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An AI-based Image Recognition System for Early Detection of Forest and Field Fires

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Abstract

Forest fires and field fires (agricultural areas, grasslands, etc.) have severe global implications, causing significant environmental and economic harm. Traditional fire detection methods often rely on human personnel, which can pose safety risks and reduce their efficiency in large-scale monitoring. There is an urgent need for real-time fire detection technology to address these challenges and minimize losses. In this research, we propose the utilization of artificial intelligence techniques, specifically Deep Learning with Convolutional Neural Networks (CNN), to tackle this issue. Our proposed system analyzes real-time images captured by IP cameras and stored on a cloud server. Its primary objective is to detect signs of fires and promptly notify users through a mobile application, ensuring timely awareness. We meticulously assembled a dataset to train our model by merging three existing datasets comprising both fire and non-fire images. Also, we incorporated images that could potentially be misinterpreted as fire, such as red trees, individuals wearing red clothing, and red flags. Furthermore, we supplemented the dataset with images of unaffected areas obtained from online sources. The final dataset consisted of 1,588 fire images and 909 non-fire images. During evaluations, our model achieved an accuracy of 93.07%. This enables effective detection, thus rapid intervention and damage reduction. It is a proactive and preventive solution to combat these devastating fires.

Keywords: Forest fires, Field fires, Real time detection, Convolutional neural network, Notification system.

1. Introduction

Vegetation plays a crucial role in maintaining ecosystem stability and ensuring agricultural productivity, which directly affects food security. However, the presence of multiple threats poses significant challenges to vegetation. One of the most pressing concerns is the occurrence of wildfires, which result in extensive damage to forests and agricultural lands. In recent years, there has been a substantial increase in the occurrence of these fires, causing devastation across various regions worldwide (Burke et al., 2021). Forest fires can be triggered by a variety of natural and human causes. Natural causes include lightning during thunderstorms, which can ignite dry plants and lead to a fire. On the other hand, forest and field fires can result from careless human activities, such as abandoning poorly extinguished campfires or mismanaging incinerable waste (Andersen, 2021). Prevention, awareness and proper management of forest fires are key to reducing their devastating impact. Existing solutions for fire detection primarily rely on traditional methods that heavily rely on human labor, resulting in limited effectiveness and high costs. (Bouguettaya et al., 2022). To address this limitation, the objective is rapidly detecting fires, enabling accurate localization and timely notification to fire units. This objective holds significant importance as it can potentially save lives and minimize damage. Hence, it is necessary to use advanced monitoring techniques for forest fires and enhance existing fire management systems. However, there is a wide array of techniques available for detecting and monitoring forest fires. These include satellite systems, optical sensors, camera systems, Wireless Sensor Networks (WSN), and drone systems. Embracing and updating these technologies can significantly enhance fire detection and monitoring capabilities (Sairi et al., 2023). Image analysis is one of the most commonly used approaches to analyze images for signs of fire such as flames, smoke and abnormal heat zones (Bouguettaya et al., 2022). At the same time, smoke detection relies on specialized sensors that detect smoke particles in the air, triggering alarms in the event of smoke (Barmpoutis et al., 2020). Object detection in computer vision has emerged as a solution that addresses the limitations of conventional outdoor methods. When it comes to fire detection, utilizing image analysis offers several advantages. This approach can be applied in expansive open areas, and it entails lower installation costs while allowing operators to confirm alarms visually. The deployment of deep learning and machine

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learning techniques enables the implementation of such a system (Pranamurti et al., 2019).

Extensive research and ongoing efforts are currently underway in the realm of fire detection, with an increasing focus on integrating Artificial Intelligence (AI) techniques. In this research, our objective is to create a system that utilizes advanced AI techniques, specifically computer vision and deep learning, for real-time detection of forest and field fires. This system involves cloud-connected cameras, with the camera stream being processed by a deep learning model. When a fire is detected, an alert, along with a captured image for confirmation, is sent to the user through a mobile application.

The remaining sections of this paper are structured as follows: In Section 2, we provide an overview of the related work in the field. Section 3 presents the proposed methodology in detail, outlining the steps involved. Section 4 presents the experimental setup of the system. The results and the findings obtained from the proposed method are discussed in Section 5. Finally, Section 6 concludes the paper, summarizing the key findings, and proposes potential avenues for future research.

1.1. Related Works

In the field of fire detection systems, two main approaches exist: sensor-based solutions and image-based solutions. Sensor-based solutions detect fires using different sensors, such as temperature, humidity, smoke, flame, air pressure, light intensity, and CO_2 sensors to detect fires (Sairi et al., 2023). Image-based solutions use video surveillance systems to identify smoke and flame from faraway locations (Geetha et al., 2021). These vision-based fire detection systems can be further categorized into two broad categories; traditional feature detection with machine learning and deep learning-based methods (Kukuk and Kilimci, 2021) (Table 1).

Kumar et al. (2020) employed machine learning methodologies, utilizing a deep learning model primarily for feature extraction, and subsequently applied various machine learning techniques for fire detection. Their study focused on detecting fires in diverse environments using videos. They experimented with different transfer learning techniques for feature extraction and several machine learning algorithms for classification. The dataset used by the authors consisted of 1,678 fire images/video frames and 1,368 non-fire images obtained from Google. Their findings indicated that the optimal combination for achieving a high accuracy of 97.80% involved utilizing RestNet-50 for feature extraction and Support Vector Machine (SVM) for classification.

A study by Pan et al. (2019) introduces an additive neural network architecture, which falls within the category of machine learning, based on a multiplication-free vector operator. This architecture is presented as an alternative approach for smoke detection to detect fires. Two datasets were employed for this purpose. The first dataset comprises 4,000 forest images, equally divided between fire and non-fire images. Performance testing of the model revealed a true detection rate of 96% along with a false alarm rate of 0.6. Speed testing and performance evaluation of the model demonstrate that the Additive Network model resides between the computational efficiency and recognition performance of CNN and the binary weight neural network.

A deep learning-based fire detection system that alerts the user and generates alarms was implemented by Regi et al. (2018). The system is constructed based on a Convolutional Neural Network model trained using a dataset consisting of images captured from camera videos. The tests successfully proved that the fire can be detected at its onset with an accuracy of over 90%.

Saeed et al. (2019) proposed a deep learning method for early fire detection using a Convolutional Neural Network. They used a dataset of images captured from a thermal camera in different scenarios, such as indoor and outdoor environments, to train and test their CNN model. The CNN model is designed to analyze thermal images and detect the presence of fire, achieving an accuracy of 98.5% for fire detection.

Kim and Lee (2019) presented a deep learning-based fire detection method that uses Faster R-CNN to detect suspected regions of fire and LSTM to classify whether there is a fire or not in a short-term period and named it DTA. The authors built their dataset, which contains images and video clips: 73,887 still images from a public dataset to which they utilize the FASTER-RCNN model and 1,309 video clips were collected from YouTube, on which the LSTM method was applied to achieve 97.92% accuracy.

Li et al. (2022) conducted a comparative study to determine the best deep learning model among six that best recognizes flames and smoke. Trained using a dataset of 5360 images that combines three subsets of flame, fog, and smoke images; the same data was used to train all models. While MobileNetV2 was able to outperform the others, the experiments revealed an accuracy of 95.8%, and a reduction in the number of parameters due to its lightweight architecture.

Mohammed (2022) proposed a deep learning system to detect fire and smoke in forest areas using transfer learning. The system utilized an Inception-ResNet-v2 model that was pre-trained on the ImageNet dataset. Subsequently, the model was fine-tuned on the smoke and fire dataset, which comprised 1102 fire images and 1102 smoke images collected from various internet sites. The study demonstrated that the model achieved a remarkable classification accuracy of 99.09%.

Guede-Fernández et al. (2021) presented an approach for smoke column detection and classification in open areas. The deep learning model was obtained by transfer learning of the RetinaNet and Faster R-CNN models for object detection. The study performed a comparison between the two previous models that achieved an F1-score and G-means of about 80% and a detection rate of 90%.

Table 1. Summary of the discussed related work

Author(s)	Year	Flame/smoke	Number of images/ videos	Machine Learning technique	Performance metrics %
Regi et al.	2018	Flame	3000 images	CNN	Accuracy: +90%
Saeed et al.	2019	Flame and smoke	35845 images	CNN	Accuracy: 98.5%
Kim and Lee	2019	Flame and smoke	1,309 videos 73887 images	Faster R-CNN and LSTM	Accuracy: 97.92%
Aslan et al.	2019	Flame	184 videos clips	DCGAN	True negative rate: 96.09 %, True positive rate: 92.2%
Pan et al.	2019	Smoke	Dataset 1: 4000 images Dataset 2: 14 videos	Additive Neural Network	True detection rate: 95.6%
Kumar et al.	2020	Flame	3046 images/video frames		Accuracy:
				SVM	97.80%
				Logistic Regression	97.73%
				Naive Bayes	94.71%
				Decision Tree	94.78%
Guede-Fernández et al.	2021	Smoke	4500 images for training, 3645 images and 24 videos for testing	Transfer learning RetinaNet and Faster R-CNN	Detection rate: 90%, F1-score: 80%, G-mean: 80%
Li et al.	2022	Flame and smoke	5360 images	MobileNetV2 CNN model	Accuracy: 95.8%
Mohammed	2022	Flame and smoke	2204 images	Transfer learning: Inception-ResNet-	Accuracy: 99.09%
Abdusalomov et al.	2023	Flame	133,020 images	Modified Detectron2 model	Precision: 99.3%

The dataset used for training consists of 1500 smoke images labeled into 3 classes (high, mid, low) based on their distance from the horizon, 1500 cloud images, and 1500 images containing no smoke objects (empty images). The test dataset contains 375 images with smoke, 1249 with clouds, and 2021 empty images. The models were also tested using 24 video sequences extracted from the public HPWREN database.

An automated approach based on the Detectron2 deep learning model for forest fire detection, aimed at mitigating natural disasters, was presented by (Abdusalomov et al., 2023). The authors curated a custom dataset for the study, consisting of 5200 fire images and 10120 non-fire images. These images were augmented using various techniques, such as rotation, brightness, and contrast, resulting in a total of 133020 images. The modified Detectron2 model exhibited exceptional performance, accurately detecting small fires even at long distances with an impressive precision of 99.3%. Nonetheless, the model does have certain limitations, such as misclassifying objects with orange colors, like the sun, as fire. Additionally, its most significant limitation is the inability to detect smoke independently, which means it relies on the appearance of flames to trigger an alarm.

Aslan et al. (2019) suggested Deep Convolutional Generative Adversarial Neural Networks method to detect flames in video. The model is tested using 72 video segments without any flames and 112 video clips with flames. The videos were partitioned into blocks, while each block allows to produce several slices. As a result, the dataset is made up of more than 210 000 slices overall from more than 1600 blocks. This research investigated the differences between four different models: DCGAN with Temporal Slices, CNN with Temporal Slices, DCGAN with Video Frames and DCGAN without refinement stage. The true negative rates were 96.09%, 87.39%, 92.55% and 86.61%, respectively. On the other hand, the positive detections were 92.19%, 93.23%, 92.39%, and 90.10%, respectively.

2. Material and Methods

To create a robust forest and field fire monitoring system, the primary objective is to detect fires as soon as they start. This allows for the quick involvement of emergency services and aims to minimize fire damage. The architecture of the proposed monitoring system consists of RGB cameras that are connected to the internet and continuously transmit images at defined intervals to a dedicated cloud platform. These images are then processed using a powerful CNN model to detect the presence of fire. When fire is detected in the processed images by the CNN model, an alert notification is immediately sent to the user. This quick notification helps take immediate action and improves the effectiveness of firefighting and prevention efforts. An overview of the proposed fire detection system is illustrated in Figure 1. The details are explained in the following subsections.

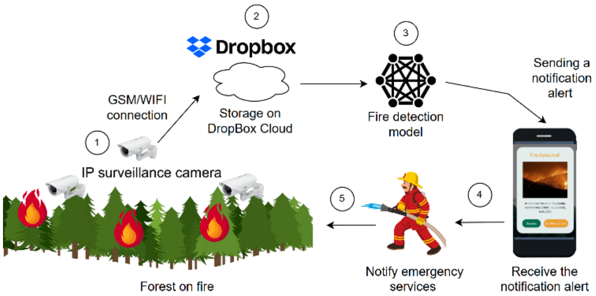

Figure 1. Architecture of the proposed system

2.1. Data Collection

The data collection step is very important when developing a deep learning model, as the dataset used for training directly determines the model's desired behavior and performance (Labed et al., 2022). In his work, we used data from three different datasets. The first one is named "Forest fire image dataset". It comprises 11,034 images, including 3,895 fire images and 7,139 non-fire images. The second dataset is named "Fire prediction". It contains 5050 images including 2,525 fire images and 2,525 non-fire images. The first two datasets are both downloaded from Kaggle. The third dataset was downloaded from Image.cv named "Datacluster Fire and Smoke Sample" and contains 100 images (Figure 2).

In our case, our goal was to detect fires at an early stage, so we had to carefully select a specific dataset. However, the majority of images in the available datasets mainly showed large fires. To address this, we manually collected a small set of data specifically focused on small fires. Additionally, we expanded our dataset by incorporating diverse images from the internet. This included not only images of small fires but also images of field fires, red trees, roses, sunsets, sunrises, and even images featuring humans wearing red clothing. The total number of added images is 54, increasing the combined image count across all datasets to 16,238 (Figure 3).

(a) (b) (c)

Figure 2. Fire images from: (a) dataset 1, (b) dataset 2, and (c) dataset 3

(a) (b) (c)

Figure 3. Added images to the dataset: (a) small fire image, (b) sunset image, and (c) red trees

2.2. Pre-processing and Data Augmentation

In order to prepare our dataset for effective training and improve the performance of our model we conducted a thorough data pre-processing phase. It involved several important steps to address issues such as duplicate images and to enhance the dataset's diversity and size.

Upon initial analysis, it was discovered that a considerable number of duplicate images were present within the collected datasets. Recognizing the potential impact of redundancy and repetition of these duplicates, the "Awesome Duplicate Photo Finder" software we employed to identify and remove these duplicate image pairs. Through careful inspection, a total of 2,306 images were eliminated from the first dataset, 2,714 images from the second, and 8,721 images after merging the two datasets. This removal process resulted in the elimination of 13,741 duplicate images from the first two datasets. Following that, the third dataset, along with the additional downloaded images, was added to the remaining 2,343 images from the first two, resulting in a total of 2,497 images. At this point, it is important to note that the combined dataset is free from any duplicate images, thereby ensuring a more balanced and unbiased training (Table 2).

Table 2. Dataset split

Dataset	Fire	Non fire	Total	Percentage
Train	1111	636	1747	70%
Test	477	273	750	30%
Total	1588	909	2497	100%

We applied various data augmentation techniques to further enhance the dataset's diversity and improve the model's ability to generalize. Specifically, we applied a shear transformation with a shear range of 0.2, a zoom transformation with a zoom range of 0.2, and a horizontal flip. By introducing these variations and augmenting the dataset, we aimed to capture a wider range of fire-related patterns and increase the robustness of our model. In addition to the data augmentation techniques, we standardized the input image size to ensure consistency during training and testing. All images were resized to a target dimension of 224x224 pixels, allowing for compatibility and ease of processing. The same set of pre-processing operations, including rescaling, shear, zoom, and horizontal flip, were also applied to the testing set to ensure uniformity in the data presented in the model. Furthermore, we randomly split the data to create separate training and testing subsets using a Python script, allocating 70% for training and 30% for testing.

2.3. Proposed CNN Model

The proposed model for the detection of forest and field fires is a modified version of the VGG16 architecture. We deliberately chose a larger and more powerful model to address the challenge of reducing false alarms in fire detection. While smaller models may offer increased mobility, they often sacrifice performance and robustness (Abdusalomov et al., 2023). In our modified architecture, several key modifications were made to enhance the performance of the model in detecting fire patterns. To capture image patterns and features, we incorporated additional convolution layers. The initial convolution layer employed 32 filters of size 3x3, facilitating the detection of simple patterns in the 224x224 pixel input images. Subsequently, a second convolution layer was added with 64 filters of size 3x3 to capture more complex features based on the outputs of the previous layer.

To reduce the dimensionality of the representation, we integrated pooling layers into the architecture. Following the second convolution layer, a max pooling layer was included, employing a 2x2 window and a stride of 2.

To regularize the model and prevent overfitting, we introduced dropout layers, randomly deactivating a percentage of activations during training. A dropout layer with a rate of 25% was implemented after the first pooling layer.

Further enhancing the model's capability to detect fire-related patterns, three additional convolution layers were added. These layers utilized 32, 64, and 128 filters of size 3x3, respectively.

Following the third convolution layer, another max pooling layer with a 2x2 window and a stride of 2 was applied, followed by a dropout layer with a rate of 25. Continuing the architecture, two more convolutional layers were included, employing 64 and 128 filters of size 3x3, respectively. To further reduce the spatial size of the representation, another max pooling layer with a 2x2 window and a stride of 2 was implemented after the second convolution layer. This was followed by a dropout layer with a rate of 50%.

To convert the output of the last convolutional layer into a one dimensional vector, a flatten layer was applied. The resulting vector was then passed through a dense layer with 64 neurons, introducing non-linearity and complex combinations of the extracted features. An additional dropout layer with a rate of 50% was added after this dense layer.

Finally, the model was completed with an output layer consisting of two neurons and a sigmoid activation function. This layer produced probabilities for each class, indicating the likelihood that the image belongs to either the fire or non-fire class. Table 3 presents detailed information about the architecture, including the number of parameters in each layer. This table offers a comprehensive overview of the model's complexity and provides insights into the computational requirements of the network. Figure 4 illustrates the architecture of our modified model, highlighting the different layers and their connections.

Table 3. Model summary

Layer and Activation Function	Output Shape	Parameters
Conv2D (ReLu)	None, 224, 224, 32	896
Conv2D (ReLu)	None, 224, 224, 64	18496
MaxPooling2D	None, 112, 112, 64	0
Dropout	None, 112, 112, 64	0
Conv2D (ReLu)	None, 112, 112, 32	18464
Conv2D (ReLu)	None, 112, 112, 64	18496
Conv2D (ReLu)	None, 112, 112, 128	73856
MaxPooling2D	None, 56, 56, 128	0
Dropout	None, 56, 56, 128	0
Conv2D (ReLu)	None, 56, 56, 64	73792
Conv2D (ReLu)	None, 56, 56, 128	73856
MaxPooling2D	None, 28, 28, 128	0
Dropout	None, 28, 28, 128	0
Flatten	None, 100352	0
Dense	None, 64	6422592
Dropout	None, 64	0
Dense (Sigmoid)	None, 2	130

Total parameters: 6,700,578
Trainable parameters: 6,700,578
Non-trainable parameters: 0

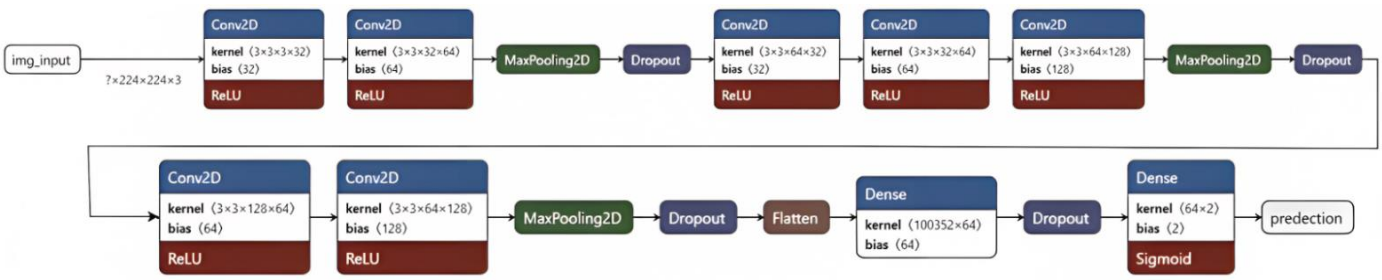

Figure 4. Proposed model architecture

3. Results

3.1. Model Training Results

In the evaluation of a model, the selection of appropriate hyperparameters plays a crucial role in determining its performance. We carefully chose the following parameters to train our model. Firstly, we opted for the "binary-cross entropy" loss function, which is commonly used in classification problems. This loss function effectively measures the dissimilarity between predicted and actual class probabilities, facilitating robust convergence during model training. Additionally, its intuitive formulation makes it a straightforward choice for guiding the optimization process in binary classification tasks (Shambhu et al., 2021). To optimize the model's weights, we employed the Adam optimizer with a default learning rate of 0.001. The choice of a relatively small learning rate was made to ensure gradual and stable updates to the model's parameters during training. A smaller learning rate helps prevent overshooting the optimal parameter values and promotes finer adjustments. Additionally, we opted for the Adam optimizer for its capability to handle sparse gradients effectively and its tendency to converge rapidly, factors that align well with our training setup and contribute to overall improved optimization performance. For efficient training, we set the batch size to 32, indicating that each iteration during training utilized a subset of 32 training examples. Moreover, we conducted training over 100 epochs, representing the number of times the learning algorithm traversed the entire training dataset. These parameter choices were made based on their effectiveness in similar scenarios and were fine-tuned to align with our specific requirements. Following the completion of training for 100 epochs, our model demonstrated promising results.

During the training phase, the model showed an average loss of 0.0734, which means it was good at reducing errors in predicting labels. Moreover, the average accuracy was 0.9772, indicating that the model correctly predicted labels for around 97.72% of the training examples. Moving on to the validation data, the model had a loss of 0.3345, slightly higher than the training loss. This might suggest that the model is slightly overfit to the training data, which could result in lower performance on unseen data. However, the average accuracy on the validation data was 93.07%, which is still high. This shows that the model can generalize well and make correct predictions for most of the validation examples. Figure 5 displays the results of the model's loss function, while Figure 6 illustrates the training and validation accuracies of the model.

These findings suggest that the model performs effectively in the classification task with trained data. EA testing will conduct in a real-world situation in the next section to further assess the model's performance and validate its generalization ability.

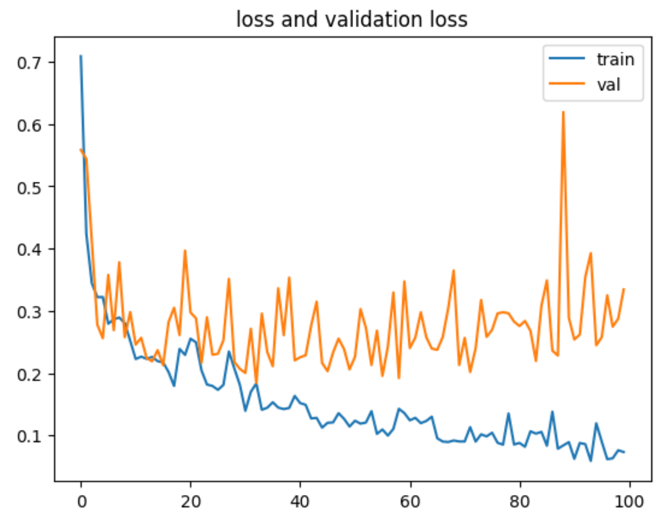

Figure 5. Model loss results

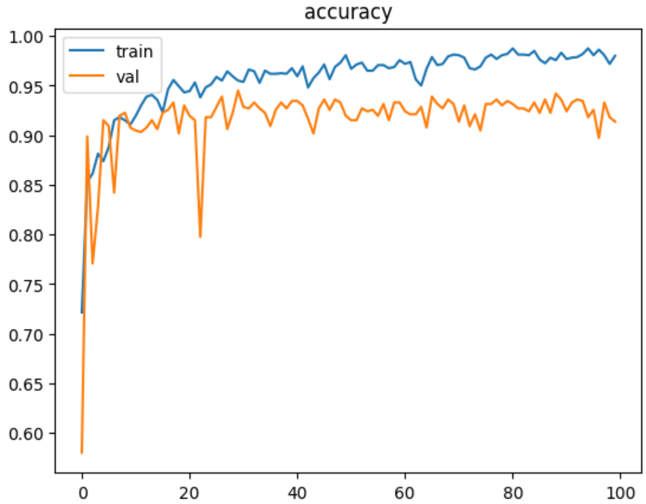

Figure 6. Train and validation (test) accuracy results

3.2. Experimental Setup Results

In order to evaluate the real-world performance of the proposed system, we conducted an experimental setup using a V380 IP camera. The camera was connected to a DropBox cloud platform, which was a central storage for the transmitted images. These images were then processed using our CNN model, which was integrated into the system (Figure 7).

Figure 7. Illustration of image transmission from IP camera to Dropbox

Our selection of the V380 IP camera for the experimental setup was driven by its specifications, which aligned well with the goals of our research. To begin with, the camera has 180-degree field of view. This wide coverage capability enables the camera to effectively monitor and capture data from extensive open areas. Furthermore, complementing its wide field of view, the camera features a 1280 by 720-pixel resolution. Although this resolution is not extravagant, it remains adequate for our model to identify essential fire-related details within the images. Moreover, the camera offers an array of advantageous features, including night vision capabilities, dedicated SD card storage, and cloud storage options. What holds the greatest importance, however, is its notably budget-friendly pricing. This financial benefit is particularly pertinent when evaluating situations like forest coverage, where cost-efficiency emerges as a primary concern. We prioritized Dropbox as our cloud storage solution primarily because of its advanced console. This console has essential tools that seamlessly integrate our real-time monitoring system with Dropbox's storage infrastructure. This integration automates vital tasks such as image transmission and retrieval, optimizing our system's efficiency.

To simulate real-time monitoring, the camera was configured to capture and transmit an image to the cloud platform in every single minute. The transmitted images were continuously analyzed by the CNN model to detect any anomalies indicative of fire. In the event that the model identified a potential fire, a notification is immediately sent to a mobile application, alerting the user about the detected anomaly. The mobile application is associated with the system functions by retrieving and processing images captured by the V380 IP camera, which are stored in Dropbox. A Python API is used to retrieve these images from Dropbox and process them in the Google Colab environment by the CNN model. The application also incorporates a fire progression monitoring feature that facilitates tracking and documentation of the fire's spatial expansion over time.

Furthermore, the application possesses the capability to store and archive historical fire data, facilitating subsequent analysis and exploration. This archival function enables users to conduct comprehensive examinations of past fire incidents, allowing for the identification of trends, patterns, and relevant factors associated with the occurrence and development of fires.

To assess the efficacy of our fire detection system, we conducted a practical test in the real-world. In collaboration with forest guards, we selected a controlled testing site where we intentionally ignited multiple controlled fires. We directed the IP camera's focus towards the targeted area. As a result, our system rapidly detected these fires and transmitted notifications to users via mobile application. This real-world assessment reaffirms the system's capability to identify fires in real-time and underscores its potential as a tool in forest and field fire prevention and early intervention. Figure 8 depicts the operational implementation of the system, showcasing the image acquisition process by the camera and the subsequent transmission of a notification to the user.

Figure 8. Image acquisition and user notification process

4. Discussion

The primary objective of this study was to develop an automatic system based on image recognition for early fire detection in forest and field areas. To address this objective, computer vision techniques were employed, specifically utilizing a (CNN) to analyze images captured by surveillance cameras.

The key finding of our study is that the developed system demonstrates the capability to detect even small fires. Comparing our results to the existing literature, we observed that most studies typically rely on a single dataset for model training. In contrast, our approach involved the utilization of three diverse datasets, and we conducted manual examination of the images to ensure the provision of relevant and informative data to the CNN model. This comprehensive dataset and the meticulous selection process enhance the robustness and generalizability of the system.

The significance of our study lies in the early detection of forest fires, which can lead to prompt response and effective firefighting measures, thereby minimizing the potential damage to the natural environment. However, it is important to acknowledge the limitations and challenges faced by the proposed system. One notable limitation pertains to the system's reliance on a consistent network connection for seamless image transmission. While we successfully implemented the system using Wi-Fi cameras, it is imperative to recognize that the adoption of GSM cameras, particularly in open forest and field areas, presents a more convenient solution. However, this convenience can potentially introduce complications in the transfer of high-definition images. In the case of utilizing GSM cameras, fluctuations in signal strength and potential network outages could disrupt the timely and reliable transmission of images, thereby obstructing the effectiveness of the system. Furthermore, our proposed model does demonstrate intermittent lapses in fire detection accuracy. Although it displays competence in identifying fires, these occasional inaccuracies emphasize the ongoing need for fine-tuning and optimization. Therefore, sustained refinement and adaptation are essential to enhance the system's performance, ensuring its resilience and practical effectiveness.

In conclusion, our study demonstrates the successful development of an automatic system for early fire detection using image recognition techniques. This research opens up opportunities for advancements in the field of fire detection and contributes to the protection and preservation of natural ecosystems.

5. Conclusion

Fires in forest and field areas pose significant threats to the environment and human safety. The objective of this study was to develop an automatic system based on image recognition for early fire detection. By employing computer vision techniques, specifically a CNN, we aimed to accurately identify fire-related images captured by cameras. Our model achieved an accuracy of 93.07%, indicating its effectiveness in detecting fires. A notable aspect of our research was the use of three diverse datasets, including manual examination of images, which enhances the reliability and robustness of the system. Despite the challenges posed by limited availability of relevant data, our system demonstrated promising performance and potential for real-time fire detection. Future studies can focus on expanding the dataset and exploring advanced techniques such as transfer learning and multiclass classification to further enhance the system's capabilities. Overall, this research underscores the power of image recognition and CNN-based techniques in mitigating the devastating impact of fires, thereby contributing to environmental preservation and safeguarding lives.

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