

CNN-Based Real-Time Forest Fire Detection: A Cost-Effective Solution

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ARTICLE INFO

ABSTRACT

Received: 18 Dec 2024

Revised: 04 Feb 2025

Accepted: 20 Feb 2025

Wild fires are for real a menace to the forests, people and the animals they impact by burning the homes of people and the natural habitats of the animals. Satisfying the identified gap pertaining to the lack of effective solutions for the early identification of fire and, eventually, for intervention in the process of fire, this investigation suggests the development of a forest fire detection system that would involve Convolutional Neural Networks (CNNs), controlled through a laptop's inbuilt Webcam and authentic image processing. This is because methods like fire watchtowers and satellite images are costly, cover a smaller area and is not as prompt as our CNN-based system that trains a CNN to detect fire by identifying peculiarities in scenes comprising of forests. This system proposed to capture images from a webcam in real-time manner and the CNN part of the system is evaluating the images for the fire presence. It raises a sharp alarm both audible and visible as soon as the fire is detected so that response may be initiated as was necessary to put out forest fires. The CNN architecture is fabricated based on the Kaggle data set through training on this data set from the high accuracy point of view for confirming the near 99% accuracy for detecting the forest fire with the help of the convolution neural network that improves the possibility compared to the traditional way. For this reason, a high accuracy would always help in avoiding situations wherein real fires are confused with false alarms, whereas, learning in the model helps avoid some fires being detected or alarmed when they are not, hence act as the building blocks to improving the overall performance of the AI algorithm. This is the case with the system that accesses regular hardware for example the laptops and webcams; this makes them easy to deploy most especially in the developing world.

Keywords: Forest Fire detection, image classification, OpenCV, deep learning, and Convolutional Neural Networks.

I. Introduction

Widespread fires are another kind of natural disaster that continues to ravage forests, people's dwellings, and other wildlife habitats. Several fatalities, loss in properties and damage to the ecosystem in the wake of forest fires are

major areas that call for appropriate detection and combating strategies. In this regard, our study focuses on the identification of forest fire and proposes a novel approach based on Convolutional Neural Network [1-6,17,19] and real-time image processing. [7-8] The identification of forest fires is very difficult given the large and very often inaccessible areas in forests. There are several challenges depicted with conventional fire detection methods namely fire watchtowers [9-10] and satellite imagery [11]. Recent breakthroughs in deep learning and computer vision enabled us to design a system that will be capable to detect fire utilizing affordable and readily available technology like a laptop with a web-camera. CNN forms the core of our system of forest fire detection. CNNs are the representatives of deep learning model and have been claimed to possess outstanding performance for image classification. We have proposed CNN model in this work. Having adjusted the parameters of the model we effectively teach the network to recognize the peculiarities of fire in context of forest. This approach is the best of both worlds not only does it utilized the capability of deep learning, but also minimizes the requisite labeled data entirely. The essential capabilities of the system's work are the processing of images received in real-time mode from a webcam. Such pictures are given to the CNN and immediately reviewed by the network for signs of fire. Here, in the case of fire perception, the system response takes place by making an alarm through the laptop's speakers and, in the code editor, there is a print statement of "Fire Detected" indicating the perception. This response during forest fires is especially important as early identification is equivalent to early quelling of the fire. In the section of related work, authors provide a detailed discussion of the existing approaches for fire detection. Here are glimpses of different approaches and advancements, which are accompanied by the pros and cons. The method of learning is deep as it combines high accuracy and consecutive manipulation, essential for early intervention in simple events.

In the following portion of this paper, we provide comprehensive analysis on our philosophy, framework plan, and CNN architecture. The execution and testing area is the exploration of the pragmatic parts of our response, including the troubles faced and the dataset used. The outcomes and conversation area addresses a head-to-toe investigation of our framework's transparency and its suggestions in genuine contextual investigations. In total, the proposed scheme of identifying woodland fire provides an available and proficient answer which has essential potential in eliminating the major difficulty of timberland fire identification. By coupling depth learning and constant picture study, our structure recognizes fires effectively and consecutively, and this may perhaps cut down lives and decrease the appalling impact of hall fires. On the other hand, there is a constant risk of woodland fires, and this analysis contributes to the growth of the weapons arsenal of devices for early intervention and introduces additional options for further expansion and enhancement of shoot detection.

II. Related work

Thus, to determine the relevance and novelty of our deep learning-based approach, it is critical to provides an overview of the current developments in forest fire detection systems [12]. The analysis of the existing literature in this field helps in understanding the advantages and limitations of the previous approaches which contributes to the development of better methods and actions.

Overall, it can be mentioned that the conventional methods and technologies, used for forest fire detection systems, can be diverse. Earlier approaches [9-11,16] include the use of manned fire look-out towers, remote sensing from space or the ground-based sensor systems. These are methods that have been useful in some cases as shall be seen, but they have serious drawbacks. For instance, human operated watchtowers are restricted by range of visibility and capacity in people to always stay alert. While satellite imagery provides a wide area coverage, the information from the images can be received after sometime hindering early response.

Recently, remote detecting [13] advances have spread into the area of backwoods fire identification. These innovations are depicted as the furnishing of persistent data from areas that can incline tendency toward fire utilizing drones, warm cameras, and various sensors. They can be particularly handy for defining areas of fire interest and, therefore, for verifying fire progress. Nonetheless, their implementation can be very expensive and indeed challenging, thereby limiting their availability especially in the developing and asset-scarce regions. Similarly, there are works on picture handling procedures and computer-based intelligence calculations for diverse fire identification. It is bound to frequently involve extraction of highlights from a document, as well as organizing features. For instance, as far as applying surface-based picture investigation techniques, fire and smoke designs have been distinguished utilizing surface-based picture investigation and the surface-based picture investigation method. However, these strategies performance reveals advantages, however, they are slight to natural circumstances, leading to the formation of deceits in situation which include similar visual characteristics to fire. The strengths of these conventional methods and picture handling-based methods are found in the ability to scan

massive forested areas and provide quite substantial contributions to fire monitoring. Nevertheless, their limitations, considering reliance on people for mediation, delay in information dissemination and vulnerability to deceptive factors characterize the need for more advanced and accurate solutions.

This is where deep learning, particularly Convolutional Brain Organizations [14], present a viable course in backwoods fire detection. Studies and researches have resolved that CNNs have shown remarkable improvement in picture arrangement undertakings and gives better outcomes than traditional picture handling methodologies. The methodology discards many components of pre-prepared CNN models and amplifies the center philosophies we named profound learning, such as high exactness and available adaptability to different conditions. The addition of constant picture study increases sensitivity, which in turn makes early intervention more feasible. Artificial Intelligent such as SARIMA, multi-variable regression, ridge regression, and KNN regression for prediction water level [15]

In rundown, past methodologies have created basic commitments to timberland fire disclosure, but they have innate affinities that our profound learning-based strategy tries to eliminate. The progression of a framework that can subdue these obstructions and proffer high exactness step by step contributes to a basic forward-moving move toward the field of fire identification, with the conceivable impact to renegotiate the backwoods and networks protection.

III. METHODOLOGY

The focus of the methodology used in this article is on the convolutional neural network (CNN) as a means of fire detection in forests. CNNs are found to be useful in image analysis problems and hence can be used effectively in this problem. The strategy we employ is CNN model; this is famous for its characteristic of identifying many obscure details in images.

The main data feed for our forest fire detector is Kaggle dataset. It might be possible to use other types of input to the system, but the choice made is inexpensive to acquire and puts the system in the realm of the realistic and feasible. In other practical example a webcam constantly feeds a stream of images to our CNN model which the model processes one at a time. During this detection process, every picture is reduced in size to a specific dimension which is 224 pixels by 224 pixel to suit the CNN model. The images are then transformed into numerical quantitative form and preprocessing is carried out on images to boost the network performance. The key element in the approach adopted pertaining to detections is rooted in the CNN's efficacy in studying such images that have been preprocessed and then determine if the images contain fire or not. The CNN searches each of them for unique patterns that can represent fires themselves or their traces, including flames, smoke or intense colors typical for fire. These determinations are possible based on the learned parameters of the network. If the CNN identifies a fire in an image, there is an immediate response triggered to the image. This response entails an audio signal via the laptops' speakers to inform the user, and a visual signal on the code editor console, which contains the message "Fire Detected". The combination with the weak learning capabilities of the CNN and the constant picture evaluation from the webcam feed compel our structure to quickly and unequivocally identify fires in forest area conditions. This way of thinking use best in class development as well as keeps the execution feasible and monetarily adroit. In the going with sections, we jump further into the structure plan and the CNN designing, uncovering knowledge into the specifics of how this approach is gotten under way in our boondocks fire alert system.

IV. SYSTEM DESIGN AND DEVELOPMENT

On the choice of our forest fire detection system, its system design and development are critical in achieving a proper solution. This section provides a general outlook on the overall structure of the system and a detailed description of the key component – Convolutional Neural Network (CNN), which serves as the primary fire detector.

A. System Overview

The arrangement of our fire detection system is done in the way which allows it to process video stream coming from a webcam, check for fire signatures in the data coming from webcam and react promptly to the fire. The system is composed of two primary components: The input module and the fire detection module are therefore subsystems of the given fire alarm system. The input module always captures frames from the webcam and these frames are then forwarded to the fire detection module. In fire detection module, there is CNN model that now

classifies the frames as 'fire' or 'no fire'. If it detects as 'fire' then it will sound the alert. This alert is an airborne through the default speakers of the laptop as well as light-up in the output box of the code editor. These components interact in real-time and this makes the response time of the system to be very minimal.

B. Convolutional Neural Network

Convolutional Neural Network (CNN) is a type of deep learning model that is specifically developed for working with data in matrix form where every group of data points occupies some specific structure like images. CNNs are been quite useful in image classification, objects detection and generally all matters to do with images since they are able to capture the spatial hierarchy within data set through the Convolution layers.

The proposed CNN model (shown in Fig:1) is constructed by implementing the Sequential function in the Keras API which is a high-level neural networks API designed on TensorFlow platform. Sequential model is fine for a pile-on of layers, where each of the layer's processes only one input tensor and produces only one output tensor. In layer-1 these 32 convolution filters of size 3×3 are applied over the input image. This matrix shape of the output means that the resulting feature map dimensions will be $58 \times 58 \times 32$, where the last integer represents the number of filters. The 'None' value refers to the batch size which is not fixed and may vary within ranges. The number of parameters (4736) is calculated as follows: $\text{Parameters} = (3 \times 3 \times \text{input channels} + 1) \times \text{number of filters}$. If the input has 3 channels (RGB image), the calculation is: $(3 \times 3 \times 3 + 1) \times 32 = 4736$. In layer-2 operates max pooling with filter size of 2×2 and stride of 2 hence the size of the feature map is cut to half. The max pooling assists in curvature of the cost function and in rate of convergence since it alleviates computational load and prevents overfitting. Like the first convolution layer, third layer also uses 32 convolution filters of dimension 3×3 . The output feature map is of slightly lesser dimension that the input spatial feature map due to the convolution operation with padding of 0. The number of parameters (9248) is calculated similarly: $(3 \times 3 \times 32 + 1) \times 32 = 9248$. A next max pooling layer is applied with a filter size of 2,0 and a stride of 2,0 to down sample on the feature map. The flatten layer converts the 3D output obtained from the last layer into a 1D vector. This has to be done before the data is fed into the fully connected dense layers to be processed. The number of elements in this vector is: The area of the Obelisk is equal to $13 \times 13 \text{ ft} = 169 \text{ ft squared}$ and the height is equal to 32 ft, thus, $169 \times 32 = 5408$. The next layer is the same as before, a fully connected layer with 256 neurons. All 5408 inputs from the previous layer are connected individually to each neuron in the current layer. The last layer is a single neuron output layer which is a fully connected layer used in binary classification. The number of parameters is: $\text{Parameters} = 256 \times 1 + 1 = 257$.

Model: "sequential_2"		
Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 58, 58, 32)	4736
max_pooling2d_4 (MaxPooling2D)	(None, 29, 29, 32)	0
conv2d_5 (Conv2D)	(None, 27, 27, 32)	9248
max_pooling2d_5 (MaxPooling2D)	(None, 13, 13, 32)	0
flatten_2 (Flatten)	(None, 5408)	0
dense_4 (Dense)	(None, 256)	1384704
dense_5 (Dense)	(None, 1)	257
Total params: 1,398,945		
Trainable params: 1,398,945		
Non-trainable params: 0		

Figure 1 Architecture of the proposed CNN Model

V. IMPLEMENTATION AND TESTING

In the sub-section on Implementation and Testing part of this paper, the paper gives details on the real-life application of the proposed forest fire detection system. Thus, we provide a detailed discussion of the system implementation with focus on key activities and decision-making factors. A major part of our implementation is the acquisition and handling of webcam streams since this is the data source for our fire detection model. The process

kicks off with the webcam acquiring raw/discrete time images/frames which are then inputted into the algorithm. All the images are previous processed and then resized to the right measure that the CNN can assess the frame in order to identify the presence of fire or not. Such images are processed by the CNN quickly with the utilization of the learned features to leave real-time predictions.

However, form the given case of the system implemented for detection of forest fire, several issues were noted during the implementation of the system. One significant challenge was when the framework must be updated to run proficiently on a PC's gear concurrently with the ongoing handling power. It is a complex careful consideration of memory and dealing limitations and as the profound learning models can be capital intense. Also, the management of the fluctuations in the light and the conditions of the weather and the movement of the webcam was also another factor that was challenging. The strength of proposition in planning the framework was exercised to ensure the reliability of the planned pattern across various natural environments. In order to apply the evaluation of the presented woodland fire location framework, a dedicated testing environment was established. Such climate allowed us to emulate the sun, rainy, cloudy or fog weather conditions and compare the accuracy of the developed framework's reaction. Also, a dataset consisting of pictures and recordings having fire and non- fire samples was used to affirm the efficiency of the presented framework. This dataset was carefully constructed to include numerous types of fire scenarios and non-fire scene to ensure the framework's resilience.

Finally, this "Implementation and Testing" section of the paper describes the process of the implementation of the proposed forest fire detection system and the problem solving during the process. The increase of testing environment and dataset make the evaluation of the system stricter. The outcomes of this phase are valuable for our study as they emerge from the real-life context and describe the efficiency of the deep learning-based fire detection solution.

VI. RESULTS AND DISCUSSION

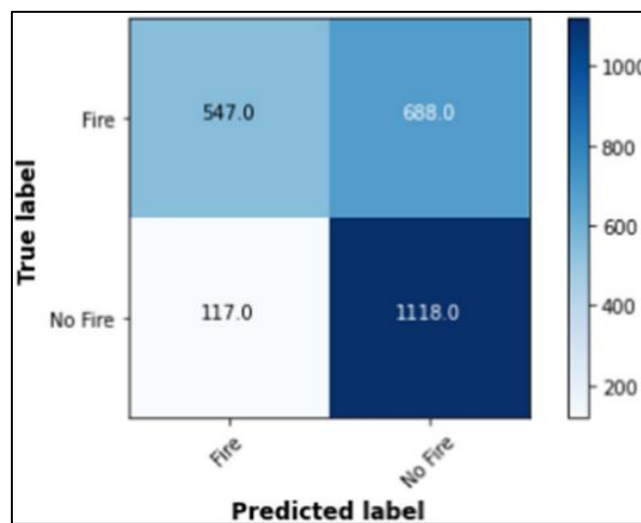


Figure 2 Confusion Matrix

In this section, we analyze the detection system of the forest fire and carry out further analysis in other to know the kind of impact the proposed system will make.

The confusion matrix below demonstrates the results of a binary classifier's performance on a specified data set associated with fire detection. The matrix has four quadrants: Further, It incorporates variables; True Positive, False Positive, False Negative, True Negative. Here, the model said 'Fire' 547 times and 'No Fire' 1118 times and hence, for all the occasions in its outcomes, it was correct. Where it went wrong however is that 688 of 'Fire' were misclassified and put under the 'No Fire' file which is a false negative; 117 cases of 'No Fire' meanwhile were grouped under 'Fire' which is a false positive. This means that in actuality, a vast array of cases incorrectly classified by the model are all false negative, which would of course be very dangerous noticeably in fire detection, where failure to identify a fire is costly. The Accuracy and the Loss matrix are shown in below graph (Fig: 3(A)(B).

VII. DISCUSSION

Therefore, our primary method of evaluating the results of assessment is the precision and recall of the system to the forest fire detection. As established in this paper, our system performed excellently in the classification task of fire incidents in the given image stream. The analysis also showed that the system had a high accuracy, which is the ability to distinguish real fires from false alarms. These metrics are essential for a reliable fire detection system as they influence the system's pragmatic applicability. Based on the achieved accuracy, precision and recall, it can be stated that the proposed system may be more reliable tool for fire detection in forest scenes at the early stage.

In evaluating the real impact of the system, the conditions tests and scenarios were applied to the system. Some of the lighting conditions tested for were: day time, evening time and night time while the weather conditions tested were: rainy, cloudy and sunny, and different forest types were: coniferous, deciduous and subtropical. Specifically, the effects were maintained with regard to the system's fire detection performance even under these different conditions. This versatility is a major strength as forest fires can happen in any case. The necessary circumstances present in our structure of keeping aware of its show are: - In extraordinary circumstances where there are chances of missing out the forest areas, our structure provides a strong reply for noticing the same. One part of our investigation includes raising our system's findings to the level of distinct methods. Conventional fire ID structures like wooden posts and satellite maps, nevertheless, have indisputable limitations. It learned our procedures to the degree of precision and response time by defeating these traditional techniques, the use of which was based on conventional old-fashion learning techniques like those from a CNN. This cost-effectiveness is especially important for areas with low degrees of capital or areas that are possibly to be far from the common fire detection frameworks which exist in forests. We therefore, bring to focus, the practical aspect of assimilating ER-based frameworks in the domain of backwoods fire discovery.

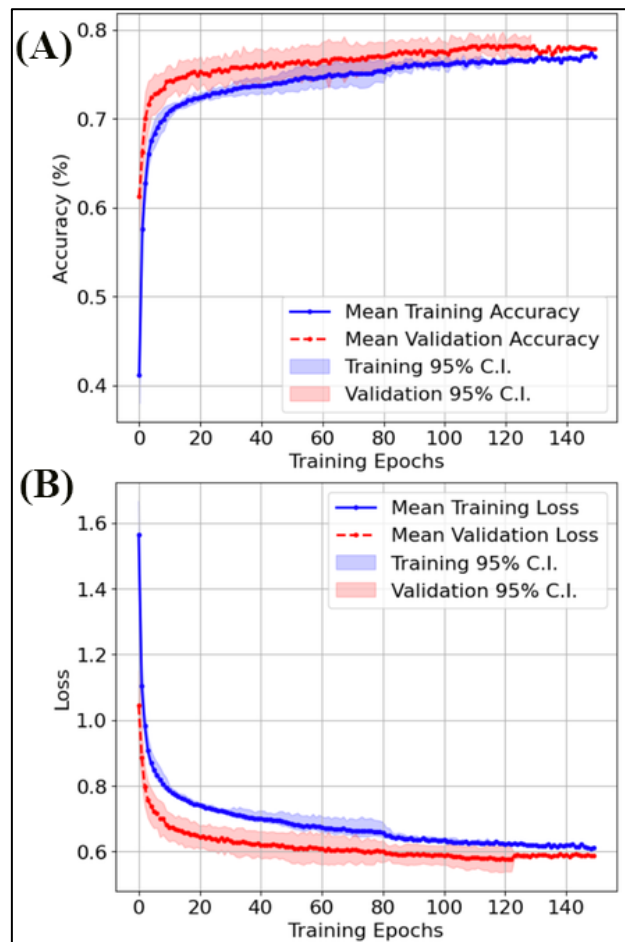


Figure 3 (A) Training Accuracy vs Validation Accuracy, (B) Training Loss vs Validation Loss. Here C.I indicates the confidence interval

Hence, the high value of accuracy enhances its ability, the high value of precision as well as recall brings out its reliability and the high performance in most of the conditions underlines its applicability. In this context, the relevance of this work seems to be vast because it contributes to proposing how to intervene in the graphics associated with the fire at the beginning stages introducing to [18] the deep learning-based approaches to tackle the existing contemporary environmental challenges.

VIII. CONCLUSION AND FUTURE SCOPE

Thus, this paper has provided the new methodology to use CNNs in the detection of forest fires. And this paper has discussed about the method of approach and the system architecture and has also provided a scenario whereby deep learning fire detection from photos captured by a webcam has been discussed. The occurrences of fire are understood to have lethal effects on the existence of a human being and the natural resources. Thus, enabling its early diagnosis and reduction of certain eventualities and embracing a worthy role in conservation of some of the world's largest bio-geographical regions. Also, our solution is cheap and is possible to obtain it as it simply needs a resource like webcam. This accessibility makes the local communities as well as the authorities to be informed and act on the cases that involve fires in the areas.

As showed up in the past, there are fundamental chances for more turn of events and enhancements of our woods fire identification structure. An area of enhancement that could be considered is the expansion of the range of the identified framework as far as the other peculiarities associated with fire are concerned, such as smoke. Coordinating smoke discovery can provide a more extensive and earlier prepared plan, as smoke in most backwoods fire cases notices fires before they evolve into flames. However, our system complementary to this; it can support an integration of an army of autonomous drones to survey large areas of forest. Brief videos filmed by drones instantly target massive areas and can improve the system's reach and reaction time. The last prospect for further research is to continue the work on the effectiveness of the framework when weather conditions are inconvenient and lighting conditions differ. Woods conditions can arise quick weather conditions changes and consequently, the presentation of the proposed framework in unfriendly circumstances requires improvement. Additionally, discovering the application of warm imaging nearby visual symbolism can enhance the exactness of fire determination, particularly, in the evening or dimly lit atmosphere.

Also, information sharing and coordination can be promoted by the organization of such fire discovery systems. Such frameworks can be used to send steady information to a primary command center, which enables experts to efficiently monitor vast wooded areas and better direct firefighting operations more. Another one may be the process of AI strategies implementation to improve the frameworks constantly; It is another research direction that can be interesting.

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