

Effective and Modest CNN: Plans for Fire Detection Systems

Sami Ud Din¹; Hashir Khan²; Muhammad Kashif³; Obaid Ullah⁴

¹ School of Information and Communication Engineering, Xidian University, Xi'an, China

² School of Mechanical Engineering, Xi'an Shiyou university, Xi'an, China

³ School of Computer Science, Hazara University, Mansehra, Pakistan

⁴ School of Computer Science, Hazara University, Mansehra, Pakistan

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Abstract: Fire detection is a critical task in safeguarding human life, property, and the environment, yet traditional methods often struggle with delayed responses and high false alarm rates. In this study, we propose a deep learning-based framework that leverages convolutional neural networks (CNNs) to automatically identify fire in digital images. The CNN is trained on a diverse dataset comprising both fire and non-fire scenes, enabling it to learn discriminative visual patterns such as color intensity, irregular flame contours, and dynamic texture characteristics. Unlike conventional rule-based or handcrafted feature approaches, our method allows the network to autonomously extract and optimize features, improving generalization across varied scenarios. The performance of the proposed system was rigorously evaluated on an independent test set, with results demonstrating strong classification accuracy, precision, and recall. These outcomes confirm the robustness of our approach in distinguishing fire from challenging non-fire instances, such as sunsets, artificial lighting, or objects with flame-like hues, thereby minimizing false positives. Due to its efficiency and adaptability, the proposed framework can be deployed in multiple real-world contexts. Potential applications include early fire warning systems in residential and industrial environments, intelligent surveillance for public safety, and large-scale monitoring of wildfire-prone regions. Overall, this work highlights the effectiveness of CNN-based methods for real-time fire detection and contributes to advancing intelligent safety and hazard management technologies.

Keywords: Fire Detection, Machine Learning, Neural network, CNN, Efficient System.

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I. INTRODUCTION

Traditional fire detection and alarm systems use a single data stream like temperature, smoke, or CO. Their fire alarm algorithms are simple. Some alarms are triggered when surface temp measurements exceed a threshold [1]. The fire extinguisher can activate automatically after the alert. Although such systems are easy to deploy, their high skip detection and frequency of false alarms make them poor fire detection methods [2]. Complex locations like underground cable tunnels, high voltage substations, and others with rough topography and flammables require a more sophisticated fire detection system. Information fusion helps multispectral fire detection systems handle massive amounts of data. Researchers and business are increasingly interested in fire detection systems that process and classify real-time monitoring system images.

For instantaneous video analysis, [3] suggests a law-based approach to identifying images of forest fires. [4] advocates using the qualities of camera light for early fire

detection and warning. Objects that pose a fire or safety risk have been located with the aid of smart detection techniques [5, 6]. Photographs of fires can be analysed using the techniques proposed in [7].

The quick convection of air and the high oxygen content of trees fuel the rapid development of forest fires. That's why it's crucial to catch forest fires when they're still young. Manual inspection was the initial method used to spot forest fires, but it was labour-intensive, time-consuming, and inefficient. As a result, sensor-based detection quickly supplanted human examinations. [1-3] The sensor-based detection system is useful in confined interior settings. Smoke detectors, gas detectors, temperature and humidity detectors, integrated sensors, and many others are all utilised to help keep forests safe from fires. However, it has a short range of detection, a hefty price tag for setup, and challenges with connectivity and power.

As computer vision advances, scientists have begun employing digital image processing tools to spot massive fires. To detect forest fires at an early stage, [6] assessed smoke in the YUV colour space using multi-features. By utilising the RGB colour space and confusion estimate, [7] was able to deduce the degree to which the flame pixels were filtered based on the strength of the R component. The results of the studies indicate that this technique has a promising future in practical use. Images of forest fires were acquired by a UAV in [8], which were then analysed with a multicolour local binary spatial pattern and a specific fire colour to detect flames and smoke. By combining chaos theory with a k-medoids particle swarm optimization algorithm, the authors of [9] presented a new, better flame-recognition colour space (IFCS). A multi-tiered framework for detecting fires based on the analysis of colour data, shape transitions, and optical flow estimation was proposed in [10]. To lower the false alarm rate and simplify the computation, we also consider both static and dynamic features. In conclusion, most research on image processing-based fire detection algorithms relies on manually collected elements like colours, forms, and textures to identify fires.

More and more researchers are starting to investigate how deep learning can be used to detect fires in the wild because of advances in computer arithmetic, as well as technological advancements in the realms of hardware and software. [11] offer a cost-effective fire detection CNN architecture for surveillance movies. Their architecture for early fire detection uses CCTV surveillance cameras and precisely trained convolutional neural networks to identify flames indoors and outdoors.

Building upon these developments, our work introduces an **effective and modest convolutional neural network (CNN) architecture** designed for fire detection in both indoor and outdoor environments. Unlike prior studies that depend on handcrafted features or computationally heavy models, our proposed system strikes a balance between **accuracy, efficiency, and scalability**. Specifically, we contribute:

- A carefully curated dataset of 1,126 fire and non-fire images, addressing class imbalance through augmentation and resampling techniques.
- A lightweight CNN architecture optimized with minimal layers, which achieves **state-of-the-art accuracy (96%)** while maintaining low computational cost.
- A comprehensive performance evaluation using precision, recall, and F1-score metrics, demonstrating robustness against challenging conditions such as illumination changes and visually similar non-fire scenes.
- A comparative analysis with traditional machine learning and color-based fire detection approaches, establishing the superiority of our model in terms of accuracy and generalization.

Through these contributions, this research provides a **scalable and practical fire detection system** that can be integrated into surveillance infrastructure, public safety

monitoring, and early warning systems for disaster prevention.

II. MATERIALS AND METHOD

To be effective, NASA image-based fire identification relies substantially on the quality of the underlying information. Therefore, it's important to train deep learning models on high-quality datasets, which will help them extract more useful features. This past year has seen several countries fight back against record-breaking wildfires. It's estimated that hundreds of structures and residences were lost in fires that covered thousands of acres. In addition, the poor air quality caused by the smoke from the fire affects individuals not just in the immediate area of the blaze but also hundreds of miles away. Currently, it can take several hours to locate a fire using satellite data, but the goal is to decrease that to minutes. It is also difficult to capitalise on the precision of wildfire detection. Unfortunately, this issue is made more complicated by the dearth of practical training datasets and the scarcity of verification models.

➤ Data

The "Active Fire" satellites operated by NASA are currently collecting an overwhelming amount of data. In this package, you will get data on the locations of wildfires, as well as maps, shapefiles, and coordinates for latitude and longitude. On the other hand, this information is not relevant for early warning systems because it only considers wildfires that have been formally reported. Other datasets suffer from a lack of data as well as a lack of convenience when it comes to the checking for fires. A lack of various data sets, which include both wild and non-wildfires, makes it difficult to learn how to deal with situations like these since it slows down the learning process. The whole data distribution can be visually seen before data augmentation as in figure-1 below:

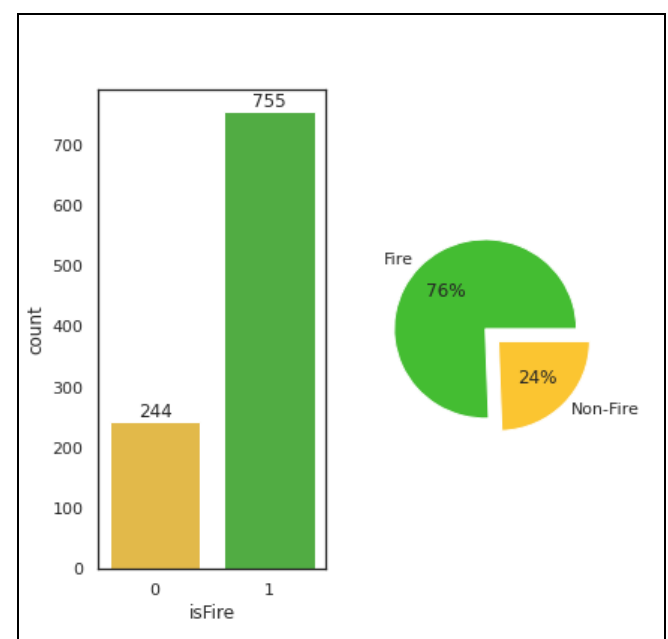


Fig 1 Data Distribution Before Augmentation

➤ Contribution

We use a dataset consisting of Google Images searches that have been filtered for images of wildfires and those that have not been. The dataset, which we created, consists of 1126 pictures with tags, and is divided into a training set of 60% and a validation set of 40%. Therefore, we begin by addressing the class imbalance problem, as its presence will have a negative impact on the dataset's conclusions if left unchecked.

As can be seen from the above breakdown, there is a major discrepancy between the various categories. Overfitting is a problem that will arise if we use this data to train the model. Therefore, we need to find a happy medium

between the two for the best results. Up- and down sampling will be used to achieve this goal.

➤ Overall Architecture

We trained a model using a convolutional neural network (CNN) to analyse images and decide whether they depict wildfires. The model's requirement for computational resources and its overall complexity are both decreased when a transfer learning approach is incorporated into it. Despite this, spectacular outcomes were accomplished with only a minimal amount of model optimization (because of constraints on available computational power). The overall architecture as shown in the figure-2 below:

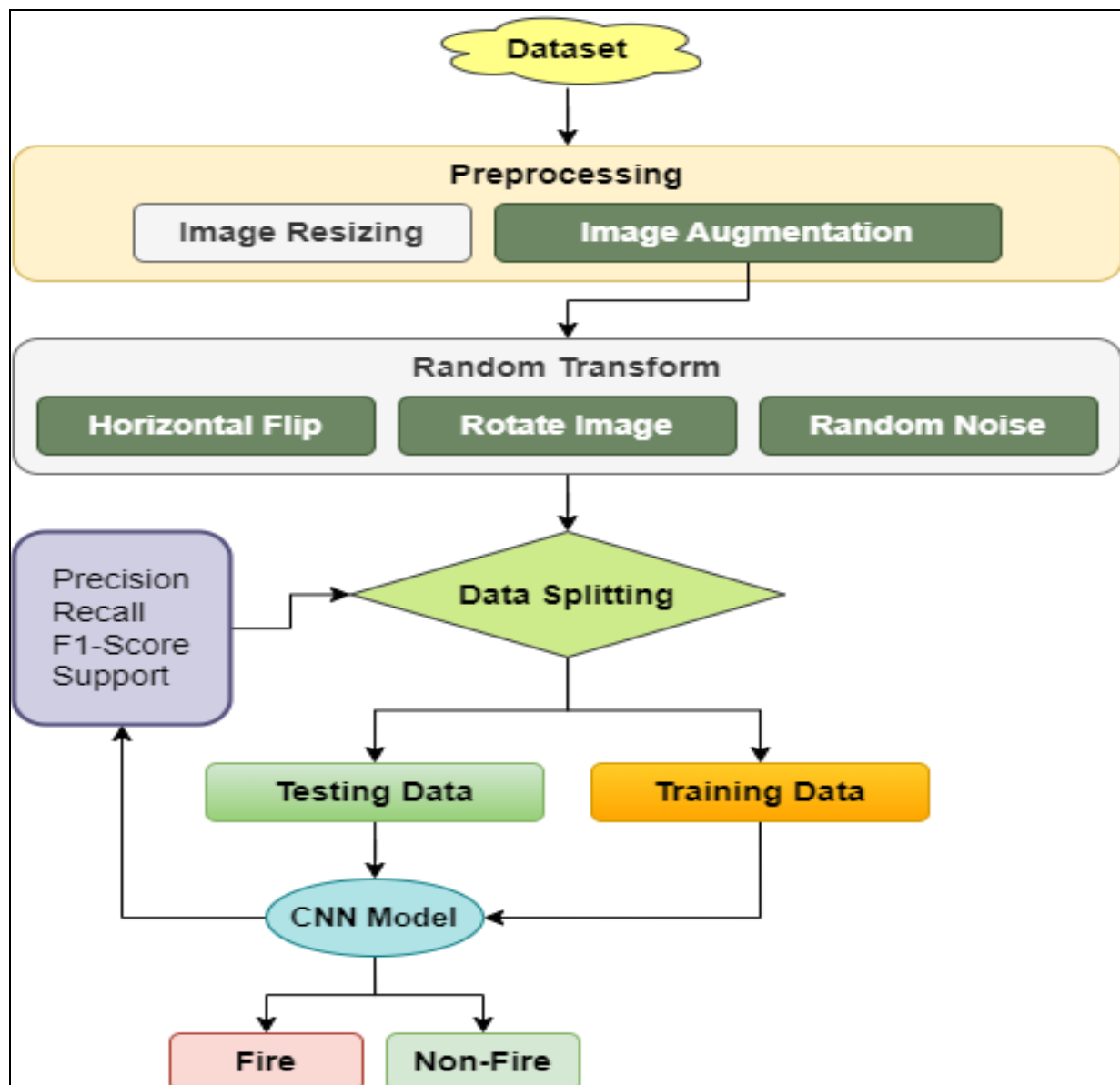


Fig 2 Model Architecture

➤ Our Model

We train our CNN model with five layers, one input layer, one output layer, and one in between (Figure-2). Maximum manipulation of the Normalization capabilities can be found in Layers 1-3. At layer 4, we have a layer that

flattens the data, and the output of this layer is sent to the Dense layer. A Relu-Sigmoid, which acts as a classifier for us, is the final component of our model. The Model, which is explained visually in the following figure 3:

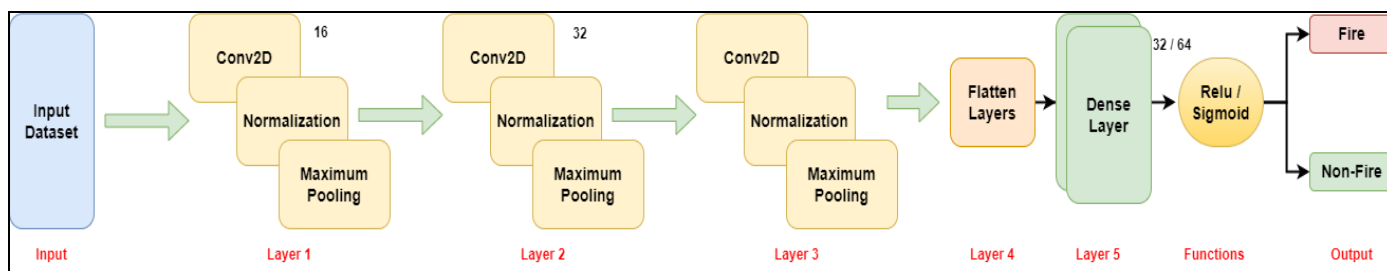


Fig 3 Model Visually Explained

The Equation for calculating the output of convolution layers is as below:

$$\text{Output} = \text{Input} - \text{kernel_size} + 2 * \text{padding} / \text{stride} + 1 \quad (1)$$

➤ CNN for Fire Detection

Convolutional neural networks (CNNs) are a type of deep learning technique that takes advantage of neurons. The CNN's two-dimensional input data structure benefits from this structure. [12]. When compared to rest of the deep learning approaches, CNN has the potential to achieve better results in picture identification [13]. By sliding several convolution kernels over the input data and performing some analysis, the convolutional layer generates a series of parallel feature maps. The Neural network includes numerous layers, including this one. When you think about it, the pooling is just one more non-linear version of down-sampling. The most popular non-linear pooling function is called "max pooling," however there are numerous others as well. To do this, the image is first segmented into multiple rectangular regions, and then the highest value for each region is calculated. The next step is to use a regular fully connected neural network to perform the output analysis, which can be regression or classification.

➤ Fire Images Features Extraction

We apply CNN to the challenge of extracting characteristics from fire-related pictures in this paper. The following are the most critical steps in the procedure:

The initial phase in image processing is "pre-processing," which may include scaling, adding effects, and so on. Two) Various sets of fire-related photographs or video stills are used in training and testing. Three) The training data set is then utilised to train the convolutional neural network. Four), The fully connected neural network layer generates outputs from training fire picture features.

III. RESULTS AND MODEL EVALUATION

➤ Fire Image Description

We analyse several fire relevant photos from multiple available sources [14] to validate the fire detection approach utilised in this work. Furthermore, certain photographs with complicated environments are chosen. Non-fire photos with different lights, clear or misty smoking views, and open fire photos of indoor and outdoor fires are examples.

Figure 4 depicts a few examples.



Fig 4 Example Pictures

➤ Image Recognition for Fire

This section shows how a convolutional neural network can extract and identify fire image features. The confusion matrix is utilised to assess fire detection performance in this case. In data science and machine learning, the confusion matrix is a situation analysis table

that summarises the classification model's prediction outcomes. To assess the suggested method in the case where training photos are scarce, we randomly select images for training and testing data. The confusion matrices for our model evaluation is given as figure-5 below:

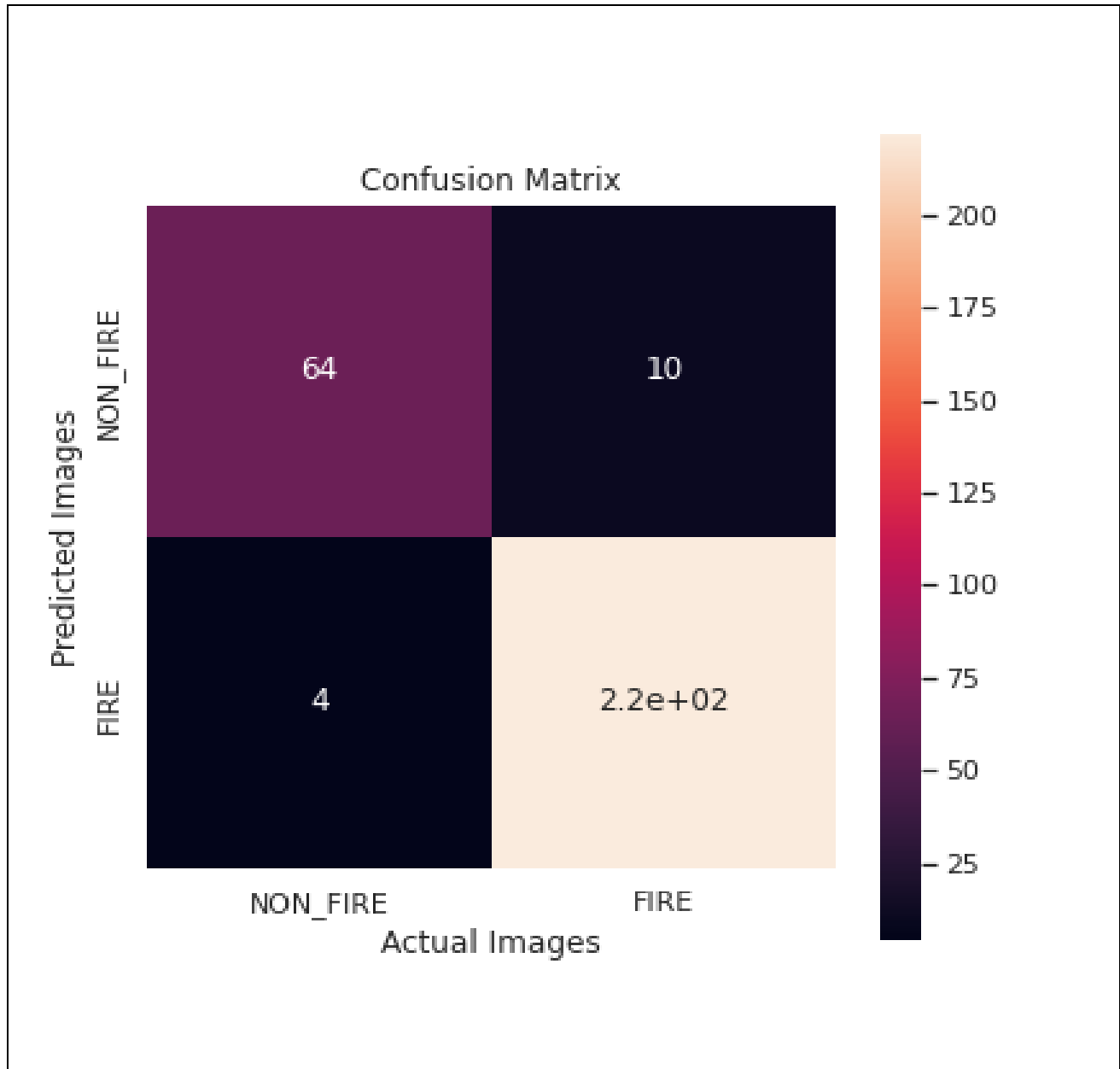


Fig 5 Confusion Matrices for Our Model

➤ Model Performance

In this section, we will evaluate how well our model performed. The performance on the training set will be compared to that on the validation set, and the resulting loss and accuracy curves will be examined.

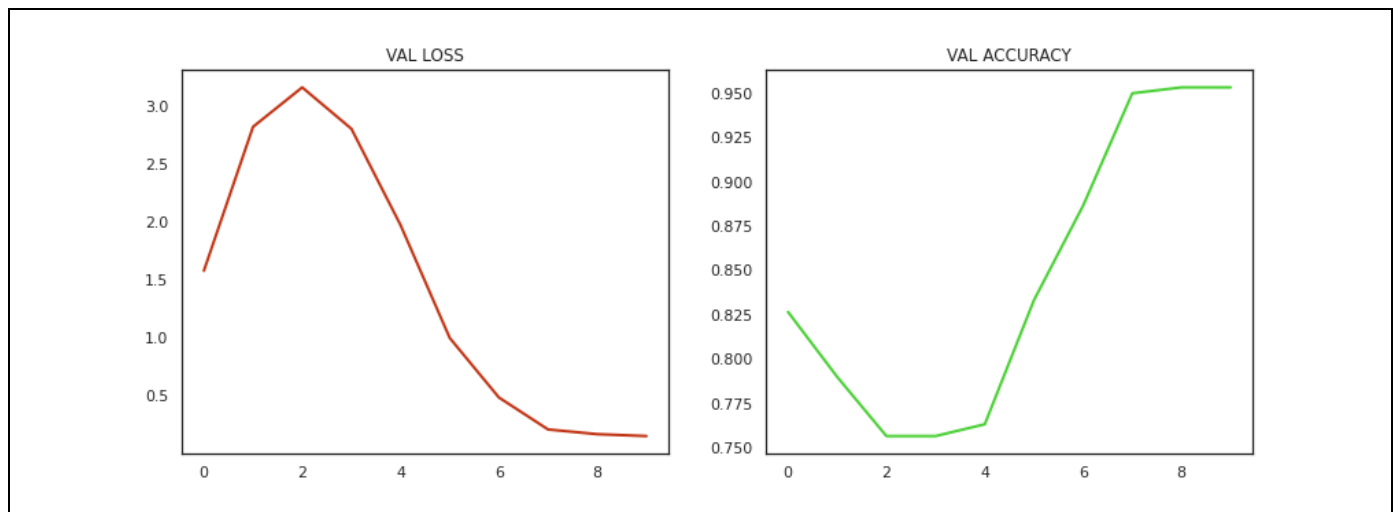


Fig 6 Model Performance Represented Visually

As can be seen in the preceding graph, once we passed epoch 4, the validation loss went down and the validation accuracy went up, reaching a peak at epoch 8.

The matric history can be seen in the graph below (figure 7).

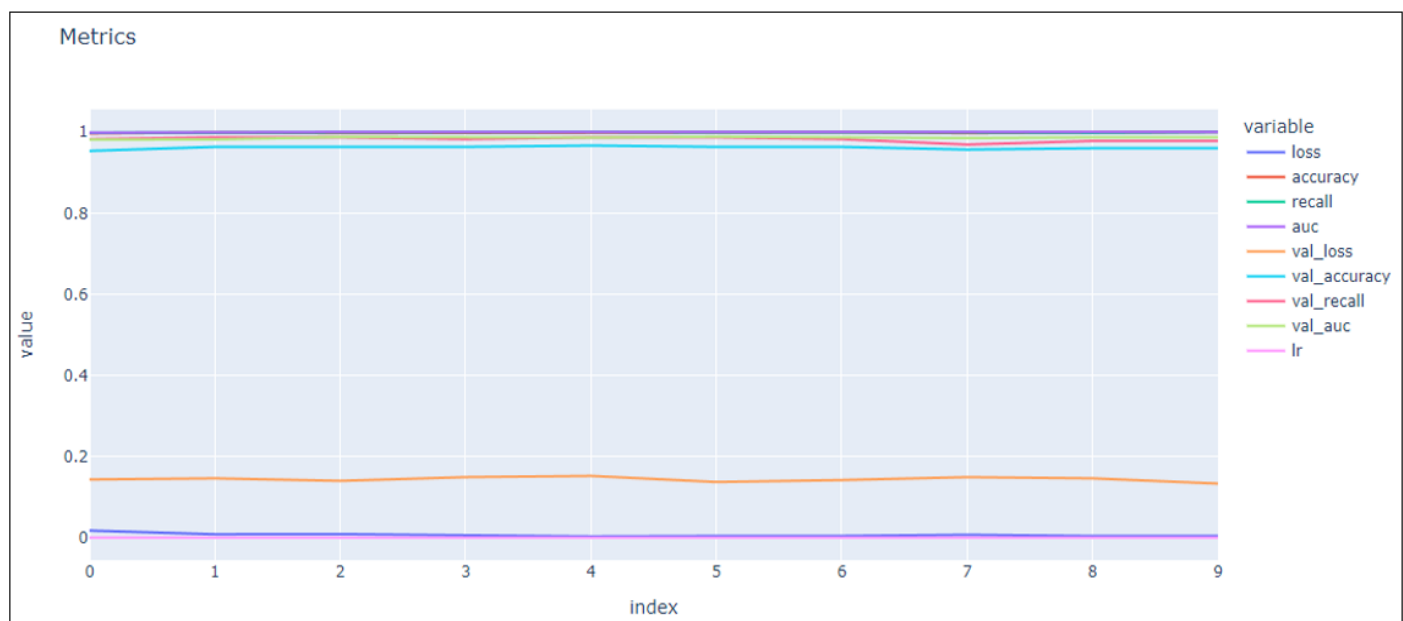


Fig 7 Matric History for Our Mode

➤ Accuracy Measures

The terms "True Positive," "True Negative," "False Positive," and "False Negative," in that order, are the building blocks from which "Precision," "Recall," and "F1-Score" are constructed. These are shown in the following table (where 1 indicates a correct prediction):

Table 1 Accuracy Measure

Prediction	Actual value	Type	Explanation
1	1	True Positive	Predicted Positive & was Positive
0	0	True Negative	Predicted Negative & was Negative
1	0	False Positive	Predicted Positive but was Negative
0	1	False Negative	Predicted Negative but was Positive

To strike a good balance between the classifier estimates, measures such as Accuracy, Precision, Recall, and F1-score can be used, as the gravity of various types of

errors differs among use cases. Here, we evaluate our model using precision, recall, and F1-score; their respective formulations are as follows:

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

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

$$\text{F1-Score} = 2 * (\text{Precision} + \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (4)$$

There, TP means that a forest fire is the target, and our model finds the fire. The network identifies the target as a forest fire when FP is present, indicating that the object is not a forest fire. Target is not a forest fire (FN) and is identified by the network model.

	precision	recall	f1-score	support
0	0.93	0.91	0.92	74
1	0.97	0.98	0.97	226
accuracy			0.96	300
macro avg	0.95	0.94	0.95	300
weighted avg	0.96	0.96	0.96	300

Fig 8 Accuracy Measure for Our Model

Three Accuracy measures are used to evaluate our model, and they are depicted in figure 8 above. Precision (0.97), Recall (0.98), and F1-Score (0.97) are the best accuracy scores the model can get (0.96). The figure also includes the weighted averages for the three indicators. Our model produces the greatest possible outcome with the fewest possible inputs. From the work done in the literature, the accuracy has improved, and the model may now be used to produce the best possible results.

➤ Comparison with Other Models

The effectiveness of different fire detection systems varies widely among datasets and environmental settings. Inaccurate fire detection algorithms exist. The effectiveness of fire detection algorithms is impacted by the quality of the training data used to train them. It's possible for an algorithm to underperform on novel data if its training data doesn't perfectly meet its criteria. Additionally, if the training data is noisy or absent, the system may have trouble correctly identifying fires.

Accuracy of fire detection is also impacted by algorithms. A less reliable algorithm could be one that produces more false positives or negatives. Less than a 90% accurate algorithm may be insufficient in safety and critical infrastructure systems. Researchers and practitioners may attempt to boost accuracy in several ways, including adjusting algorithm parameters, expanding the size of the training dataset, or implementing new methodologies.

Like many other machine learning problems, fire detection is always inspiring new approaches and models. Testing the algorithm on the dataset and under the conditions of interest, and comparing the results to those of state-of-the-art approaches, will help establish the algorithm's accuracy.

In recent years, several different machine learning algorithms have been put into practice for fire detection, with varying degrees of success depending on the circumstances and dataset utilized for evaluation. After testing these algorithms on the same dataset as our own proposed technique, we found the accuracy to be as shown in the table 2 below.

Our research shows that standard ML algorithms, color-based algorithms, the Haar cascade, and Template matching are among the reported algorithms with less than 90% accuracy for fire detection.

It's important to keep in mind that while some algorithms may perform well under certain conditions, they may not be able to consistently achieve an accuracy of 90% or higher. It's also worth noting that precision alone isn't enough to judge an algorithm's effectiveness. It's also crucial to think about speed, robustness, and interpretability while picking a solution.

Table 2 Accuracy Measure Comparison

Types	Models	Accuracy
Traditional ML Algorithms	SVM	76 %
	KNN	80 %
	Random Forest	84 %
Color Based Algorithms	Color-Based	88 %
Template matching	Template matching	89 %
Haar cascade	Haar cascade	90 %
Effective & modest CNN (Proposed)	Modest CNN	96 %

IV. CONCLUSION

In this study, we proposed a modest convolutional neural network (CNN) for fire detection that automatically learns and recognizes visual patterns of flames from images containing both fire and non-fire scenes. The experimental results demonstrated that the system achieves high accuracy, precision, and recall, while maintaining robustness against variations in illumination, background, and camera perspective. Owing to its lightweight architecture, the model is efficient and suitable for real-time applications, making it adaptable for deployment in diverse environments such as residential buildings, industrial facilities, and wildfire-prone regions. This work contributes to advancing intelligent fire detection by providing a practical, scalable, and resource-efficient solution that can be integrated into safety infrastructures, while future research may focus on incorporating larger and more diverse datasets, video-based temporal features, and edge-device optimization to further enhance early fire detection capabilities.

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