FireNet-Micro: Compact Fire Detection Model with High Recall

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Abstract. Fire occurrences and threats in everyday life incur substantial costs on ecological, economic, and even social levels. It is crucial to equip establishments with fire prevention systems due to the notable increase in fire incidents. Numerous studies have been conducted to develop efficient and optimal fire detection models in order to prevent such mishaps. Initially, thermal/chemical methods were used, but later, image processing techniques were also employed to identify fire occurrences. Recent approaches have capitalized on the advancements in deep learning models for computer vision. However, most deep learning models face a trade-off between detection speed and performance (accuracy/recall/precision) to maintain a reasonable inference time (for real-time applications) and parameter count. In this paper, we present a bespoke and highly lightweight convolutional neural network specifically designed for fire detection. This model can be integrated into real-time fire monitoring equipment and potentially applied in future methods suhc as CCTV surveillance cameras, traffic lights, and unmanned aerial vehicles (drones) for fire monitoring in futuristic smart city scenarios. Despite having significantly fewer trainable parameters, our customized model, FireNet-Micro, outperforms existing low-parameter-count models in fire detection. When evaluated on the FireNet dataset, FireNet-Micro, with only 171,234 parameters, achieved an impressive overall accuracy of 96.78%. In comparison, FireNet-v2 attained 94.95% accuracy with 318,460 parameters (which is almost double the parameter count of the proposed FireNet-Micro).

1 Introduction

Fire hazards pose a significant threat to human life and property, making fire detection a crucial factor in preventing potentially fatal fire incidents. In the year ending March 2020, the overall economic and social impact of fires in England amounted to £12.0 billion. Out of this total, £3.2 billion represents the additional costs incurred after the fires, known as marginal costs. The remaining £8.8 billion

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corresponds to the proactive measures implemented to prevent fires or minimize their damage and effects, referred to as anticipation costs [1].

Traditional fire detection methods, such as thermal, photometric, and chemical detectors, have limitations as they require a substantial amount of smoke or fire to activate and are prone to false triggering [2,3]. Moreover, these methods are not suitable for outdoor detection in places like forests, streets, playgrounds, and industries. To address these shortcomings, there is a shift towards utilizing hand-designed detectors that leverage advancements in digital camera and computer vision technology, along with intelligent video approaches. Initially, researchers focused on extracting color and shape characteristics of smoke to differentiate it from fire in images and videos using hand-designed features. However, with technological advancements, image processing, computer vision, and artificial intelligence (AI) techniques have been introduced to overcome previous challenges. These cutting-edge fire detectors offer enhanced resilience, speed, and reliability. Unlike traditional methods, they do not rely on smoke accumulation, allowing them to operate effectively in outdoor settings with fewer false triggers and quicker response times. This improvement can be mainly attributed to the reduced inference times of the models used in these detectors. With the widespread presence of cameras and closed-circuit television (CCTV) systems in various locations such as streets, highways, businesses, shopping centers, parks, and buildings, the integration of visual-based fire detectors with surveillance setups has become feasible. This integration takes advantage of the interconnected networking infrastructure and the Internet of Things (IoT) to visualize objects and activities through cameras and CCTVs, enabling efficient monitoring.

One of the notable advantages of visual-based fire detectors is the elimination of hardware and materials used in thermal/chemical fire detectors. Instead, these detectors rely on software constructs, specifically AI models, to analyze real-time images or video frames for fire detection. Modern fire detectors leverage deep learning (DL) models, which eliminate the need for manual feature extraction and enable automatic feature extraction directly from images or video frames in real-time [4]. This approach offers several benefits, including improved accuracy, reduced false triggering rates, enhanced robustness, and increased reliability compared to traditional methods.

Contribution and Novelty: In this research paper, our focus is on an improved version of FireNet[5] and FireNet-*v2* [6]. This enhanced version exhibits a significant reduction in trainable parameters and a notable better Recall (sensitivity) as compared to its predecessors – which is particularly relevant in fire detection scenarios where the detection of true positive cases is crucial, and a high Recall helps ensure that the model is capturing as many positive instances (fire) as possible. What sets this lightweight model apart is its bespoke design for fire detection purposes. We proceed to demonstrate that, despite having substantially fewer parameters, the proposed model outperforms its predecessors, making it a formidable contender among modern integrated fire detectors driven by deep learning based computer vision methods.

The paper is structured as follows: Sect. 2 provides a concise yet relevant discussion on previous research regarding manually created features and AI methods used for fire detection. Section 3 presents the detailed architecture of the proposed DL model, FireNet-Micro, along with the rationale behind choosing it over FireNet and FireNet-*v2*. Section 4 includes a comprehensive analysis of the results obtained from the experiments, along with a comparison to other published works in the field. Lastly, Sect. 5 presents concluding remarks summarizing the findings and highlighting the key contributions of the study.

2 Related Works

Extensive research has been conducted to develop effective fire detection systems in order to mitigate fire risks. Modern fire detection systems commonly employ ion-based, infrared, or optical sensors, which require proximity to the fire source or location for activation. However, these sensors may not be suitable for certain settings such as markets, schools, and open areas.

As an alternative to these sensors, vision-based sensors have emerged as a preferred substitute, offering several advantages over traditional sensors. These advantages include lower costs, faster response times, and broader surveillance coverage [7]. Nevertheless, vision-based sensors also come with significant drawbacks, including their reliance on scene complexity, varying lighting conditions, and variable image quality.

In the early stages, researchers focused on the motion and color aspects of flame detection, developing custom algorithms specifically designed for fire detection [8–10]. These algorithms, known as manually-engineered fire detection algorithms, are computationally efficient and can be implemented on resource-constrained embedded hardware like the Raspberry Pi, achieving reasonable performance in terms of frame rates. However, they have a drawback of requiring human extraction of features from raw fire-scene images. This flaw results in time-consuming and often ineffective manual feature engineering, particularly when dealing with large datasets containing numerous images.

In view of this, manually crafted vision-based fire detection systems are being substituted by deep learning (DL)-based techniques that have shown superior performance across various parameters compared to less accurate alternatives with a higher false triggering rate. DL approaches have the advantage of automatically extracting meaningful features from the input data, making the overall process more efficient, less dependent on human operators, and significantly advancing the state-of-the-art in image classification and object recognition [4,11].

Numerous DL algorithms have been proposed in the technical literature for fire detection [11–17]. However, these research models are not suitable for practical fire detection applications in the field, where low-cost, resource-constrained hardware is typically available. Consequently, there has been a significant amount of academic work focusing on developing lightweight DL models specifically designed for edge devices with limited resources [18]. Examples of such lightweight DL models can be found in areas like vehicle and drone trajectory prediction [19,20], machine learning supported disease detection [21], image forgery detection [22], and various other real-life applications [18]. Notable models for fire detection in diverse situations include, but are not limited to, [23–30].

Although these works are innovative and effective, their reported results are based on different datasets. In this paper, we will only consider works that have presented their test results on the FireNet dataset, which has been utilized in our study, for the purpose of comparing the performance of the proposed model.

3 Proposed Model

The remarkable success of Convolutional Neural Networks (CNNs) in various computer vision tasks has led researchers to explore their application in fire detection from images and videos. CNNs consist of three main types of layers. The convolutional layer plays a crucial role by applying convolutions to the input data. Non-linear activation functions like ReLU are commonly employed after the convolutional layer to introduce non-linearity and capture complex interactions between input and output. Pooling layers such as max pooling or average pooling are used to reduce the spatial dimensions of the data, enhancing computational efficiency and reducing sensitivity to minor spatial variations. By combining these layers, CNNs can capture important details while discarding less critical information. The final component of a CNN typically consists of one or more fully-connected layers, sometimes with dropout layers in between, enabling the network to learn increasingly complex and abstract features from raw pixel input. CNNs are highly effective for various computer vision tasks due to their hierarchical nature.

As mentioned earlier, several CNN variants have been employed to improve the accuracy of fire detection and reduce false alerts, inspired by advancements in edge computing capabilities and deep feature extraction [12–16,31–33]. However, these CNN models have a heavy architecture that makes them challenging to deploy on low-cost hardware. To address this, we propose a lightweight neural network called FireNet-Micro, which maintains fire detection performance while significantly reducing the number of parameters compared to its predecessors, namely FireNet [5] and FireNet-*v2* [6].

3.1 Motivation for FireNet-Micro

The selection of an appropriate DL model has always been crucial for diverse applications where deep learning is leveraged. In such scenarios, having a model that is both swift and accurate is indispensable, as even minor delays can lead to significant consequences in terms of human lives and financial resources. Initially developed, FireNet aimed to surpass other available CNN models of its time. Its advantage resided in its relative simplicity compared to earlier deep learning-based fire detection techniques, which typically involved extensive Convolutional Neural Networks (CNN) capable of real-time fire detection at a minimum frame rate of 24 frames per second or higher. FireNet effectively operated in real-time applications for continuous fire detection and was also well-suited for deployment on resource-constrained embedded and mobile devices. It could run on affordable single-board computing platforms like the Raspberry Pi, achieving a frame rate surpassing 24 frames per second. Subsequently, FireNet-*v2* was introduced as an improved iteration of FireNet, offering enhanced performance metrics and a reduced number of parameters.

FireNet-Micro was motivated by the desire to reduce both the computational requirements and the number of trainable parameters compared to its predecessors, while still achieving improved accuracy. In this paper, we will provide a detailed explanation of how FireNet-Micro surpasses the original FireNet and the enhanced FireNet-*v2*, despite having a reduced parameter count. Specifically, the modifications made in our work from the previous versions can be summarized as follows:

- In contrast to the previous iterations, FireNet-Micro utilizes only 2 fully connected (Dense) layers, leading to a substantial decrease in the number of trainable parameters. The most noteworthy advantage of this approach is the remarkably low parameter count of the network, which amounts to only 171,234 parameters.
- The activation function of choice employed throughout the network is 'ReLU', except for the last Dense layer, which utilizes a SoftMax activation. The SoftMax activation is necessary for the final layer as the desired output type involves two classes[1].
- Considering the significance of Recall in scenarios where the detection of true positive cases is crucial, such as in the fire detection use-case (other examples include medical diagnosis, fraud detection), and considering that Precision and Recall oftentimes exhibit a 'trade-off', the FireNet-Micro model was trained specifically to improve the Recall – and achieving a Sensitivity of 97.47%.

3.2 FireNet-Micro Architecture

In the FireNet-Micro model, we utilized the initial (input) layer with image dimensions of $64 \times 64 \times 3$, serving as the first convolutional layer. The intermediate layers consist of a sequential model comprising convolutional layers, average pooling layers, and dropout layers, with the activation function being ReLU (rectified linear unit). All three convolutional layers are accompanied by Maxpooling layers. The first layer employs 16 filters, the second layer uses 32 filters, and the third layer employs 64 filters. The dropout values for these layers can be observed in Fig. 1. The kernel size is fixed at 3×3 for all convolutional

[1] Selecting SoftMax over Sigmoid for binary classification does not result in any performance degradation since both functions essentially serve the same purpose in this context.

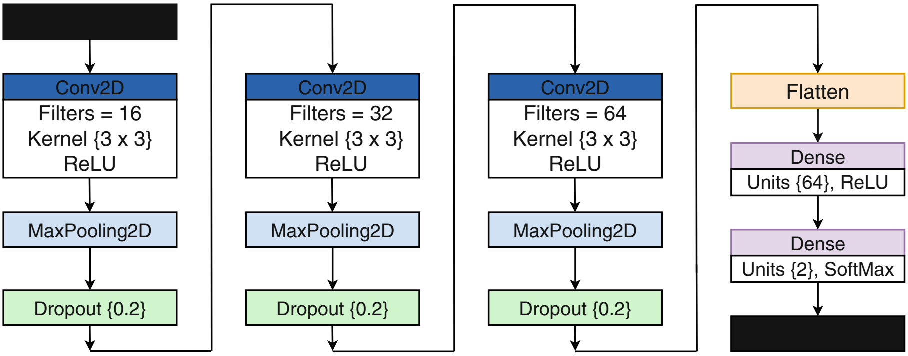

Fig. 1. Architecture of the proposed FireNet-Micro

layers. Following the convolutional layers, there is a Flatten layer. This Flatten layer serves the purpose of reshaping the tensor at the output of the third convolutional layer into a one-dimensional vector. This allows for the transition from the convolutional layers, which process spatial information, to the fully connected layers, which require one-dimensional input. The fully-connected part of the network architecture contains a Dense layer with 64 neuron, employing ReLU as the activation function. The final fully-connected Dense layer, which has 2 neurons, utilizes the 'Softmax' activation function and serves as the prediction layer, producing either 'Fire' or 'Non-Fire' signals (only one of these signals will be dominant at any given time). The detailed model architecture, consisting of only 9 layers (excluding Dropout), is depicted in Fig. 1. Overall, the model contains a minimal number of 171,234 parameters, and is only 2.1 MB on disk.

4 Results

This section presents comprehensive information regarding the dataset employed, the conducted tests, and the resulting outcomes.

4.1 Dataset

Despite the remarkable progress of deep learning (DL) models in computer vision applications over the past decade, their performance is heavily dependent on the quality and quantity of available training data. Unfortunately, there is a scarcity of high-quality datasets specifically tailored for DL models in the field of fire detection. In this study, the dataset initially created for FireNet [5] was utilized to train and test the FireNet-Micro model. This dataset consists of 46 movies depicting fire scenarios and 16 videos where fire is absent (non-fire).[2] It is important to note that this dataset is openly accessible for further research. A total of 1124 images depicting fire and 1301 images without fire (non-fire images)

[2] https://github.com/arpit-jadon/FireNet-LightWeight-Network-for-Fire-Detection.

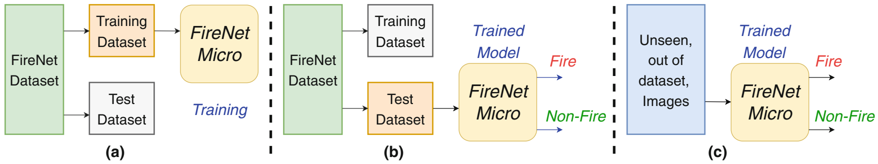

Fig. 2. (a) Training and (b) testing phases of the proposed FireNet-Micro lightweight deep learning on the FireNet dataset; (c) testing the trained FireNet-Micro model on unseen images from the World Wide Web

were employed in this study. Although the training samples from the FireNet dataset may not be numerous, they exhibit a wide range of realistic images, thereby posing a greater challenge for training the model. This assertion will be substantiated in a subsequent section, where it will be demonstrated that the accuracy of the FireNet-Micro model remains uncompromised even when confronted with unseen samples obtained from the World Wide Web.

4.2 Training Details

Figure 2 illustrates the training and testing phases of our approach. The hyper-parameters and activation functions employed in FireNet-Micro are summarized in Table 1. Since the model produces outputs in a 'one-hot' encoding format, where there are two outputs and only one is activated for each test image (representing fire or non-fire), we chose the Softmax activation for the final layer instead of Sigmoid. This choice ensures that the model decreases the estimated probabilities of the other classes while increasing the estimated probability of a specific class. By using Softmax activation, the assigned probabilities for the two output classes sum up to unity, leading to a clearer classification of fire and non-fire scenarios.

For the training process, we utilized a batch size of 32 and employed the ADAM optimizer, which incorporates adaptive learning rates based on estimates of first and second moments of gradients. ADAM combines the advantages of root mean square propagation and momentum-based methods. Its adaptive learning rate and momentum contribute to faster convergence, particularly when dealing with sparse gradients or noisy data. We trained the model for 50 epochs using the ADAM optimizer.

The training and testing of the model for FireNet-Micro was performed in the Google Colaboratory environment with the following resource specifications: Google Compute Engine backend running TensorFlow/Keras 2.12.0 on Python 3.10.12 utilizing 12 GB of RAM.

Table 1. Specifications of the trained FireNet-Micro model

(a) Details of parameters

Parameter	Value
Validation split	0.3
Number of parameters	171,234
Batch size	32
Epochs	50
Optimizer	Adam
Loss	Sparse categorical
	Crossentropy

(b) Activation functions

Layer	Activation
Conv2D Layer 1	ReLU
Conv2D Layer 1	ReLU
Conv2D Layer 1	ReLU
Fully-connected layer	ReLU
Output dense layer	Softmax

4.3 Model Performance

The FireNet-Micro model underwent training and testing using the FireNet dataset. The model's predictions were categorized into four classes: False Positives (FP), True Positives (TP), False Negatives (FN), and True Negatives (TN). These classifications are visualized in the form of a Confusion matrix in Fig. 3, which demonstrates the strong performance of FireNet-Micro on the dataset, as evidenced by the low percentages of FN and FP. Table 2 provides a comprehensive comparison between the proposed FireNet-Micro model and its predecessors, clearly demonstrating that FireNet-Micro surpasses the others in terms of Accuracy, Recall, and F1-Score metrics, while maintaining a lower parameter count. Additionally, Fig. 4 in the first two rows, showcases several examples of correctly classified images by FireNet-Micro, encompassing both 'fire' and 'no-fire' scenarios, and the last row contains examples of images that FireNet-Micro failed to classify accurately.

Table 2. Performance comparison of FireNet-Micro with FireNet-*v2* and FireNet

Models	FireNet-Micro	FireNet-***v2***	FireNet
Metrics	(%)	(%)	(%)
Accuracy	**96.78**	94.95	93.91
Recall	**97.47**	93.25	94
Precision	97.80	**99.28**	97
F1-Score	**97.63**	96.17	95
No of parameters	**171,234**	318,460	646,818

In the following portion of this section, we present a comparison between the proposed FireNet-Micro model and existing state-of-the-art (SoA) fire identification systems that demonstrate high performance. As mentioned earlier, the key distinguishing feature of the proposed model lies in its notably shallow

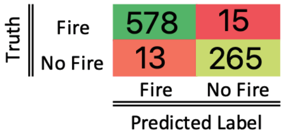

Fig. 3. Confusion Matrix for the FireNet-Micro model over the FireNet dataset

Table 3. Comparison of testing accuracy of FireNet-Micro model with other existing works on FireNet dataset

Work	Accuracy (%)	Number of parameters
Saponara [34]	93.60	**23,482**
FireNet [5]	93.91	646,818
FireNet-*v2* [6]	94.95	318,460
Ayala [35]	96.33	956,226
Saponara [36]	96.58	≈50 Million
FireNet-Micro	**96.78**	171,234

architecture, resulting in a significantly reduced number of trainable parameters (171,234). It is important to acknowledge that there are advanced fire detection technologies available in the literature that offer enhanced performance. However, their practical implementation and commercial utilization are hindered by their heavyweight architectures, characterized by large parameter counts and/or long inference times. Therefore, we consider the comparison of the proposed model with other lightweight models to be highly relevant in this context.

This part of this section presents the quantitative comparisons between the proposed approach and other existing methods. Table 3 provides a comparison of accuracy and the number of parameters among different techniques. These results are based on the inferences made by the trained model using the Test subset from the FireNet dataset, which consists of 778 images. Additionally, Table 3 includes relevant recent publications on fire detection that utilize the same dataset, to the best of our knowledge [34–37]. The performance comparison of FireNet-Micro with other available approaches, which report test results on the FireNet dataset, is visualized in Fig. 5. It is evident from Fig. 5 that FireNet-Micro achieves higher accuracy while maintaining a significantly lower parameter count. It should be noted that for [36], the published work does not provide the exact number of parameters, and the value presented in Table 3 is an estimated count considering the use of YOLOv2 in the fire detection model of [36].

Finally, to evaluate the classification performance of the proposed model on new and unseen images, a set of 200 random images was collected from the world wide web.[3] This set consisted of 100 images with fire and 100 images without fire. The trained FireNet-Micro model was utilized to make predictions on these

[3] https://github.com/Asra-Aslam/UnseenNet.

Fig. 4. The first two rows depict samples of images which were correctly classified as fire and non-fire images. The third row presents samples of incorrectly classified images by the FireNet-Micro model from test subset of the FireNet dataset.

images. The tests yielded the following performance metrics: Precision: 89.90%, Recall: 98%, F1-Score: 93.77%, Accuracy: 93.50%. An important observation was that the Recall metric achieved was quite high, indicating that the model successfully identified almost all instances of fire, missing only 2 (out of 100). Moreover, upon further investigation, it was discovered that the lower-than-expected accuracy on the 200 Internet images was due to several 'NoFire' images that closely resembled 'Fire' images. Some examples of such images are illustrated in Fig. 6. The model misclassified these similar-looking images as 'Fire' instead of 'NoFire.'

5 Conclusion

In this study, a lightweight deep learning model with a remarkably low number of parameters was introduced for the classification of images into fire and non-fire categories. The proposed model, called FireNet-Micro, is an enhanced version of the previous models FireNet and FireNet-*v2*, and it boasts a significantly reduced number of trainable parameters compared to its predecessors. To evaluate its performance, FireNet-Micro was tested on the FireNet dataset,

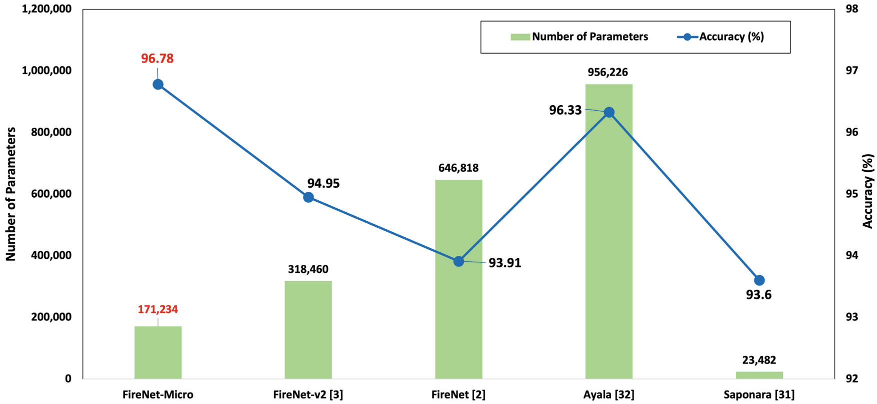

Fig. 5. Comparison of accuracy and number of parameters of FireNet-Micro with available counterparts over FireNet dataset.

Fig. 6. The FireNet-Micro model's overall classification accuracy was impacted by the presence of certain 'NoFire' images from the Internet that closely resembled 'Fire' images. This figure contains a few examples of such images that contributed to this effect.

and its inference accuracy was found to be superior to existing low-parameter-count models. For instance, FireNet-Micro achieved an accuracy of 96.78% using only 171,234 parameters, outperforming FireNet, which achieved an accuracy of 96.53% with 646,818 parameters, and FireNet-*v2*, which achieved an accuracy of 94.95% with 318,460 parameters. Another significant feature was the high recall of 97.47% which implies that the proposed model missed only a very small proportion of the actual fire scenarios.

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