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Wildfire detection using modified particle swarm optimization algorithm

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Abstract

Wildfires claim many lives yearly and cause huge environmental and economic damage. Some of the worst wildfire disasters can be found in world history. Reducing CO2 emissions is critical to prevent irreversible change in the world climate in the era of global warming. Wildfire is the primary factor that leads to high CO2 emissions, promoting global warming. Early detection and prevention of wildfires are essential tasks of computer vision. An automated wildfire classification system can help prevent wildfires at an early stage. Many methods are used to identify wildfires and automate categorizing wildfires based on images. This paper offers a new path to wildfire classification based on a wildfire image dataset. This paper introduces a modified particle swarm optimization algorithm for classifying forest fire images using the image dimensions and characteristics that identify forest fires. The proposed approach uses a dataset to identify forest fires. Whether it is classified as a fire is based on the images of fire and smoke in the air. The proposed approach used an image dataset to validate and test the algorithm and outperform it in terms of precision, recall, F-score, and accuracy.

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Keywords: *Particle swarm optimization, Engineering optimization, Nature inspired algorithm, Natural disaster.*

1. Introduction

Wildfire is a crucial threat to ecosystems and human lives, necessitating a proactive approach to detection. The increasing frequency and intensity of wildfires globally underscore the urgency of developing advanced early-stage detection systems, like other computer vision approaches [1]. Many wildfire disasters have been found in history, causing enormous environmental and economic damage [2].

Chardonnet et al. [3] highlighted problem associated with forest fire like potential nutritional value, ecological role, and significance to society. The threat of wildfire conservation was also discussed, including reducing wildfires. Ward et al. [4] describe a novel predictive system that uses a thermal camera and onboard system to identify heat.

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Govil et al. [5] developed a prototype system to detect smoke from a fire within 15 minutes. This system relies on machine learning algorithms and the image recognition process of cloud-based scanning cameras. Habiboglu, Gunay, and Cetin [6] proposed subtracting wildfire smoke plumes visible before flames and setting a color threshold to find smoke in videos. Sousa, Moutinho, and Almeida [7] proposed a framework in which the author used images of 35 real fire events. Sousa, Moutinho, and Almeida [7] comprehensively analyzed various patterns causing misclassification.

Bosch, Serrano, and Vergara [8] proposed a remote monitoring multi-sensor wireless network system to detect wildfires. The system performance is measured using the first alarm's time and number of alarms. Toulouse et al. [9] evaluated the wildfire detection algorithm, which deals with many image datasets. Hossain et al. [10] proposed a model to detect flame and smoke from a single image based on color and texture with the help of an artificial neural network. The model can detect wildfires consistently across various conditions.

This paper explores the development of wildfire detection methods, emphasizing the critical need for early-stage detection to increase response times and reduce the devastating impact of these natural disasters. This paper uses an image dataset to detect fires in forest areas. This work utilized recently developed variant of PSO (DIW-PSO) for feature selection. DIW-PSO is based on dynamic inertia weight control using fitness metric. To classify forest fire and non-forest fire based on images, use the SIFT algorithm to extract features and use modified PSO to select important features. Based on the experiment, it was found that the modified PSO gives better results.

The significant contribution of this paper is deployment of DIW-PSO to detect wildfire. The performance and result analysis of the proposed model are also discussed in the paper.

The rest of the paper is organized as follows: Section 2 discussed wildfire detection methods. Section 3 presents wildfire detection using DIW-PSO and classifiers—results for the considered dataset analyzed in section 4, followed by a conclusion in section 5.

2. Literature Survey

Wildfire detection technology covers a wide range of research and development efforts intended for the early and efficient detection of wildfires. This review highlights different aspects of wildfire detection using image and non-image datasets, including sensor technologies, remote sensing, deep learning, optimization techniques, and machine learning applications. This review also provides an overview of the advancements in particle swarm optimization algorithms.

Mohapatra and Timothy [11] discussed the trends and advancements in four categories: camera networks, unmanned aerial vehicles, sensor nodes, and satellite surveillance, which have challenges and shortcomings. Mohapatra and Timothy [11] also discussed different analytical approaches to finding fire input datasets. In this paper, the author focuses on the early detection of wildfires using advanced mechanisms.

Wu, Millhouse, and Oladeji [12] explore the Sentinel satellite to address the problem of wildfire detection. This approach uses a deep learning method on extracted features to get true color, moisture content, and vegetation index to detect wildfire. In this article, the author used three methods on an 11,000-image dataset to detect wildfires. The first base model used a simple CNN model for true color satellite imagery layer. The second model consisted of three layers with eight channels, including normalized burn ratio, burned area index, and normalized difference vegetation index. The third model used ResNet-50 CNN architecture and observed that the second model obtained high accuracy. Table 1 shows some more methods to detect wildfires at an early stage.

Slavkovikj et al. [13] use different methods to use social media as a sensor for large-scale disaster events. The author focused on wildfire use cases and other hazard management systems and suggested a social sensor-based platform to detect wildfires. As wildfire is a natural disaster and requires early detection, social media provides a human-centric sensor network. This information is used to allocate resources and increase awareness.

Table 1

Methods for wildfire detection

Author [Ref]	Approach Used	Description
Kelly et al. [14]	Autoregressive integrated moving average model Support vector classification.	A natural language processing algorithm is used to classify the relevant data and generate alerts when cases exceed the pre-defined threshold value. The alert thresholds are established using a supervised machine learning algorithm using 3081 cases and assigned a pre-diagnostic classification.

Yang et al. [15]	CNN Network, YOLOv5s, RetinaNet, and Faster-RCNN	Proposed variant of YOLOv5s network model to monitor wildfires and detect complex forest environments. The dataset is used from the Hunan Hupingshan National Nature Reserve to train the model.
Jindal et al. [16]	Deep Learning Algorithm, CNN Network	Real-time wildfire detection to control the loss of the ecosystem. The author used the CNN models YOLOv3 and YOLOv4 to detect forest smoke and evaluate both models based on different parameters.
Verma et al. [17]	IoT-based wireless Sensor network, Tunicate Swarm Algorithm	Proposed an energy optimized framework based on sleep scheduling to detect wildfire with the least delay. This framework works using a two-fold method.
Bouguettaya et al. [18]	Deep Learning Algorithm and Computer Vision	UAV remote sensing technology is used to fight forest fires. This technology can provide high-resolution images from complex forests in real-time.
Toreyin and Cetin [19]	Computer Vision, Least Mean Square, Weighted Majority Algorithm	Developed a computer vision-based algorithm to detect wildfire early in the early stages. This algorithm includes four sub-parts: slow-moving objects, rising regions, gray regions, and shadows.

3. Wildfire detection using modified PSO

The proposed method is used to classify the images into their respective class categories: fire and non-fire. The complete methodology of the proposed model is depicted in Figure 1. This model includes three major steps: feature extraction using the Scale Invariant Feature Transform

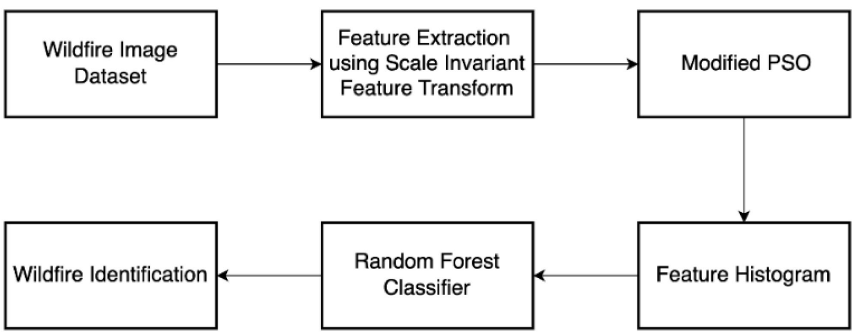


Figure 1

The proposed wildfire image identification method

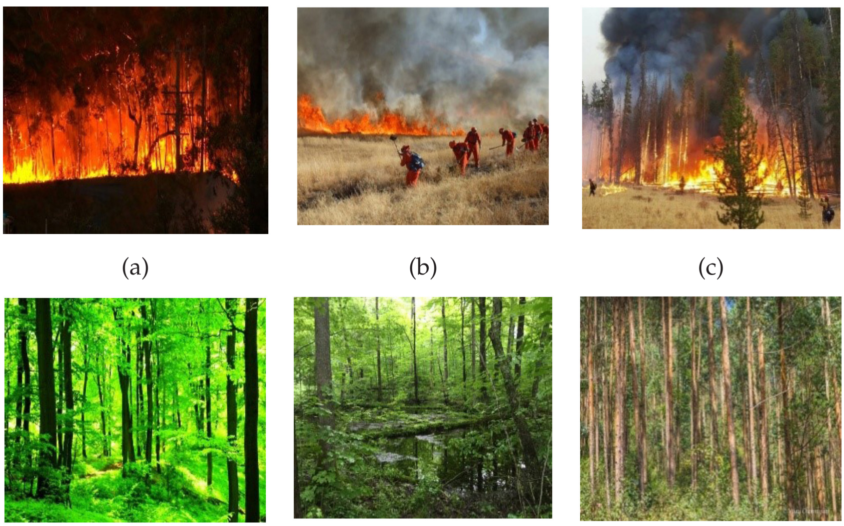
(SIFT), clustering using the optimization algorithm, and classifying images using the Random Forest Classifier. These steps help to identify whether the image data is wildfire or not. A detailed explanation of each stage is specified in subsequent sections.

3.1 *Feature Extraction SIFT*

SIFT is an invariable image scaling and rotation technique. This technique majorly involves five steps to extract the features of an image. This technique ignores the noise and identifies the distinct point. Locates and extracts the key point of an image and matches the pattern from the other images.

3.2 *Feature Extraction SIFT*

The extracted features are passed to the modified PSO to select the important features. In this step, the modified PSO selects useful notable features to classify the images into different categories to improve accuracy.



(a) (b) (c)

(d) (e) (f)

Figure 2

(a), (b), and (c) symbolized fire, and (d), (e), and (f) symbolized non-fire images.

3.3 *Classification using Random Forest Classifier*

Once the images are in the clusters and the generator histogram, the random forest classifier is used to classify the images. The random forest algorithm works on many decision trees and uses the bagging method to create an individual tree by selecting a random subset from the entire dataset.

4. Experimental Results

This section tests the performance of the optimization algorithm using the wildfire image dataset. This dataset consists of more than 700 images for each wildfire category and more than 500 for the non-fire category [20]. 70% of images from each category are used for training and 30% for testing. This paper contains two categories for validating and testing the proposed method: wildfire and non-fire images. Sample images from each category are depicted in Figure 2. The first three images, (a), (b), and (c) represent the forest fire scenario. The following three images, (d), (e), and (f), represent the scenario in which any kind of disaster is not included.

Table 2

The comparison of the different algorithm

S. No.	Algorithm	Class	Precision	Recall	F1-score	Overall Accuracy
1	DE	Fire	0.64	0.67	0.66	66.39%
		Non-fire	0.69	0.66	0.67	
2	SCA	Fire	0.7	0.82	0.76	73.77%
		Non-fire	0.78	0.66	0.71	
3	SSA	Fire	0.63	0.72	0.67	64.75%
		Non-fire	0.67	0.57	0.62	
4	WOA	Fire	0.65	0.61	0.63	63.93%
		Non-fire	0.63	0.67	0.65	
5	PSO	Fire	0.72	0.66	0.69	67.21%
		Non-fire	0.62	0.69	0.66	
6	Modified PSO	Fire	0.84	0.72	0.77	**75.41%**
		Non-fire	0.67	0.8	0.73	

Table 2 shows performance comparison for proposed approach with PSO [21], SSA [22], DE [23], SCA [24] and WOA [25]. The comparison of different optimization algorithms with different measured parameters. The comparison includes six algorithms: WOA, DE, SSA, SCA, PSO, and Modified PSO, and four measurement parameters: recall, F1-score, precision, and accuracy. Precision measures correct positive predictions.

F1-score calculates the harmonic mean with the help of recall and precision. Here, the F1 score is used to check the balancing concerning accuracy. Accuracy represents all the correct predictions, including all true and false positive outputs. This measurement includes all the correctly predicted fire images and all the correctly predicted non-fire images. The accuracy of the modified PSO is 75.41%, which is better than that of the other optimization algorithm; therefore, the proposed method is better than the existing system.

5. Conclusion

This paper employed a recent variant of PSO with a modified inertia weight function for wild fire detection using a fire and non-fire image datasets and finds that modified PSO gives better results than other existing algorithms. The new variant of PSO algorithm balances the exploration and exploitation phase. The results of modified PSO were compared with other meta-heuristics algorithms such as DE, SSA, WOA, SCA, and PSO, and better results were found than those of other algorithms. In the future, this algorithm will address different image classification-based problems and real-world optimization problems. In addition to this, the algorithm can add or modify other parameters to solve the optimization problems very efficiently.

References

[1] G. Abdelhady, A. Mohsen, and N. Abdelnaser, "Hybrid CNN models for suspect facial recognition system," *Journal of Information and Optimization Sciences,* vol. 47, no. 2, pp. 539–551 (2026), doi: 10.47974/JIOS-1606.

[2] M. Goel, P. Ranjan, R. Yadav, and N. Ojha, "Bihar urban flood 2019 and disaster management: A case study," *Journal of Statistics and Management Systems*, vol. 26, no. 3, pp. 755–762 (2023), doi: 10.47974/JSMS-1064.

[3] P. Chardonnet, B. D. Clers, J. Fischer, R. Gerhold, F. Jori, and F. Lamarque, "The value of wildlife," *Revue scientifique et technique – Office international des épizooties,* vol. 21, no. 1, pp. 15–52 (2002).

[4] S. Ward, J. Hensler, B. Alsalam, and L. F. Gonzalez, "Autonomous UAVs wildlife detection using thermal imaging, predictive navigation and computer vision," in *Proc. IEEE Aerospace Conf.,* pp. 1–8 (2016).

[5] K. Govil, M. L. Welch, J. T. Ball, and C. R. Pennypacker, "Preliminary results from a wildfire detection system using deep learning on remote camera images," *Remote Sensing,* vol. 12, no. 1, p. 166 (2020).

[6] Y. H. Habiboglu, O. Gunay, and A. E. Cetin, "Real-time wildfire detection using correlation descriptors," in *Proc. 19th Eur. Signal Process. Conf.,* pp. 894–898 (2011).

[7] M. J. Sousa, A. Moutinho, and M. Almeida, "Wildfire detection using transfer learning on augmented datasets," *Expert Systems with Applications,* vol. 142, p. 112975 (2020).

[8] I. Bosch, A. Serrano, and L. Vergara, "Multi-sensor network system for wildfire detection using infrared image processing," *The Scientific World Journal,* Art. no. 2013 (2013).

[9] T. Toulouse, L. Rossi, A. Campana, T. Celik, and M. A. Akhloufi, "Computer vision for wildfire research: An evolving image dataset for processing and analysis," *Fire Safety Journal,* vol. 92, pp. 188–194 (2017).

[10] F. M. A. Hossain, Y. Zhang, C. Yuan, and C. Y. Su, "Wildfire flame and smoke detection using static image features and artificial neural network," in *Proc. 1st Int. Conf. Ind. Artif. Intell.* (2019).

[11] A. Mohapatra and T. Timothy, "Early wildfire detection technologies in practice—a review," *Sustainability,* vol. 14, no. 19, p. 12270 (2022).

[12] E. Wu, G. Millhouse, and O. Oladeji, "Satellite imagery based wildfire detection: CS230-Winter 2020 final paper," (2020).

[13] V. Slavkovikj, S. Verstockt, S. Van Hoecke, and R. Van de Walle, "Review of wildfire detection using social media," *Fire Safety Journal,* vol. 68, pp. 109–118 (2014).

[14] T. R. Kelly, P. S. Pandit, N. Carion, D. F. Dombrowski, K. H. Rogers, S. C. McMillin, D. L. Clifford, A. Riberi, M. H. Ziccardi, E. L. Donnelly-Greenan, and C. K. Johnson, "Early detection of wildlife morbidity and mortality through an event-based surveillance system," *Proc. R. Soc. B*, vol. 288, no. 1954, p. 20210974 (2021).

[15] W. Yang, T. Liu, P. Jiang, A. Qi, L. Deng, Z. Liu, and Y. He, "A forest wildlife detection algorithm based on improved YOLOv5s," *Animals,* vol. 13, no. 19, p. 3134 (2023).

[16] P. Jindal, H. Gupta, N. Pachauri, V. Sharma, and O. P. Verma, "Real-time wildfire detection via image-based deep learning algorithm," in *Soft Computing: Theories and Applications: Proceedings of SoCTA* 2020, Springer (2021).

[17] S. Verma, S. Kaur, D. B. Rawat, C. Xi, L. T. Alex, and N. Z. Jhanjhi, "Intelligent framework using IoT-based WSNs for wildfire detection," *IEEE Access*, vol. 9, pp. 48185–48196 (2021).

[18] A. Bouguettaya, H. Zarzour, A. M. Taberkit, and A. Kechida, "A review on early wildfire detection from unmanned aerial vehicles using deep learning-based computer vision algorithms," *Signal Processing,* vol. 190, p. 108309 (2022).

[19] B. U. Toreyin and A. E. Cetin, "Wildfire detection using LMS based active learning" *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*. *IEEE* (2009).

[20] FIRE Dataset. (2020, February 25). Kaggle. https://www.kaggle.com/datasets/phylake1337/fire-dataset.

[21] J. Kennedy and R. Eberhart, "Particle swarm optimization" in Neural Networks, 1995. Proceedings., *IEEE International Conference on*, vol. 4. IEEE, pp. 1942–1948 (1995).

[22] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp swarm algorithm: A bio-inspired optimizer for engineering design problems" *Advances in Engineering Software*, vol. 114, pp. 163–191 (2017).

[23] K. Price, "Differential evolution: a fast and simple numerical optimizer" in Fuzzy Information Processing Society, 1996. NAFIPS. 1996 Biennial Conference of the North American. IEEE, pp. 524–527 (1996).

[24] S. Mirjalili, "SCA: a sine cosine algorithm for solving optimization problems" *Knowledge-based systems,* vol. 96, pp. 120-133 (2016).

[25] S. Mirjalili and A. Lewis, "The whale optimization algorithm" *Advances in engineering software*, vol. 95, pp. 51-67 (2016).

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