IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 4, December 2024, pp. 4095~4105
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i4.pp4095-4105

A novel pairwise based convolutional neural network for image preprocessing enhancement

Chaitra Ravi[1], Siddesh Gaddadevara Matt[2]
[1]Department of Computer Science and Engineering, Ramaiah Institute of Technology Bengaluru, Vivesvaraya Technological University, Belagavi, India
[2]Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning), Ramaiah Institute of Technology Bengaluru, Vivesvaraya Technological University, Belagavi, India

Article Info

Article history:

Received Nov 17, 2023
Revised Mar 23, 2024
Accepted Apr 17, 2024

Keywords:

Non-maximum suppression
Pairwise region proposal
Region based convolutional neural network
Wildfire detection
Wrapped images

ABSTRACT

Wildfires are untamable and devastating forces that impact both urban and rural regions. While predicting wildfires is challenging, efforts are made to mitigate the damage they inflict. The previous researches have limitations such as not being able to find a small region of fire in the dataset. In this research, pairwise region-based convolutional neural network (PR-CNN) is proposed for wildfire detection. The dataset used for wildfire detection is the fire luminosity airborne-based machine learning evaluation (FLAME) dataset that is pre-processed through normalization and hue, saturation, and lightness (HSV) color space to improve the image quality. Pre-processed images are taken as input to region-based convolutional neural network (R-CNN) for detection, the R-CNN has a region proposal layer that is enhanced by pairwise region and named PR-CNN. These wrapped images are fed into CNN architecture to extract and features to detect wildfire. Additionally, post-processing technique like soft-non-maximum suppression (NMS) is utilized to eliminate the duplicate detection from PR-CNN for enhancing the detection accuracy. The proposed method achieves a higher accuracy of 97.44%, a precision of 97.32%, recall of 97.31%, and f1-score of 96.67%, which is comparatively superior to the existing algorithms like recurrent neural network (RNN), and R-CNN.

Corresponding Author:

Chaitra Ravi
Department of Computer Science and Engineering, Ramaiah Institute of Technology
Belagavi, India
Email: chaitrabindu@gmail.com

1. INTRODUCTION

Wildfire is one of the most critical and highly spread natural disasters globally that leads to high environmental and economic loss in forest resources and human society [1]. Wildfires spread quickly and is hard to control, causing damage to surroundings, humans, and resources [2]. Due to the escalating frequency of wildfires attributed to climate change, management grapples with substantial annual expenses [3]. Wildfires occur worldwide, with forest fires posing a considerable risk and the potential for extensive destruction that impacts social and economic progress [4]. Unlike other types of fires, forest fires inflict significant damage due to their unique environmental context [5]. In an open environment and with enough oxygen, fires are much more likely to start and spread in forests, leading to serious safety risks and economic loss [6]. Early fire detection is an efficient way to minimize harmful forest fires. Hence, experiments on early forest fire detection and warning attract wide attention [7].

The wildfire detection techniques are classified into three types namely, sensor detection methods, image processing techniques, and object detection techniques [8], [9]. Fire alarm sensors like temperature, optical, infrared and gas sensors attain superior performance, however, their high coverage of cost and vulnerability to exterior factors like wind and ambient temperature, limit their use in external environments [10], [11]. Image processing techniques are utilized to detect fires by manually choosing the fire features [12]. Even though those techniques are hugely utilized, they extract simple features and lack scalability, making them insufficient in critical wildfire detection scenes [13], [14]. The manual choosing of every fire feature demands more time and expertise, limiting its practical application in the detection of wildfire [15], [16].

Wang *et al.* [17] implemented a reduce VGGnet for wildfire image classification and optimized convolutional neural network (CNN) for wildfire detection using fire luminosity airborne-based machine learning evaluation (FLAME) dataset. The implemented method is divided into two stages where, reduce VGGnet was utilized for wildlife image classification, and optimized CNN method was utilized for wildlife detection through the integration of temporal and spatial features. In the implemented method, method causes more convergence, and the convergence speed of method was faster. Even then, the method had complexity of noise data like smoke and clouds.

Zhang *et al*. [18] introduced an FBC-Anet structure that combined the boundary enhancement and context-aware modules for lightweight encoder-decoder method for wildfire detection using the FLAME dataset. The introduced method extracted deep semantic features from the dataset and improved the shallow edge features. The method utilized Xception network to the encoder for extracting features in various scales from the dataset. Then, by transferring the extracted features by confidentiality, integrity, and availability (CIA) module, the method's featuring learning capacity for fire pixels was improved and made feature extraction much robust. The introduced method combined a decoder with a boundary enhancement module (BEM) mechanism to improve shallow edge feature extraction. The introduced method found a little fire areas, and the complexity of the background segmented more accurately. Even then, the introduced technique was not directly applied to the unmanned aerial vehicle (UAV) images.

Zhang *et al*. [19] developed an fine tuning depth on residual network 50 (FT-ResNet 50) method based on transfer learning for wildfire detection in the FLAME dataset. The developed method transferred the dataset and initialized the parameters for dataset identification of wildfire. Integrated with features of the target dataset, adam functions were utilized for fine-tuning 3 conv blocks of ResNet, focal loss function and network architecture were updated for optimizing the ResNet network for extracting efficient semantic data from datasets. However, the developed method needed a huge amount of quality images to obtain many detection results.

Jain *et al*. [20] suggested color-based technique for wildfire detection called CIELAB in FLAME dataset. The suggested technique detected fire based on fire color in CIELAB color space and trained by CNN for detecting the fire. CNN and image processing had balancing strengths and integrated their strengths to develop an ensemble model. The suggested method utilized two CNNs and the CIELAB method, and performed major voting to predict whether or not the fire was present. The suggested method was performed based on pixel-wise classification of fire, so it was utilized for segmentation of fire flame, and the method reduced the training time. However, the suggested method ignored certain images in the detection process.

Chen *et al*. [21] presented a CNN for wildfire detection in the FLAME dataset. The presented method developed a hybrid model through a deep learning classifier and localization of fire detection for frames labeled as fire by performing dual-free imagery. The deep learning-based methods were implemented with red, green, and blue (RGB) thermal fusion for efficient fire. The presented method had fewer parameters and utilized less time for training. However, the method had a higher chance of misclassification because the method was only suitable for certain weather and light conditions.

Ghali *et al*. [22] implemented an ensemble method that integrated EfficientNet-B5 and DenseNet-201 methods for detection and classification of wildfires in the FLAME dataset. The implemented method optimized the deep learning methods for detecting wildfire in the early phase. Furthermore, two vision transformers such as TransUNet, TransFire, and EfficientSeg were activated for wildfire region segmentation, which identified exact fire regions. The implemented method eliminated the problem of vanishing-gradient, enhanced feature propagation and the count of parameters was reduced. However, the method lacked of fire annotation image samples.

Wang *et al*. [23] introduced a novel method for wildfire detection in complex scenes named as FireDetn method. The introduced method utilized four various detection heads for FireDetn detection in various size frame objects. Next, the combined transformer encoder blocked with multi-head attention in FireDetn for improving their capacity to capture global features and contextual data, which enhanced the average precision in complex scenes. Lastly, the integration of spatial pyramid pooling architecture had advantages in the detection of multiple scale fame objects. The introduced technique attained balance among average precision and detection speed. Yet, the introduced technique had a restricted quantity of energy and required data performing.

Wang *et al*. [24] developed a class activation map (CAM) based on a non-local attention method for wildfire detection. The developed method explored weakly supervised fire detection (WSFD) that provided image-level annotations. Particularly, the deep neural networks were trained by non-local attention as a classifier to find fire and non-fire images. Next, a classifier was utilized to develop CAM for all fire images in the phase of inference and produced a consistent bounding box following every integrated CAM domain. The method accurately detected the wildfire in images. However, the CAM was noisy and lost certain spatial information.

In present times, deep learning-based detection techniques have enhanced their capacity to automatically learn and extract the complex features from image datasets. The existing methods had limitations like the complexity of noise data, requiring a huge quantity of quality images to obtain high detection accuracy, and ignoring certain images in the detection process. Then, existing methods doesn't detect a small region of fire in dataset images.

In this research, new region-based method is proposed for wildfire detection. The dataset taken for research is the FLAME dataset, where normalization and hue, saturation, and lightness (HSV) color space techniques are taken for data pre-processing. The pairwise region-based convolutional neural network (PR-CNN) is proposed to detect wildfire and the soft non-maximum suppression (NMS), a post-processing technique, is utilized to eliminate the duplicate detection from PR-CNN method. The functionality of the research is given as: i) the normalization and HSV technique are taken for preprocessing of images, which improves the image quality and converts the RGB image to HSV image; ii) the selective search algorithm proposes pairwise region proposal method for segmentation process in PR-CNN to detect wildfires; and iii) the post-processing technique like soft-NMS is utilized to eliminate the duplicate detection and choose much related bounding boxes which corresponds to the detected images.

This research paper is in the following format: section 2 describes the proposed method. Section 3 gives the explanation of the research methodology. Section 4 provides the results and discussion of the research method, and section 5 provides the conclusion of this research.

2. PROPOSED METHODOLOGY

In this research, new region-based method is proposed for wildfire detection. The dataset taken for research is the FLAME dataset, and is given as input to normalization and HSV color space techniques for data pre-processing. After that, the PR-CNN is presented to detect wildfire, while the detected image is given to soft-NMS that is a post-processing technique to eliminate the duplicate detection in PR-CNN method. Figure 1 depicts the process of the proposed wildfire detection method.

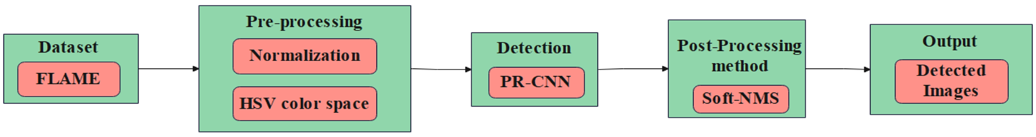

Figure 1. Process of proposed PR-CNN method

2.1. Dataset

The dataset taken for wildfire detection in this research is the FLAME dataset [25]. The dataset is a fire video dataset gathered by various types of cameras and UAVs on sediment burning in the Arizona pine forest. The dataset has raw videos, image files, and mask data format. In Table 1, the description of various data in the FLAME dataset is given, and the sample images of the FLAME dataset are represented in Figure 2.

Table 1. Dataset description

Type	Format	Duration	Resolution
Video	MOV	89 s	640×512
Video	MOV	305 s	640×512
Video	MOV	25 min	640×512
Video	MOV	17 min	3840×1920
Image	JPEG	2003 frames	3840×1920
Mask	PNG	2003 frames	3840×1920

Figure 2. Sample images in dataset

2.2. Pre-processing

Pre-processing is an essential phase in image processing field due to which, the quality of images from the dataset is improved. The pre-processing methods taken are normalization and HSV color space techniques. Normalization is a procedure that modifies the pixel intensity scores range [26]. The HSV technique is less affected by dissimilarities in lighting conditions, wherein their independent color order gives much more reliable and accurate color image detection [27].

2.1.1. Normalization

Normalization is a technique used in data preprocessing, helpful for training and testing of region-based convolutional neural network (R-CNN) technique. In the dataset taken, all pixels of the image have RGB colors and intensities ranging from $0\ to\ 255$. The input image is scaled between the range of 0 and 1. The numerical expression for normalization is represented as given in (1).

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where, x_i defines the input data, x_i' defines the output data, x_{min} refers to the minimum (0) probable value, and x_{max} refers to the maximum (255) probable value.

2.1.2. Hue, saturation, and value

The HSV technique converts the RGB image in a dataset into an HSV color technique, which is the same as how humans observe colors, and is utilized to detect color-based images and numerous applications. Hue in HSV shows color distributions based on red, saturation shows a degree of lightness and darkness of color, and the value corresponds to color brightness. The range of hue, saturation, and value of the HSV color technique, while the range of colors is limited for filtering those pixels have flames presented in the Table 2. The numerical expression for HSV color space is represented as (2). In (2) H represents hue, S represents saturation, and V represents value.

$$H = \begin{cases} 0 if max = min \\ \left(60^o \times \frac{g-b}{max-min} + 0^o\right) mod 360^o if max = r \\ 60^o \times \frac{b-r}{max-min} + 120^o if max = g \\ 60^o \times \frac{r-g}{max-min} + 240^o if max = b \end{cases}$$

$$s = \begin{cases} 0 if max = 0 \\ \frac{max-min}{max} = 1 - \frac{min}{max} otherwise \end{cases}$$

$$v = max \tag{2}$$

Table 2. Color range of HSV color technique

HSV	Range	Greater than	Less than
Hue	0-179	5	90
Saturation	0-255	40	255
Value	0-255	220	255

3. PAIRWISE REGION-BASED CONVOLUTIONAL NEURAL NETWORK FOR DETECTION

The normalized and HSV color change the pre-processed images that are fed into a R-CNN as input for wildfire detection. The detection of wildfire is performed by utilizing the PR-CNN which has three stages region proposal, feature extractor, and classification layers. Region proposals are smaller areas of an image that probably have the images required as input image. To reduce the region proposals in R-CNN, an algorithm known as selective search is utilized. The produced 2000 region proposals are fed into CNN to extract features and detect the wildfire in dataset images. The fire images in the FLAME dataset are given as input to the search algorithm for extracting the region proposals. Next, those wrapped images are given as input to CNN architecture and at last, the regions are detected by it. Figure 3 gives a detailed description of the proposed PR-CNN method.

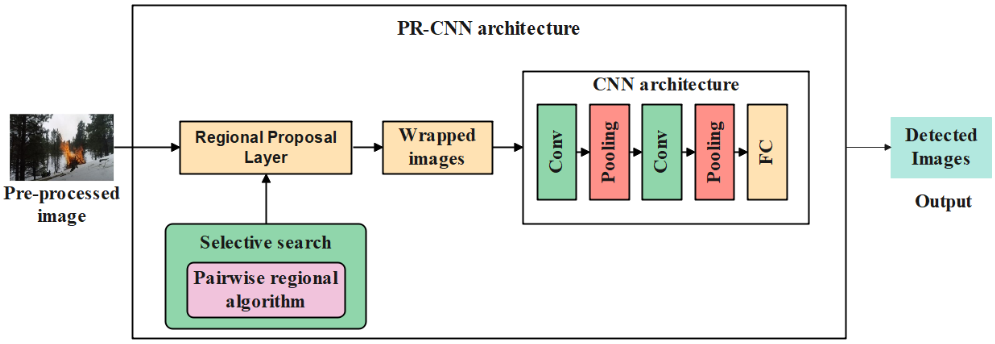

Figure 3. PR-CNN

3.1. Region proposal layer

Region proposals are smaller areas of an image that probably require images as input. For reducing region proposals in R-CNN, an algorithm known as selective search is employed. The selective search algorithm utilizes both exhaustive search and segmentation; the segmentation requires a separate algorithm for various shapes in an image by assigning them with various colors. The effective graph-based segmentation uses a pairwise region proposal algorithm that combines the anchor boxes which is not in the desired shape.

3.1.1. Effective graph-based segmentation for selective search

In image segmentation, graph graph-based technique is significant as it separates a digital image into integral regions or segments for image analysis or detection. In the graph-based segmentation technique, $G = (V, E)$ is considered as undirected graph with vertices $v_i \in V$, and edges $(v_i, v_j) \in E$ with relevance to neighboring pairs' vertices. Every edge $(v_i, v_j) \in E$ has respective weight $w\left((v_i, v_j)\right)$ and non-negative measure of non-similar among neighboring elements v_i and v_j. In image segmentation, elements in V are pixels and edge weight is measured by differences among two pixels merged through the edge. In this method, S represents a partition of V to elements such that each region $C \in S$ respective to the merged element in the graph $G' = (V, E')$, where $E' \subseteq E$. There are several ways to calculate segmentation quality, but in general require components to be the same and dissimilar. The edges among two vertices in similar element have respectively lesser weights while the edges among vertices in various elements have high weights.

3.1.2. Pairwise region proposal algorithm

The effective graph-based segmentation uses a pairwise region proposal algorithm that combines the anchor boxes which are not in the desired shape. D is described as a predicate to evaluate the presence and non-presence of boundary among two elements in segmentation. The predicate depends on calculating dissimilar among components along two elements' boundaries to calculate dissimilarity between the neighboring components within two elements. The results of the predicate are compared with inter-component variants to intra element variants and adaptive in relation to data local characteristics.

The internal variance of element $C \subseteq V$ is highest weight in the less spanning tree element $MST(C, E)$. The mathematical formula of internal difference is given as (3). The mathematical formula of difference is given as (4).

$$\int(C) = \underset{e \in MST(C,E)}{max} w(c) \tag{3}$$

$$Dif(C_1, C_2) = \underset{v_i \in C_1, v_j \in C_2, (v_i, v_j) \in E}{min} w\left((v_i, v_j)\right) \tag{4}$$

Where $Dif(C_1, C_2) = \infty$ when there is no edge connecting. The calculation variance is in problematic principle that reflects only a little edge weight among two elements. Furthermore, the definition of calculation variance is modified to attain median weight to make it much more robust for outliers. A small modification to the segmentation technique causes many changes. The region comparison predicate estimates that there is a boundary among pairs by checking the variance among components $Dif(C_1, C_2)$ which represents related to internal differences. The threshold function is utilized for controlling the degree differences. The mathematical formula for pairwise comparison prediction is given as (5). Where $MInt$ represents minimum internal difference. The mathematical formula of minimum internal difference is given as (6).

$$D(C_1, C_2) = \begin{cases} trueifDif(C_1, C_2) > MInt(C_1, C_2) \\ falseotherwise \end{cases} \tag{5}$$

$$MInt(C_1, C_2) = min \tag{6}$$

Where T represents the threshold function that controls degree of variance among two elements to be higher than the internal differences to ensure the presence of a boundary among them. For less elements, $\int(C)$ is not a superior evaluation of local characteristics of information. In exterior case, $|C| = 1, \int(C) = 0.$ So, a threshold function is used based on its component size, while the mathematical formula is given as (7).

$$\tau(C) = k/|C| \tag{7}$$

Where $|C|$ represents the size of C, k represents the parameter, and τ represents the threshold function. Small elements are allowed while there is sufficient huge difference among neighboring elements. The non-negative function of a single element is utilized for τ without modifying algorithm results. For example, it is probable to have a segmentation technique that prefers elements of some shapes by determining τ for huge components which is not suitable for non-desires and small shapes. But, the pairwise region proposal algorithm combines the anchor boxes which are not in the desired, small shapes. The smaller regions into are combined into larger regions and this method considers three types of similarities such as color, texture, and size for combining the regions. This selective search algorithm produces 2,000 region proposals approximately, and these region proposals are fed into CNN architecture to compute the CNN features.

3.2. Convolutional neural network

The produced 2,000 region proposals are fed into CNN to extract features and detect the wildfire in the dataset images. Feature extraction is the process of converting actual information into numerical features which are processed when protecting data in the actual dataset. After feature extraction, it provides better outcomes than when applying raw data to machine learning directly. In the research, the CNN is utilized for feature extraction which is a neural network that takes image features as input and classifies the images. A convolutional layer is a fundamental layer of CNN structure that performs feature extraction, including a combination of linear and non-linear operations. Then, these extracted features are given as input to a fully connected layer to detect the wildfire in images. By using PR-CNN method, the wildfire images in the FLAME dataset are detected much more accurately along with the small regions also detected effectively. These images are given as input to the post-processing technique for eliminating the duplicate detection in results.

3.3. Soft-non-maximum suppression

NMS is a post-processing technique utilized to detect objects or images to eliminate duplicate detections and choose related bounding boxes in the detected image. The image detection method produces a huge count of region proposals and every region proposal contains related scores that lead to false detection, while certain overlapping images are missed. To overcome this issue, the NMS technique that sets the intersection over union (IoU) threshold for a particular class of image is utilized, bounding box M has the highest score and that is chosen from the generated bounding box B series and kept in the last detection output R. The NMS technique repeated the aforementioned process till B is empty and at last D results. The mathematical formula of NMS is given as (8).

$$s_i = \begin{cases} s_i IoU(M, B_i) < p \\ 0 IoU(M, B_i) \geq p \end{cases} \tag{8}$$

Where p represents the IoU threshold, s_i represents the result of NMS, M and B_i represent the bounding boxes. From the aforementioned (8), the NMS technique directly modifies the score of bounding boxes of adjacent class to 0, which causes certain overlapping images to be missed. So, the soft-NMS technique which is an enhancement of a NMS technique and rescored a bounding box is utilized. If the bounding box is overlapped with M, it will provide a lower score. If the overlap degree is low, the score is constant. The mathematical formula of soft-NMS is given as (9).

$$s_i = \begin{cases} s_i IoU(M, B_i) < p \\ s_i \times \left(1 - IoU(M, B_i)\right) IoU(M, B_i) \geq p \end{cases} \tag{9}$$

At the same time, a bounding box with a high score is M, while the bounding boxes with high scores are recombined. The position of remerged bounding boxes is weighted and meaned through respective score weights to the actual bounding box. Figure 4 represents the results of the detected wildfire images in FLAME dataset.

Figure 4. Results of detected wildfire images

4. RESULTS AND DISCUSSION

The proposed method detects the wildfire in images much more accurately along with the small fire regions in images also detected effectively. The pairwise region proposal algorithm combines the anchor boxes that are not in the desired and small shapes, then these results are evaluated. The proposed PR-CNN technique is implemented with Python environment with system requirements of processor intel core i7, and RAM 16 GB. The performance metrics utilized to evaluate the proposed method are accuracy, precision, recall, and f1-score. Accuracy is referred to as a measure used to determine the correctness of the proposed PR-CNN method. Precision is referred to as the ratio of correctly predicted positive observations to the total number of predicted observations for positives. The recall is referred to as the ratio of correctly predicted false modules. F1-measure is referred to as the calculation of accuracy test, determined as average of precision and recall. The mathematical formula for the performance metrics is given as (10) to (13):

$$Accuracy = \frac{(TruePositive + TrueNegative)}{TotalInstances} \quad (10)$$

$$Precision = \frac{TruePositive}{(PredictedInstances = True)} \quad (11)$$

$$Recall = \frac{TruePositive}{ActualnumberofInstancesasTrue} \quad (12)$$

$$F1Measure = \frac{2 * Precision * Recall}{Precision + Recall} \quad (13)$$

4.1. Quantitative analysis

The performance of the proposed PR-CNN method is analyzed with existing algorithms like recurrent neural networks (RNN), CNN, and R-CNN. The proposed method attains an accuracy 95.58%, precision 95.06%, recall 94.83%, and f1-score 94.41% which is better when compared to the existing algorithms. Figure 5 represents the performance comparison of the proposed detection method.

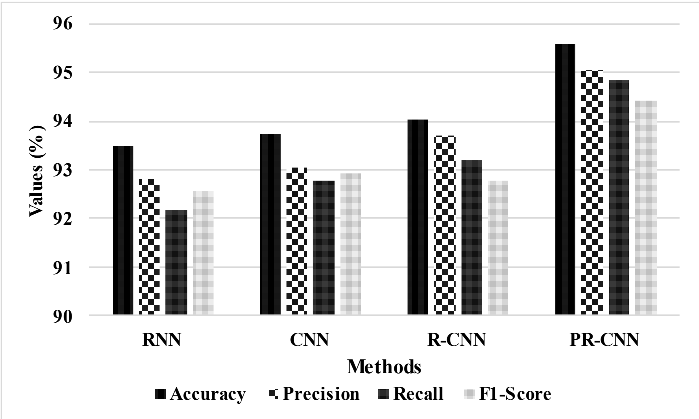

Figure 5. Performance comparision of proposed PR-CNN method

The research utilized post-processing methods such as soft-NMS technique and its performance is evaluated with other post-processing techniques like robust and efficient post processing (REPP), NMS, and adaptive non-maximum suppression (ANMS). The utilized soft-NMS technique obtains an accuracy of 92.03%, precision of 91.83%, recall of 91.58%, and f1-score of 90.98% which is superior to the existing techniques. Figure 6 represents the Execution of post-processing technique.

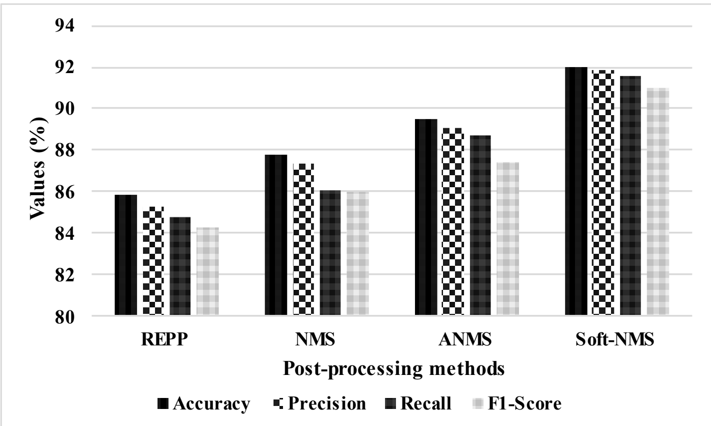

Figure 6. Execution of soft-NMS technique

The performance of the proposed method with post processing is evaluated with another classification method that utilizes post processing technique. The existing methods such as R-CNN-REPP, R-CNN-NMS, and R-CNN-ANMS are utilized for evaluating the proposed method. The proposed PR-CNN soft-NMS technique attains an accuracy of 97.44%, precision of 97.32%, recall of 97.31%, and f1-score of 96.67%, which is superior to the existing techniques. Figure 7 illustares the performance of the proposed method with post-processing technique.

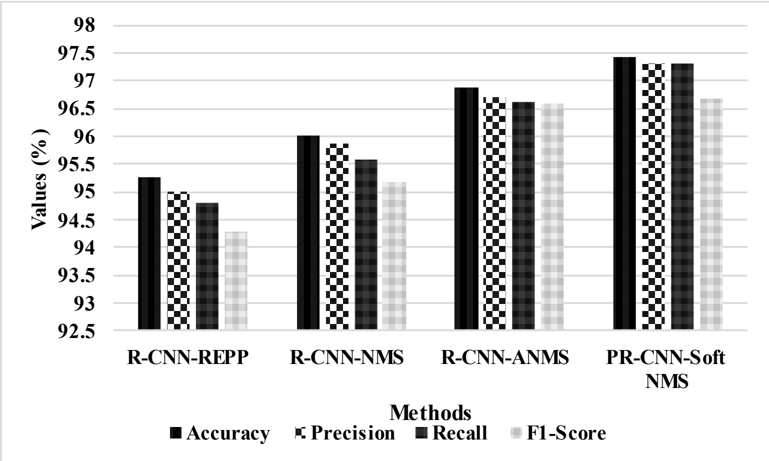

Figure 7. Performance of PR-CNN soft-NMS technique

From Figure 7, it is evident that the proposed PR-CNN method outperforms by accomplishing higher accuracy of 97.44%, which is better than that of the other existing methods. The post-processing technique utilized for the research also performs superiorly and attains more preferable accuracy of 92.03% which is higher than that of the existing methods. From the above experimental analysis, it is evident that the introduced method outperforms other methods in terms of accuracy, precision, recall, and f1-score.

4.2. Comparative analysis

In this research, the performance of proposed PR-CNN method is evaluated with other existing methods like reduce VGGNet [16], FBC-Anet [17], and ensemble method [21] on the FLAME dataset. The introduced method obtains an accuracy 97.44%, precision 97.32%, and recall 97.31%, which is comparatively higher than other existing methods. Table 3 represents the performance of the proposed method with other existing methods.

Table 3. Comparative analysis of proposed PR-CNN

Method	Dataset	Accuracy (%)	Precision (%)	Recall (%)
Reduce-VGGNet [16]	FLAME	97.35	97.22	97.22
FBC-Anet [17]		-	92.19	89.37
Ensemble method [21]		85.12	-	-
Proposed PR-CNN		97.44	97.32	97.31

4.3. Discussion

In present times, deep learning-based detection techniques have enhanced their capacity to automatically learn and extract complex features from image datasets. The existing methods have limitations like the complexity of noise data, requiring a huge quantity of quality images to obtain high detection accuracy, and ignoring certain images in the detection process. Moreover, they do not find small regions of fire in dataset images. This section illustrates the proposed method's advantages and existing methods' limitations. The existing model Reduce VGGNet [16] had some limitations of having complexity in noise data. The FBC-Anet [17] method needed huge quantity of high-quality images to obtain many detection results. The ensemble method [21] did not identify the small regions of fire in the image. To overcome these limitations, the PR-CNN is proposed in a regional proposal layer of RCNN. The proposed method effectively detects wildfire in images and merges the small regions which are in non-desired shape. It obtains superior accuracy of 97.44%, precision of 97.32%, recall of 97.31%, and f1-score of 96.67%, thereby being comparatively superior to the existing algorithms like reduce VGGNet [16], FBC-Anet [17], and ensemble method [21].

5. CONCLUSION

Wildfire detection is a process of identifying the fire pixel according to the temperature difference between surface energy emitting and ambient temperature. In this manuscript, a PR-CNN is proposed for wildfire detection. The dataset taken for this research is the FLAME dataset, then normalization and HSV color space techniques are utilized as pre-processing methods for improving the image quality. The detection process is performed by R-CNN with a pairwise algorithm in the regional proposal layer. After detecting the wildfire in dataset images, PR-CNN output is given as input to post-processing techniques like soft-NMS to eliminate duplicate detection in PR-CNN results. The proposed method efficaciously detects the wildfire in images much more accurately, alongside small fire regions in images. In the future, various CNN-based methods and pre-processing methods can be developed for improving the accuracy and speed of wildfire region detection.

REFERENCES

[1] F. Khennou and M. A. Akhloufi, "Improving wildland fire spread prediction using deep U-Nets," *Science of Remote Sensing*, vol. 8, 2023, doi: 10.1016/j.srs.2023.100101.

[2] A. Zhang and A. S. Zhang, "Real-time wildfire detection and alerting with a novel machine learning approach: a new systematic approach of using convolutional neural network (CNN) to achieve higher accuracy in automation," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 8, pp. 1–6, 2022, doi: 10.14569/IJACSA.2022.0130801.

[3] M. Grari, I. Idrissi, M. Boukabous, O. Moussaoui, M. Azizi, and M. Moussaoui, "Early wildfire detection using machine learning model deployed in the fog/edge layers of IoT," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 2, pp. 1062–1073, 2022, doi: 10.11591/ijeecs.v27.i2.pp1062-1073.

[4] A. Khan, B. Hassan, S. Khan, R. Ahmed, and A. Abuassba, "Deepfire: a novel dataset and deep transfer learning benchmark for forest fire detection," *Mobile Information Systems*, vol. 2022, 2022, doi: 10.1155/2022/5358359.

[5] M. Prakash, S. Neelakandan, M. Tamilselvi, S. Velmurugan, S. B. Priya, and E. O. Martinson, "Deep learning-based wildfire image detection and classification systems for controlling biomass," *International Journal of Intelligent Systems*, vol. 2023, 2023, doi: 10.1155/2023/7939516.

[6] S. T. Seydi, V. Saeidi, B. Kalantar, N. Ueda, and A. A. Halin, "Fire-net: a deep learning framework for active forest fire detection," *Journal of Sensors*, vol. 2022, 2022, doi: 10.1155/2022/8044390.

[7] J. S. Almeida, C. Huang, F. G. Nogueira, S. Bhatia, and V. H. C. D. Albuquerque, "Edgefiresmoke: a novel lightweight CNN model for real-time video fire-smoke detection," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 11, pp. 7889–7898, 2022, doi: 10.1109/TII.2021.3138752.

[8] R. A. Aral, C. Zalluhoglu, and E. Akcapinar Sezer, "Lightweight and attention-based CNN architecture for wildfire detection using UAV vision data," *International Journal of Remote Sensing*, vol. 44, no. 18, pp. 5768–5787, 2023, doi: 10.1080/01431161.2023.2255349.

[9] H. Yar, T. Hussain, M. Agarwal, Z. A. Khan, S. K. Gupta, and S. W. Baik, "Optimized dual fire attention network and medium-scale fire classification benchmark," *IEEE Transactions on Image Processing*, vol. 31, pp. 6331–6343, 2022, doi: 10.1109/TIP.2022.3207006.

[10] F. M. Talaat and H. ZainEldin, "An improved fire detection approach based on YOLO-v8 for smart cities," *Neural Computing and Applications*, vol. 35, no. 28, pp. 20939–20954, 2023, doi: 10.1007/s00521-023-08809-1.

[11] S. Jana and S. K. Shome, "Hybrid ensemble-based machine learning for smart building fire detection using multi modal sensor data," *Fire Technology*, vol. 59, no. 2, pp. 473–496, 2023, doi: 10.1007/s10694-022-01347-7.

[12] R. Zhang, W. Zhang, Y. Liu, P. Li, and J. Zhao, "An efficient deep neural network with color-weighted loss for fire detection," *Multimedia Tools and Applications*, vol. 81, no. 27, pp. 39695–39713, 2022, doi: 10.1007/s11042-022-12861-9.

[13] G. Tzoumas, L. Pitonakova, L. Salinas, C. Scales, T. Richardson, and S. Hauert, "Wildfire detection in large-scale environments using force-based control for swarms of UAVs," *Swarm Intelligence*, vol. 17, no. 1–2, pp. 89–115, 2023, doi: 10.1007/s11721-022-00218-9.

[14] K. Ahmad *et al.*, "FireXnet: an explainable AI-based tailored deep learning model for wildfire detection on resource-constrained devices," *Fire Ecology*, vol. 19, no. 1, 2023, doi: 10.1186/s42408-023-00216-0.

[15] M. Mukhiddinov, A. B. Abdusalomov, and J. Cho, "A wildfire smoke detection system using unmanned aerial vehicle images based on the optimized YOLOv5," *Sensors*, vol. 22, no. 23, 2022, doi: 10.3390/s22239384.

[16] T. Bhandarkar, V. K, N. Satish, S. Sridhar, R. Sivakumar, and S. Ghosh, "Earthquake trend prediction using long short-term memory RNN," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 2, pp. 1304-1312, 2019, doi: 10.11591/ijece.v9i2.pp1304-1312.

[17] L. Wang, H. Zhang, Y. Zhang, K. Hu, and K. An, "A deep learning-based experiment on forest wildfire detection in machine vision course," *IEEE Access*, vol. 11, pp. 32671–32681, 2023, doi: 10.1109/ACCESS.2023.3262701.

[18] L. Zhang, M. Wang, Y. Ding, T. Wan, B. Qi, and Y. Pang, "FBC-ANet: a semantic segmentation model for UAV forest fire images combining boundary enhancement and context awareness," *Drones*, vol. 7, no. 7, 2023, doi: 10.3390/drones7070456.

[19] L. Zhang, M. Wang, Y. Fu, and Y. Ding, "A forest fire recognition method using UAV images based on transfer learning," *Forests*, vol. 13, no. 7, 2022, doi: 10.3390/f13070975.

[20] Y. Jain, V. Saxena, and S. Mittal, "Ensembling deep learning and CIELAB color space model for fire detection from UAV images," *ACM International Conference Proceeding Series*, 2022, doi: 10.1145/3564121.3564130.

[21] X. Chen *et al.*, "Wildland fire detection and monitoring using a drone-collected RGB/IR image dataset," *IEEE Access*, vol. 10, pp. 121301–121317, 2022, doi: 10.1109/ACCESS.2022.3222805.

[22] R. Ghali, M. A. Akhloufi, and W. S. Mseddi, "Deep learning and transformer approaches for UAV-based wildfire detection and segmentation," *Sensors*, vol. 22, no. 5, 2022, doi: 10.3390/s22051977.

[23] X. Wang, Z. Pan, H. Gao, N. He, and T. Gao, “An efficient model for real-time wildfire detection in complex scenarios based on multi-head attention mechanism,” *Journal of Real-Time Image Processing*, vol. 20, no. 4, 2023, doi: 10.1007/s11554-023-01321-8.
[24] W. Wang, L. Lai, J. Chen, and Q. Wu, “CAM-based non-local attention network for weakly supervised fire detection,” *Service Oriented Computing and Applications*, vol. 16, no. 2, pp. 133–142, 2022, doi: 10.1007/s11761-022-00336-6.
[25] A. Shamsoshoara, F. Afghah, A. Razi, L. Zheng, P. Fulé, and E. Blasch, “The FLAME dataset: aerial imagery pile burn detection using drones (UAVs),” *IEEE Dataport*, 2020, doi: 10.21227/qad6-r683.
[26] A. K. Z. R. Rahman, S. M. N. Sakif, N. Sikder, M. Masud, H. Aljuaid, and A. K. Bairagi, “Unmanned aerial vehicle assisted forest fire detection using deep convolutional neural network,” *Intelligent Automation and Soft Computing*, vol. 35, no. 3, pp. 3259–3277, 2023, doi: 10.32604/iasc.2023.030142.
[27] J. Ryu and D. Kwak, “A method of detecting candidate regions and flames based on deep learning using color-based pre-processing,” *Fire*, vol. 5, no. 6, 2022, doi: 10.3390/fire5060194.

BIOGRAPHIES OF AUTHORS

Chaitra Ravi is an energetic and accomplished researcher, currently serving as a research scholar at Ramaiah Institute of Technology. She embarked on her academic journey by attending both her Master's and Bachelor’s degrees in Computer Science Engineering from the prestigious Visvesvaraya Technological University (VTU), establishing a strong foundation for her career in technology. Her academic trajectory has been characterized by a profound interest and expertise in the fields of artificial intelligence (AI) and machine learning. Her research pursuits extended into the realms of generative AI and image processing, showcasing, a comprehensive understanding of cutting-edge technology that is reshaping the future. She can be contacted at email: chaitrabindu@gmail.com.

Siddesh Gaddadevara Matt has completed his Ph.D. in Computer Science and Engineering. Presently, he is a Professor and Head in the Department of Computer Science and Engineering (Artificial Intelligence and Machine Learning) at MS Ramaiah Institute of Technology in Bangalore. His significant research output is evident in the numerous papers he has published at both international conferences and journals. He is an expert in the fields of Data Science and Distributed Computing. His research work has been published in more than 50 peer-reviewed international journal/conferences. He has authored several books in his areas of expertise that have gained widespread recognition and appreciation. His contributions to the field of computer science have been significant, and he continues to inspire and mentor students and researchers in the pursuit of excellence. He can be contacted at email: siddeshgm@gmail.com.