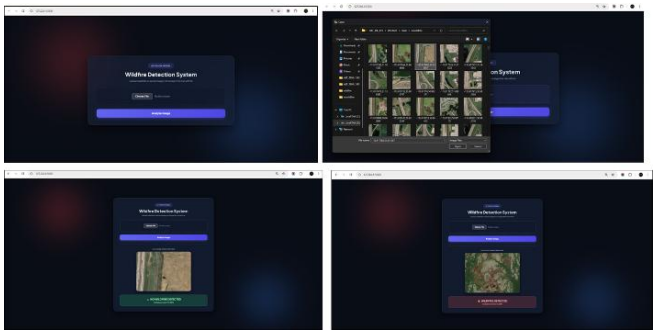


Figure 13: *Flask based wildfire detection application*

The interface of the Flask application with the satellite image upload and the prediction results is shown in Figure 13. It shows the uploaded images and categorizes them as Wildfire or Non-Wildfire.

Table 3: *Performance comparison of wildfire classification methods*

Method	Accuracy	Precision	Recall	F1 Score
CNN	97%	92%	-	-
VGG-16	94%	-	96%	-
CNN-LSTM	96%	94%	96%	96%
Proposed	98	98	98	98

Table 3 compares CNN (97%, 92%), VGG-16 (94%, 96%), CNN-LSTM (96%, 94%, 96%, 96%) and the proposed model (98% accuracy, precision, recall and F1-score) which shows better classification performance

6. Conclusion

The proposed GOA-based Swin Transformer model offers a robust solution for satellite image-based wildfire prediction. It uses a combination of image enhancement, thresholding-based segmentation, and HOG feature extraction to analyse the satellite images and identify essential wildfire-related features for classification. The model implemented in Python achieves high accuracy, precision, recall, and AUC-ROC in classifying wildfires, with better results than CNN, VGG-16, and CNN-LSTM models. The

GOA optimizes the classification process, and the Flask application provides easy visualization of wildfire prediction results. The proposed model provides reliable classification results and has great potential for identifying wildfires early and monitoring them from satellite images. Future work include larger satellite datasets, meteorological data, real-time monitoring and wildfire spread prediction.

References

1. Rafik Ghali; Moulay A. Akhloufi, Year: 2023, “Deep learning approaches for wildland fires using satellite remote sensing data: Detection, mapping, and prediction, Fire, Vol: 6, No: 5, pp. 192.
2. George L. James; Ryeim B. Ansaf; Sanaa S. Al Samahi; Rebecca D. Parker; Joshua M. Cutler; Rhode V. Gachette; Bahaa I. Ansaf, Year: 2023, “An efficient wildfire detection system for ai-embedded applications using satellite imagery”, Fire, Vol: 6, No: 4, pp. 169.
3. Henintsoa S. Andrianarivony; Moulay A. Akhloufi, Year: 2024, “Machine learning and deep learning for wildfire spread prediction”, Fire, Vol: 7, No: 12, pp. 482.
4. Yu Zhao; Sebastian Gerard; Yifang Ban, Year: 2024, “Ts-satfire: A multi-task satellite image time-series dataset for wildfire detection and prediction”, Scientific Data, Vol: 12, No: 1, pp. 1817.
5. Ioannis Papakis; Vasileios Linardos; Maria Drakaki, Year: 2025, “A multimodal ensemble deep learning model for wildfire prediction in greece using satellite imagery and multi-source remote sensing data”, Remote Sensing, Vol: 19, No: 17, pp. 3310.
6. Mounia Aarich; Awatif Rouijel; Aouatif Amine, Year: 2024, “Deep learning approaches for forest fires detection and prediction using satellite images”, Procedia Computer Science, No. 251, pp. 758-763.
7. Harikesh Singh; Li-Minn Ang; Sanjeev Kumar Srivastava, Year: 2025, “Active wildfire detection via satellite imagery and machine learning: An empirical investigation of Australian wildfires”, Natural Hazards, Vol: 121, No: 8, pp. 9777-9800.
8. Ioannis Papakis; Vasileios Linardos; Maria Drakaki, Year: 2025, “A multimodal ensemble deep learning model for wildfire prediction in greece using satellite imagery and multi-source remote sensing data”, Remote Sensing, Vol: 17, No: 19, pp. 3310.
9. Thu Huong Nguyen; The Long Nguyen; Anna Gennad'evna Shmeleva, Year: 2026, “Application of the VGG-16 convolutional neural network for the intelligent analysis of forest fire imagery”, Journal of Computational and Engineering Mathematics, Vol: 1, No: 13, pp. 39-49.
10. Linjun Yao; Zhaobin Wang; Yaonan Zhang, Year: 2025, “CSLTNet: A CNN-LSTM dual-branch network for particulate matter concentration retrieval”, Remote Sensing, Vol: 17, No: 21, pp. 3616.
11. Zhiyu Chen; Weiwei Song; Xiaoqing Zuo; Siyuan Li; Huyue Chen; Bowen Zuo, Year: 2026, “A Hybrid U-Net and Attention-Based BiLSTM Framework for Wildfire Prediction Using Multi-Source Remote Sensing and Meteorological Sensor Data”, Electronics, Vol: 15, No: 9, pp. 1893.
12. Yassine Bouteraa; Mohammad Khishe, Year: 2025, “Fractal and chaotic map-enhanced grey wolf optimization for robust fire detection in deep convolutional neural networks”, Scientific Reports, Vol: 15, No: 1, pp. 11495.

13. Ioannis Karakonstantis; George Xylomenos, Year: 2026, “Optimizing Fire Perimeter Geometry in Cellular Automata Wildfire Models Using Ant Colony Optimization”, Fire, Vol: 9, No: 5, pp. 212.
14. Anshika Salaria; Amandeep Singh, Year: 2025, “A forest adaptive sensor topology enhanced artificial bee colony algorithm (FAST-ABC) for early detection of wildfire”, Engineering Research Express, Vol: 7, No: 4, pp. 045327.
15. Desti Destiansari Istinabiyah; Dwi Mei Rita; Iga Apria; Andry Meylani, Year: 2026, “OPTIMIZATION OF CUBESAT-BASED HEAT MAPPING SYSTEM FOR EARLY DETECTION OF FOREST FIRE”, Journal Informatic, Education and Management (JIEM), Vol: 8, No: 1, pp. 1115-1119.