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Research Article

CNN Based Real-Time Fire Detection System

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Abstract

The early detection and rapid response to fires are vital in minimizing damage and protecting lives and property. This study presents a camera-based fire detection system utilizing advanced image processing techniques and Artificial Intelligence (AI). The system, employing Convolutional Neural Networks (CNNs) for image analysis, achieves an accuracy rate of 89% in detecting fire. Upon detection, the system sends real-time notifications to users through Telegram, enabling swift intervention and enhancing emergency response times. This approach significantly improves fire detection capabilities, particularly in large, complex environments where traditional detection methods are less effective. The integration of CNN-based image processing with communication technologies such as Telegram bots provides a flexible, accessible, and scalable solution. The proposed system demonstrates its potential as an innovative tool for enhancing fire safety and response efficiency, ensuring timely intervention and minimizing the impact of fires.

Keywords: Deep learning, fire detection, telegram bot, convolutional neural network

Konvolüsyonel Sinir Ağı Tabanlı Gerçek Zamanlı Yangın Tespit Sistemi

Öz

Yangınların erken tespiti ve hızlı müdahale, hasarın en aza indirilmesi, can ile mal güvenliğinin korunması açısından hayati öneme sahiptir. Bu çalışma, gelişmiş görüntü işleme teknikleri ve Yapay Zekâ (AI) kullanan kamera tabanlı bir yangın tespit sistemi sunmaktadır. Görüntü analizinde Konvolüsyonel Sinir Ağları (CNN) kullanan sistem, yangın tespitinde %89 doğruluk oranına ulaşmaktadır. Yangın tespit edildiğinde, sistem kullanıcılara Telegram üzerinden gerçek zamanlı bildirimler göndererek hızlı müdahale imkânı sağlayıp acil durum yanıt sürelerini iyileştirmektedir. Bu yaklaşım, özellikle geleneksel tespit yöntemlerinin daha az etkili olduğu büyük ve karmaşık ortamlarda yangın tespit yeteneklerini önemli ölçüde artırmaktadır. CNN tabanlı görüntü işlemenin, Telegram botları gibi iletişim teknolojileriyle entegrasyonu, esnek, erişilebilir ve ölçeklenebilir bir çözüm sunmaktadır. Önerilen sistem, yangın güvenliği ve müdahale verimliliğini artıran yenilikçi bir araç olarak potansiyelini göstermekte, zamanında müdahaleyi sağlayarak yangınların etkisini en aza indirmeyi amaçlamaktadır.

Anahtar Kelimeler: Derin öğrenme, yangın tespiti, telegram botu, konvolüsyonel sinir ağı.

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1. Introduction

The early detection and rapid response to fires are crucial in preventing loss of life and property. Traditional fire detection systems primarily rely on smoke, heat, and flame sensors. However, recent advancements in image processing and artificial intelligence technologies have enabled the development of camera-based fire detection systems. These systems offer significant advantages in monitoring large areas and detecting fires in their early stages.

Camera-based fire detection systems operate on the principle of analyzing images obtained through optical and/or thermal cameras. Image processing algorithms detect fires by identifying the characteristic features of flames and smoke. These systems provide an effective solution, especially in large and high-ceiling areas, dusty or polluted environments, where the effectiveness of traditional detectors is limited.

In recent years, AI-powered camera systems have also been used for early detection of wildfires. For example, in the forested areas of Victoria, Australia, AI-powered cameras have been developed to detect fires instantly [1]. Similarly, AI-powered sensors used in California play a crucial role in the early detection of fires and preventing their spread [2].

Advancements in mobile devices and the Internet of Things (IoT) have made fire detection systems more flexible and accessible. For instance, applications running on mobile devices and utilizing deep learning algorithms can detect fire and smoke in real time [3]. Additionally, IoT-based fire alarm systems collect data from various sensors, such as gas, motion, temperature, and smoke sensors, and transmit it to cloud servers via Wi-Fi, allowing users to access and analyze this data from anywhere in the world [4]. Engin and Kökhan have developed an automatic model based on image processing and artificial intelligence for wildfire detection [5]. For example, in reference [6], Convolutional Neural Networks were used for fire and smoke detection on mobile devices. A new goal programming model has been developed for the preparation of the exam Schedule [7].

In this study, Telegram is used. Telegram is a cloud-based messaging platform with APIs for building custom bots and communication solutions [8]. Numerous studies have been conducted using Telegram. In reference [9], the Internet of Things (IoT) is integrated with a Telegram Bot as a tool to expand the alert system's notification capabilities. The Home Assistant operating system, its mobile application, and the Telegram chatbot are utilized in the reference 10 [10]. Mobile application is used for children's learning, development in the reference 11. In reference [12], a Telegram chatbot is used for real-time applications. In the study, communication tools such as a Telegram bot are used to improve user experience and expand the potential applications of the assistant [13]. In reference [14], a mask detection system is implemented, and then the detected photo is sent to the Telegram bot [14].

In conclusion, camera-based fire detection systems represent a significant innovation in early fire detection and rapid response processes, thanks to advanced image processing technologies and AI-powered analytical capabilities. Compared to traditional fire detection methods, these systems offer significant advantages in monitoring larger areas and detecting fires in their early stages.

2. Material and Methods

In the event of fire detection, integrated communication modules can instantly notify authorities or relevant units. For example, fire detection systems quickly trigger an alarm when a fire is detected, enabling early intervention and minimizing potential damage. This study has been conducted for this purpose.

In this study, image processing and communication techniques are used. Convolutional Neural Networks are used for image processing, while Telegram/Bot is used for communication. When a fire is detected, the system sends a notification message to the user, allowing immediate action to be taken. The flowchart of the system is shown in Figure 1.

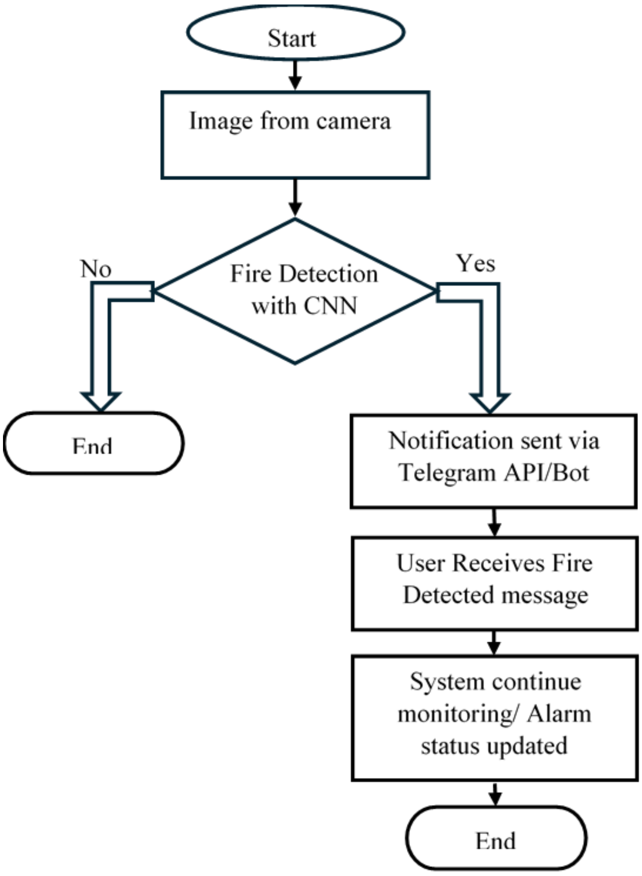

Figure 1. The flowchart of fire detection system

The dataset used is from Kaggle [15], a comprehensive dataset that brings together various indoor and outdoor scenarios for fire detection. The images were all normalized to (224,224) resolution and saved as JPG files. Some sample images from the dataset are presented as Figure 2.

Figure 2. Sample images from the dataset

Convolutional Neural Networks (CNNs) are deep learning models widely used in image processing. These networks automatically learn features from images, achieving high performance in tasks such as classification, object recognition, and segmentation.

The fundamental building block of CNNs, the convolutional layer, applies a filter to the input image to generate feature maps. This process enhances specific features in the image, such as edges and corners.

After the convolution operation, an activation function is applied. ReLU (Rectified Linear Unit) is a widely used activation function in deep learning models. Mathematically, the ReLU function f(x) returns x when x is positive, and 0 when x is negative or zero. This is expressed in equation 1. This function returns x if the input value x is greater than 0; otherwise, it returns 0.

Pooling layers reduce the size of feature maps, thereby decreasing computational cost and enhancing the model's robustness to variations such as translation and scaling. The most commonly used pooling method is max pooling, which selects the highest value within a specific window. The CNNs architecture utilized in this study is shown in the Figure 3.

Telegram is a cloud-based instant messaging application with a wide user base around the world. Telegram bots are computer programs that can interact with users through the popular messaging app, Telegram. They offer a wide range of functions, from providing information and scheduling appointments to hosting games.

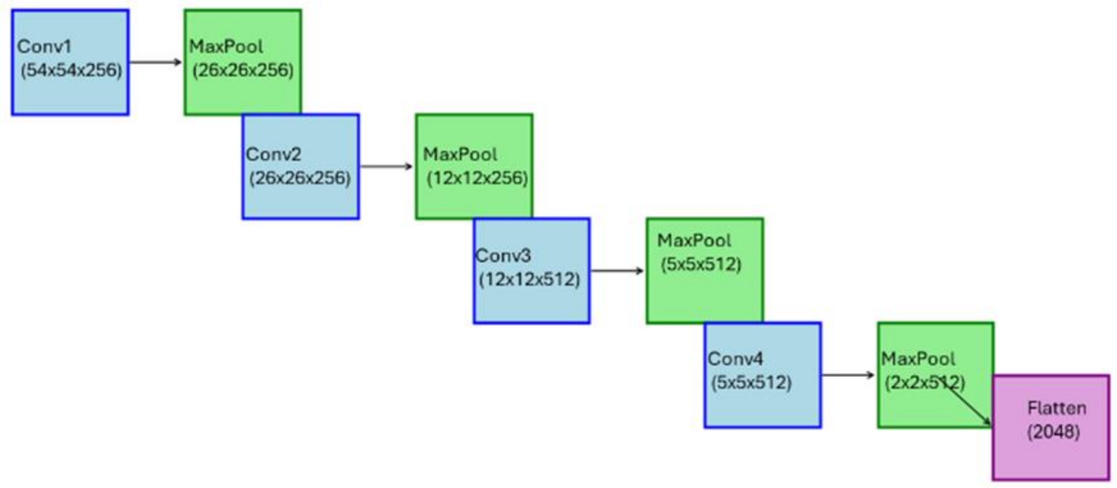

Figure 3. The CNN's archictecture

Businesses can utilize Telegram bots to improve customer service and optimize tasks by providing fast and automated responses. The application allows for the fast and secure transmission of various types of data, such as text messages, media files, documents, and voice messages. API and Bot Support: By offering extendable APIs and bot support for developers, it enables automation and integration of third-party services within the application. The general structure of the system is given in Figure 4. The proposed model in this study is not limited to training and validation processes but is also integrated into a real-time application scenario. Utilizing the Python-based OpenCV library, images from a camera feed are actively processed. Each frame is passed to the pre-trained CNN model to promptly determine whether a fire is present. If a fire is detected, a mobile notification titled "Fire detected!" is sent to a designated user via the Telegram Bot API.

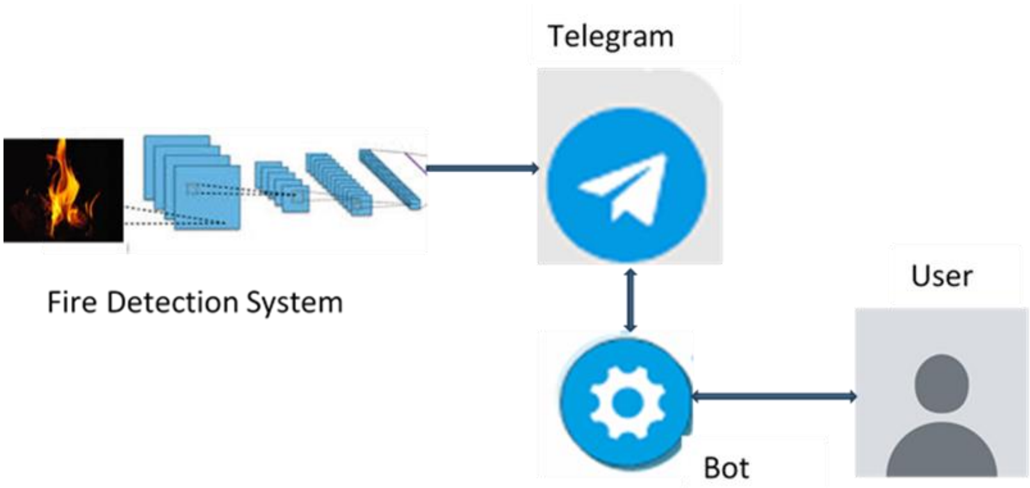

Figure 4. The general structure of the system

Telegram is a messaging application that stands out for its extensive feature set and cross-platform support. APIs and bot support for developers. It enables automation and integration of third-party services within the application. To retrieve data, Telegram's own service, BotFather, which provides API services for bots, has been used. BotFather is a service that manages all bots, helping to create new ones and modify settings for existing ones [16]. Figure 5 shows the Transition between CNN and Mobile section.

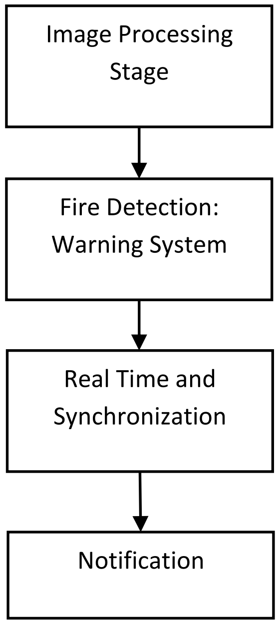

Figure 5. Transition between CNN and Mobile section

The system processes images from a camera stream using Python and OpenCV. It is sent to a pre-trained CNN model. The model detects whether there is a "fire" in the image. This detection process is based on the classification of the characteristic features for the first stage. The pseudocode is shown in Figure 6.

```
Import cv2
Import numpy as np
Import pygame
Initialize camera capture
Loop indefinitely
  Read a frame from the camera
  If frame not successfully read Then
    Print "Camera feed not available!"
    Break the loop
  Predict class probabilities using pre-trained model
  If predicted class is fire pred == 1 then
    Set label To "Fire!!!"
  Else
    Set label To "Normal"
  If predicted class is fire and Then
    Call send_telegram_message("Fire detected! Please take immediate action.")
```

Figure 6. Transfer of CNN results to Telegram-1

For the second and third stages; if the CNN model detects a fire; HTTP requests are prepared via the Telegram API using the requests library in Python. The Telegram bot has been previously created via BotFather and integrated into the system. The bot sends a message directly to the defined user ID. This message notifies that a fire has been detected. The pseudocode is shown in Figure 7.

```
Function send_telegram_message (message)
    Set bot_token To 'your_bot_token_here'
    Set chat_id To 'your_chat_id_here'
    Set url To "https://api.telegram.org/bot" + bot_token + "/sendMessage"
    Create payload
        Set payload['chat_id'] To chat_id
       Set payload['text'] To message
    Try
        response ← Send HTTP Post Request To url Wıth payload as Data
        If response is Successful then
            Print "Message sent: "
        Else
        Print "Failed to send Telegram message: "
End Function
```

Figure 7. Transfer of CNN results to Telegram-2

Thus, the system gains reactive notification feature instead of active monitoring. Even if the user is not at the system, they can intervene immediately in an emergency thanks to the message sent to their mobile phone.

3. Results

The primary aim of this study is to ensure the operability of the system within a real-time, camera-based environment and to develop a system prototype supported by alert mechanisms in the event of a fire. In the first phase of the study, the CNN model. Figure 8 shows the activation maps after each convolutional layer. This process helps us understand how the model processes the input image. These maps allow us to visualize the filters applied by the model at each convolutional layer, helping us understand which features of the input image are being emphasized.

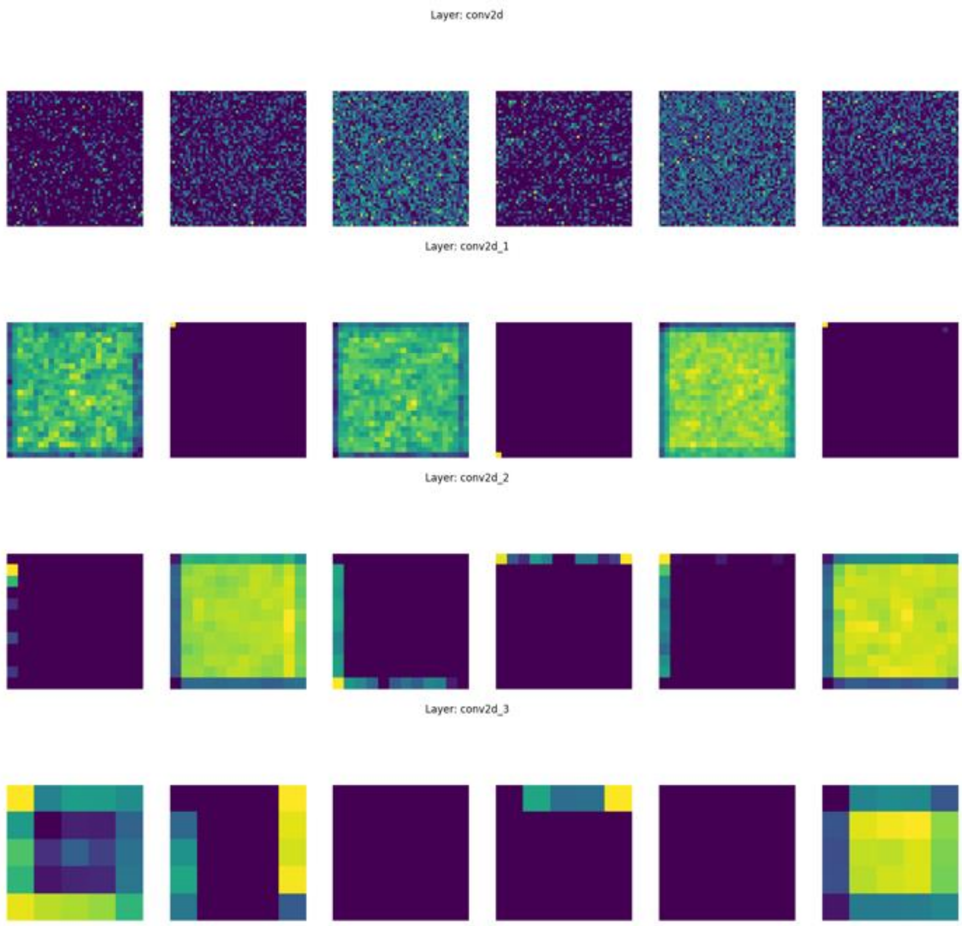

Figure 8. After each convolutional layer, the activation maps

The confusion matrix obtained at the end of the training is shown in the Figure 9.

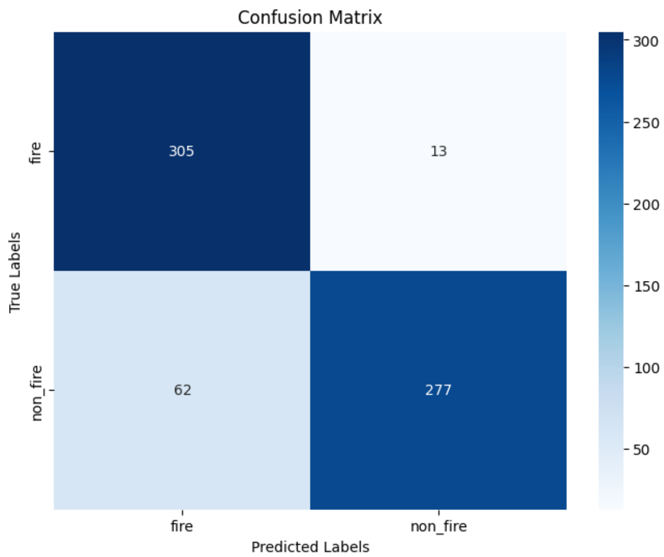

Figure 9. The confusion matrix

Classification report is given in Figure 10.

	precision	recall	f1-score	support
fire	0.83	0.96	0.89	318
non_fire	0.96	0.82	0.88	339
accuracy			0.89	657

Figure 10. Classification report

Accuracy is useful for evaluating overall performance when the classes in the dataset are balanced. Precision and recall are often assessed together to maintain a balance. The F1-score establishes a trade-off between precision and recall, making it particularly useful for imbalanced datasets [17,18]. True Positive (TP), instances where the model predicts "positive" and the actual class is also positive. True Negative (TN), instances where the model predicts "negative" and the actual class is also negative. False Positive (FP) instances where the model predicts "positive" but the actual class is negative. False Negative (FN) instances where the model predicts "negative" but the actual class is positive. These concepts play a fundamental role in the calculation of performance metrics. Table 1 presents the confusion matrix [17,18,19,20]. Performance metric calculations are shown in equation (2-3-4-5).

Table 1. Confusion Matrix

	Actual Positive (+)	**Actual Negative (-)**
Predicted Positive (+)	TP (True Positive)	FP (False Positive)
Predicted Negative (-)	FN (False Negative)	TN (True Negative)

$$Precision = \frac{T_P}{T_P+F_P} \tag{2}$$

$$Recall = \frac{T_P}{T_P+F_N} \tag{3}$$

$$F1 - Score = 2x\frac{PrecisionxRecall}{Precision+Recall} \tag{4}$$

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \tag{5}$$

The accuracy and loss graphs for training and validation are presented respectively in the Figures 11-12.

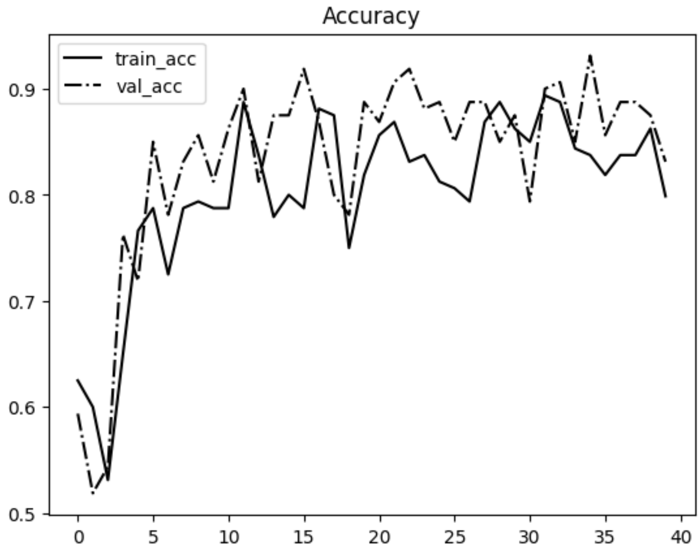

Figure 11. The accuracy graphs

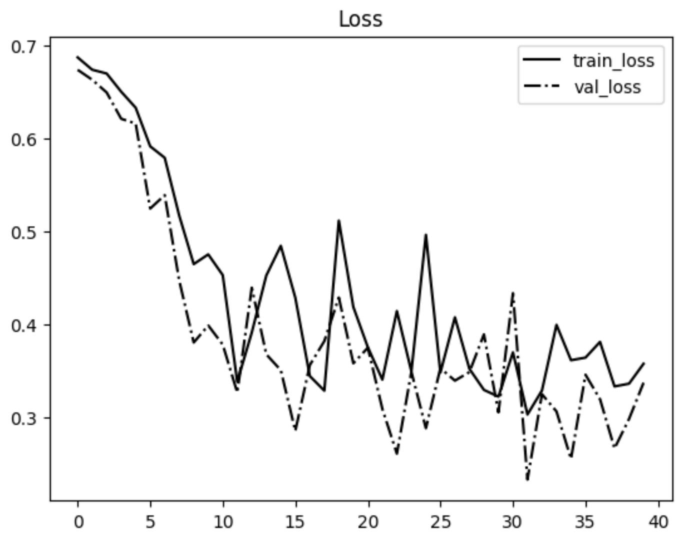

Figure 12. The loss graphs

The Receiver Operating Characteristic (ROC) curve is a graphical tool used to evaluate the performance of a model in binary classification problems [21]. The ROC curve illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) for different threshold values. True Positive Rate (TPR): The ratio of true positives to the total number of actual positives. False Positive Rate (FPR): The ratio of false positives to the total number of actual negatives. The ROC curve plots FPR on the x-axis and TPR on the y-axis. The area under the curve (AUC - Area Under the Curve) summarizes the overall performance of the model. The closer the AUC value is to 1, the better the model's classification ability. The ROC curve for this study is presented in Figure 13.

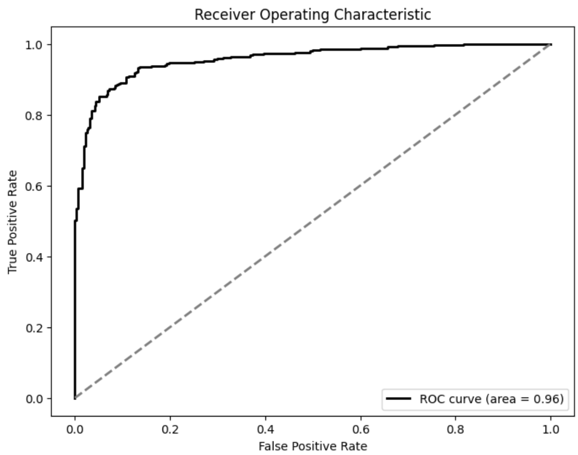

Figure 13. The Roc curve

Based on all these results, randomly selected images that were not present in the database were shown to the camera via a mobile phone. The Telegram bot was created via Telegram BotFather and integrated into the system using the *requests* library in Python. In the event of fire detection, the bot sends a direct message (mobile notification) to a predefined user ID. This mechanism ensures that the user is informed of the emergency even if they are not actively monitoring the system. Example scenarios are presented in the Figure 14. As clearly seen in the Figure 14, a warning message is sent to the phone as soon as the fire is detected.

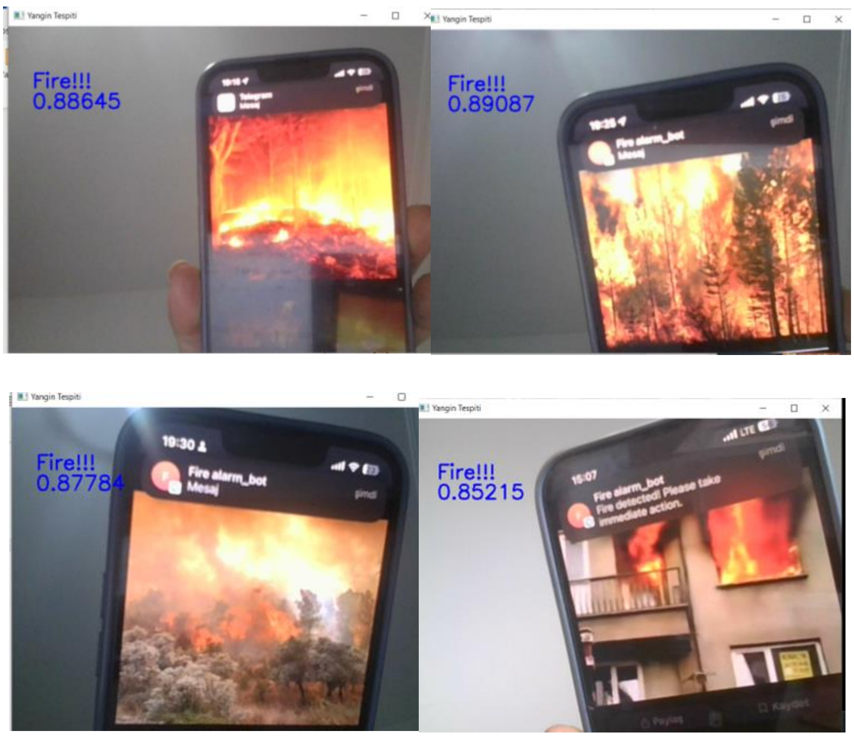

Figure 14. Example scenarios

After the fire was detected, the screenshot of the message sent via Telegram is shown in the Figure 15.

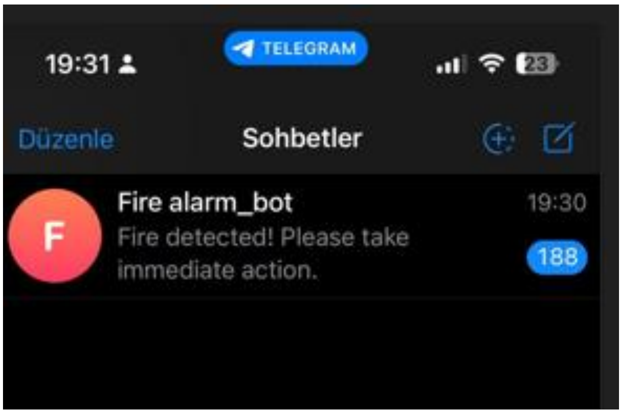

Figure 15. Message sent via Telegram

The conducted study demonstrates a fire detection accuracy of 89% and subsequently transmits fire-related alerts to users via Telegram. This capability enables the early identification of potential fire hazards and ensures prompt notification, thereby facilitating a significantly faster and more efficient emergency response.

4. Conclusion

In conclusion, camera-based fire detection systems, leveraging advanced image processing technologies and AI-powered analysis capabilities, represent a significant innovation in early fire detection and rapid response processes. These systems offer considerable advantages over traditional fire detection methods, particularly in monitoring large areas and detecting fires in their early stages. Furthermore, the use of communication technologies such as Telegram bots enhances the flexibility and accessibility of these systems. Real-time notifications via Telegram allow immediate action, minimizing potential damage and improving emergency response times.

The dataset utilized in this study indoor and outdoor fire scenarios, and the application of CNNs for image processing, demonstrates the robustness and reliability of the proposed system. The combination of image processing, deep learning, and communication tools ensures a comprehensive fire detection solution that is both efficient and scalable.

Overall, the study highlights the critical role of modern technologies in enhancing fire safety measures. By integrating CNN, image processing, camera-based fire detection systems provide an effective and timely solution for fire prevention and management, ensuring greater protection of lives and property.

Ethics in Publishing

There are no ethical issues regarding the publication of this study.

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