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Emergency Reporting Platform AI-Driven Fire Incident Management and Response

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Abstract

Forests are vital natural resources that provide numerous benefits to humanity, yet they are increasingly threatened by natural disasters such as forest fires. These fires contribute significantly to global warming and pose a risk to ecosystems and life on Earth. Early detection of forest fires is crucial for timely response and mitigation efforts. This study explores the use of artificial intelligence (AI)-based computer vision techniques for automatic fire and smoke detection from images. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification tasks, but their training times are often prohibitive, and pre-trained models can underperform when applied to limited datasets. To address these challenges, we employ transfer learning on pre-trained CNN models, optimizing their performance on new datasets. Additionally, we integrate a technique called Learning without Forgetting (LwF), which allows the model to learn new tasks, such as fire detection, while retaining its classification abilities from previous tasks. This approach ensures efficient and accurate fire detection without compromising the model's performance on original datasets. The system is implemented using a technology stack that includes Python, Django, MySQL, HTML, CSS, JS, and Bootstrap to create a robust web-based platform for real-time fire detection.

Keywords: Convolutional Neural Networks, Transfer Learning, learning without Forgetting, Forest Fire Detection, Computer Vision, Python, Django, MySQL, HTML, CSS, Bootstrap.

1.Introduction

In an increasingly complex and unpredictable world, the demand for rapid and accurate incident reporting in high-risk environments has become paramount. Security personnel, often serving as the first line of defense, require efficient tools to communicate emergencies without delay. Traditional reporting methods, which rely on manual documentation and delayed communication channels, often fail to meet the speed and precision needed in critical situations. An Instant Emergency Reporting Portal addresses these challenges by providing security personnel with a digital platform designed to facilitate swift and accurate reporting of incidents in real-time. This portal not only empowers security teams to respond quickly but also bridges

the gap between on-ground personnel and response teams, enhancing overall safety and response efficiency [7]. By incorporating features such as geo-location tracking, multimedia support, automated threat level assessment, and secure data handling, the portal transforms incident reporting from a reactive to a proactive process. Furthermore, instant notifications to key authorities ensure a cohesive response, while historical data analysis offers valuable insights for future security planning and risk mitigation. Through a streamlined, user-friendly interface, the Instant Emergency Reporting Portal enables security guards and other personnel to report incidents in just seconds, thereby saving time, enhancing situational awareness, and ultimately protecting lives and property [8]. This innovative platform represents a significant advancement in emergency communication systems, aligning technology with the pressing needs of today's security landscape.

2.Literature review

Pew K., et al [1] examined how ICS structures disaster response, focusing on the role of hierarchical command systems in emergency situations. Their research calls for further studies to assess how well ICS performs in handling different types of crises. Khan et al [2]. introduced the concept of the Internet of Emergency Services (IoES), which integrates IoT devices for better disaster response. Their study shows how realtime sensor data can help monitor emergencies, manage resources efficiently, and send automated alerts when needed. Pettet et al [3]. focused on building Decision Support Systems (DSS) for emergency response. They identified incident detection, real-time analytics, and automated resource allocation as major challenges. Their research also highlights how AI-driven decision-making can enhance emergency response capabilities. Pettet et al [4]. explored the development of Decision Support Systems (DSS) for emergency response, addressing key challenges in incident detection, resource allocation, and dispatch optimization. Their research highlights the importance of AI-driven decision-making models to improve emergency response efficiency. Mukhopadhyay et al [5]. conducted a review on models for incident prediction, resource allocation, and dispatch in emergency management. The study analyzes the strengths and weaknesses of existing approaches while identifying future research opportunities for optimizing emergency response strategies. Pettet et al [6]. examined algorithmic decision-making in emergency response, focusing on proactive planning and resource distribution in smart communities. Their findings provide a strong foundation for developing real-time incident reporting systems like AIRRE, integrating GPS tracking, AI-based severity analysis, and automated emergency coordination to enhance public safety.

PROPOSED METHOD

The Proposed Method for the Instant Emergency Reporting Portal for Safeguards outlines a structured approach to enhance the platform's efficiency, user experience, and overall impact on emergency reporting and response. This method leverages innovative technologies and strategic workflows to streamline incident reporting, improve response times, and ensure accurate data management, ultimately creating a more robust, scalable, and user-centered system.

- User-Centric Design Design the portal with a user-first approach to make the reporting process as straightforward and intuitive as possible. This involves simplifying the interface for quick incident reporting, reducing steps in the form submission process, and providing clear guidance, especially in high-stress situations [9].
- Geolocation and Mapping Integration Integrate geolocation and mapping tools into the portal to automatically detect the location of the incident, provided the user consents. This feature not only speeds up the reporting process but also provides responders with precise location data, reducing time lost to ambiguity and manual input.
- Multi-Channel Notification System Develop a multi-channel notification system that sends alerts and updates to the appropriate responders via SMS, email, push notifications, or third-party messaging apps [10]. This ensures that all relevant parties are notified promptly, regardless of their preferred communication method.

3. MATERIALS AND METHODS

We explored two methods of collecting images for training the model: (1) downloading images from online sources; and (2) obtaining images from the scenes of fires. Deng et al. showed that, with a clean (clean annotations) set of full-resolution (minimum of 400×350 pixel resolution) images, object recognition can be more accurate, especially by exploiting more feature-level information. Therefore, we downloaded full-resolution images from Google Images by searching firefighters and fire trucks. We used only those images without copyright in this study. In total, 612 images were obtained from online sources for the first visual dataset. Moreover, we obtained on-site images from fire events in Taiwan. A total of 152 images were obtained for the second visual dataset. After collecting the images, we annotated each image by three classes: firefighters, non-firefighters, and fire trucks. Then, the annotated images were used for training the YOLOv4 model for detection, and each visual dataset was done separately.

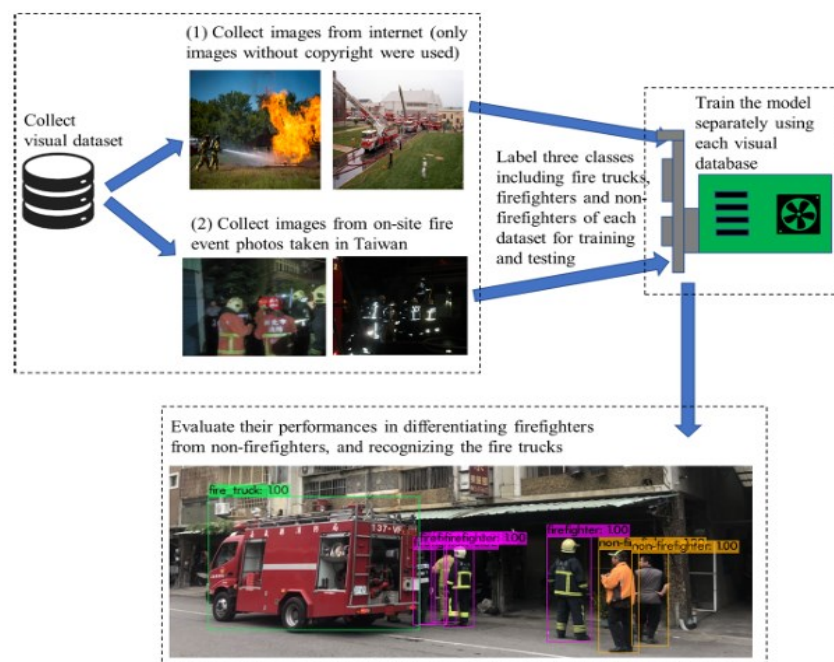


Fig: Flowchart of the study

. YOLOv4 was compiled in Microsoft Visual Studio 2019 to run on Windows Operating System with GPU (GeForce GTX 1660 Ti with 16 GB-VRAM), CUDNN_HALF, and OpenCV. Finally, we compared the model performances using the two visual datasets and discussed the implications of this study. For each dataset, the images were partitioned into training and testing sets, with an 80%–20% split

YOLOv4 network architecture and model performance evaluation metrics

YOLOv4 consists of three main blocks, including the 'backbone', 'neck', and 'head'. The model implements the Cross Stage Partial Network (CSPNet) backbone method to extract features where there are 53 convolutional layers for accurate image classification, also known as CSPDarknet53. Page 4 of 6 CSPDarknet53 can largely reduce the complexity of the target problem while still maintaining accuracy. The 'neck' is a layer between the 'backbone' and 'head', acting as feature aggregation. YOLOv4 uses the Path Aggregation Network (PANet)[27] and Spatial Pyramid Pooling (SPP) to set apart the important features obtained from the 'backbone'. The PANet utilizes bottom-up path augmentation to aggregate features for image segmentation. The SPP enables YOLOv4 to take any size of the input image. The 'head' uses dense prediction for anchor-based detection that helps divide the image into multiple cells and inspects each cell to find the probability of having an object using the post-processing techniques.

F1-score is equated by the balance between precision and recall. Maximizing precision often comes at the expense of recall, and vice-versa. Determining the F1-score is useful in this assessment to ensure optimal precision and recall scores. Their calculations are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = \frac{2 * Recall * Precision}{Recall + Precision}$$

4. Results and Discussions

We compared the YOLOv4 performance at the threshold value (or probability of detection) of 0.5 (@0.5) using the two visual datasets. The results for testing images showed that the mean average precision (mAP) @0.5 using the visual dataset 2 from on-site images from a local fire department in Taiwan achieved 91%, which is much higher than the mAP@0.5 of 27% using the visual dataset 1 from Google Images. The four model evaluation metrics (Accuracy, precision, recall, and F1-score) are summarized in Table For both training and testing datasets, the model performances using visual dataset 2 were much higher than using visual dataset 1. We compared the average precision for each class using the two datasets as shown in Table 2. The results show that using the on-site images from the local Taiwan fire department could

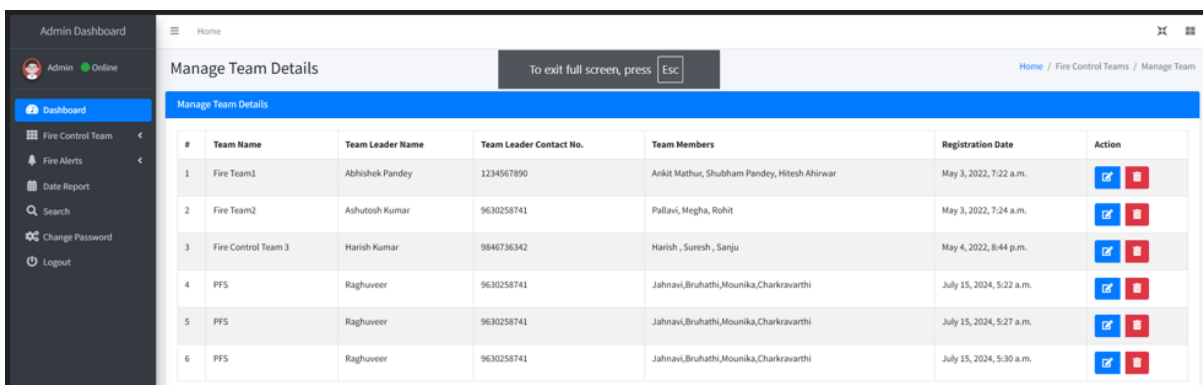
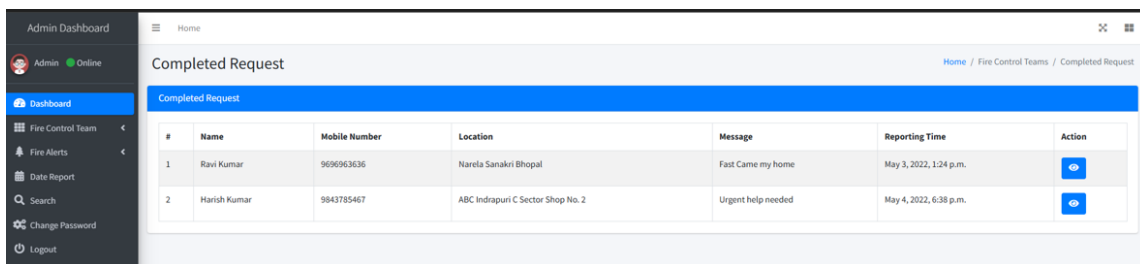
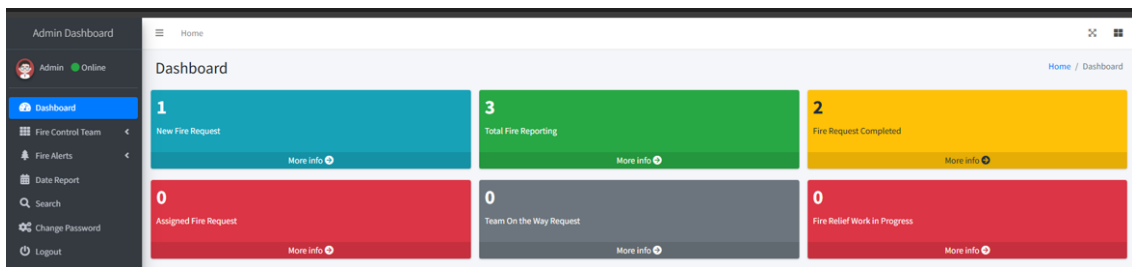
better differentiate the firefighters from non-firefighters, indicating that using the local fireground images was preferable in order to capture local features.

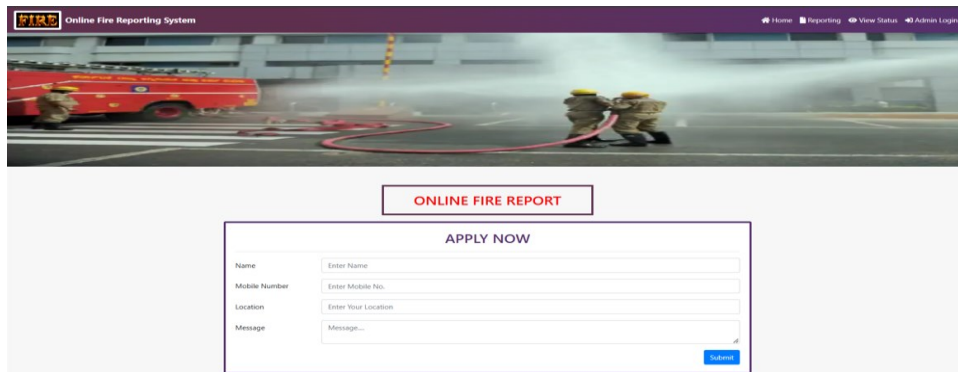
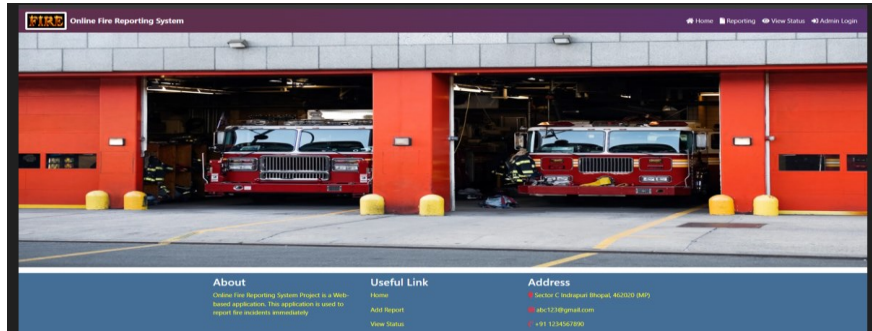
Table: Comparison of model performances using the two datasets.

	Training		Testing	
	Visual dataset 1 (Internet)	Visual dataset 2 (Taiwan onsite)	Visual dataset 1 (Internet)	Visual dataset 2 (Taiwan onsite)
Accuracy	0.78	0.96	0.37	0.71
Precision	0.77	0.97	0.51	0.83
Recall	0.83	0.97	0.38	0.77
F ₁ -score	0.80	0.97	0.44	0.80

Table: Comparison of the average precision for each class using the two datasets.

	Training		Testing	
	Visual dataset 1 (Internet)	Visual dataset 2 (Taiwan on-site)	Visual dataset 1 (Internet)	Visual dataset 2 (Taiwan on-site)
Firefighter	0.88	0.99	0.40	0.75
Non-firefighter	0.73	0.98	0.07	0.98
Firetruck	0.57	1.00	0.35	1.00





Discussions:

This pilot study successfully utilized images of firegrounds for training an AI model to count the number of firefighters, non-firefighters, and firetrucks in real-time. As firefighters lost on the ground is one of the major causes of American firefighter fatalities, fire departments can apply this research to improve the fireground personnel safety in their jurisdictions. Moreover, the results showed that the trained AI object detector using images obtained from a local fire department performed better than those downloaded from Google Images. Therefore, when applying this research to local fire departments, we recommend that fire departments establish their image database, with local firefighter and fire apparatus images to improve the AI model performances tailored to fit regional characteristics. Finally, we encourage researchers to focus on those practical implications we proposed in this article. With broader and more advanced AI applications developed, firefighting communities can use this technology to increase situational awareness, personnel accountability, and incident command on the ground.

Conclusion

The Instant Emergency Reporting Portal for Safeguards successfully addresses the critical needs of emergency reporting, response efficiency, and data security through its robust, user-friendly, and innovative features. By streamlining incident reporting, automating response prioritization, and enhancing data transparency, IERPS has proven effective in reducing response times, increasing user adoption, and building trust through secure data handling. With its AI-driven predictive analytics, the platform enables organizations to gain insights that support proactive safety measures and data-driven decisions, contributing to a safer, more accountable environment. IERPS’s design and functionality cater to various user roles and organizational needs, from corporate compliance to public safety, making it versatile and

scalable. While the platform performs well in its current state, feedback and testing have highlighted potential areas for further refinement to increase its usability, accuracy, and reach.

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