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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: In recent years, wildfires have become a major threat to human lives, property, and the environment. Timely response in the beginning phase of a fire is key to minimizing loss and risk. Conventional wildfire detection systems are based on bystanders reporting the fire, resulting in a delayed response time, during which the fire can spread out of control. This paper investigates the question: "Can AI object detection minimize the delay of wildfire detection and response?". An early fire detection system is introduced, which utilizes state-of-the-art hardware-based on AI (artificial intelligence) object detection, and can be integrating it to emergency services to improve the response time for wildfires. DSPL is a proprietary technology Read Smart Sensor, short for DSPL (Dynamic Spatial sensor platform), a cloud based system working on high-definition panoramas of our sky for detection of objects within our space, utilizing solar powered energy & COMM infrastructure for on-time communication. Once activated, the AI model continues to analyze camera images every 60 seconds, detecting early signs of smoke that signal the likelihood of a fire and informing the fire department before it gets out of control. We describe the system architecture, the AI model framework, the training process, and the results obtained from testing and validation. In conclusion, the system proved to be effective in having the timely detection and reporting of fire incidents, by coordinating with responsive departments and minimizing the time required to mitigate a fire outbreak. With this, we have proved that AI object detection can be a powerful ally in the fight against wildfires, thus saving lives, assets, and biodiversity.

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

1. Introduction

Wildfires can be devastating, threatening lives, property and the environment. The period during which a fire first ignites is critical in determining how destructive and dangerous it can be, and a swift response is essential. Traditional methods for detecting wildfires often depend on reports from bystanders, which can prolong response times and allow fires to spiral out of control. According to Daily Star, Australia has 50,000 to 60,000 bush fires every year, with damage estimated between hundreds of thousands and millions, depending on the intensity and location.

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.

*__Corresponding author:__ Leendert Remmelzwaal, Department of Electrical Engineering, University of Cape Town, South Africa. Email: rmmlee001@uct.ac.za

Many industries have started using artificial intelligence (AI) to improve how they work. One type of AI, called convolutional neural networks (CNNs) [1], is being used in areas like fire detection and emergency response. CNNs are known for doing well in tasks such as image classification [2–6], object detection [7–12], and object segmentation [13–19]. These models have been tested on well-known image datasets and have performed successfully. AI is also used in self-driving cars, robotics, and video surveillance. In fire detection, object detection is especially important because it helps find where things like smoke or flames are in an image and what they are.

In this paper, we explain a new early fire detection system. It uses simple, ready-made hardware and AI to detect fires. It also connects easily with emergency services. This system could help detect wildfires faster and improve how quickly people respond.

Our system uses high-resolution cameras that can move (pan and tilt) and zoom. Each installation can run on solar power or mains, and they use high speed communication tools (e.g. Starlink). Every 20 seconds, the camera takes a high definition image. An AI model checks each image for any hint of smoke that could mean a fire has recently started. If it finds something, it alerts the fire department right away (Figure 1). This helps emergency response teams respond quickly and reduces how much damage wildfires can cause, usually saving many lives. 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,

Figure 1
Detection of bushfire

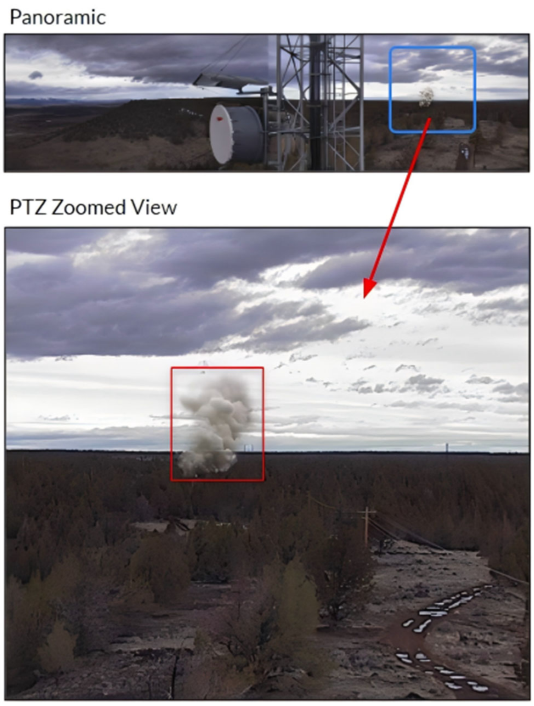
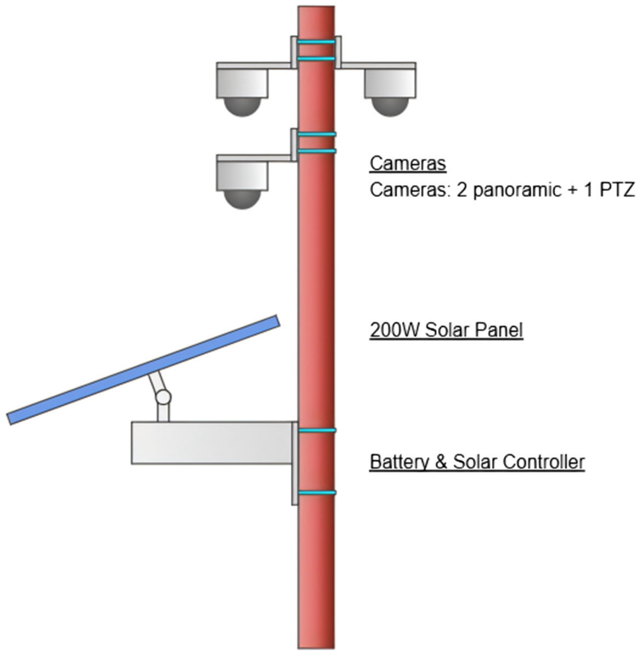


Figure 2
Camera and solar panel hardware



communication infrastructure, and public interface. Section 3 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 presents a new early fire detection system. It uses high-definition cameras and AI to analyse images and spot signs of wildfire. The system sends accurate, real-time information to emergency services. This can help reduce the damage caused by wildfires and protect both people and property.

2. Review of Early Fire Detection Approaches

Early fire detection using cameras has become a hot topic of study in the last few years. Numerous approaches have been tried. The most often occurring ones and the related studies are examined in this part.

1) Flame Detection: One common approach is spotting flames by searching for characteristics including their color, shape, and flutter. According to Celik, flame detection AI models are capable of finding these characteristics and determining whether there is not only a fire, but also whether it is a live moving [20].
2) Smoke Detection: Another common method looks for signs of smoke in images. These signs include the smoke's colour, texture, and movement. Töreyin et al. showed that tracking smoke movement helps detect fires early [21].
3) Thermal Imaging: Thermal cameras can view heat and convert it into images. This allows the camera to identify fire in poor lighting conditions such as night-time, mist, fog or even dense smoke [22].
4) Fire Detection Based on AI: Thanks to better machine learning and computer vision, new AI models can now detect fires by learning patterns from data. Bouguettaya et al. [22] reviewed deep learning methods that use drone images to spot wildfires. Akagic and Buza [23] created a lightweight fire detection system using deep CNNs. Wang et al. [24] also used CNNs to detect forest fires.

For this project, we didn't have thermal cameras. We only had access to panoramic cameras. But we were able to use cloud computing, so we weren't limited to edge devices. Because of that, we chose to use an AI-based method for fire detection.

This paper presents an AI model that processes panoramic images in real time. We use advanced object detection methods, which sets our system apart from earlier work like Bouguettaya et al. [22]. Their system uses image tessellation and object classification. Our method is more efficient because it doesn't need to split images into smaller parts.

3. System Architecture

Our early fire detection system consists of an off-the-shelf hardware setup (cameras and solar panels) and standard communications (Starlink). What is unique is the integration of AI Object Detections models to analyze images in real-time, and the communications sent to the fire department when a fire is detected. The following sections describe the major elements of the system architecture and how they work together to facilitate timely 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

Our camera system can work in any environment, whether indoor or outdoor. It uses solar panels, a solar power controller, and smart charging solar batteries. These ensure optimal charging and battery life. We were able to deploy this as a stand-alone system without relying on mains power. The batteries we chose also have a long life expectancy of five years, meaning they require less frequent replacement.

3.3. Communication infrastructure

The system includes a reliable Starlink / 4G connection that keeps it online all the time. This lets the cameras stream images to a cloud server 24/7. The fast connection also sends real-time instructions to the pan-tilt-zoom (PTZ) cameras. This makes sure the cameras and AI system work well together. High-speed video links also send images quickly to the AI system and the Fire Department so they can respond fast (see Figure 3).

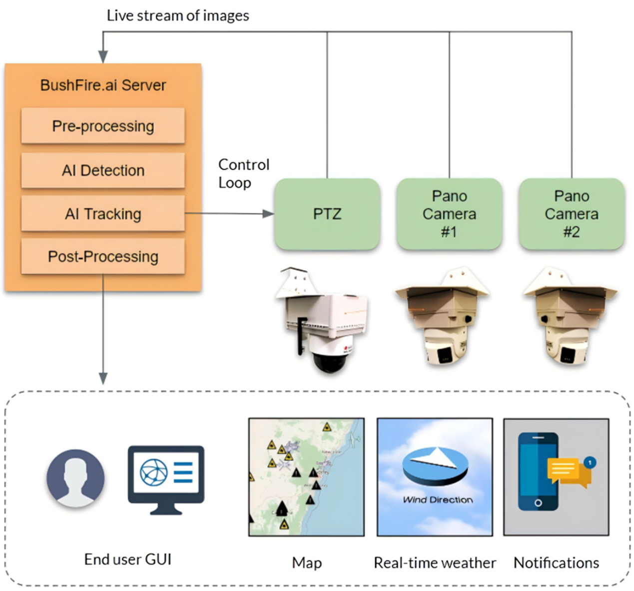
3.4. Public access and interface

People can visit the website bushfire.ai to see real-time images from the camera system. They can also get updates on any fires that are detected. This helps raise awareness and encourages the public to be part of fire prevention.

3.5. System summary

The full system includes smart cameras, solar power, fast communication tools, and an easy-to-use public website. These parts work together to create a strong fire detection system. It can be used in many places and gives real-time data to help stop fires early.

Figure 3
System architecture



People can visit the website bushfire.ai to see real-time images from the camera system. They can also get updates on any fires that are detected. This helps raise awareness and encourages the public to be part of fire prevention.

4. AI Model Architecture

The artificial intelligence (AI) part of the fire detection system is very important. It checks the images from the cameras and looks for patterns of smoke that might mean a fire has started. This section explains how the AI works, including the model design, object detection, how the data was collected, and how the model was trained.

4.1. Methodology

In this paper we discuss an AI-powered fire detection system complete with camera and cloud server. It takes into consideration a full 360-degree panoramic image to find signs of smoke or fire. The only space that we cannot see is the area obscured by the camera pole. The cloud server uses high-performance object detection AI models to detect smoke (true positive) as well as not-smoke (true negatives) such as trees, roads, cars, clouds, mist, and glare. In addition to this, it uses weather data available online via an API to predict the movement of the fire (direction and speed) allowing us to send email and SMS warning notifications.

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 utilizes cutting-edge object detection methods to detect smoke or fire images with high precision. Largely about training up the model on a dataset of annotated images with smoke & fire to allow it to learn the distinguishing features of these phenomena and thus separate them from the rest of the objects in the scene. The AI model monitors the progression of a fire's plume over time to infer its movement, growth rate, and size. This enables the system to understand the dynamic characteristics of the smoke over time and extract important information to describe the fire.

The AI model then uses the data about the direction of wind, to map the direction of smoke movement, and thus correlate to the direction of growth of the fire. By analyzing such data, the probable direction of the fire can be triangulated, thus helping to make firefighting more targeted and efficient. The efficiency of detecting bushfires in their initial stages will increase using these methodologies as it will enable the AI-based early fire detection system to address a variety of fire types, through integration, along with reducing false readings.

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.

One of the AI models used in this system is based on YOLOv5. This is a powerful deep learning model known for being fast and accurate at finding objects in images [25–30]. We used the PyTorch framework to build it. The model looks at images that are 640 by 640 pixels in size. This high resolution helps it detect fires more precisely.

4.3. Dataset creation

To train the AI model, we collected 20,000 images using panoramic cameras in the United States and Australia. The images were gathered over a full year to capture different seasons and weather conditions. This made sure the dataset was varied and realistic. We used 70% of the images to train the model and 30% to check how well it was learning during training.

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

We used data augmentation during training to make the AI model stronger and more flexible. This means we slightly changed the training images in different ways, like flipping them horizontally, changing their size, or adjusting the brightness and colours. We didn't flip images vertically, since that wouldn't make sense for wildfire detection and could confuse the model.

4.5. Model training

The AI model was trained for 679 rounds, called epochs. It reached a mean average precision (mAP) score of 0.04 and an accuracy of 93.5% (see Table 1). Training was stopped at that point because the model wasn't getting any better. If we had kept going, it could have overfitted, meaning it would only work well on training data and not on new images.

The process trained the AI model so that by analyzing the input images, it was able to recognize patterns indicating smoke at a fire's early stages. The fires3 learned to control the PTZ camera as well through the feedback loop, adjusting the camera's settings for pan, tilt, and zoom to capture and analyze fires more effectively.

To sum up, those are the main technical parts of the AI model architecture, they are an efficient object detection model with a diverse dataset, data augmentation, and optimized training. Rather, with this holistic approach, the smoke tracking is tracked over the time period aiding the early fire detection algorithm to pinpoint the smoke pattern and identify the movement pattern of the smoke.

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

In this section of the report we evaluate the performance of the AI object detection model. We are interest in whether it can detect fire in a complex scene. We share our findings from the testing and validation phase, highlighting the effectiveness of the AI models.

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. The results suggest that the model can detect smoke patterns, indicating the presence of fire, in the incoming images with remarkable accuracy (refer Figure 4). The AI model trained could accurately recognize initial ignition fires and alert the fire department to respond quickly.

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 notifies the relevant fire department upon detecting a potential fire

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

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 software is available to everyone at https://bushfire.ai. This helps get the community involved in watching for wildfires and staying informed. People can see live images from the cameras and get updates about any fires that are found. The platform also helps people feel more connected and responsible for fire prevention.

These extra benefits show that the system does more than just find and report fires. It also helps people respond faster, improves coordination during emergencies, and gets the public involved. This can reduce the damage to people, homes, and the environment.

6. Future Work

To sum up, the early fire detection system in this project has shown good results, but there's still room to make it better. In this section, we explain a few ideas for future work that could improve how well the system detects fires, how fast it responds, and how reliable it is.

We could improve the AI model by testing other powerful object detection methods, like Faster R-CNN, SSD, or EfficientDet. Another idea is to use transfer learning, where we take a model trained on a huge dataset like ImageNet and adapt it to our task. This could save time and still give strong results. We could also try using more than one model together (model ensembling) or build a step-by-step detection system to increase accuracy and reduce false alarms.

We could make the training dataset better by including images from more places with different climates, plants, and landscapes. This would help the AI model learn how fires behave in different environments. We can also add more data by using computer-generated images or image editing techniques to create new examples.

Adding multispectral or hyperspectral cameras to the system could give us more details about fires. These types of cameras can show things like temperature, chemicals in the air, and how a fire is burning. This extra information could help emergency teams understand the fire better and respond more effectively.

Using real-time weather data in the system could also improve how well it predicts and detects fires. Wind speed, humidity, and temperature all affect how fires move. By including this data, the system could help emergency services know where a fire might go and how to respond.

A fire spread prediction model could also be built using details like terrain, vegetation, and weather. This would help emergency teams guess how a fire might grow and plan the best way to fight it. It could lead to better decisions about where to send people and equipment.

We could also improve how the system communicates. One option is to create a special network just for emergency teams. Another is to use edge computing to process data faster and reduce delays. Or, we could build a system that shares communication across different places to make it stronger and more reliable.

Overall, there are many ways we could keep improving the early fire detection system. With upgrades like these, it could become a powerful tool for stopping wildfires and protecting lives, homes, and nature.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Leendert Remmelzwaal: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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