A Camera-Based Automatic Wildfire Detection and Monitoring System

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BACKGROUND

Wildfires burned over 4 million acres during 2020 in California alone, obliterating communities and devastating families [1]. Due to climate change and more frequent droughts these fires are occurring in exponentially more areas, requiring more robust fire detection methods than anytime before. Current monitoring systems use numerous cameras to look over large areas of land, such as AlertWildfire [2], but these cameras are mainly used to observe fires currently in progress, rather than proactively search for fires at all times. This lack of constant monitoring leaves the door open for developing automatic detection methods.

WILDFIRE DETECTION AND MONITORING SYSTEM

System Design: The monitoring system consists of multiple devices distributed over large areas and connected to a central web server. Each device is housed in a weatherproof enclosure with a camera that can rotate panoramically to take pictures and monitor its surroundings. A microcomputer running an artificial intelligence algorithm automatically detects fires if they present in the pictures. After processing, fire images are uploaded to a database and web server, where the images are able to be reviewed by users and monitoring personnel.

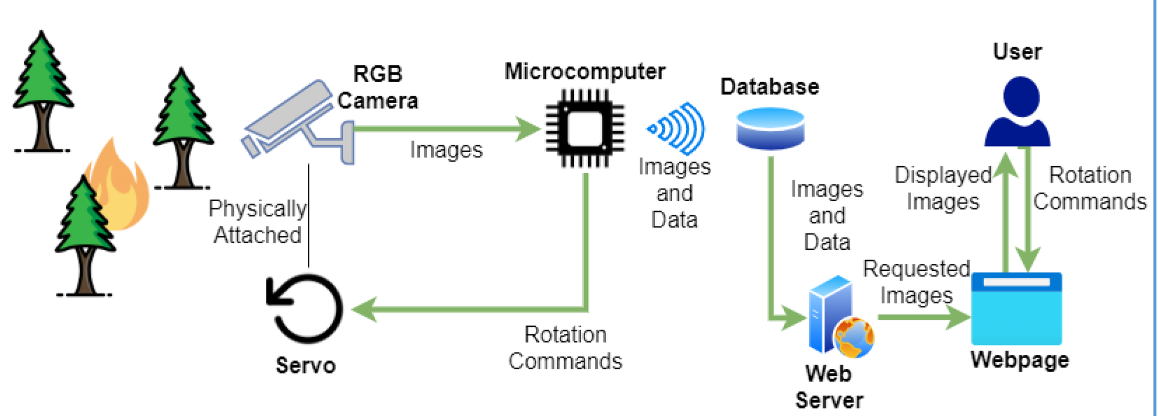

Fig. 1. Automatic wildfire detection system diagram

Machine Learning: For the artificial intelligence algorithm, we chose YOLOv5 (You Only Look Once) due to its high accuracy and flexibility based on our previous research [3]. We created a dataset based on a fire-smoke detection dataset [4] and a landscape dataset [5]. A Python program was used to randomly select 2000 fire images and 2000 non-fire/landscape images for training, and 200 fire images and 200 non-fire/landscape images for validation. We trained the network and validated the model. The validation images were then processed by the detector. Based on how many fires and non-fires the detector correctly labeled, the F1-score which is a measure of an algorithm's accuracy for a dataset was calculated. An F1-score of 1 means that all fires and non-fires were correctly identified. Fig. 2 shows the F1-score of the trained model running on a microcomputer (Raspberry Pi 4). The score reached a peak of 0.928.

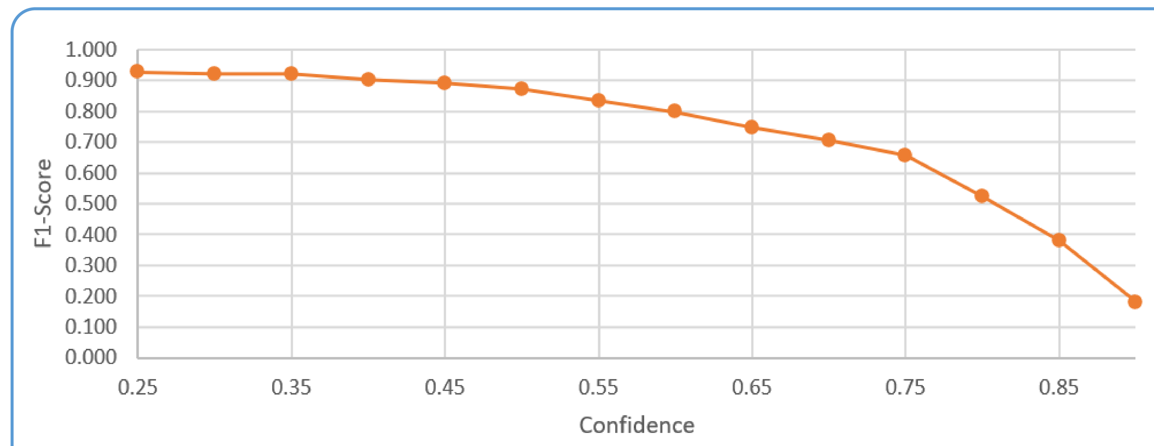

Fig. 2. F1-score

Camera Subsystem: The subsystem uses a 12.3 megapixel Sony IMX477 sensor with a 16mm lens and a servo that enables panoramic picture taking. Fig. 3 shows The camera, lens, and microcomputer all enclosed in a weather-proof enclosure in our prototype system.

Fig. 3. The prototype system

Monitoring Website: Once a fire is detected from the pictures taken, the image is automatically uploaded to the monitoring website and displayed. Multiple distributed detection systems can be connected to the website through wireless networks. Each device uploads its images to the server storage specific to its unique hardware address. Fig. 4. presents a screenshot of the website that displays a number of recent fire images which were automatically uploaded by the distributed systems during a test. The web address is www.acrefree.com.

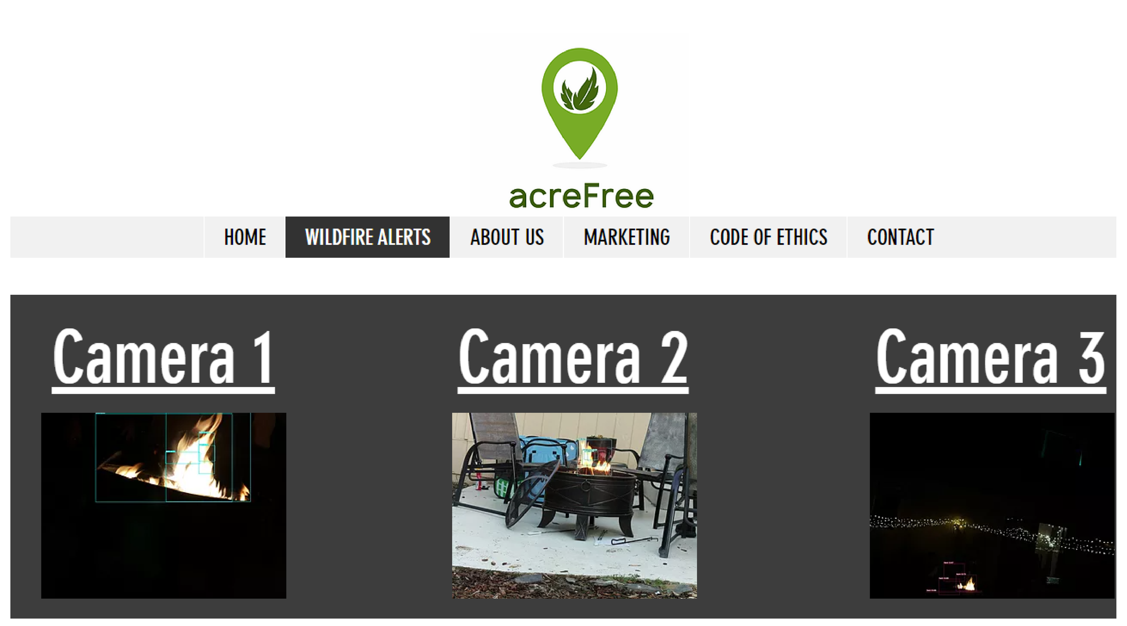

Fig. 4. The website that used to monitor the fire images

EXPERIMENT RESULTS

The real-world experiment of the system started with the detection of controlled fires. The system was first put at 5 feet from a fire source. In this setting, the fire takes up about 14% of the total area of the image taken. 10 pictures were automatically captured in a sequence by the system. Then we moved the camera back to 15 feet where the fire takes up about 2.8% of the total area of the image and another 10 pictures were taken. We repeated this process until the system was 65 feet away from the fire source. The experiment has been conducted in both lowlight and nighttime conditions. Fig. 5 is an example of the detection results of one of the images captured during the test. The green annotation boxes were marked by the detector and show the locations of the detected fires.

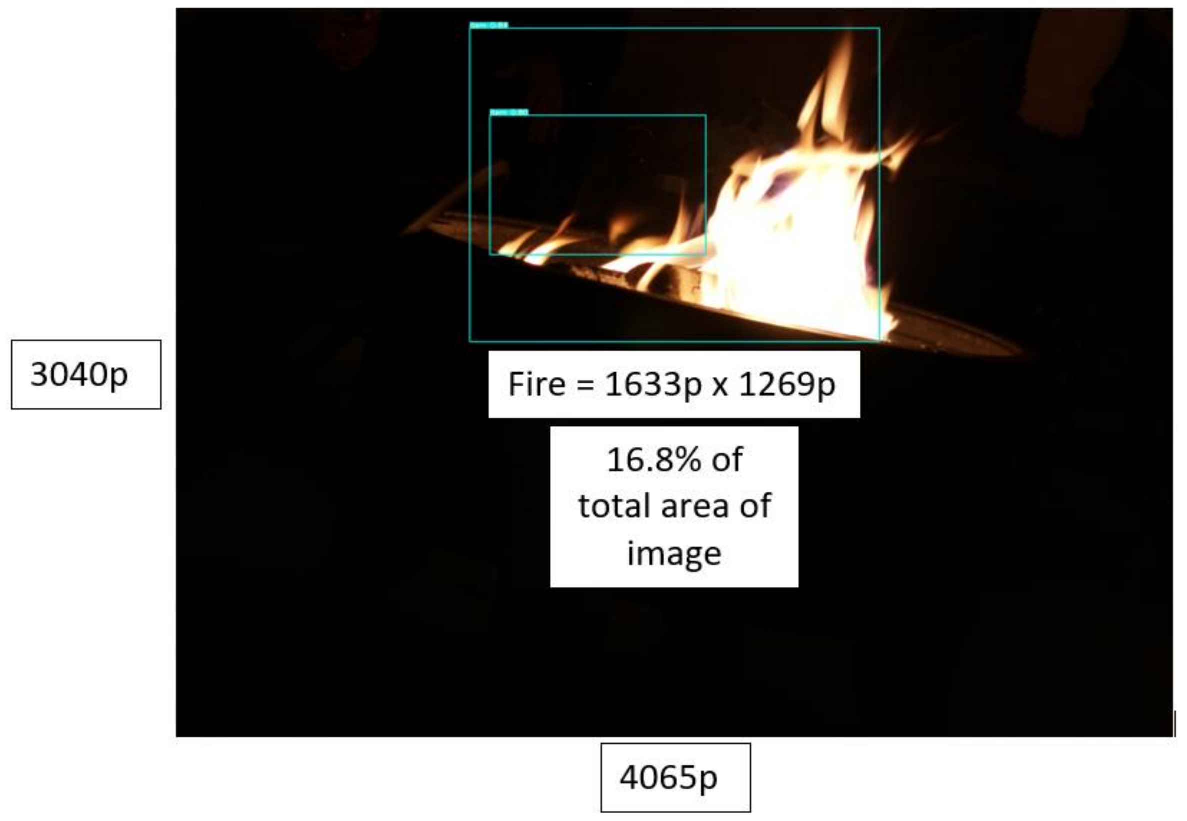

Fig. 5. Detection result example: a fire that takes up 16.8% of the total area of the image, captured by the system at nighttime.

Detection Performance: The results of the experiment are shown in Fig. 6. The horizontal axis represents the ratio of $\frac{Fire\ Area}{Total\ Area}$ which is calculated from each picture taken using our device. The vertical axis is the successful detection rate that the model had with each collection of pictures. For example, the system detected 90% of night images at a $\frac{Fire\ Area}{Total\ Area}$ ratio of 1.2%, which means that it should detect 9 out of 10 fires when a very small area of 1.2% of fire is present in these pictures. Both lowlight and nighttime experiment results are plotted in this figure.

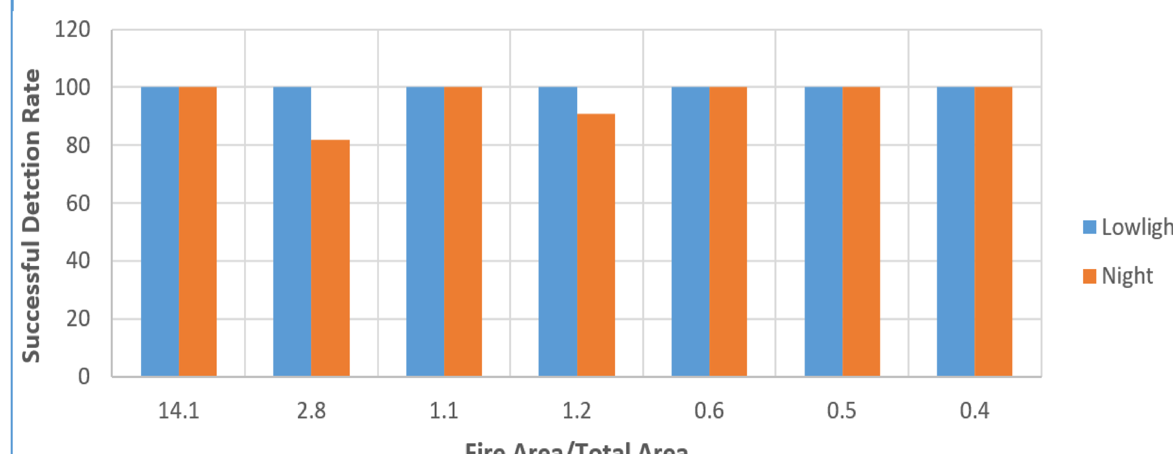

Fig. 6. Detection results from the experiment

Sustainability of the System: During the experiment, we measured that the system consumed 4.18 W during startup, 4.70 W when capturing images, 6.08 W when running fire detection, and 4.51 W during image uploading using WiFi. The total energy consumption of one complete cycle of detection which completes in 65.42 seconds is 345.59 J. The system consumed 0.015 W during hibernation. Therefore, an example setting for the system to wake up and operate three-time an hour with about 20 minutes of hibernation in between wake-ups will consume 1088.07 J per hour. In this setting, a six 18650 cell power bank rated at 20100 mAh at 3.7V can support the system for 10 days and 6 hours. In addition, a 1.2 W solar panel should be sufficient to provide recharge to the system and make it sustainable in terms of energy consumption.

CONCLUSION

Our research and tests prove that artificial intelligence used in automatic wildfire detection systems is certainly possible in real-world situations. The system design can be scaled to a large amount of distributed systems to survey a very large scale of landscapes. This system of proactive monitoring will improve our ecological sustainability by finding fires more quickly before they have a chance to devastate local communities and contribute more to global warming, which would continue this destructive cycle of fires.

FUTURE WORK

With these first prototypes developed, the next steps would be a refinement of the current systems and preparation for scaling the system to include many more devices. Further field tests should also be done to check the viability of this device with fires at much larger distances.

ACKNOWLEDGEMENTS

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References

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[5] Landscape Pictures Dataset: www.kaggle.com/arnaud58/landscape-pictures.