



ACNN-IFD: An Improved Image Fire Detection System Based on Advanced Convolutional Neural Networks

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Abstract: Fire detection by recognizing flames from images is an important area of current research. Early fire detection by visual means will allow quicker responses in potentially dangerous or life-threatening situations. However, traditional methods for detecting fires through images have been shown to be unreliable in complex scenes due to variations in how different types of flames appear and the possibility of similar-looking objects being present in the scene that are not actual fires. Therefore, the purpose of this study was to propose a new image fire detection system. This proposed image fire detection system includes a two-step approach combining a candidate region refinement process based upon the color features and outline features of potential flame candidates with a classification step utilizing an Advanced Convolutional Neural Network (ACNN). The proposed image fire detection system was tested using a data set available from Kaggle consisting of 999 images that include 780 images of fires and 219 images of no fires. Candidate regions of interest identified within each image were resized to 180×180 pixels and normalized prior to being inputted into the ACNN. The experimental results obtained from testing the proposed image fire detection system on the employed data set demonstrated a test accuracy of 95%. These results indicate promise in the ability of the proposed system to detect fires under the conditions tested. However, since the proposed system was validated only against the employed data set, additional testing on other data sets would need to be performed to assess its generalizability.

Keywords— Deep Learning; Feature Extraction; Data Normalization; Data Resizing.

1. INTRODUCTION

Fire causes far more risk to human safety, property, and health, and has resulted in significant increases in both financial and humanistic losses in recent years. Fires are caused by unanticipated events such as changing fuel management policies, rapid expansion in rural areas, and climate change [1]. Image fire detection (IFD) has recently been a popular research domain owing to its numerous advantages, including early fire detection, adaptable system installation, high accuracy, and fire detection capabilities in complex structures and large spaces [2]. IFD systems use algorithms to examine digital camera image data and determine whether a fire or fire risk is present in the images.

Consequently, the detection method is important to this technology and directly influences the image fire detector's performance [3], [4], [1], [5].

In the age of deep learning (DL) algorithms, IFD systems are mainly divided into three stages: (i) image preprocessing, (ii) feature extraction, and (iii) fire detection [6]. Among these phases, feature extraction is the most important aspect of algorithms [7]. Conventional IFD system algorithms depend on machine learning classifiers and manual fire feature selection [8]; however, the drawback of these algorithms is that human feature selection necessitates expertise. Furthermore, only basic image aspects like edges, color, and basic textures are revealed, despite the researchers' efforts to examine the image features of flames or smoke. Algorithms that extract low and middle-complex image features find it difficult to differentiate between fire and fire-like objects because of the complexity of fire types and scenes, as well as the many interferences that occur in real-world applications, leading to lower accuracy and weak generalization ability [9]. Deep learning (DL) algorithms are therefore used to address these limitations as they can learn and extract complex visual data automatically.

Convolutional Neural Network (CNN) algorithms have recently been used in the domain of image fire recognition. CNN has piqued the interest of various specialists because of its superior performance in medical diagnosis [10], Object recognition [11], automatic driving [12], biometric recognition [13], cybersecurity [14], and energy management [15]. Hence, several researchers have used CNNs in the field of IFD to design self-learning systems for gathering fire image properties [16], [17], [18]. Although CNN-based fire detection algorithms demonstrate superior detection accuracy in complex scenes compared to traditional machine learning algorithms, several challenges remain unresolved. Consequently, this research seeks to address the limitations of existing systems by developing effective fire detection algorithms framed around the following research questions:

- a) What are the limitations of the existing solutions regarding the IFD systems?
- b) How could the algorithms of IFD be improved?
- c) How can the proposed system be evaluated for improvement?

To address these questions, the major objectives of this research are:

- a) To investigate the problems of IFD systems and the techniques used for solving the problems.
- b) To develop IFD systems with better accuracy and reduced false alarm rates using an advanced CNN algorithm (ACNN).
- c) To evaluate the performance of the proposed system using various performance metrics, such as accuracy, recall, precision, and F1-score.
- d) The arrangement of this article is as follows: Section covers a critical review of the existing IFD system, while Section 3 covers the proposed methodology. Section 4 presents the results of the evaluations of the proposed method, while Section 5 presents the major conclusions from the study.

2. RELATED WORKS

Currently, studies on image-based fire detection have offered methods based on deep neural networks, such as CNNs, with promising results. As a result, investigators have recently introduced studies in the domain of fire detection using CNNs to enhance performance. Some ideas for fire detection systems that take into account shape, texture, color, and movement are based on recent developments. For instance, a smoke detection algorithm has been developed [16] based on the examination of smoke motion properties. With the help of a dark channel prior algorithm and background dynamic updating, CNN created suspicious features using an autonomous learning-based technique, resulting in a comprehensive, simple method. Additionally, the suspected smoke patches were enlarged using an implicit enlargement method, which improved the detection's timeliness.

A hybrid model has been developed using an Adaboost-MLP neural model to predict fire outbreaks [17]. The Regions of Interest (ROIs) were created using an Adaboost-LBP model, and a CNN was used to identify fires using the security camera footage and images. The design of a deployable model on mobile devices, as well as a lightweight deep neural network system, has been presented [19] for fire detection using videos captured in unknown surveillance situations. The proposed network is considered computationally inexpensive because it lacks dense, fully connected layers.

A lightweight framework for detecting fires using images that is based on deep learning and uses the tiny-YOLOv3 architecture has been presented [20]. By adjusting some parameters, the resulting model improved detection accuracy while reducing complexity during the training stage. To improve the thresholding mechanism in the RGB color space, Rafiee et al. [21] investigated a multi-resolution 2D wavelet analysis; the proposed method significantly reduced the false alarm rates by considering changes in shape and energy; however, this approach could record higher false alarms for the case of rigid body movements within the frames, such as human arm movement in the scene.

A modified version of [21] based on a YUC color model was provided by the authors in [22], and it outperformed the RGB version. An SVM classifier and color information are used similarly in another study [23]; although this technique can process 20 frames per second, it is unable to identify minor or distant fires, which can happen in actual surveillance footage. With the differences in brightness and shadows, color-based techniques usually produce more false alarms and frequently misidentify individuals wearing red clothing or vehicles. To address this issue, Mueller et al. [24] tried to analyze changes in the shape of a fire and the movement of rigid objects as they proposed an algorithm that can differentiate between a flame and rigid moving objects based on the physical behavior of a fire, as well as on a feature vector extracted from the optical flow.

Early studies focused on both hand-crafted feature based and deep learning methods for detecting fires using images. Most early hand-crafted feature based approaches utilized visual characteristics (such as color, movement, shapes, textures, and optical flow) to determine locations of possible flames or smoke. While these methods produced useful preliminary results and sometimes decreased processing time, they usually were adversely affected by

variations in light, false positives (fire like objects), rigid motion, and complexity in the backgrounds in which they operated. The resulting poor performances in most surveillance settings led to an interest in developing hand-crafted feature based methods. More recently, researchers developed CNN based and lightweight deep learning architecture's for detecting fires. These improvements significantly enhanced the ability to automatically learn features, and thus greatly increased the effectiveness of the systems over those that used traditional techniques. However, there are still many areas of improvement. For example, some methods primarily focus on improving classification accuracy, but typically fail to describe how the regions that would be classified as potential fire locations are initially identified prior to classification. Also, some researches use very small data sets and/or do not adequately investigate the issue of determining whether a detected object represents a fire or just looks like one. Furthermore, while it has been demonstrated that various lightweight architectures can be designed, methodological development and reproducibility issues are also frequently overlooked. Therefore, the literature appears to indicate a need for a more clearly defined and computationally efficient framework for detecting fires in images that includes region-of-interest (ROI) refinement based on color and contours followed by ACNN-based classification for improved fire detection. Therefore, motivated by this gap, the current study presents a hybrid method that incorporates ROI refinement based on color and contours with ACNN-based classification for improved detection of fires under the tested conditions.

3- PROPOSED METHODOLOGY

The research's methodology, datasets, and the development of the suggested approach are covered in this part. The proposed study primarily aims to use an attention-based ACNN model to detect fire images with high accuracy and low false alarms. The image datasets used to train the suggested system are called Kaggle, and they are created from fire images that have been recorded by videos and converted into frames [25]. Other images (out of the dataset) with 256×256 image dimensions were also considered, some of which are images of fire eruptions, and the others are not. The suggested IFD-ACNN system combines the advantages of the CNN model, such as feature extraction, learning capabilities, and high accuracy, with the power of image processing techniques for rapidly identifying and choosing possible fire regions. Fig1 provides an explanation of our training and development process.

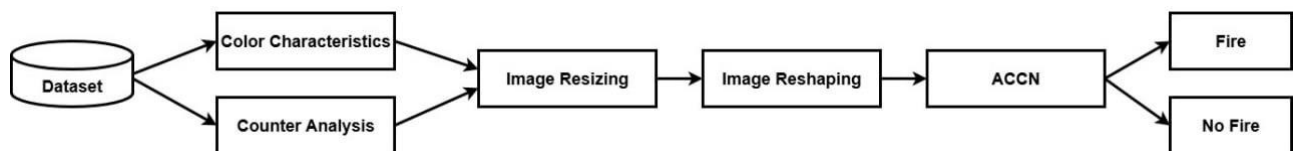


Fig .1. The Framework Of The Proposed ACNN-Based IFD System

The suggested ACNN-based IFD system consists of the following processes:

- a) Dataset: Fire & Non-Fire Images for this study were sourced from the Kaggle data set [25]. This included 999 images with 780 of these (fire) and 219 (non-fire), thus representing a moderate class bias. Each candidate region that was chosen was resized to 180 x 180 pixels. Normalization was then performed prior to each image being reshaped and fed into the CNN. Although no cross-dataset evaluation was completed; therefore, we recommend that the results presented herein are viewed as applicable solely to the data set employed herein until it is evaluated using an independent benchmark data set. Figure 2 (ai) shows a sample of the utilized fire and non-fire images of the Kaggle dataset.
- b) Color characteristics analyzer: The process examines and evaluates an image's possible fire characteristics, selecting the ROI if it detects fire or areas that resemble fire. Techniques like filtering and thresholding algorithms can be applied to isolate fire and fire-like zones.
- c) Contour Analysis: This procedure will utilize contours to isolate the flame (or like) areas of interest within the input image as well as work simultaneously with the Color Characteristics Algorithm Block. The Convexity, Area and Aspect Ratio filters will be utilized. For this project, Contour Analysis is being used as a pre-classification ROI Refined Stage. Once Candidate Regions have been extracted by the color-based system, the remaining candidates will be filtered using Area, Convexity and Aspect Ratio Filters to eliminate any rigid or geometrically improbable regions. The Candidates that remain after filtering will then be resized and sent to the CNN where they can be evaluated for Fire, thus reducing Background Interference and increasing Sensitivity to Small Irregular Flames.
- d) Image Resizing: This procedure can enlarge or reduce the size of the images it receives, of possible flames, provided that just the ROI of the prospective fires is selected. Furthermore, by concentrating on the ROI of fires, the resizing procedure enhances the accuracy of the CNN model and speeds up its performance. Image sizes from the Kaggle dataset were adjusted to (180,180).
- e) Image Reshaping: The images of the Kaggle dataset are reshaped to (1, 180, 180, 3) and saved as a linear array in this process.
- f) CNN model: The Kaggle dataset, which was created as detailed in the section below, is used to train the developed ACNN. The processed ACNN model learns to distinguish between areas that are burning and those that are not by using characteristics extracted from the scaled images.

To express the reshaping of the image to the desired form (1,180,180,3) in mathematical notation, the following process should be done.

1. Original fire image dimensions:

Let's the original fire image have dimensions (H_{orig} , W_{orig} , C_{orig}) (1) where:

- H_{orig} is the original height of the fire image.
- W_{orig} is the original width of the fire image.
- C_{orig} is the number of channels (RGB) of the fire image.

2. Resizing the fire image:

Resize the fire image to the target size (180, 180) for the height and width:

$$Image\ resize = f(Image, 180, 180) \quad (2)$$

Where f is a resizing function that resizes the image to the target dimensions (180, 180), this operation changes the height and width of the fire image, not that the number of channels C_{orig} RGB remains the same.

3. Reshaping the fire image:

The fire image is then reshaped to add a batch dimension (1) in the front, resulting in the shape (1,180,180,3):

$$Image\ reshaped = reshape(f(Fire\ Image, 180, 180, 3)) \quad (3)$$

Thus, the formula for reshaping can be given as:

$$Image\ reshaped = reshape(f(Fire\ Image, 180, 180, 3), (1, 180, 180, 3))$$

This equation indicates the following steps:

- First, the image is resized to (180, 180).
- Second, the batch dimension is added to reshape the fire image to (1, 180, 180, 3), where 1 represents the batch size (single image).



Fig.2. (ai)- Sample of the utilized fire and non-fire images of the Kaggle dataset

3.1. Building the proposed ACNN

Since image fire detection requires fast processing, the proposed ACNN algorithm has a lightweight architecture. Several kernels of different sizes are used in the proposed ACNN to create feature maps from the input data; there are numerous 3×3 convolution filters in the model. A ReLU function is used to activate the feature maps. The feature map's positive area is rapidly updated using this function. These features are fed into the next operation, max pooling, where these feature maps are subjected to a pooling layer with a 3×3 kernel size and an additional convolution layer. Then, the 2D feature maps are converted into vectors that may be put into the fully linked layer using a flattening layer. To improve the representation of the input data, the weights of the neurons in the convolution and fully connected layers between these three main activities are learned and adjusted during training. A dense layer is an example of matrix vector multiplication; the matrix values represent trainable parameters that are changed during backpropagation; as a result, the output is an m -dimensional vector. Finally, an activation function, such as Sigmoid, can be used to identify the outputs as fire or non-fire. The sigmoid function generates a probability distribution with an output range of 0 to 1. It is therefore used as the last classification layer in the model. The model is built using an Adam optimizer, which provides an adjustable learning rate, to ascertain the specific learning rate of each

parameter; the binary cross-entropy loss function is used in this classification. The ACNN method utilized in this paper is explained in Fig 3.

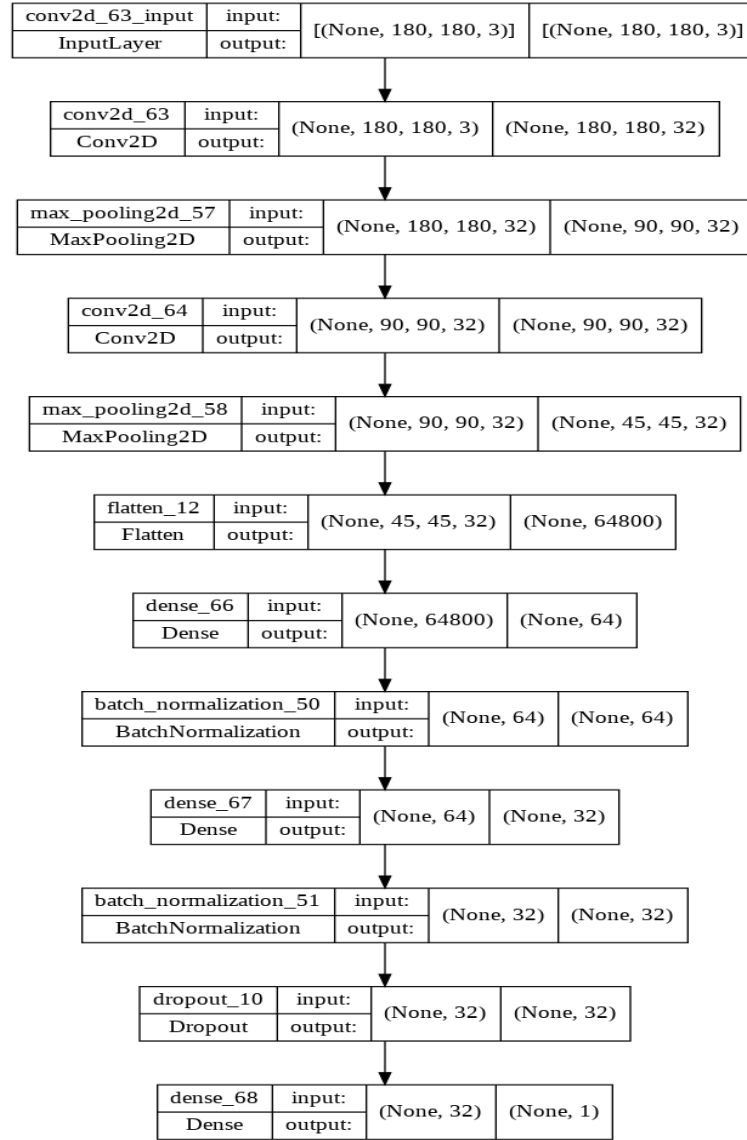


Fig.3. The process of the ACNN algorithm used in the proposed system

3.2. Experimental Environment

In this paper, the experiments were conducted using a PC with the following specifications: All-in-One Desktop; 10th Intel i7-10700; w/UHD Graphics; 32GB DDR4; 1TB SSD + 1TB HDD; WiFi 6, Bluetooth 5, RJ45, HDMI COM; Windows 10 Pro. Various libraries have been used with Python programs in this research, including Python, Scikit Learn, Numpy, and TensorFlow.

4. Results and Discussion

After the training process, the proposed ACNN model obtained high accuracy and low loss, with an accuracy of 97 % on the training set and an accuracy of 95 % on the test set. In this work, several metrics were used to evaluate the system's performance, including accuracy, accuracy, f1-score, precision, and recall [26], [27], [28].

4.1. Accuracy

It is determined as the extent of a model's performance across all classes. It is an important metric used when all classes are of equal importance. Mathematically, accuracy is determined as the number of correct predictions out of all predictions; it is often the most important statistic for judging a model, given as follows:

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (1)$$

Where:

- TP is True positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

Figs 4 and 5 depict the accuracy and loss during each epoch, respectively.



Fig.4. The training and validation accuracy of the proposed model

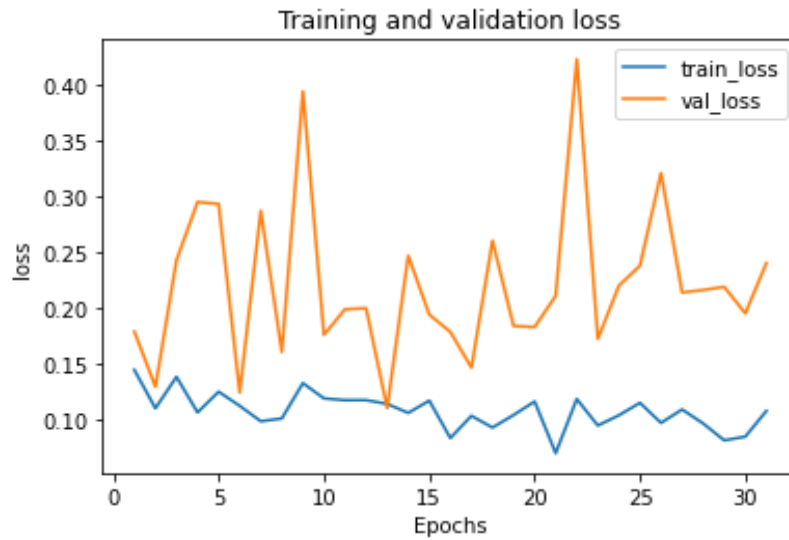


Fig.5. The training and validation loss of the proposed model

4.2. Precision Metric

This is a measure of the ratio of the number of accurately recognized positive instances by the model against the total number of positive instances (either correctly or incorrectly). A model's precision reflects its accuracy in positive sample identification; it is mathematically calculated as follows:

$$recision = \frac{TP}{TP + FP} \quad (2)$$

Where:

- TP is True positive
- FP = False Positive

Fig 6 depicts the training and validation of the precision of the proposed model during every epoch.

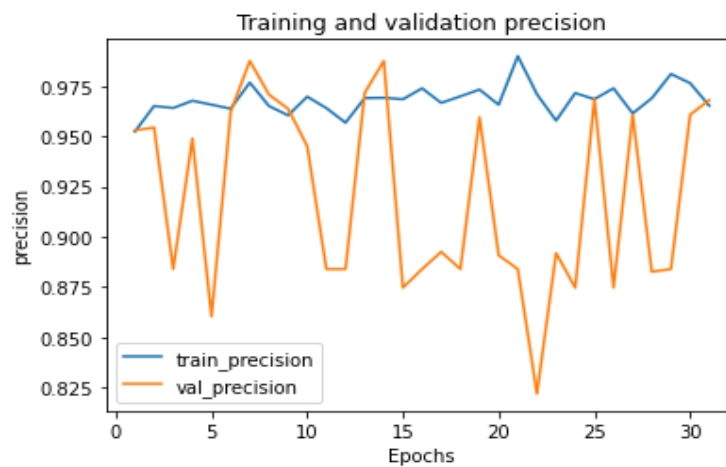


Fig.6. The training and validation of the precision of the proposed model

4.3 Recall

The ratio of correctly detected positive samples to the total number of positive samples is known as the recall. The model's recall assesses its capacity to recognize positive samples; it is calculated as follows:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

Where:

- TP is True positive
- FN = False Negative

Fig 7 shows the training and validation of the recall of the proposed model.

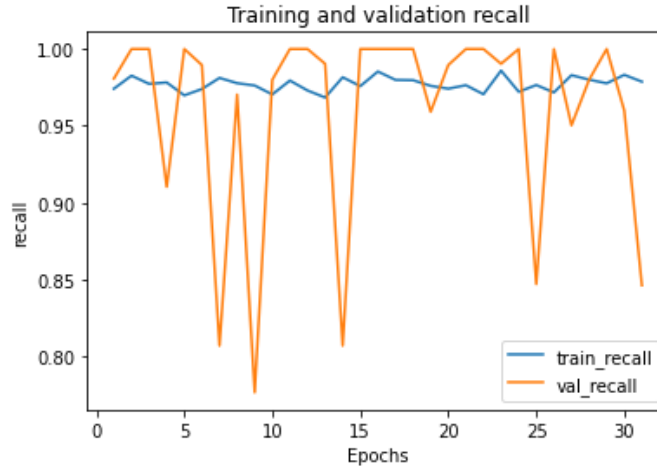


Fig.7. The training and validation of the recall of the proposed model

4.4. f1-Score

This metric is determined using precision and recall; it is determined as the harmonic mean of the recall and precision. A harmonic mean is an alternative way of finding the "average" of a given set of numbers. Compared to the traditional arithmetic mean, it is usually considered more suitable for ratios (such as recall and precision). It is mathematically computed as follows:

$$F - Measure = 2 \frac{Precision \cdot Recall}{Precision + Recall}$$

Fig 8 illustrates the training and validation F1-scores for each epoch.

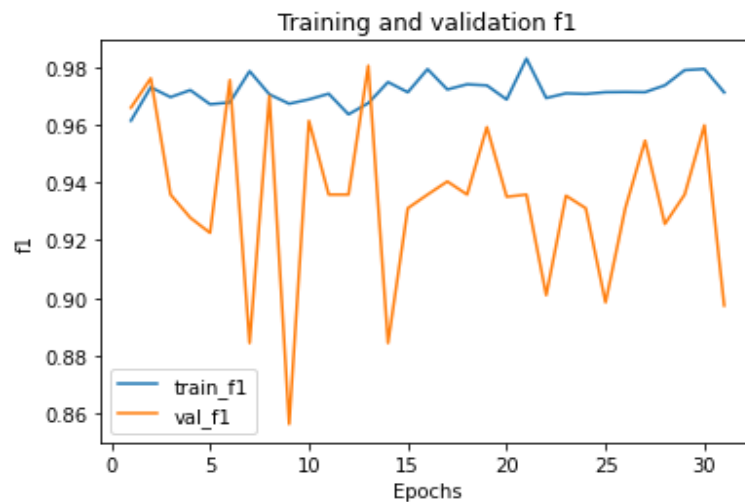


Fig. 8. The training and validation of the F1-score for the proposed model

High overall accuracy for a fire detection system does not provide sufficient evidence of practical reliability since both false negatives (undetected fires) and false positives (false alarms) will have different impacts in actual world fire safety applications. The primary difference between these two types of errors is the severity of their consequences. False negatives are typically considered the most dangerous type of error due to the fact that they signify unreported or undetected fires. Conversely, false positive alarms create unnecessary alarm conditions and may undermine the trustworthiness of the detection system when it is deployed. The recall values measured in this research project could therefore serve as indicators of the detection models' ability to detect fire events. A higher recall value indicates fewer missed detections. Additionally, precision values measure how well a detection model is able to avoid generating false alarms. Therefore, evaluation of the proposed ACNN model based on the proposed method should include both overall accuracy measures and also include a joint assessment of the three metrics - precision, recall, and F1-score. Although there were no data presented related to an explicit error analysis using a confusion matrix as part of this study, this represents a limitation of the manuscript and should be investigated in additional studies. Finally, some sample fire images were tested with the proposed IFD-ACCCN system which included images not from the original Kaggle dataset; the corresponding results are presented in Fig 9.

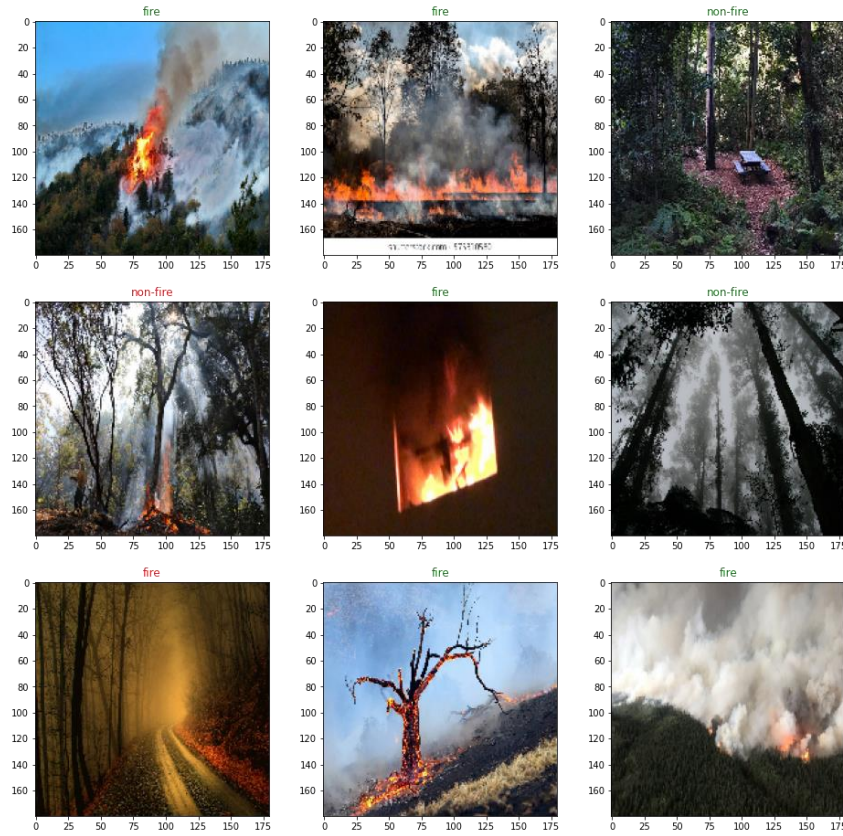


Fig 9. Testing of the proposed system on several images

Although the results from the proposed ACNN model show good quality, the validity of the results' robustness can't be confirmed as they have been tested mainly on the authors' data set. The study has shown that the proposed method works well for this specific data set; however, it does not confirm the method's ability to generalize across different domains. Thus, testing the proposed approach on common benchmark data sets for fire detection will help to increase its comparison to previously published studies and therefore, help validate how robustly the proposed method operates in a variety of realistic situations.

Table 1 : Comparison of the proposed method with related studies based on reported accuracy results.

Item	Ref.	Utilized Method	Achievements
1	[29]	Dynamic convolution YOLOv5 with K-means++	94%
2	[30]	CNN	93.7 %
3	Our Study	Advanced CNN	95%

5. Conclusion and Future Directions

The researchers tested their new fire detection system based on ACNNs on the used data set and they found out, that the new fire detection system reached a good result. They were able to report that the test-accuracy of the fire detection system reached 95%. The authors were also able to find the best way to extract fire-related visual features from images. These results have to be considered by the limitations of this research. The authors only tested the fire detection-system on one specific data set. Therefore, the authors cannot generalize

their results to other datasets (i.e., other than those already analyzed). Furthermore, there is no ablation analysis included, i.e., there is no comparison of how much the different parts of the system contribute to the final output. In addition, there is no explicit quantitative evaluation of false positives and false negatives. False positives and false negatives can cause problems in safety-critical environments where early detection of fires is crucial for preventing accidents. Therefore, future works should focus on validating the proposed method using standard benchmark-fire-datasets, conducting ablation-studies, performing a more comprehensive error-analysis and integrating smoke detection as well as IoT/Edge implementation after larger-scale experiments.

Data Availability Statement

The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

REFERENCES

- [1] F. Bu and M. S. Gharajeh, "Intelligent and vision-based fire detection systems: A survey," *Image Vis. Comput.*, vol. 91, p. 103803, 2019.
- [2] U. Dampage, L. Bandaranayake, R. Wanasinghe, K. Kottahachchi, and B. Jayasanka, "Forest fire detection system using wireless sensor networks and machine learning," *Sci. Rep.*, vol. 12, no. 1, pp. 1–11, 2022.
- [3] P. Li, Y. Yang, W. Zhao, and M. Zhang, "Evaluation of image fire detection algorithms based on image complexity," *Fire Saf. J.*, vol. 121, p. 103306, 2021.
- [4] R. Xu, H. Lin, K. Lu, L. Cao, and Y. Liu, "A forest fire detection system based on ensemble learning," *Forests*, vol. 12, no. 2, p. 217, 2021.
- [5] A. Sharma, P. K. Singh, and Y. Kumar, "An integrated fire detection system using IoT and image processing technique for smart cities," *Sustain. Cities Soc.*, vol. 61, p. 102332, 2020.
- [6] A. Jahagirdar, N. Sathe, S. Thorat, and S. Saxena, "Fire detection in nano-satellite imagery using Mask R-CNN," *Int. J. Signal Imaging Syst. Eng.*, vol. 13, no. 1, pp. 19–26, 2024.
- [7] F. Gong *et al.*, "A real-time fire detection method from video with multifeature fusion," *Comput. Intell. Neurosci.*, vol. 2019, 2019.
- [8] A. Kar, N. Nath, and U. Kempriai, "Performance analysis of support Vector Machine (SVM) on challenging datasets for Forest Fire Detection," *arXiv Prepr. arXiv2401.12924*, 2024.
- [9] A. Gaur, A. Singh, A. Kumar, A. Kumar, and K. Kapoor, "Video flame and smoke based fire detection algorithms: A literature review," *Fire Technol.*, vol. 56, no. 5, pp. 1943–1980, 2020.
- [10] S. A. Schnawa, M. Rafie, and M. S. Taha, "DAE-DBN: An Effective Lung Cancer Detection Model Based on Hybrid Deep Learning Approaches," in *International Conference of Reliable Information and Communication Technology*, Springer, 2023, pp. 108–118.
- [11] N. S. Ali, A. F. Alsafo, H. D. Ali, and M. S. Taha, "An Effective Face Detection and Recognition Model Based on Improved YOLO v3 and VGG 16 Networks," *J. homepage http://ieta.org/journals/ijcmem*, vol. 12, no. 2, pp. 107–119, 2024.
- [12] V. Totakura, B. R. Vuribindi, and E. M. Reddy, "Improved safety of self-driving car using voice recognition through CNN," in *IOP Conference Series: Materials Science and Engineering*, IOP Publishing, 2021, p. 12079.
- [13] Z. S. Naser, H. N. Khalid, A. S. Ahmed, M. S. Taha, and M. M. Hashim, "Artificial Neural Network-

- Based Fingerprint Classification and Recognition,” *Rev. d’Intelligence Artif.*, vol. 37, no. 1, 2023.
- [14] A. A.-A. Hadad, H. N. Khalid, Z. S. Naser, and M. S. Taha, “A Robust Color Image Watermarking Scheme Based on Discrete Wavelet Transform Domain and Discrete Slantlet Transform Technique,” *Ing. des Syst. d’Information*, vol. 27, no. 2, p. 313, 2022.
- [15] F. S. Hanoon, M. Çevik, and M. S. Taha, “A fault classification for defective solar cells in electroluminescence imagery based on deep learning approach,” in *AIP Conference Proceedings*, AIP Publishing, 2024.
- [16] Y. Luo, L. Zhao, P. Liu, and D. Huang, “Fire smoke detection algorithm based on motion characteristic and convolutional neural networks,” *Multimed. Tools Appl.*, vol. 77, no. 12, pp. 15075–15092, 2018.
- [17] F. Saeed, A. Paul, P. Karthigaikumar, and A. Nayyar, “Convolutional neural network based early fire detection,” *Multimed. Tools Appl.*, vol. 79, no. 13, pp. 9083–9099, 2020.
- [18] K. Muhammad, J. Ahmad, Z. Lv, P. Bellavista, P. Yang, and S. W. Baik, “Efficient deep CNN-based fire detection and localization in video surveillance applications,” *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 49, no. 7, pp. 1419–1434, 2018.
- [19] K. Muhammad, S. Khan, M. Elhoseny, S. H. Ahmed, and S. W. Baik, “Efficient fire detection for uncertain surveillance environment,” *IEEE Trans. Ind. Informatics*, vol. 15, no. 5, pp. 3113–3122, 2019.
- [20] L.-W. Kang, I.-S. Wang, K.-L. Chou, S.-Y. Chen, and C.-Y. Chang, “Image-based real-time fire detection using deep learning with data augmentation for vision-based surveillance applications,” in *2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, IEEE, 2019, pp. 1–4.
- [21] A. Rafiee, R. Dianat, M. Jamshidi, R. Tavakoli, and S. Abbaspour, “Fire and smoke detection using wavelet analysis and disorder characteristics,” in *2011 3rd International conference on computer research and development*, IEEE, 2011, pp. 262–265.
- [22] P. Foggia, A. Saggese, and M. Vento, “Real-time fire detection for video-surveillance applications using a combination of experts based on color, shape, and motion,” *IEEE Trans. circuits Syst. video Technol.*, vol. 25, no. 9, pp. 1545–1556, 2015.
- [23] Y. H. Habiboglu, O. Günay, and A. E. Çetin, “Covariance matrix-based fire and flame detection method in video,” *Mach. Vis. Appl.*, vol. 23, no. 6, pp. 1103–1113, 2012.
- [24] M. Mueller, P. Karasev, I. Kolesov, and A. Tannenbaum, “Optical flow estimation for flame detection in videos,” *IEEE Trans. image Process.*, vol. 22, no. 7, pp. 2786–2797, 2013.
- [25] A. Khan, B. Hassan, S. Khan, R. Ahmed, and A. Abuassba, “DeepFire: A novel dataset and deep transfer learning benchmark for forest fire detection,” *Mob. Inf. Syst.*, vol. 2022, no. 1, p. 5358359, 2022.
- [26] H. A. Alrikabi, W. Annajjar, A. M. Alnasrallah, S. T. Mustafa, and M. S. M. Rahim, “Using FFNN Classifier with HOS-WPD Method for Epileptic Seizure Detection,” in *2019 IEEE 9th International Conference on System Engineering and Technology (ICSET)*, IEEE, 2019, pp. 360–363.
- [27] A. S. Ahmed, A. A.-A. Haddad, R. S. Hameed, and M. S. Taha, “An Accurate Model for Text Document Classification Using Machine Learning Techniques,” *J. homepage <http://iicta.org/journals/isi>*, vol. 30, no. 4, pp. 913–921, 2025.
- [28] N. K. Jabbar, M. Naderan, and M. S. Taha, “HybridIoMT: A Dual-Phase Machine Learning Framework for Robust Cybersecurity in Internet of Medical Things,” *Int. J. Intell. Eng. Syst.*, vol. 18, no. 4, 2025.
- [29] An, Qing, et al. "A robust fire detection model via convolution neural networks for intelligent robot vision sensing." *Sensors* 22.8 (2022): 2929.
- [30] Labed, Said, et al. "An ai-based image recognition system for early detection of forest and field fires." *European Journal of Forest Engineering* 9.2 (2023): 48-56.