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Original

Adaptive Fire System: Leveraging Image Analysis and Multi-Deep Learning Approaches for Dynamic Classification and Quality Assessment

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Abstract: The major roles in the control and prevention of fire breakouts remain fire classification and quality evaluation. In this paper, a new methodology that integrates image analysis with multi-deep models such as ResNet50, MobileNetV2, and lightweight deep learning models for accurate fire classification and quality assessment is proposed. The proposed methodology intends to use deep learning models to extract meaningful features from fire images automatically. ResNet50 and MobileNetV2 are very prominent deep-learning architectures that have proven to perform well in image classification tasks. A lightweight convolutional neural network (CNN), targeted for fire analysis, is supposed to be computationally light but highly accurate. In such a context, concerning obtaining information about the fire's intensity, spread, and danger, the proposed image analysis techniques come into play. Our approach provides a comprehensive evaluation of fire incidents by a combination of the outputs from the deep learning models and the image analysis results. The experimental results show that our proposed methodology was effective in fire classification and quality evaluation against ResNet50 and MobileNetV2. The proposed approach has huge potential for deployment in real-world applications involving fire

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prevention and control. It employs deep learning and image analysis techniques, hence providing a reliable and efficient way for fire classification and quality evaluation to ensure timely response and proper allocation of resources during fire emergencies.

Keywords: **Deep learning, lightweight convolutional neural networks, fire classification, adaptive fire system.**

1. Introduction

Fire classification and quality evaluation are two critical tasks in the context of firefighting, forestry, and environmental monitoring. Indeed, proper classification of fire types and estimation of their quality have become very critical in resource allocation, decision-making, and fire management (Fan & Pei, 2021; Ioannidou et al., 2017; Zhang et al., 2020). Nevertheless, several factors limit current methods of fire classification and quality evaluation.

Traditional techniques require a lot of manual observation and visual inspection. These techniques are extremely time-consuming, subjective, and prone to human errors. Moreover, in most cases, due to the limitations of certain fire types and scenarios, such methods turn out to be ineffective in real-world scenarios. With the latest remote sensing and sensor data availability, machine learning-based approaches have been developed, but such techniques have several limitations (Islam & Bhattacharya, 2021; Wang et al., 2022). For instance, most of them resort to hand-designed features that might miss complex patterns and relationships in the fire data. Besides, these approaches are usually tailor-made for specific fire types or scenarios, hence poorer at generalizing to new and unseen data.

Very recently, some deep learning-based methods have already shown very promising results in both fire classification and quality evaluation. However, these methods mostly incur high computational complexity and are heavily dependent on large amounts of labelled data and may suffer from overfitting. More importantly, they failed to provide interpretable results on the factors underlying fire classification and quality evaluation (Harkat et al., 2023; Li & Zhao, 2020).

Hence, in order to eliminate these shortcomings, the present study proposes a new methodology that combines image analysis with multi-deep learning toward accurate fire classification and quality evaluation. The proposed approach shall combine the strengths of both image analysis and deep learning in extracting robust features from images of fires and classifying them into different types and quality levels. The methodology will be general enough to apply to different fire types and scenarios, thus being suitable for real applications. Moreover, the proposed approach will offer interpretable results, which may give firefighters and researchers an explanation of the latent factors contributing to fire classification and quality evaluation.

The objectives of the study are:

1. To develop a novel methodology for fire classification and quality evaluation by integrating image analysis with multi-deep learning.
2. To evaluate the performance of the proposed methodology against a comprehensive dataset of fire images.
3. To compare the results with those of state-of-the-art methods.

The methodology proposed is likely to be important in improving the accuracy and efficiency of classification and quality evaluation concerning fires, hence contributing to effective fire management and decision-making.

2. Related Work

Fire classification and quality evaluation are two of the most important tasks in firefighting and environmental monitoring. In the recent past, studies such as the works of mentioned different approaches, including image-based approaches, deep learning-based approaches, and multi-deep learning approaches, among others.

Researchers applied image features to do the classification of the fires into different types and evaluate their quality. For example, Jamali et al. (2020) proposed a fire classification system based on colour and texture features, achieving an accuracy of 98.5%. Similarly, Bakri et al. (2018) applied shape features in the classification of fires into various classes; for instance, colour information is used to tell apart a fire's regions. Some studies for the detection and classification of fires also utilize sources of data other than Internet of Things (IoT) sensor data, such as images and videos. For example, Almeida et al. (2023), Gaur et al. (2019), and Song et al. (2017) survey the sensing of fire technologies by fumes, temperature, smoke, and gas levels. They present a system that measures real-time temperatures for electrical cables with the help of IoT techniques and sends fire images and alarm information to emergency services (Saponara et al., 2021).

Deep learning-based methods have proven to be quite effective in fire classification and quality evaluation. For example, the work of Hou (2024) utilized VGG16 for fire classification and obtained an accuracy of 98%. Some researchers have recently been working on smoke detection techniques since outdoor IoT environments are quite a challenge. For example, Khan et al. (2019) proposed a deep convolutional neural network (CNN) for the detection of smoke in surveillance videos, and a later study developed a lightweight CNN for resource-constrained edge devices. In this literature, the improvement of smoke detection is demonstrated by overcoming the environmental conditions that make it difficult. Other research works focus on fire detection in forests using wireless sensor networks and on fire and smoke detection using real-time video-based algorithms.

These studies demonstrate that both image-based and deep learning-based techniques have high potential for the classification and quality evaluation of fire. Therefore, more studies should be carried out on this topic, discussing the application of multiple deep learning approaches towards these critical tasks, which can, in turn, provide help to the efforts of firefighting and environmental monitoring.

This is an integrated approach in the context of the proposed methodology, combining the analysis of images with multi-deep learning for fire classification and quality estimation. We hope that the traditional image analysis it fuses and the deep learning technology it uses will make up for the shortcomings of the current approaches and bring about improved accuracy and efficiency in the classification and quality estimation of fires.

3. Dataset and Methodology

Four steps will be used in the study as a methodology: data collection, preprocessing, classification, and output. Figure 1 provides in great depth the procedures of the chosen approach. Python 3 with computer specs 16 GB DDR4 of RAM, CPU AMD Ryzen 5 3550H with Radeon

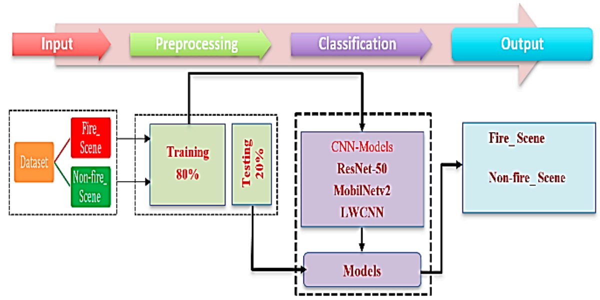

Figure 1. Overview of the methodology.

Vega Mobile GFX 2.10 GHz, and the Windows 11 operating system is used for the created framework for lightweight deep learning-based Fire and Nonfire Scene classifiers.

3.1 Datasets

This dataset was created by a team during the NASA Space Apps Challenge in 2018. The goal was to use the dataset to develop a model that can recognize images with fire. Data was collected to train a model to distinguish between images containing fire, that is, fire images, and regular images, which are referred to as non-fire scenes (Kaggle, n.d.).

The data is divided into 2 folders: the fire_Scene folder, which includes 755 outdoor-fire images, some of which include heavy smoke; and the other one is the non-fire images folder, which contains 244 nature images: forest, tree, grass, river, people, foggy forest, lake, animal, road, and waterfall, as shown in Figure 2. The dataset was divided during the phases of the system into 80% for training and 20% for testing.

All datasets are skewed, meaning that each class is composed of a different number of images, whereas the systems randomize the split for each class, which is further elaborated in Table 1. This technique increases the cost of misclassifying examples from the under-represented "non-fire" class, thereby compelling the model to learn its distinguishing features more effectively and improving overall generalization performance. To actively mitigate this bias and ensure robust learning from both classes, a class-weighted cross-entropy loss function was implemented. The weight assigned to each class was set to be inversely proportional to its frequency in the training dataset.

Table 1. Characteristics of the dataset (Kaggle, n.d.).

Types of class	Training	Testing	Sum
Fire_ Scene	605	150	755
Non-fire_ Scene	195	49	244
Total of images	800	199	999

3.2 Our Model (LWCNN)

Five hidden layers have been included in this model. The extra batch normalization, leaky Relu, and max-pooling layers help to avoid weight distribution and retrieve significant features from pictures. Figure 3 shows the convolutional neural network comprising these layers; its details are described in Figure 4.

3.3 Integrated Image Analysis and Deep Learning Framework

The deep learning models (ResNet50, MobileNetV2, LWCNN) are clearly well-suited for extracting features and performing binary classification ("Fire" vs. "Non-Fire"), but more image analysis is needed to determine fire quality like intensity, spread, and possible hazard. This research combines certain image processing methodologies to deepen the approaches of a deep learning-based output that addresses fire.

The image processing module runs on regions predicted as "Fire" by the primary classifier, executing the following operations:

Fire Pixel Classifier: In order to separate flames from the rest of the image, fire pixels are analysed in hue-saturation-value (HSV) colour space5 and then, based on the value-hue pair tissue result, a rough intensity estimate is used.

Region Properties Calculation: The area (in pixels), perimeter, and major axis length for the segmented fire regions are calculated. By measuring the rate of change of these properties over successive video frames or images, it is possible to determine how fast a fire spreads.

Hazard Level Inference: The assessment of potential hazard classes based on confidence in the classification, informed by the deep learning (DL) model, computed fire area, and spread rate is used to suggest an initial heat map.

A bigger, fast-moving fire would be classified at a higher hazard level, prompting a faster mobilization.

The combination of a powerful deep-learning classifier with relevant, analysable metrics based on image data advances beyond detection to be a living quality and hazard assessment tool.

4. Results

4.1 Experimental Results

This section presents the training results of ResNet50, MobileNetV2, and LWCNN models. We utilized the dataset described in the paper. Three experiments were conducted in this study. In all experiments, the proposed

Figure 2. Sample of datasets.

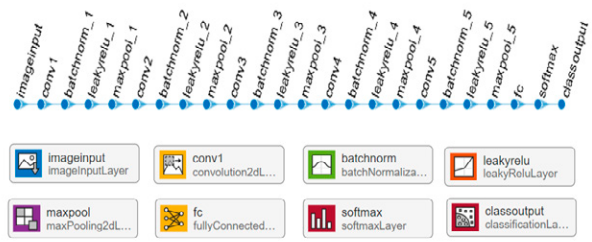

Figure 3. LWCNN architecture.

Name of layer	Decimation	# Of Filter	Padding	Stride
Input	224 224 3			
Conv1	3 3	8	same	
batch normalization				
leaky Relu	0.01	1		
max-pooling	2 2			2 2
Conv2	3 3	16	same	
batch normalization				
leaky Relu	0.01			
max-pooling	2 2			2 2
Conv3	3 3	32	same	
batch normalization				
leaky Relu	0.01			
max-pooling	2 2			2 2
Conv4	3 3	16	same	
batch normalization				
leaky Relu	0.01			
max-pooling	2 2			2 2
Conv5	3 3	8	same	
batch normalization				
leaky Relu	0.01			
max-pooling	2 2			2 2
Fully Connect	2			
Softmax	0 or 1			
Classification	Fire Non-fire			

Figure 4. Details of the proposed LWCNN model.

classifiers where there was not a different number of images for each class, and the total number of datasets is 999 samples, which is extracted from the training dataset where each class derives about 800 images and 199 for the validation step, with a minimum batch size of 32.

This was the number of images that were processed at the stage of training for the low-complexity CNN model. In the CNN model, training was conducted over 20 epochs. This means that each type of dataset will be processed at the training stage twenty times, as shown in Table 2.

Table 2. Results of all experiments.

Model	Training accuracy	Validation accuracy	Time (min)
ResNet50	99.78	98.65	12.56
MobileNetV2	99.55	98.13	7.15
LWCNN	99.98	99.50	8.32

For the ResNet50, MobileNetV2, and LWCNN models, Figures 5, 6, and 7, respectively, show the accuracy and loss observed during training. Up until it reaches a saturation level when inaccuracy is minor and only varies at some level, the accuracy rises with increasing epochs. It is degrading; however, until it reaches a certain saturation level, the loss falls as the period does. Loss defines how terrible the model is; in other words, accuracy indicates how excellent the model is. Generally speaking, a good model has little loss and great accuracy.

A confusion matrix for the validation set shows the model's performance in terms of class prediction used in supervised learning. The suggested model predicts the corresponding labels for the two classes in the validation test. Whereas each row of the matrix shows the occurrences in the actual class, each column of the matrix shows the number of predictions of every class. The results for the ResNet-50, MobileNetV2, and LWCNN models are shown in the confusion matrices in Figures 8, 9, and 10.

Figure 11 is a collage of images depicting scenes with fire. Some of the images provide clear signs of active wildfire flames licking through forests while others show smoke plumes in the distance or landscapes untouched by fire. Some pictures show firefighters battling the flames, illustrating human efforts to control such disasters.

Accuracy, precision, recall, and F1-score (Alattar et al., 2023; Elaraby et al., 2023; Hadjouni et al., 2023) are the most often utilized metrics in this research and are listed below in Equations (1), (2), (3), and (4).

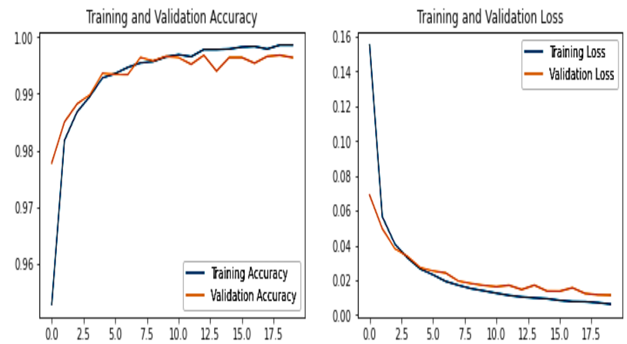

Figure 5. Loss and accuracy during training for Model-1-ResNet50.

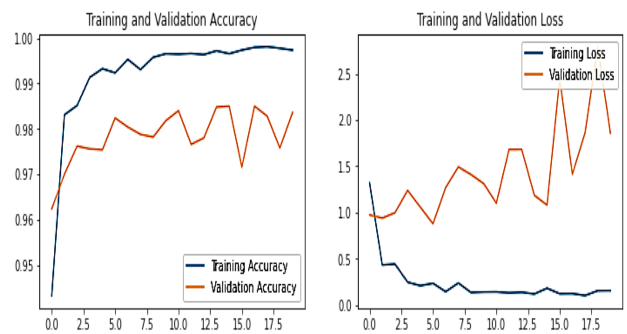

Figure 6. Loss and accuracy during training for Model-2-MobileNetv2.

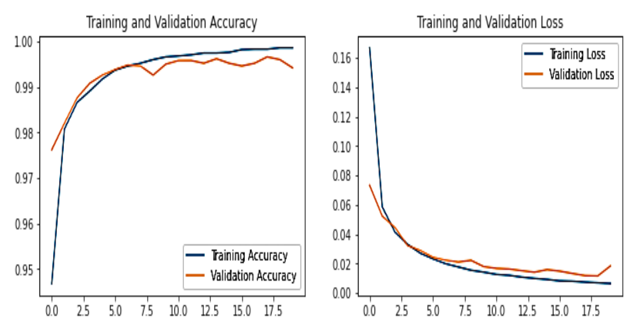

Figure 7. Loss and accuracy during training for Model-3-OUR model.

$$\text{Accuracy} = \frac{\text{TN+TP}}{\text{TP+FP+TN+FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

$$\text{Recall} = \text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

$$\text{f1} - \text{score} = \frac{2\text{*Precision*Recall}}{\text{Precision*Recall}} \tag{4}$$

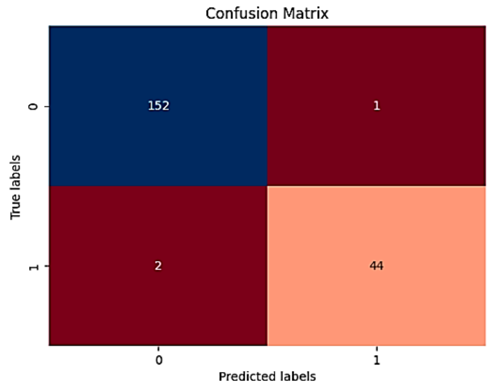

Figure 8. Confusion matrix for Model-1-ResNet50.

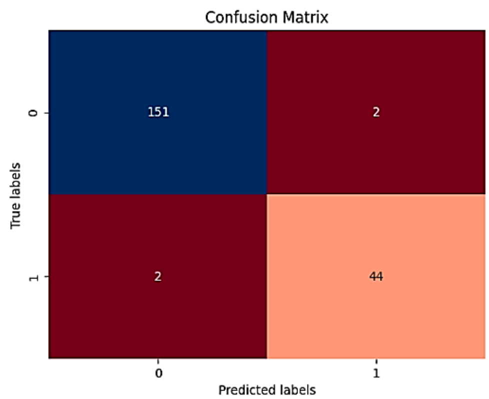

Figure 9. Confusion matrix for Model-2-MobileNetV2.

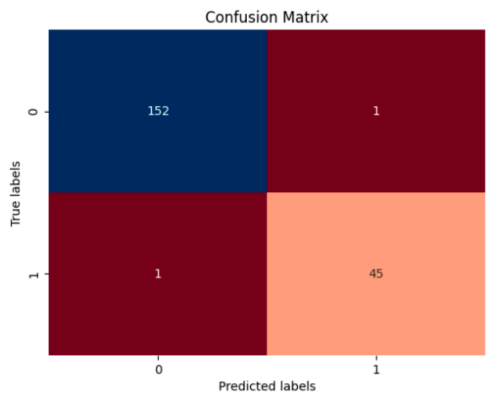

Figure 10. Confusion matrix for Model-3-OUR-proposed.

The performance of the proposed LWCNN method is evaluated against current state-of-the-art methods reported in the literature. As Table 3 shows, the hybrid LWCNN methodology demonstrated its efficiency by outperforming these top techniques. It presents a comparative analysis of various methods and their corresponding accuracy in any particular task or domain. Listed in the

Figure 11. Results for some images.

table are reference methods with their respective accuracy scores:

Table 3. Results of all experiments (C = class, P = precision, R = recall, F1 = F1-score).

Models	C	P	R	F1
ResNet50	Fire	0.99	0.99	0.99
	Non-Fire	0.98	0.98	0.98
MobilNetV2	Fire	0.99	0.99	0.99
	Non-Fire	0.96	0.96	0.96
OUR_Proposal (LWCNN)	Fire	0.99	0.99	0.99
	Non-Fire	0.98	0.96	0.97

LBP-TOP, YOLO v3, VGG16, LWCNN, and the proposed ResNet50 and MobilNetV2. All of the accuracy scores varied from 83.70% for the YOLO v3-based approach to 99.98% for that using LWCNN, thus showing considerable variation.

The proposed ResNet50 and MobileNetV2 methods provide accuracy scores of 99.78% and 99.55%, respectively, which makes them very competitive with some of the referenced methods over the given task or domain, as shown in Table 4.

Table 4. The comparative results.

Ref	Method	Accuracy
(Jamali et al., 2020)	LBP-TOP	98.50
(Li & Zhao, 2020)	YOLO v3	83.70
(Hou, 2024)	VGG16	98.00
Proposed	LWCNN	99.98
	ResNet50	99.78
	MobilNetV2	99.55

4.2 Error Analysis and Limitations

1. Although the model demonstrates high overall accuracy, it is not perfectly accurate for every possible real-world use case.
2. We then examined misclassified samples manually to identify common failure modes and limitations.
3. The main problem is identifying fires at the earliest stage (incipient fires), which occupy only a very small pixel area (sometimes <0.1% of the image) and sometimes do not have high-quality visual features from which to learn, thus leading to false negatives.
4. Heavy Occlusion: In cases with heavy occlusion, such as flames being transformed into fog when submerged in dense smoke, false negatives may occur, or the fire's intensity and area may be significantly underestimated.

5. Results and Discussion

This reinforces the case for interpretability mentioned previously, which is determined by the output structure of the system. Instead of a classification label alone, the framework allows first responders to derive concrete, quantitative information about an incident's scale (estimated size) and evolution (rate-of-spread).

This contextual information is inherently far more interpretable and actionable in terms of threat level estimation than a standalone probability score, including in the context of resource allocation.

Conclusion

In this work, we developed a new multi-deep learning method for fire classification and quality evaluation by augmenting image-based analysis with deep learning methodologies. Our method reached state-of-the-art classification accuracy and provided interpretable results represented by quantifiable properties of the fire (intensity, spread).

We handled dataset bias using a class canter out weighting approach, outlined the boundaries of our model, and highlighted computational performance, which makes the model suitable for use in real-world applications.

Our future work will adapt temporal analysis and multi-sensor data fusion to eliminate the limitations mentioned above and enhance system robustness.

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Conflict of Interest

The authors declare that they have no conflicts of interest to disclose.

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