Mediterranean Smart Cities Conference (MSCC 2024)
2-4 May, 2024, Martil, Morocco

Low-Cost Real-Time Fire Detection in Smart Cities: Leveraging AI and IoT

Ohamouddou Said
National High School for Computer Science and Analysis,
Mohamed V University in Rabat
Rabat,Morocco
said_ohamouddou@um5.ac.ma

Boulaich Mohamed hamza
National High School for Computer Science and Analysis,
Mohamed V University in Rabat
Rabat, Morocco
Mohamedhamza_boulaich@um5.ac.ma

Meliani Hibatallah
National High School for Computer Science and Analysis,
Mohamed V University in Rabat
Rabat,Morocco
hibatallah_meliani@um5.ac.ma

Ennasar Mohammed Ali
National High School for Computer Science and Analysis,
Mohamed V University in Rabat
Rabat, Morocco
Mohammed-ali_ennasar@um5.ac.ma

El Afia Abdellatif
National High School for Computer Science and Analysis,
Mohamed V University in Rabat
Rabat, Morocco
abdellatif.elafia@ensias.um5.ac.ma
ORCID. 0000-0003-1921-4431

Abstract—

While fire has historically served crucial roles in human society, its position is evolving in modern, electricity-dependent smart cities. Paradoxically, the risk of fire has escalated due to variables including increased electrical device usage and wiring density. This necessitates the development of speedy and efficient fire detection systems. This research presents a low-cost Internet of Things (IoT) based solution for real-time fire detection employing deep learning. Our approach leverages a pre-trained VGG16 convolutional neural network (CNN) for feature extraction, followed by classification utilizing multiple machine learning methods like Support Vector Machines (SVM), Random Forests, and others. Importantly, SVM achieved the highest accuracy of 98.9% in classifying fire and non-fire scenarios. Upon fire detection, the system triggers SMS alerts to relevant authorities. This integrated method promises to provide a timely and reliable response to fire breakouts, boosting public safety and infrastructure protection in smart cities, all while retaining an emphasis on cost-effectiveness.

Keywords—Smart cities;Fire detection;Internet of Things (IoT);Deep learning;Artificial intelligence (AI)

I. INTRODUCTION

For millennia, fire has played a central role in human life, serving an array of daily tasks including food preparation, heating, and even tool making. However, this role of fire has evolved with the advent of smart cities, where electricity has largely replaced fire for many applications. Despite this evolution, the risk of fire in modern urban environments has significantly increased for various reasons. The intensive use of electrical appliances and the density of wiring heighten fire risks, posing a constant threat to the safety of inhabitants and the integrity of urban infrastructures. Short circuits, electrical overloads, and appliance malfunctions are among the factors that can ignite fires, often with devastating consequences. In this context, rapid and efficient fire detection becomes crucial to minimize damage and ensure the safety of citizens. The integration of Internet of Things (IoT) technologies and machine learning into fire detection systems offers a promising solution. These technologies enable real time monitoring and increased responsiveness to fire outbreaks, thus providing protection in increasingly connected and automated cities. In our study, we propose an IoT-based system dedicated to the real-time detection of fires, utilizing a pre-trained convolutional neural network (CNN) model for feature extraction, paired with various machine learning models serving as classifiers. This system is designed to alert the relevant authorities via SMS alerts in case of fire detection. Through this integrated approach, combining the power of AI and the efficiency of IoT, our solution aims to offer a quick and reliable response to fire outbreaks, thereby contributing to the protection of populations and the preservation of infrastructures in urban environments.

II. RELATED WORK

In reviewing the body of recent research on fire detection within smart cities and various environments, we observe a trend towards integrating advanced technologies like IR thermal imaging, deep learning, UAVs, and IoT for more effective and early fire detection systems. [1] outlines the foundational work on using IR thermal imaging cameras and dedicated image processing for fire detection. The authors demonstrate through four distinct experiments that even low-cost, low-resolution bolometric detector modules can efficiently detect fire's hot spots,

showcasing the utility of infrared cameras in identifying early signs of fire. [2], [4], and [8] focus on smart city applications, leveraging the power of deep learning, specifically the YOLOv8 and YOLOv2 algorithms, to detect fires in real-time with high accuracy and low false alarms. These studies propose a multi-layered smart fire detection system (SFDS) architecture that integrates Application, Fog, Cloud, and IoT layers, demonstrating state-of-the-art performance and potential for broader applications including gas leak and flood detection. [3] and [5] delve into the use of UAVs for fire detection, emphasizing the challenges of visual data analysis from aerial platforms. The proposed solutions employ deep multi-scale features and attention mechanisms to enhance fire detection accuracy in both smart cities and rural areas, highlighting the effectiveness of utilizing spatial object edges information and global image representations.[6] introduces a hybrid Local Binary Pattern Convolutional Neural Network (LBP-CNN) and YOLO-V5 model for fire detection in foggy conditions. This approach utilizes a two-part technique for feature extraction, achieving high precision rates in detecting fire and smoke in various environments, demonstrating the model's superiority over existing systems. [7] proposes an integrated solution combining wireless sensor technology, UAVs, and cloud computing, focused on improving the true detection rate of forest fires. This system demonstrates significant advancements in early fire detection through environmental monitoring and sensor networks. [9] addresses the limitations of existing deep learning models in fire detection, proposing a modified YOLOv5s model that integrates various enhancements for better detection performance with lower complexity. This research also contributes a new medium-scale fire dataset for further research. [10] advocates for the adoption of Edge and Fog computing principles in UAV-based forest fire detection, proposing a hierarchical architecture that optimizes resource allocation and addresses the challenges of early forest fire detection. [11] combines UAV and wireless sensor network technologies for early fire detection, highlighting the improvement in detection accuracy through the integration of image processing and IoT-based sensor data analysis.
Existing approaches, while effective, often require high computational power and incur significant costs, limiting their real-time fire detection capabilities in smart cities or even simpler environments. In contrast, our goal is to develop a low-cost prototype that is simple to deploy, enabling real-time fire detection for a wider range of applications.

III. PROPOSED METHOD

A. General architecture

The proposed fire detection system, as outlined in Figure 1, is both scalable and adaptable. It is capable of incorporating multiple cameras per Raspberry Pi unit and can integrate numerous Raspberry Pi units from various locations. Each Raspberry Pi serves as a node within a larger network, enabling widespread monitoring and increased coverage.

Here's an expansion of the system, referencing Figure 1:

1. Scalable Image Capture: Each Raspberry Pi, as indicated in Figure 1, can connect to multiple cameras. This multi-camera setup allows for comprehensive surveillance of a given area, maximizing visual coverage and improving the likelihood of early fire detection.

2. Network of Nodes: Our system is designed to support a network of Raspberry Pi units, each potentially situated at different locations. These distributed nodes can communicate with the central MQTT Broker, equipped with a GPU, to process images from all connected cameras.

3. Centralized Image Analysis with Machine Learning: The MQTT Broker, as shown in Figure 1, receives image data from the network of Raspberry Pis. The powerful GPU processes this data using a sophisticated machine learning model, capable of analyzing multiple streams of input for signs of fire.

4. Smart Notification System: Upon the machine learning model detecting a fire, the MQTT Broker identifies the specific Raspberry Pi—or nodes—that sent the images. It then sends a notification including the approximate location, which corresponds to the known location of the reporting Raspberry Pi unit.

5. Location-Specific Alerts: The GSM module issues SMS alerts that contain not just the fire detection message but also the approximate location, denoted as "place XY" in the SMS. This location corresponds to the Raspberry Pi that detected the fire, providing a location-specific response to facilitate swift action.

6. The integration of multiple cameras with each Raspberry Pi, along with the ability to connect many Raspberry Pi units, greatly extends the reach of our fire detection system. It enables a more robust and comprehensive network that can monitor vast areas, including multiple buildings or even entire neighborhoods, depending on the number of deployed nodes.

7. This scalable architecture ensures that when one of the Raspberry Pi units detects a potential fire through its camera array, it can quickly relay precise location data back to the central system. Consequently, the SMS alerts are not only timely but also location-accurate, providing first responders with critical information to expedite their response efforts.

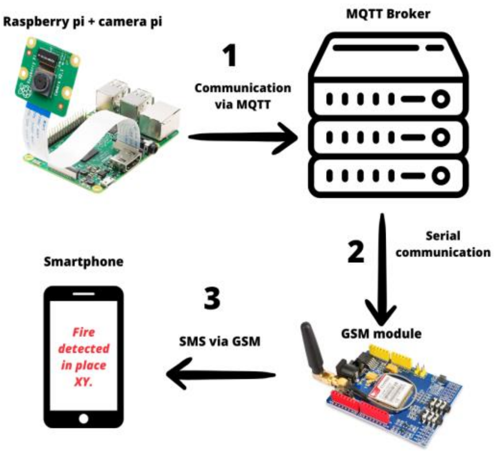

Figure 1. Our IoT Prototype for Fire Detection

B. Dataset

For the development and validation of our fire detection model, we employed the FIRE Dataset, sourced from Kaggle. This dataset is specifically curated to aid in training a binary classification model capable of distinguishing between images that depict fire ("fire images") and those that do not ("non-fire images"). The primary goal is to enable the model to accurately identify the presence of fire in various outdoor scenarios, a task that is fundamental for the implementation of effective fire detection systems.

The FIRE Dataset is systematically organized into two main folders, each representing one of the two classes under study:

• Fire Images: This folder contains a total of 755 images featuring outdoor fires. The images in this collection depict a wide range of fire scenarios, including significant occurrences of heavy smoke, which adds complexity to the fire detection task.

• Non-Fire Images: The counterpart folder comprises 244 images of natural landscapes and scenarios without any fire. These images include diverse scenes such as forests, grasslands, rivers, people, foggy conditions, lakes, animals, roads, and waterfalls.

Figure 2. Sample from the Fire Detection Dataset

C. Addressing Data Imbalance

A notable characteristic of the FIRE Dataset is its imbalance; the dataset does not feature an equal number of images for the fire and non-fire classes. Such an imbalance can potentially bias the model towards the class with more samples. To mitigate this issue and ensure a balanced evaluation, specific measures have been taken to configure the dataset split and the test set. The data is divided into training and testing sets, with 75% of the data used for training the model and the remaining 25% reserved for testing. Importantly, to address the dataset's inherent class imbalance and ensure a fair and unbiased assessment of the model's performance in distinguishing between fire and non-fire images, the test set includes an equal number of images from each class. This strategic configuration enables a more accurate evaluation of the model's effectiveness across both classes, despite the initial imbalance.

D. Image Normalization

Given that the images within the dataset vary significantly in size, a normalization step was essential to standardize the input data for model training. All images were resized to a uniform dimension of 224×224 pixels, and the pixel values were normalized by dividing each by 255. This two-fold normalization process not only facilitates the efficient processing of images by the convolutional neural network (CNN) but also eliminates potential discrepancies arising from varying image dimensions. The division of pixel values by 255 scales the input features to a range between 0 and 1, which is beneficial for the model's learning process, making it easier to converge to a solution.

E. Models

Our methodology commences with the deployment of the VGG-16 model, leveraging its pretrained weights for foundational image processing. This initial step is augmented by a flattening process, culminating in the incorporation of a distinctive, trainable fully connected (FC) layer. This layer is meticulously designed to ascertain the probability of fire occurrence within an image. The intricate details of this model's architecture are methodically illustrated in Figure 3. Following the establishment of this foundational model, our investigation progresses to an exhaustive evaluation of a comprehensive range of machine learning classifiers. These classifiers include K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, Gradient Boosting, and Gaussian Naive Bayes. The primary objective of this extensive evaluation is to discern the classifier that exhibits the optimal performance in the context of fire detection accuracy, thereby ensuring the most effective method for identifying fire-related incidents in imagery.

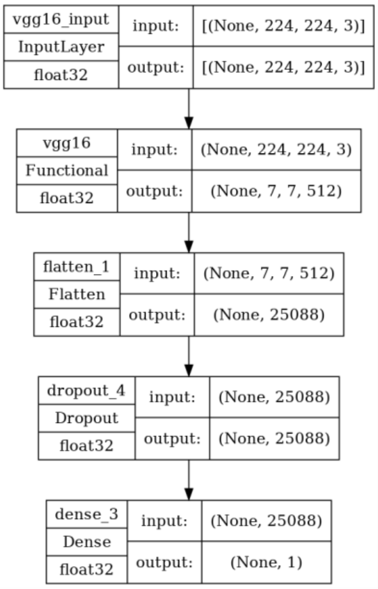

Figure 3. VGG16 Feature Extractor with an Added Fully Connected Classification Layer

D. *Evaluation Metrics*

To evaluate our classifiers for fire detection, we employ the following metrics, each providing a unique lens through which to assess performance:

1. Accuracy: Accuracy is the measure of how often the classifier makes the correct prediction. It's the ratio of correct predictions (both true positives and true negatives) to the total number of predictions. It gives us a baseline understanding of effectiveness, especially in balanced datasets where each class is equally represented.

$$\text{Accuracy} = \frac{\#\text{ correct predictions}}{\text{total }\#\text{ of predictions}}$$

2. Precision: Precision tells us the proportion of positive identifications that were actually correct. It measures the quality of the positive class predictions.In the context of fire detection, precision is crucial because it reflects the rate of false alarms — a high precision means fewer false alarms.

$$\text{Precision }(p) = \frac{TP}{TP + FP}$$

3. Recall: or sensitivity, indicates the proportion of actual positives that were correctly identified. It measures the classifier's ability to detect all positive instances.For fire detection, high recall is vital as it shows the system's capability to identify most, if not all, actual fires, minimizing the risk of missed detections.

$$\text{Recall }(r) = \frac{TP}{TP + FN}$$

4. F1 Score: F1 Score is the harmonic mean of precision and recall, providing a single metric to assess the balance between them. It's especially useful when you want to find a balance between the precision (minimizing false positives) and recall (minimizing false negatives), which is often the case in our fire detection application.

$$\text{F1\_score }(F) = \frac{1}{\left(\frac{1/r + 1/p}{2}\right)}$$

IV. EXPIREMENT RESULTS

Table 1 illustrates that both Fully Connected Layers and Support Vector Machines emerge as exemplary in their predictive prowess, with nearly perfect metrics approximating 0.99. This reflects their robust capability for precise and consistent predictions in detecting fires. On the contrary, the K-Nearest Neighbors classifier displays a substantial dip in both accuracy and F1 metrics, suggesting its probable inefficacy for fire detection despite its notable precision. Classifiers such as the Decision Tree, Random Forest, and Gradient Boosting, however, present robust performances with scores exceeding 0.96, affirming their effectiveness in this realm. The Gaussian Naive Bayes classifier, despite not reaching the zenith achieved by the Fully connected layer or SVM, still showcases a laudable performance, with scores approaching 0.96.

The divergence in performance metrics among these classifiers is indicative of the inherent challenges of fire detection tasks, which seem to particularly favor the complex decision contours generated by SVMs and Fully Connected Layers. The suboptimal performance of the KNN classifier is likely a consequence of its sensitivity to the high-dimensional feature space and the distinct characteristics of fire within images, which demand a more sophisticated discernment than what simple distance measurements can provide.

The consistently high precision observed in nearly all classifiers, KNN being the exception, highlights their effective identification of actual fire instances. However, the variance observed in recall and F1 metrics across these classifiers points to their differing abilities to generalize across instances, ensuring minimal false positives while capturing true positives efficiently.

TABLE I. OVERVIEW OF CLASSIFICATION MODEL METRICS IN FIRE DETECTION TASK

Classifier	Accuracy	Precision	Recall	F1 Score
FC	**0.989**	**0.989**	**0.989**	**0.989**
K-NN	0.462	0.821	0.462	0.465
SVM	**0.989**	**0.989**	**0.989**	**0.989**
DT	0.964	0.965	0.964	0.964
RF	**0.984**	**0.984**	**0.984**	**0.984**
GB	0.979	0.979	0.979	0.979
NB	0.964	0.965	0.964	0.964

V. CONCLUSION

This analysis reveals the distinct advantage of classifiers such as Fully Connected Layers and Support Vector Machines in the context of fire detection, noted for their unparalleled accuracy and the harmonious balance between precision and recall demonstrated through their F1 metrics. Such attributes make them particularly suited for applications where inaccuracies—either as false negatives or positives—carry significant repercussions. Nonetheless, the choice of a classifier must also reflect considerations around computational resources, data availability for training, and the specific operational conditions of the fire detection framework. Future research should concentrate on refining these classifiers further, perhaps through ensemble strategies or innovative deep learning models, to amplify their efficacy and dependability in a variety of fire detection settings.

REFERENCES

[1] G. Eason, B. Noble, and I. N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” *Phil. Trans. Roy. Soc. London, vol.* A247, pp. 529–551, April 1955. (references)

[2] J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[3] I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in *Magnetism*, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[4] K. Elissa, “Title of paper if known,” unpublished.

[5] R. Nicole, “Title of paper with only first word capitalized,” *J. Name Stand. Abbrev.*, in press.

[6] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” *IEEE Transl. J. Magn. Japan*, vol. 2, pp. 740–741, August 1987 [*Digests 9th Annual Conf. Magnetics Japan*, p. 301, 1982].

[7] M. Young, *The Technical Writer's Handbook*. Mill Valley, CA: University Science, 1989.

[8] *Annual Report of Research Institute of Intelligent Computer systems*, 2009, 71 p. (in Ukrainian)