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iDrone: IoT-Enabled Unmanned Aerial Vehicles for Detecting Wildfires using Convolutional Neural Networks

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Abstract The rise of global temperatures, over the past few decades, has disrupted the usual balance of nature. As a result of increasing temperatures, wildfires have destroyed millions of acres of land, thousands of structures, and homes. The pollution and toxic gases produced by the wildfires are carried out to thousands of miles, thus threatening the lives all around the world. Most wildfires occur due to anthropogenic factors, which cannot be predicted solely based on climate conditions. Henceforth, to detect wildfires before escalating, we propose iDrone, which is a wildfire detection system equipped with an end-to-end CNN image classification model: XtinguishNet, trained on a wildfire imagery dataset to detect the possible flames or smokes in an image. In addition, our approach also acquires the weather data and the intensity of the fire. Contrasting with existing wildfire detection systems, our proposed solution is a fusion of the Internet of Things (IoT) and Deep Learning, aiming to provide a one-stop solution for all the needs required to minimize the damage caused by wildfires. When validated and tested using various benchmark datasets, video surveillance, iDrone acquired a high accuracy of 98.36% with the least computational power.

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1 Introduction

It is estimated that an average of 1.2 million acres of US Woodland is burned every year due to uncontrolled wildfires [24]. Around 50% of recorded wildfires have no data on how they have started [24]. Smoke and other toxic gases released by these fires pose a greater risk to both bio-diverse life and the planet's ecosystem. One of the deadliest wildfires humankind has ever faced, destroyed around 3 million acres of land in Maine and New Brunswick, Canada in 1825 [10]. It is nothing new that occurrences of these wildfires are increasing day by day due to many factors like Global Warming, Pollution, etc. Even today, with rapid technology advancement, 2019-20 Australian bushfires have destroyed 46 million acres of land, 5900 buildings, and at least 31 people have lost their lives in the massacre [28]. With the prevailing situation, wildfires will become much more common around the globe in the coming years. Henceforth, to minimize the catastrophe caused by these wildfires, we have proposed iDrone, an IoT-Enabled Unmanned Aerial Vehicle. Wildfires pose a significant risk to humankind by destroying the whole ecosystem and vegetation. The main motive behind our proposal is to cut off these wildfires at their early stages, preventing them from causing more chaos. Automating the detection of wildfires has shown promising results in the past. Similarly, we propose iDrone, hoping to assist the firefighting agencies against the worldwide threat. Despite existing solutions, we believe that no other approach is as efficient and robust as iDrone. In recent years, deep learning is being widely used in limitless computer vision applications because of enormous data availability to the public [3]. To go along with our iDrone pipeline we proposed XtinguishNet, which is a Convolutional Neural Network (CNN) based image classification model trained and tested on a wildfire image data set [2] to detect the wildfires before they spiral up. Amalgamating Internet of Things (IoT) and Deep Learning [8], iDrone is capable of predicting the wildfire from the captured image using Unmanned Aerial Vehicles (UAVs). A few of the advantages of using UAV based monitoring system is its unmanned automacy and low cost [17], [23]. Furthermore, by using other miscellaneous sensors, our model outputs weather data based on the Geo-location of the affected region and attempts to estimate the intensity of the fire. Several efforts have been made to solve the wildfire problem. Few fire detection algorithms were found in the literature [20], in which the model detects fire based on the colour space. Although it is a straightforward approach tends to give higher false alarms. Apart from these, a few systems use spaceborne monitoring frameworks, which are unreliable for early detection and continuous monitoring in certain climate conditions [3]. In contrast with existing solutions, iDrone takes advantage of deep neural nets and classifies the given image into “Fire” or “No Fire”. Taking advantage of a few other electrical sensors [8], [33] integrated into the UAV, weather data like temperature, wind speed, humidity, and geo-location will be sent to the control center alongside the model’s predictions. In addition, the intensity of the fire is estimated and classified into: High Intensity, Medium Intensity, and Low Intensity. We believe that our approach is the first wildfire detection system to introduce an integrated mechanism of IoT and deep learning, (i) to detect wildfires with high accuracy (ii) acquire location and weather data of the affected region, (iii) also estimate the fire intensity. Fig. 1 illustrates the conceptual overview of our proposed IoT framework.

As discussed above, there are numerous ways to monitor wildfires. Our study uses a UAV-based approach. UAVs are more reliable compared to other monitoring methods like Satellites, Fire Outposts [35]. Several sensors can be integrated into the UAVs, which gives us the advantage of acquiring other metadata. UAVs provide a better and precise perception of fire from aerial view [18]. They cover more significant landscapes and are flexible for continuous monitoring [35]. Our UAV approach is more definitive due to its unmanned automacy and extended region of interest.

Proposed Solution and Novelty of the Current Paper

- The proposed XtinguishNet operates on significantly lesser training parameters than other CNN-based models, which conveys the efficiency and robustness of the model.
- Our iDrone can acquire the affected region’s metadata, like temperature, wind speed, geo-location, and many more.
- Seamless UAV-based detection and instant alerting to the control center.
- Early detection of the wildfire, with high accuracy of 98.36%
- Capable of real-time estimation of the Fire Intensity based on the image.

Rest of the paper is organized as follows: Section 2 explains the various existing solutions and the novelty of our approach. Section 3 explicitly outlines our proposed methodology. Section 4 emphasizes results and performance acquired by our proposed methods alongside a comparative analysis with existing solutions. Finally, the paper concludes in Section 5.

2 Existing Related Works and Advancement through the Current Paper

Breakthroughs are being made using today’s technological advancements and Artificial Intelligence (AI) [22], [23], [21]. Wildfires detection systems are no exception. Conventionally, detecting wildfires is done by Distributed Sensors [19], human observations, from watchtowers, and using other primitive tools, nevertheless, this approach is inefficient. For this purpose, other conventional sensors were initially adapted to detect temperature, smoke, and other gases. In addition, recent advancements in technology, especially in computer vision and IoT, have offered new tools for monitoring and detecting wildfires.

Several researchers have proposed several methods in an attempt to detect wildfires. A study proposed an approach where the decision was based on texture analysis by combining static and dynamic textures of the flame [9]. In comparison, their method executes with the least computational power, however, it was easily influenced by fire-like objects, which led to higher

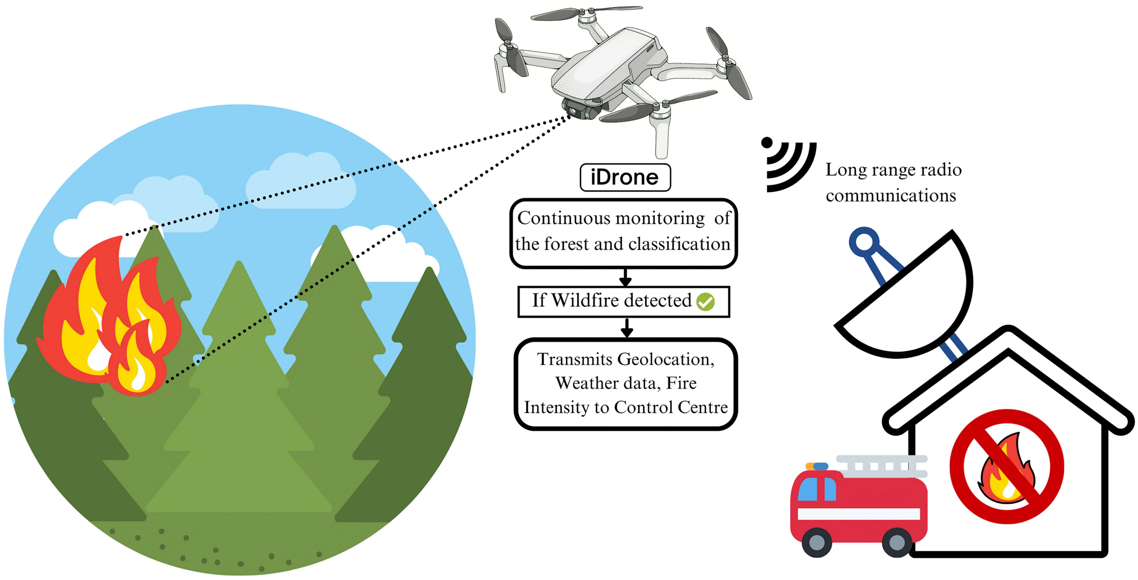

Fig. 1 A conceptual overview of the proposed solution in an IoT framework.

false alarms. Correspondingly to reduce the rate of false alarms, a detection system based on YCbCr colour space was presented in [20], which essentially separates chrominance and luminance in an image.

Furthermore, an approach using RGB, HSV, and YCbCr colour space altogether was introduced in [10], nevertheless, their approach failed to perform well under all environmental conditions[5].

On the other hand, few research used infrared sensors, which produce a binary image containing fires, thus discarding the non-fire parts of the picture [36]. The temperature of the fire is much higher than the temperature of the background. So, regions that show higher radiation than a threshold level will be considered as a possible fire. Similarly other miscellaneous sensors are used to detect smoke, gas, and other thermal radiation emitted by the fires [15]. However, when fire particles trigger these sensors, a part of the forest will already be affected. To avoid the outspread of these wildfires, detecting and acting in their earlier stage is a rudimentary step. Due to this reason, depending solely on the sensors for detection is not reliable [3]. All these models still led to a high number of false negatives and false positives.

Recently, due to the countless number of satellites orbiting around the globe and their data availability, many satellite imagery-based approaches for fire detection have been proposed. Likewise, many researchers have made efforts to detect wildfires using space-borne monitoring systems [26], [7].However, this method is highly unreliable for real-time fire detection. Even first-category satellites like Landsat or Sentinel have a long revisit time. Hence they are unreliable for real-time fire detection. Moreover, the fire and radiation emitted by the fires in their early stages are too feeble to be detected by satellite [3].

Many researchers used CNN-based systems, similar to XtinguishNet. A study used a CNN model, trained on thousands of 'fire' and 'non-fire' images, captured using UAVs and drones [16]. A similar idea was attempted with a different approach in which they finetuned a pre-trained CNN Image Classifier (AlexNet) [37]. As a result, their system had scored a high accuracy of 90% on test data. Comparatively, a study used deep neural networks to detect High impedance faults (HIFs) on overhead power lines that are known to cause fires [31]. While all these methods functioned on a single CNN model, an approach ensembling multiple CNN models (Yolov3, EfficientNet, EfficientNet) is attempted in [34]. Although these approaches showed promising results, none stated a solution to find fire intensity or acquire weather data. Table. 1 compares iDrone with the state of the art wildfire detection systems.

Previous works as mentioned above have explored various routes to detect wildfires early, there is still room for improvement. Most of the existing approaches' only goal is to detect the fire. While our proposed iDrone (i) acquires the weather data, (ii) estimates the fire intensity alongside detecting the fire.

Problem Formulation for the Current Paper

Table 1 iDrone compared with the existing wildfire detection systems

Researcher	Technology Used	Early Detection	False Alarm Rate	Fire Intensity Estimation	Information of Weather Data
Prema et al. [9]	Texture analysis (Flame based)	Yes	Very High	No	No
Mahmoud et al. [20]	YCbCr Color Space	Yes	High	No	No
Chiang et al. [6]	MASK RCNN	Yes	High	No	No
Benjamin et al. [5]	RGB, HSV & YCbCr Color Space	Yes	High	No	No
Yuan et al. [36]	Infrared Imaging	No	High	No	No
Kadir et al. [15]	Miscellaneous Sensors	No	Low	No	No
Koji Nakau et al. [26]	Satellite Imaging	No	Low	No	No
Qingjie Zhang et al. [37]	CNN Model	Yes	Low	No	No
Renjie Xu et al. [34]	CNN Model	Yes	Low	No	No
iDrone (Current Paper)	CNN Model (XtinguishNet)	Yes	Low	Yes	Yes

– Build a precise and early detection algorithm. As discussed above, most satellite and sensor-based systems did not perform well for real-time detection.iDrone uses UAV-based monitoring systems to monitor and detect wildfires actively.
– Achieve an accuracy rate with lesser false alarms. Most other traditional vision-based approaches tend to give higher false alarms and lower accuracy. File-like objects, like the sun, easily influence these straightforward algorithms. XtinguishNet solves this problem by leveraging complex neural nets. Our model achieved the highest accuracy in comparison with other proposed models.
– Acquire other miscellaneous data of affected region like Weather data and geo-location.
– Estimate the fire intensity to give the firefighters an overview of the situation's extremity.

3 iDrone: The Proposed System

Our proposed system is a combination of IoT and Machine Intelligence, aiming to provide a complete one-stop solution in detecting wildfires. Leveraging CNNs and other sensors, XtinguishNet (i) detects the fire, (ii) estimates fire intensity (iii) and analyzing weather data of the affected region. Fig. 2 illustrates a simplified version of complex XtinguishNet architecture and its working functionality.

In our approach, the whole wildfire problem is divided into three sections, namely (i) Fire detection, (ii) Estimating Fire Intensity, (iii) Acquiring weather and Geo-location data

3.1 The Proposed Convolutional Neural Network (CNN) Model For Forest Fire Detection

Convolutional neural networks have shown state-of-art performances on various computer vision applications. Compared to other CNN-based detection systems, our proposed network, XtinguishNet, performed significantly better. XtinguishNet leverages Google's EfficientNetB0 architecture as a base model, thus adapting its performance and efficiency. With well-balanced network dimensions, like image resolution, depth, and width [32], XtinguishNet has shown promising results. Compared to existing solutions, XtinguishNet's predictions are faster and more accurate. Other models have used millions of training parameters to reach accuracy greater than 90%. While our model used exactly 41,655 trainable parameters to attain an accuracy of 98.36%, which implies that, XtinguishNet can be implemented on low-powered on-board devices. The generalized working of XtinguishNet is interpreted in Fig. 3.

3.1.1 Data Preparation

We used a wildfire image dataset [2] containing a total of 1900 images (950 fire & 950 non-fire) splitted

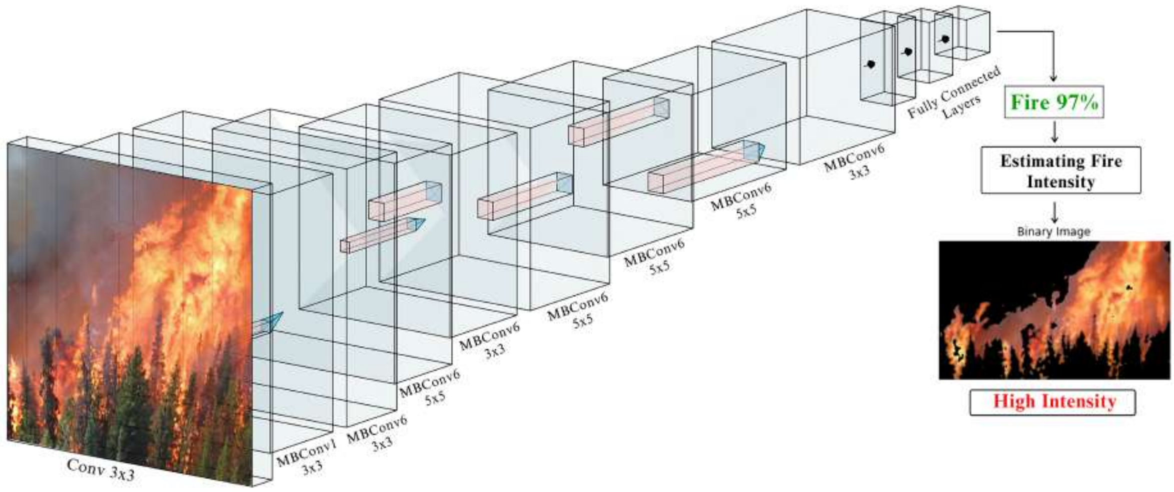

Fig. 2 A simplified version of the complex XtinguishNet algorithm and its working

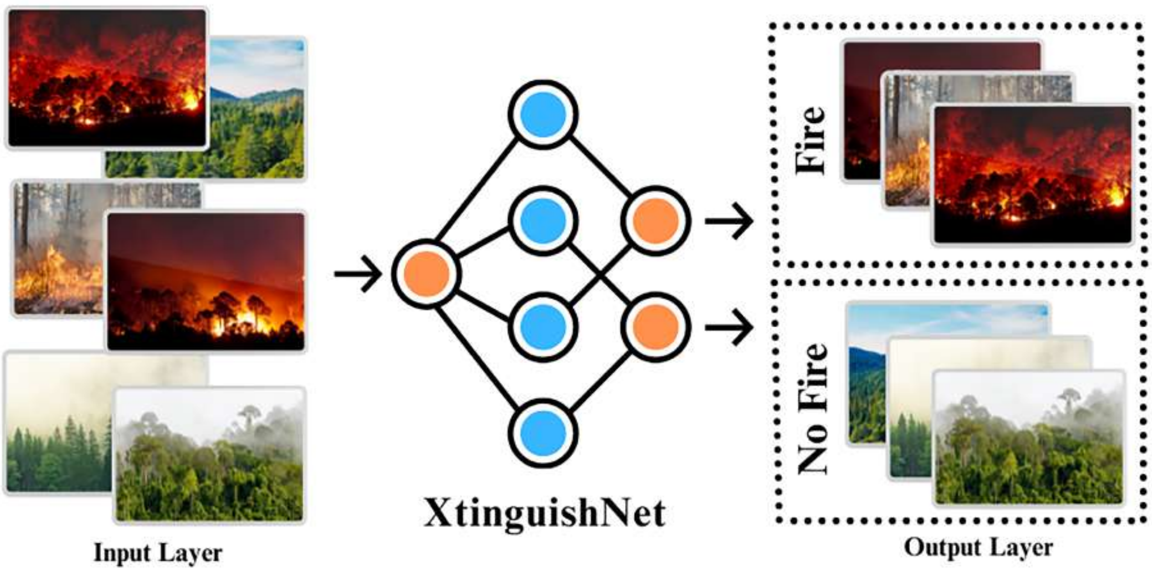

Fig. 3 Working of XtinguishNet model.

into training (80%) and validation sets (20%). Table. 2 depicts the data split. We used another benchmark dataset, FIRESENSE [21], apart from the training dataset to illustrate and test our model's performance. The results of the FIRESENSE dataset are covered in later sections. Before being fed to our model XtinguishNet, all the images are resized into 224 x 224 px. Fig. 4 illustrates a few pictures from the training dataset [2].

Table 2 Data split used to train and validate XtinguishNet

Image Class	Training set (80%)	Validation set (20%)
Non-Fire Images	760	190
Fire Images	760	190
Total Images	1520	380

3.1.2 Training Parameters

In XtinguishNet, the images are resized and clustered into the batches of 32. And then trained for 10 epochs on the Adam optimizer with a constant learning rate of 0.001. The processors used to train and test XtinguishNet are NVIDIA Tesla T40 GPU and Intel(R) Xeon(R) CPU. A loss function is used to quantify the variation between the predicted output and the ground-truth value [6]. The below equation, i.e., Binary Cross entropy, is used to calculate the loss XtinguishNet's predictions.

Fig. 4 Sample images from Khan Ali's dataset used for training and validation.

$$BinaryCrossEntropy = \frac{1}{N}\sum_{i=1}^{N} -(y_i * log(p_i) + (1 - y_i) * log(1 - p_i)) \quad (1)$$

When the detected value is 'No Fire', the first half of the equation becomes active, while the second half cancels out and vice versa when the model detects 'Fire'. Here, 'N' is the number of scalar values in the model's output p_i denotes the probability of the 'No Fire' class, and $1 - p_i$ represents the probability of the 'Fire' class. Furthermore, y_i is the class predicted by our model, i.e., 0 or 1.

3.1.3 XtinguishNet Architecture

The wildfire problem is formulated as a binary classification problem implying that the image is classified into 'Fire' or 'No Fire'. Our proposed CNN takes an image of 224 x 224 px dimensions and outputs probabilities of both 'Fire' and 'No Fire'. Fig. 5 illustrates the network architecture of XtinguishNet.

As mentioned earlier, XtinguishNet uses Google's EfficientNetB0 as its base model. Over the years, numerous CNN architectures have been developed; however, our proposed neural net, XtinguishNet, surpassed these models in efficiency, performance, and robustness when detecting wildfires.In addition, all other complex CNN architectures used millions of training parameters, while XtinguishNet used only 41,655.

XtinguishNet consists of over 200 hidden layers, each serving its purpose in detecting the fire. For instance, layers like fully connected, convolutional, pooling, and sigmoid classifiers are used for feature extraction. These layers can be categorized into a few, as mentioned below,

3.1.4 XtinguishNet - Input Layer

The images are preprocessed and are resized into 224 x 224 px sizes. Resizing and rescaling the images is the critical preprocessing step in computer vision. Finally, the model receives an input image of the shape (224, 224, 3), representing three color channels of an RGB/BGR image. Fig. 6 demonstrates the working of the input layer.

3.1.5 XtinguishNet - Convolutional Layers

Convolutional layers are the building blocks for the whole neural network [6]. They are present throughout the network at different places with different hyperparameters. These layers contain learned weights with extracted features that are used to distinguish between different images. We have seen few systems [30],[9], [20], [11], [5], [36] in which decisions are solely based on a color space but, a human eye, when looking at things, considers multiple aspects, like color, edges, contours, etc., when classifying an image. The convolutional layers mimic this phenomenon of extracting different features from the image and, in the end, categorizing the image into 'Fire' or 'No Fire'. The below expression denotes the working of the convolutional layer,

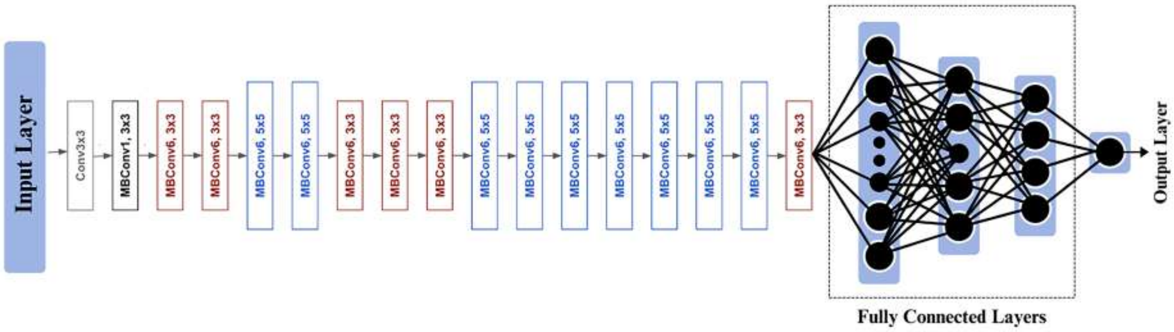

Fig. 5 The network architecture of XtinguishNet.

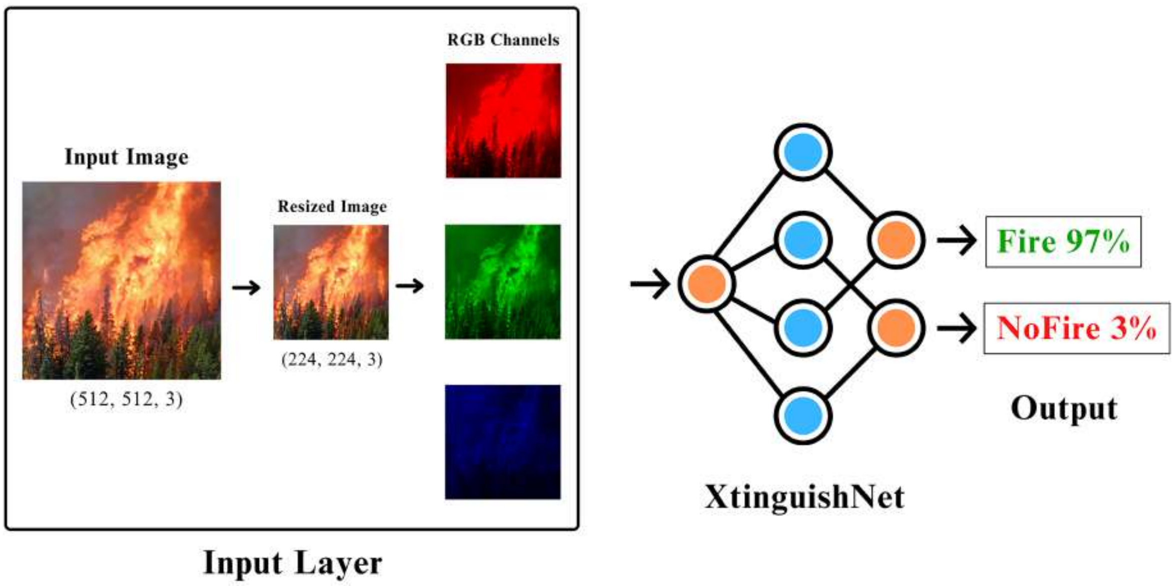

Fig. 6 Overview of working inside the input layer of XtinguishNet.

$$x_j^l = f\left(\sum_{i\epsilon M_j} x_i^{l-1} * k_{ij}^l + b_i^l\right) \quad (2)$$

Where x_j^l is j-th feature map in the layer 'l', M_j is a selection of input maps, each output is given by additive bias "b" and "k" represents the kernels.

Most of the convolution layers have Rectified Linear Unit (ReLU) activation, which turns all negative values into zeroes [1]. The below equation describes the working of the ReLU function, where x denotes input to the neuron.

$$ReLU(x) = x^+ = (0, x) \quad (3)$$

Mobile-inverted Bottleneck Convolutional, also denoted as MBConv, is the main foundation of EfficientNetB0, thus being adopted by XtinguishNet [20]. MBConv is a type of residual block that is structurally inverted for efficiency optimization [29].

3.1.6 XtinguishNet - Pooling Layer

There are many pooling layers, but they all serve the same purpose, i.e., downsampling the extracted features [12]. This reduces the number of parameters to be learned, which reduces the requirement of computational power.

3.1.7 XtinguishNet - Sigmoid Activation Layer

Sigmoid activation function, also known as logistic function, is one of the popular activation functions used in neural networks [4]. Since our problem deals with binary classification, sigmoid outputs the probability between 0 and 1. In particular, if the predicted probability for an image is closer to 0, it means that the model has detected 'Fire' in the image and vice versa. The equation below denotes the Sigmoid function is working where S(x) and e represent sigmoid activation and Euler's number, respectively. When the equation is plotted, we get an S-shaped curve, which is popularly known as sigmoid.

$$S(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

3.2 Acquiring Weather Data

When the wildfire is detected, the monitoring UAV will capture various weather data of the affected region. Different parameters like temperature, humidity, wind speed, wind direction can be acquired using small and inexpensive sensors. These obtained values could provide the fire-fighting team with an edge over the underlying situation.

3.3 Estimating the Fire Intensity

As mentioned earlier, most of the previous works only aimed to detect fires. Our model also estimates the fire intensity solely based upon the image. Crown fires are one of the most dangerous types of wildfires as they are easily influenced by the wind and atmospheric oxygen and spread rapidly [25]. From the perspective of UAVs, crown fires are easily visible as they burn on top of the trees, while most other low-intensity wildfires appear as just smoke. We concluded that the more fire visible to the UAV signifies, the more intense the fire. Based on the previous conclusion, once the model detects the wildfire, the model starts processing the image for estimating the fire intensity. In our approach, we first acquire the image in which 'Fire' was detected, resize it to 1000 x 600 pixels, apply Gaussian Blur and then turn it into HSV color format. iDrone's fire estimation algorithm then calculates the number of pixels with similar HSV values compared to a fire. Based on the count (no. of fire-like pixels), the intensity will be categorized into High, Medium, and Low Intensity. One of the main challenges was to estimate fire intensity in nighttime situations. At these times, even a tiny bushfire looks massive. However, the model is equipped with different thresholds for night and day separately, which solved the problem. Fig. 7 lays out the pipeline behind the estimation of fire intensity.

3.4 Real-time working of our model

As mentioned earlier, our proposed iDrone leverages a UAV-based system for monitoring the forest. These UAVs can monitor the forest throughout the year, every few weeks or seasonally based on the requirement. The images and videos captured by the UAV will be classified into 'Fire' or 'No-Fire' using our proposed neural network, XtinguishNet. The UAVs continue to monitor the forests until a fire is detected.

Once a wildfire is detected, our algorithm performs a sequence of steps simultaneously to estimate the fire intensity and acquire additional weather data of the affected region. Precisely, for estimating the intensity of the fire, our algorithm processes the captured image and finally outputs a binary image comprising only the fire elements in the image. Based on this segmentation, the fire intensity is classified as high, medium, or low intensity. Simultaneously, utilizing the various dedicated sensors, like temperature, humidity, and GPS sensors, which are integrated onto the UAV itself, our proposed model acquires weather attributes (temperature, humidity, wind speed, and direction) and geo-location the fire. Finally, the UAV alerts the control center and transmits the obtained information. Although these features are not included in other existing solutions, they can provide additional information about the ongoing fire situation, helping the fire department understand the magnitude of the wildfire and take respective measures to minimize it. Fig. 8 emphasizes the real-time working of our proposed solution.

4 Experimental Validation of XtinguishNet

The final accuracy score of the model, when tested on various images and datasets, is 98.36%. In addition, when compared to other existing work, iDrone gave the least amount of false alarms. Fig. 9 consists of model predictions on random images from test data, where the red label denotes the model's wrong predictions and vice versa.

When trained and evaluated on the same data [2], XtinguishNet attained higher accuracy (Fig. 10) and lower loss (Fig. 11). Fig. 10 & Fig. 11shows the results acquired on the testing dataset, used for XtinguishNet, of a few other top-tier CNN architectures like ResNet-50, InceptionNet-V3, and XceptionNet.

4.1 Evaluation Criteria

To display the robustness of the proposed method, several combinations of evaluation metrics are used.

Fig. 7 Visualization of pipeline followed for estimating Fire Intensity.

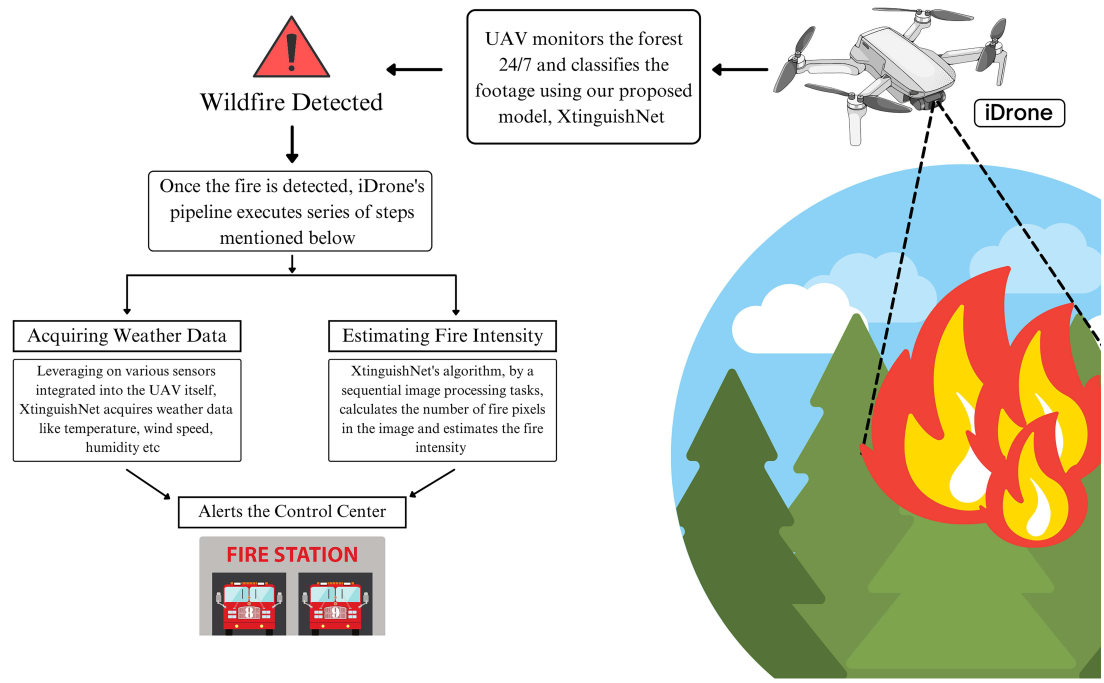

Fig. 8 Real-time working of iDrone.

Fig. 9 Model's predictions on random images from the validation dataset.

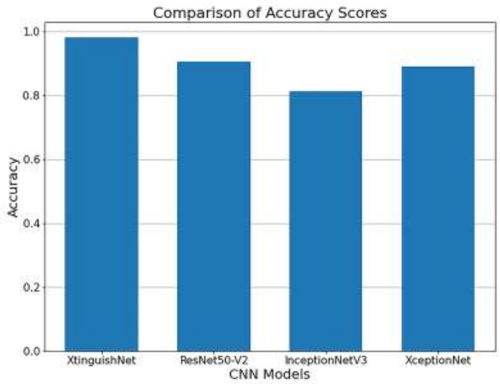

Fig. 10 Performance Comparison (Accuracy) of XtinguishNet and other benchmarked models.

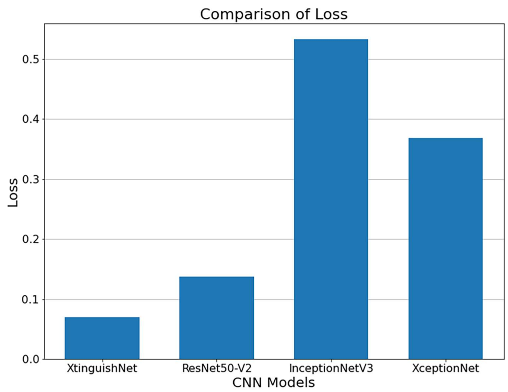

Fig. 11 Performance Comparison (Loss) of XtinguishNet and other benchmarked models

4.1.1 Precision

Model's ability to identify the possible wildfires from the image input. The below equation denotes how the precision is calculated, where P denotes precision :

$$P = \left[\frac{TP}{TP + FP} * 100\%\right] \quad (5)$$

4.1.2 Recall

Model's ability to identify all the relevant wildfires from the predicted possible wildfires. The below equation denotes how the recall is calculated, where R denotes recall

$$R = \left[\frac{TP}{TP + FN} * 100\%\right] \quad (6)$$

4.1.3 Accuracy

The ratio of correct predictions by the model to the total number of predictions. In the below equation, the numerator denotes the number of accurate predictions, and the denominator denotes the total number of predictions by model, α denotes accuracy.

$$\alpha = \left[\frac{TP + TN}{TP + TN + FP + FN} * 100\%\right] \quad (7)$$

In the above equations, TN, TP, FN, and FP denotes True Negative, True Positive, False Negative, and False Positive, respectively. Fig. 12 compares the above-discussed evaluation metrics of XtinguishNet with other CNN architectures.

With a constant learning rate of 0.001, the pattern of accuracy and loss maintained over epochs is illustrated in Fig. 13 Binary Crossentropy, also known as log loss, is used to calculate the model's loss. Binary Cross-entropy is used to compare predicted values to ground truth values, either 1 or 0.

Among other CNN-based wildfire detection systems, XtinguishNet gave the highest accuracy, precision, and recall. Table. 3 depicts the XtinguishNet accuracy score when compared to the other existing work.

Table 3 Comparison of iDrone with other proposed deep learning-based systems

Researcher	Architecture Used	Accuracy (%)
Zhentian Jiao et al. [14]	YOLOv3	83%
Xianping Zhao [38]	CapsNet	91.55%
Chiang et al. [6]	Mask RCNN	95.09%
Hongyi Pan et al. [27]	AddNet	95.6%
Y. Zhao et al. [39]	FireNet	98%
iDrone (Current paper)	XtinguishNet	98.36%

Fig. 14 illustrates the confusion matrix of the model. A confusion matrix is used to describe the model's performance on the test data. Each class breaks down the number of incorrect and correct predictions.

4.2 Model performance on a benchmark dataset

Initially, we used a training dataset [2] to train and validate the performance of our neural network XtinguishNet in which the model acquired a high accuracy of 98.36%. However, to further illustrate our proposed network's robustness and excellent performance, we have tested our network on the FIRESENSE benchmark dataset [13]. FIRESENSE is an open-source dataset for testing flame and smoke detection algorithms. This dataset contained various videos of fire and non-fire

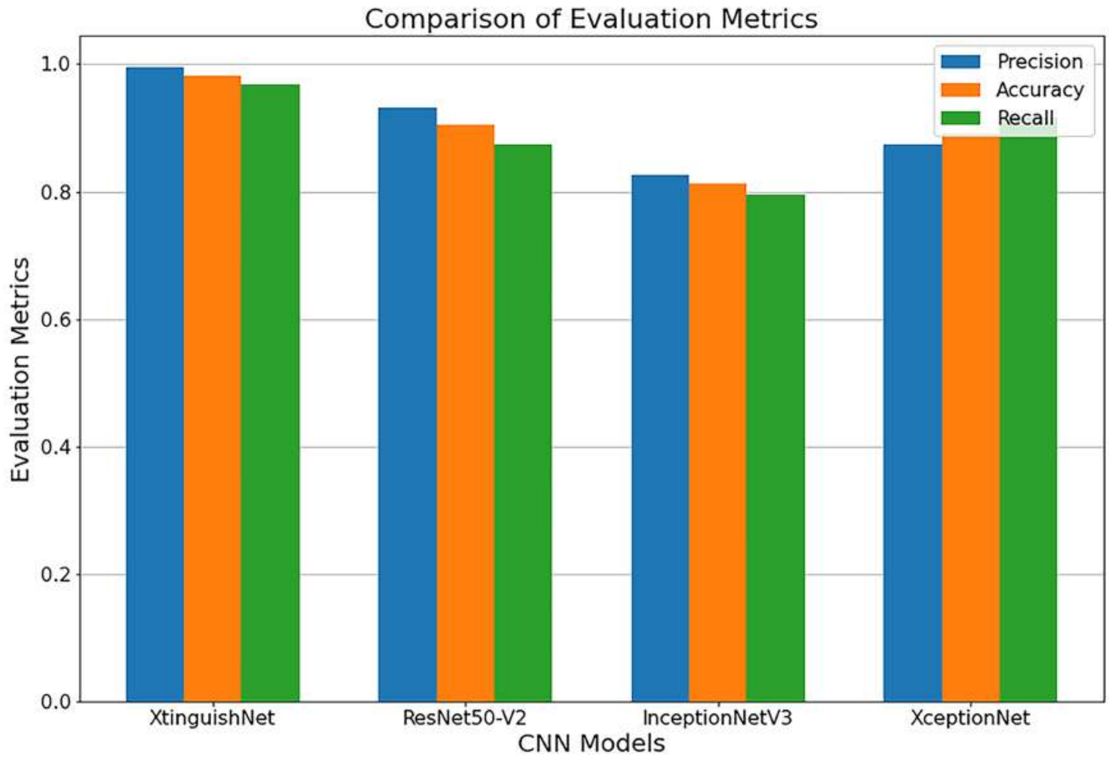

Fig. 12 Performance Comparison of XtinguishNet and other benchmarked models.

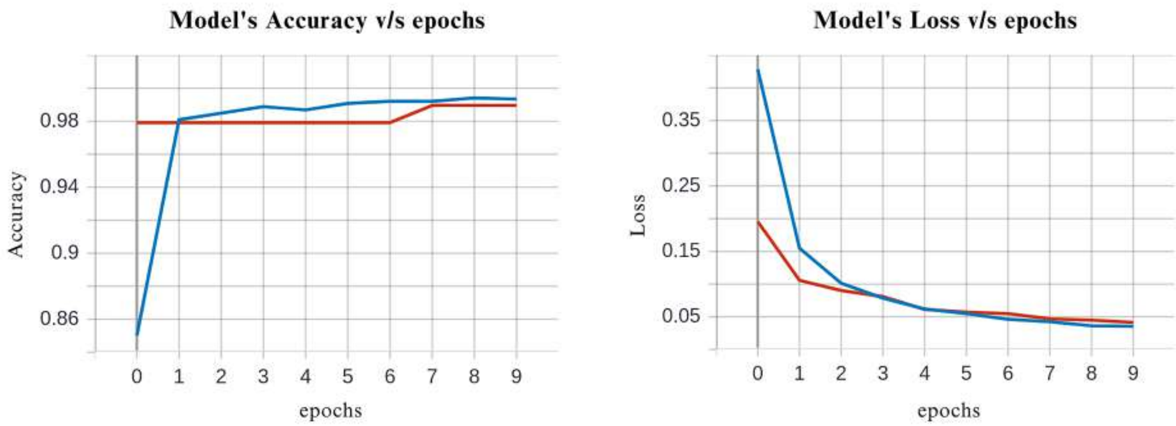

Fig. 13 Performance measures of the proposed CNN model, XtinguishNet.

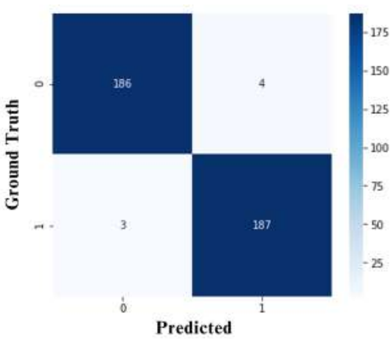

Fig. 14 Confusion Matrix on proposed model's predictions.

scenarios. Figure 15 illustrates the different fire videos from the FIRESENSE dataset.

We have tested our model on 11 different fire scenarios provided by the FIRESENSE dataset. Specifically, we have recorded the number of frames the model predicted incorrectly and compared it to the total number of frames. By tabulating the acquired results, we finally calculated the XtinguihNet's precision on the FIRESENSE dataset. Table 4 illustrates the obtained values on different videos in the FIRESENSE dataset.

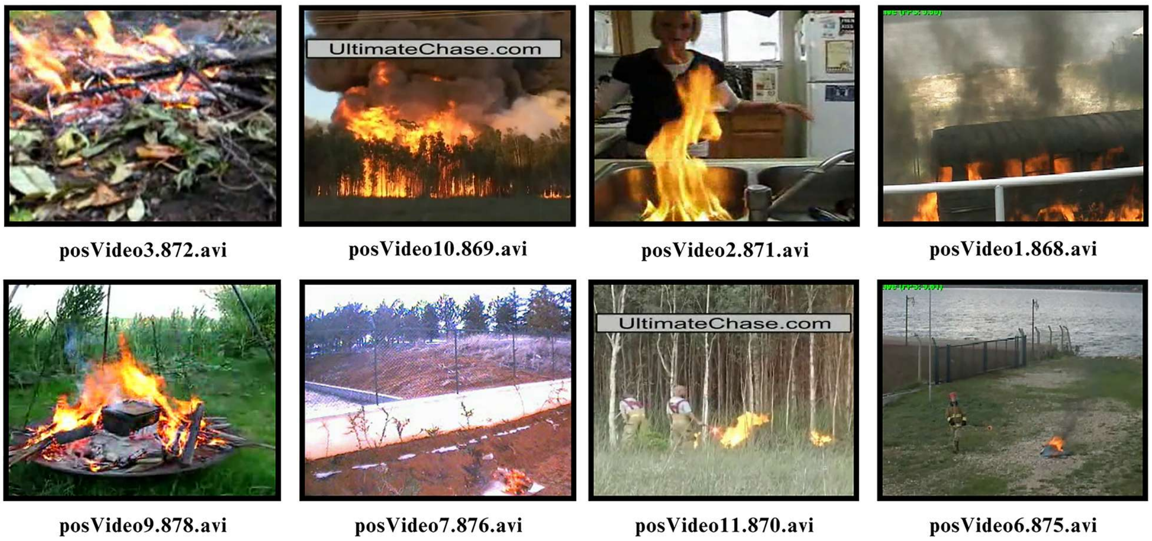

Fig. 15 Sample images from the FIRESENSE video dataset.

Table 4 XtinguishNet performance on various videos from the FIRESENSE dataset

Video Name	Total number of frames	Truly predicted frames	Falsely predicted frames	False Rate
posVideo4.873.avi	1655	1655	0	0%
posVideo11.870.avi	178	178	0	0%
posVideo1.868.avi	293	271	22	7.5%
posVideo10.869.avi	235	235	0	0%
posVideo2.871.avi	510	413	97	19.0%
posVideo3.872.avi	381	381	0	0%
posVideo7.876.avi	547	543	4	0.73%
posVideo6.875.avi	258	255	3	1.16%
posVideo5.874.avi	2406	2406	0	0%
posVideo8.877.avi	513	513	0	0%
posVideo9.878.avi	663	663	0	0%
Total	7639	7513	126	1.64%

From the acquired values, XtinguishNet obtained a false rate as low as 1.64%. In addition, the precision acquired is 98.35%. The below set of equations illustrates the calculation of precision on the FIRESENSE dataset [13]. Based on the above-obtained results, it is evident that XtinguishNet has acquired excellent results on both datasets. On that note, we concluded that our proposed framework is superior to other existing frameworks in terms of efficiency, robustness, performance, etc.

5 Conclusion and Future Research

In this paper, we proposed an efficient and robust solution for wildfire detection. Our proposed model iDrone, equipped with an end-to-end Convolutional Neural Network image classification model: XtinguishNet, aims to provide a one-stop solution for detecting and preventing wildfires. In comparison to the existing solutions, whose sole aim was to detect the fires, our model (i) detects fire in the given image, (ii) acquires weather data of the affected region (iii) estimates the intensity of the fire. Our model leveraged the architecture of a pre-built image classification model (EfficientNetB0) as a base model. Being trained and tested on the dataset by Khan Ali et al. [2] and FIRESENSE dataset [13], the model achieved an accuracy of 98.36%. In the future, we are looking forward to putting together the software described in this paper with a real-time wildfire surveillance system. By further integrating IR sensors, our model could take advantage of both image and IR data to fetch more promising results, which can potentially be a future improvement.

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Compliance with Ethical Standards

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