Received: 17 April 2023 | Revised: 9 June 2023 | Accepted: 12 June 2023 | Published online: 27 June 2023

RESEARCH ARTICLE

Artificial Intelligence and Applications
2023, Vol. 00(00) 1–6
DOI: 10.47852/bonviewAIA3202975

BON VIEW PUBLISHING

An AI-Based Early Fire Detection System Utilizing HD Cameras and Real-Time Image Analysis

Leendert Remmelzwaal[1,*]

[1]Department of Electrical Engineering, University of Cape Town, South Africa

Abstract: Wildfires pose a significant threat to human lives, property, and the environment. Rapid response during a fire's early stages is critical to minimizing damage and danger. Traditional wildfire detection methods often rely on reports from bystanders, leading to delays in response times and the possibility of fires growing out of control. In this paper, ask the question: "Can AI object detection improve wildfire detection and response times?". We present an innovative early fire detection system that leverages state-of-the-art hardware, artificial intelligence (AI)-powered object detection, and seamless integration with emergency services to significantly improve wildfire detection and response times. Our system employs high-definition panoramic cameras, solar-powered energy sources, and a sophisticated communication infrastructure to monitor vast landscapes in real time. The AI model at the core of the system analyzes images captured by the cameras every 60 s, identifying early smoke patterns indicative of fires and promptly notifying the fire department. We detail the system architecture, AI model framework, training process, and results obtained during testing and validation. The system demonstrates its effectiveness in detecting and reporting fires, reducing response times, and improving emergency services coordination. We have demonstrated that AI object detection can be an invaluable tool in the ongoing battle against wildfires, ultimately saving lives, property, and the environment.

Keywords: wildfire detection, artificial intelligence, object detection, panoramic cameras, solar-powered system

1. Introduction

Wildfires pose a significant threat to human lives, property, and the environment. The rapid response during a fire's early stages is critical in determining the level of damage and danger it can cause. Traditional wildfire detection methods often rely on reports from bystanders, leading to delays in response times and the possibility of fires growing out of control. On average, Australia experiences around 50,000–60,000 bushfires annually, with estimated damage varying significantly depending on the severity and location of the fires.

A recent example of the devastating impact of wildfires can be seen in the Margaret River bushfires in Western Australia in 2011. These fires ravaged the area, destroying more than 30 homes and forcing over 200 residents to flee to safety. Smoke from the inferno engulfed the region, creating hazardous conditions and complicating firefighting efforts. The annual cost of bushfire damages in Australia is around AUD 1.6 billion, but this figure can be much higher in years with particularly severe fires, such as the 2019–2020 Australian bushfire season, which resulted in damages estimated to exceed AUD 10 billion. Given the potentially disastrous consequences of wildfires, there is a pressing need for more advanced and efficient detection methods to enable a faster and more effective response.

Recent advancements in artificial intelligence (AI), specifically convolutional neural networks (CNNs) (Sun et al., 2021), have demonstrated their potential to revolutionize various industries, including fire detection and response. CNNs have achieved exceptional performance in object classification (He et al., 2016; Krizhevsky et al., 2012; Simonyan and Zisserman, 2015; Szegedy et al., 2017), object detection (Bochkovskiy et al., 2020; Li et al., 2022; Lin et al., 2017; Liu et al., 2016), and object segmentation (Chen et al., 2018; He et al., 2017; Long et al., 2015; Long et al., 2015; Ronneberger et al., 2015) on established image datasets and have found applications in autonomous driving, robotics, and video surveillance. Among these tasks, object detection is particularly relevant for fire detection, as it involves identifying the location and category of objects within an image, such as smoke or flames.

In this paper, we present an innovative early fire detection system that utilizes state-of-the-art hardware, AI-powered object detection, and seamless integration with emergency services to significantly improve wildfire detection and response times.

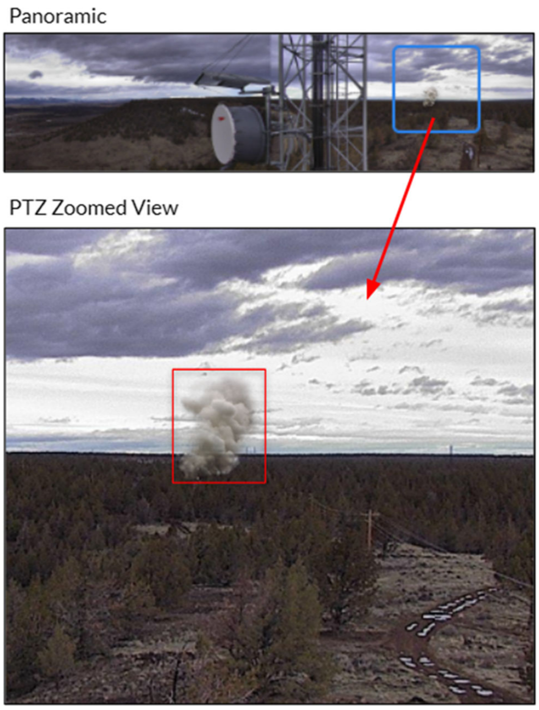
Our system combines high-definition panoramic cameras, solar-powered energy sources, and a sophisticated communication infrastructure to monitor vast landscapes in real time. The AI model at the core of the system analyzes images captured by the cameras every 60 s, identifying early smoke patterns indicative of fires and promptly notifying the fire department (see Figure 1). This approach ensures rapid response and coordination, minimizing the potential damage caused by wildfires.

This paper is organized as follows: Section 2 details the system architecture, including the camera system, solar power system, communication infrastructure, and public interface. Section 3

*Corresponding author: Leendert Remmelzwaal, Department of Electrical Engineering, University of Cape Town, South Africa. Email: leen@firststep.ai

© The Author(s) 2023. Published by BON VIEW PUBLISHING PTE. LTD. This is an open access article under the CC BY License (https://creativecommons.org/licenses/by/4.0/).

Figure 1
Detection of bushfire



outlines the AI model architecture, focusing on the object detection model, dataset creation, and training process. Section 4 presents the results obtained during the testing and validation of the system, demonstrating its efficacy in detecting and reporting fires, reducing response times, and improving emergency services coordination. Finally, Section 5 discusses potential future work and enhancements to further improve the system's performance and capabilities.

In summary, this paper introduces a cutting-edge early fire detection system that combines high-definition cameras and AI-driven image analysis to revolutionize wildfire monitoring and response. By providing accurate, real-time information to emergency services, the system has the potential to significantly reduce the damage caused by wildfires and protect human life and property.

2. Review of early fire detection approaches

In recent years, the application of cameras for early fire detection has garnered significant attention, with several methodologies emerging as the most prevalent. The following literature review explores these methods and the research that underpins them:

Flame detection: One of the widely used techniques for fire detection involves the identification of unique flame features, such as flickering behavior, color, and shape. Celik (2010) demonstrates that flame detection algorithms typically rely on image processing techniques to extract these features and recognize the presence of fire in captured images (Celik, 2010).

Smoke detection: Another common approach to fire detection is the analysis of images for specific smoke characteristics, including color, texture, and motion. Töreyin et al. (2006) reveal that by detecting and tracking the movement of smoke, these algorithms can provide early warning of a developing fire (Töreyin et al., 2006).

Thermal imaging: Thermal cameras detect heat and create visual representations of temperature variations in the scene. By identifying temperature anomalies, this method can detect fires even in low visibility conditions, such as in the presence of smoke or fog (Bouguettaya et al., 2022).

Machine learning-based detection: With the advancements in machine learning and computer vision, various models have been proposed for fire detection using features learned by algorithms. Bouguettaya et al. (2022) discuss the effectiveness of deep learning-based computer vision algorithms for early wildfire detection from unmanned aerial vehicles (Bouguettaya et al., 2022). Akagic and Buza (2022) present a lightweight wildfire image classification method using deep CNNs (Akagic & Buza, 2022). Wang et al. (2019) explore forest fire image recognition based on CNNs (Wang et al., 2019).

For the current project, access to thermal imaging was unavailable, with only panoramic cameras at our disposal. However, we were not constrained to edge processing and had access to cloud computing power. Consequently, we opted to utilize the machine learning-based detection approach for our fire detection system.

This research paper introduces an AI model capable of real-time processing of panoramic images. Notably, we employ cutting-edge object detection techniques, which distinguish our methodology from previous studies, such as the work conducted by Bouguettaya et al. (2022), which utilizes image tessellation and object classification. Our approach, centered around object detection, demonstrates higher efficiency due to its independence from the need for image tessellation.

3. Research methodology

The proposed early fire detection system consists of a sophisticated hardware setup and a communication infrastructure that seamlessly integrates with the AI model and fire department resources. This section outlines the key components of the system's architecture and their roles in ensuring effective and efficient fire detection and response.

3.1. Camera system

The entire hardware solution comprises three cameras and a solar power unit, mounted on a pole (see Figure 2). Two high-definition 180-degree cameras work together to create a comprehensive 360-degree panoramic view of the monitored landscape. A single high-definition pan–tilt–zoom (PTZ) camera is employed for detailed fire imaging and investigation. This PTZ camera can be remotely controlled from the control tower or by the AI system, allowing for adjustments in pan (x-axis), tilt (y-axis), and zoom as needed. The integration of a feedback loop between the software and the PTZ camera ensures optimal imaging and analysis.

3.2. Solar power system

The system utilizes state-of-the-art solar panels, a solar controller, and solar batteries with smart charging capabilities to ensure continuous operation in any environment (see Figure 2). The solar power system eliminates the need for external power supplies, making it suitable for remote deployment. The batteries have a life expectancy of 5 years, reducing the need for frequent maintenance and replacement.

3.3. Communication infrastructure

A reliable 4G connection is incorporated into the system, enabling 24/7 real-time internet connectivity for live streaming of images from the cameras to a cloud server. This high-speed connection also facilitates real-time feedback to the PTZ

Figure 2
Camera and solar panel hardware

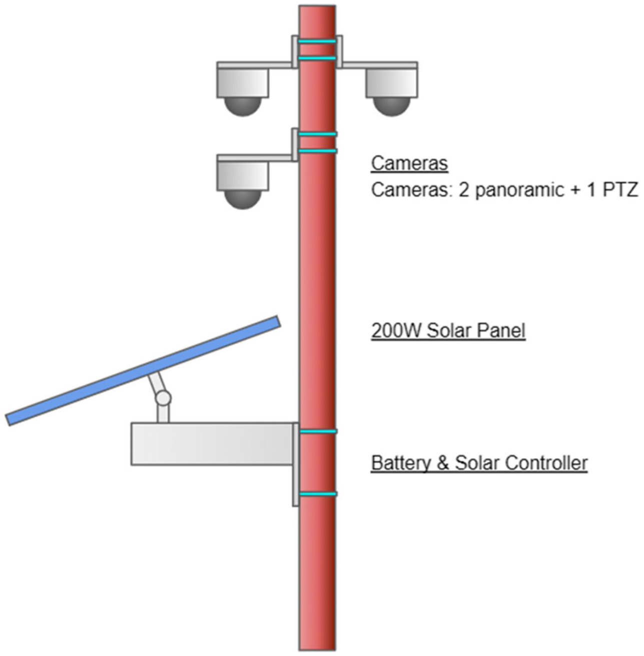
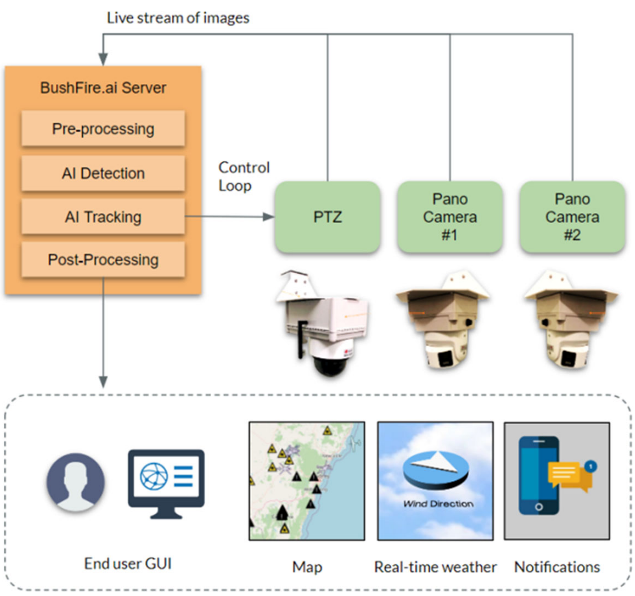


Figure 3
System architecture



controller, ensuring efficient communication between the hardware components and the AI system. High-speed video links provide seamless transmission of images to the AI system and the fire department for rapid analysis and response (see Figure 3).

3.4. Public access and interface

The software for the fire detection system is accessible to the public through the website bushfire.ai. This platform allows users to view real-time images from the camera system and receive information on detected fires, fostering awareness and community engagement in wildfire monitoring and prevention.

In summary, the system architecture consists of an advanced camera system, a solar power system, a communication infrastructure, and a user-friendly public interface. These components work together to create a robust and reliable early fire detection system that can be deployed in various environments, providing real-time data and images for effective fire detection and response.

4. AI model architecture

The AI component of the early fire detection system plays a crucial role in analyzing images captured by the camera system and identifying smoke patterns indicative of fires. This section describes the architecture of the AI model, including the methodology, object detection model, dataset creation, and training process.

4.1. Methodology

In this paper, we present a methodology for the development of an AI component for early bushfire detection. The AI model is designed to analyze 360-degree panoramic images, identify distinctive smoke trails and signs of fire, utilize object detection to recognize smoke or fire, track the movement of smoke over time, and map the direction of movement with known wind direction to correlate the direction of growth.

To process the images, the AI system employs a camera system that captures 360-degree panoramic images at a rate of one image per minute. These high-resolution images provide comprehensive coverage of the monitored area, enabling the early detection of emerging fires. The primary objective of the AI model is to identify distinctive smoke trails and signs of fire within the captured images, which is achieved by analyzing the visual features of the images, such as color, texture, and shape, to pinpoint potential fire-related patterns.

The AI model leverages advanced object detection techniques to accurately identify smoke or fire within the images. This involves training the model on a comprehensive dataset containing annotated images of smoke and fire, allowing it to learn the unique characteristics of these phenomena and distinguish them from other objects in the scene. In order to determine the direction of movement, rate of growth, and size of a detected fire, the AI model tracks the movement of smoke over time. By comparing consecutive images, the system can analyze the changing patterns of smoke and infer valuable information about the progression of the fire.

Lastly, the AI model maps the direction of smoke movement with known wind direction data to correlate the direction of growth of the fire. This information can be used to predict the likely path of the fire, facilitating more efficient and effective firefighting efforts. By integrating these methodologies, the AI-based early fire detection system can rapidly and accurately detect emerging bushfires, ultimately assisting in the timely mitigation of potential damages and loss of life.

4.2. Object detection model

The system incorporates a multitude of intricate steps, including pre-processing, various AI detection and classification models, and post-processing. This discussion provides a glimpse into one specific object detection model utilized within the pipeline. However, other components of the system are proprietary and cannot be disclosed.

Among the AI object detection models employed in this system, one is founded on the YOLOv5 architecture, an advanced deep learning model recognized for its exceptional accuracy and efficiency in identifying objects within images (Bochkovskiy et al., 2020; Jocher, 2022; Redmon et al., 2016; Thuan, 2021). Utilizing the PyTorch framework, the YOLOv5 model is configured to process input images with dimensions of 640 × 640 pixels, ensuring high-resolution analysis for precise fire detection.

4.3. Dataset creation

To train the AI model, a dataset of 20,000 images was created using panoramic cameras deployed across the United States and Australia. The images were collected over a 12-month period to account for variations in seasons and weather conditions, ensuring a diverse and representative dataset. The dataset was split into a 70% training set and a 30% validation set to evaluate the model's performance during the training process.

The dataset includes images with and without fire, and the model is trained to recognize both scenarios. Images were annotated by wildfire experts. Images without annotations, i.e., those without visible fires, are not ignored during training. This approach informs the model about the absence of fires, enhancing its ability to differentiate between fire and non-fire conditions.

4.4. Data augmentation

To improve the model's robustness and generalization capabilities, data augmentation techniques were applied during the training process. These techniques include horizontal flipping, scaling, brightness adjustments, hue changes, and saturation modifications. Vertical flipping was excluded from the augmentation process, as it may introduce unrealistic scenarios for wildfire detection.

4.5. Model training

The AI model was trained for 679 epochs, achieving a mean average precision (mAP) score (IoU@0.05:0.95) of 0.04 and an accuracy of 93.5% (see Table 1). The training process was halted at 679 epochs because the model's loss did not improve further, and additional training epochs led to overfitting and reduced generalization.

During the training process, the AI model learned to detect early smoke patterns from fires by analyzing the input images. It also learned to control the PTZ camera through the feedback loop, adjusting the camera's pan, tilt, and zoom settings to better capture and analyze fires.

In summary, the AI model architecture combines a powerful object detection model with a diverse dataset, data augmentation techniques, and an optimized training process. This comprehensive approach enables the early fire detection system to effectively identify and track the movement of smoke over time, enhancing the overall performance and utility of the system in wildfire monitoring and response.

4.6. Possible shortcomings

Within the domain of camera systems, the orientation of the cameras, in conjunction with the application of Zoom functionality and the presence of image distortion, holds the potential to exert an influence on the outcomes of AI detection. To ensure the adaptability and reusability of trained AI models, it is imperative to undertake the process of normalizing and deskewing raw images prior to their submission for AI inference. By implementing these measures, the effectiveness of AI detection can be enhanced, allowing for the preservation and continued utilization of trained AI models.

5. Results

The performance of the early fire detection system's AI model was evaluated based on its ability to accurately identify and report fires in their early stages. This section presents the key results obtained during the testing and validation process, demonstrating the system's efficacy and its potential to enhance fire response efforts.

The AI model achieved a mAP score (IoU@0.05:0.95) of 0.04 and an accuracy of 93.5% during the training process. These results indicate that the model is highly effective at detecting smoke patterns indicative of fires within the input images (see Figure 4). The trained AI model was able to identify early-stage fires with high precision, ensuring prompt notification of the fire department and facilitating rapid response efforts.

In addition to the detection performance, several anecdotal benefits have emerged from the implementation of the system:

Reduced response time: Anecdotal evidence suggests that the proposed system, which continuously monitors large areas with high-resolution cameras and employs the AI model for real-time image analysis, has significantly reduced response times compared to traditional fire reporting methods. This improvement in response time has the potential to greatly reduce the scale of wildfires and the associated damage to human life and property.

Web portal for first responders: The early fire detection system features a real-time dashboard tailored for first responders, integrating AI processing and facilitating communication and coordination among emergency services. This web portal not only

Table 1
Fine tuning parameters

Parameter	Value
Framework	PyTorch
Model	Similar to YOLOv5
Input size	640 × 640 pixels
Dataset size	20,000 images
Data augmentations	Horizontal flip, scale, brightness, hue, saturation
Number of epochs	679
Accuracy	93.5%
Loss	Not improved after 679 epochs
mAP score	0.041 (IoU@0.05:0.95)
Train/Val split	70% / 30%

Figure 4
Example detection of a fire

notifies the relevant fire department upon detecting a potential fire but also provides high-resolution images of the fire location, satellite map data with a weather overlay, and real-time information about fire department aircraft, which enhances situational awareness and decision-making.

Public engagement and awareness: The system promotes community engagement and awareness in wildfire monitoring and prevention by making the software accessible to the public through the https://bushfire.ai website. This platform allows users to view real-time images from the camera system and receive information on detected fires, fostering a sense of ownership and responsibility among community members.

These anecdotal benefits underscore the overall value of the early fire detection system in not only detecting and reporting fires but also improving response times, coordination of emergency services, and public engagement. The system's performance highlights its potential to significantly mitigate the impact of wildfires on human life, property, and the environment.

6. Future work

While the current implementation of the early fire detection system has shown promising results, there are several areas for future research and development to further enhance its capabilities, effectiveness, and robustness. In this section, we discuss potential future work that could lead to improvements in fire detection, response times, and overall system performance.

The AI model could be improved by exploring other state-of-the-art object detection algorithms, such as Faster R-CNN, Single Shot MultiBox Detector (SSD), or EfficientDet. Additionally, incorporating transfer learning from pre-trained models on large-scale image datasets like ImageNet could potentially boost performance and reduce training time. Moreover, employing techniques such as model assembling or employing a multi-stage detection pipeline could help increase the overall accuracy and reduce false positives.

To further improve the AI model's generalization and robustness, the training dataset could be expanded to include images from diverse geographical regions, climates, and vegetation types. This would allow the model to better adapt to varying environmental conditions and fire behavior patterns. Furthermore, incorporating synthetic data generated through computer graphics or data augmentation techniques could help increase the dataset's size and diversity.

Integrating multispectral or hyper spectral imaging into the camera system could provide additional information about fires, such as temperature, chemical composition, and combustion stages. This additional data could be used to improve fire detection accuracy and provide more detailed information to emergency services, enabling them to better assess the situation and allocate resources accordingly.

Incorporating real-time weather data into the system's decision-making process could help improve the accuracy of fire detection and prediction. Factors such as wind speed, humidity, and temperature can significantly influence fire behavior and spread. By considering these factors, the system could potentially anticipate fire growth patterns and provide more accurate alerts and recommendations to emergency services.

Developing a fire spread prediction model based on factors such as terrain, vegetation, and weather conditions could help emergency services better anticipate the evolution of a fire and plan their response accordingly. By providing an estimation of the fire's future behavior, this prediction model could enable more effective resource allocation and response strategies.

To ensure reliable and real-time communication between the system, emergency services, and the public, the communication infrastructure could be further improved. This might include the implementation of a dedicated communication network for emergency services, the use of edge computing to reduce latency and improve data processing, or the development of a decentralized communication protocol to enhance system resilience.

In conclusion, there are numerous opportunities for future work to improve the early fire detection system's performance and capabilities. By addressing these areas, the system could become an invaluable tool in the ongoing battle against wildfires, ultimately saving lives, property, and the environment.

Acknowledgments

The AI modeling and training tools utilized in this project were made available by https://firststep.ai/. Public access to the AI fire detection tool is available at https://bushfire.ai/.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

References

Akagic, A., & Buza, E. (2022). LW-FIRE: a lightweight wildfire image classification with a deep convolutional neural network. *Applied Sciences*, *12*(5), 2646.

Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). YOLOv4: Optimal speed and accuracy of object detection. *arXiv preprint:2004.10934*. https://arxiv.org/abs/2004.10934.

Bouguettaya, A., Zarzour, H., Taberkit, A. M., & Kechida, A. (2022). A review on early wildfire detection from unmanned aerial vehicles using deep learning-based computer vision algorithms. *Signal Processing*, *190*, 108309.

Celik, T. (2010). Fast and efficient method for fire detection using image processing. *ETRI Journal*, *32*(6), 881–890.

Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). Deeplab: semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 40*(4), 834–848.

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. In *Proceedings of the IEEE International Conference on Computer Vision*, 2980–2988.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770–778.

Jocher, G. (2022). ultralytics/yolov5: v7. 0-YOLOv5 SOTA realtime instance segmentation. https://doi.org/10.5281/zenodo,7347926.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 1097–1105.

Li, X., Liang, J., Li, S., Shen, S., & Liu, L. (2022). Neural architecture search for object detection: a survey. *IEEE Transactions on Neural Networks and Learning Systems, 33*(1), 73–89.

Lin, T. Y., Dollár, P., Girshick, R., He, K., Hariharan, B., & Belongie, S. (2017). Feature pyramid networks for object detection. *Artificial Intelligence and Applications, 31*(1), 211–220.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: single shot multibox detector.

In *European Conference on Computer Vision*, 21–37. Cham: Springer.

Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 3431–3440.

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 779–788.

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: convolutional networks for biomedical image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 234–241.

Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. In *International Conference on Learning Representations*.

Sun, J., Wu, J., Wu, C., Zhang, L., Zhang, X., & Wang, Y. (2021). Object detection in smart manufacturing: a comprehensive review. *Journal of Intelligent Manufacturing*, *32*(3), 629–656.

Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. A. (2017). Inception-v4, inception-ResNet and the impact of residual connections on learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 4278–4284.

Thuan, D. (2021). Evolution of YOLO algorithm and YOLOVv5: the state-of-the-art object detection algorithm.

Töreyin, B. U., Dedeoğlu, Y., Güdükbay, U., & Cetin, A. E. (2006). Computer vision based method for real-time fire and flame detection. *Pattern Recognition Letters*, *27*(1), 49–58.

Wang, Y., Dang, L., & Ren, J. (2019). Forest fire image recognition based on convolutional neural network. *Journal of Algorithms & Computational Technology*, *13*, 1748302619887689.

How to Cite: Remmelzwaal, L. (2023). An AI-Based Early Fire Detection System Utilizing HD Cameras and Real-Time Image Analysis. *Artificial Intelligence and Applications* https://doi.org/10.47852/bonviewAIA3202975