acreFree: An Automatic Wildfire Detection System and Network

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INTRODUCTION

Wildfires are a constant threat to millions of people and ecosystems, requiring immediate and effective detection methods. In 2020, 4 million acres were burned in California alone which devastated families and left billions of dollars in damages [1]. Current wildfire monitoring companies, like AlertWildfire [2], have setup hundreds of cameras around California to monitor fires. However, these cameras are not autonomous and cannot find fires on their own. Furthermore, they must be installed by hardwiring internet and electricity which makes setup expensive, time-consuming, and difficult for smaller entities.

SYSTEM ARCHITECTURE

Our system consists of two main parts: the device and the website. First, the device includes a camera for taking pictures of the monitoring areas, an artificial intelligence algorithm to detect fires in the taken images, and a microcomputer that automates these processes and interfaces with the website. Second, the custom website that each device will upload fire images to. Our website will store and organize each image based on the device, then display it for the public to view.

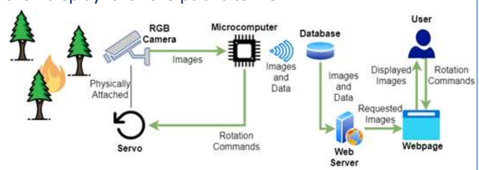

Fig. 1. Automatic wildfire detection system diagram

INTERNET CONNECTIVITY

To make our device easily deployable in areas of interest, we have decided to use wireless internet for our devices instead of hardwiring like current solutions. There are multiple service providers from satellite internet to cellular to LoRa, each with their own pros and cons. Each device only requires a small amount of internet bandwidth due to how few images it sends, so slower providers with larger ranges would be possible. First, LoRa (Long-Range internet) is a great low-cost option but requires setting up gateway networks wherever we would like to place a device. Second, satellite is high speed and may reach even the most isolated areas but is extremely expensive for the number of devices we would deploy. Third, cellular data networks are widespread in many areas with a good amount of speed and adequate range, but this prevent us from placing our devices in far-away forests or national parks.

POWER CONSUMPTION

Battery life is essential for these devices to constantly monitor large areas over long periods of time. Once the automation processes of our prototype were finalized, we tested the power usage of 10 automatic cycles and averaged their energy usage as seen in Fig. 3. Taking pictures and uploading images have similar power requirements, while the algorithm uses nearly 100% of the CPU and memory while it processes each image. From these tests, we found that each automatic cycle uses 832.7 Joules. Using 2 automatic cycles per hour with a 20100 mAh battery pack at 3.7 Volts, our device would last 6 days and 17 hours. Adding a 5 Watt solar panel would add more than enough power to make this system self-sufficient.

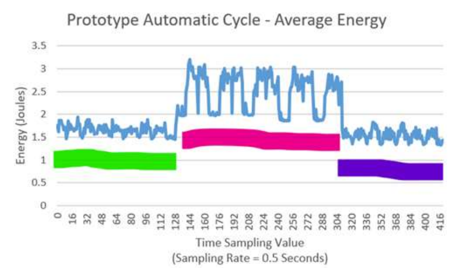

Fig. 3. Power usage during a single automatic cycle. Green is when the device takes pictures with the camera. Magenta/red is when our algorithm detects fires in the images. Purple is when the images are uploaded to our website.

WEBSITE INTEGRATION

Our custom website has three primary functions: uploading, organizing, and displaying. First, each device automatically uploads fire images to the website, along with their unique identifier. Next, the website automatically stores and organizes each uploaded image to different datasets based on the unique identifiers. Finally, the fire images are displayed for each device and available for viewing by the public. This system allows numerous devices to be quickly added and start uploading new images without redesigning the system. The web address is http://www.acrefree.com/ .

Fig. 4. Website used to display the fire images from each device

AUTOMATIC FIRE DETECTION

Our device uses a machine learning algorithm that we trained with 2000 fire images and 2000 non-fire images (all randomly selected from larger datasets [3][4]). Once training was finished, we setup a real-world test to ensure that the wildfire detector and camera worked as a complete system. We placed the device 5 feet from a stationary firepit and took 10 pictures of the fire with our camera (as seen in Fig. 7). At this distance of 5 feet, the fire takes up about 14% of the total image area. Then, we moved the device back to 15 feet (fire takes up about 2.8% of the total image) and took another 10 images. We repeated this until 65 feet was reached and did this entire experiment for lowlight and nighttime situations. An example of the detection results can be seen in Fig. 5, with the green boxes being made by our machine learning detector.

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.

The results of our experiment can be seen in Fig. 6. Our graph is the Fire Area/Total Area on the horizontal axis, and the successful detection rate on the vertical axis. The successful detection rate was calculated by the number of images that the detector correctly identified as fires. We took a total of 140 images between lowlight and nighttime situations, with the fires taking up 14.1% to 0.4% of the total image area. In all 140 images, our device only missed 3 fires.

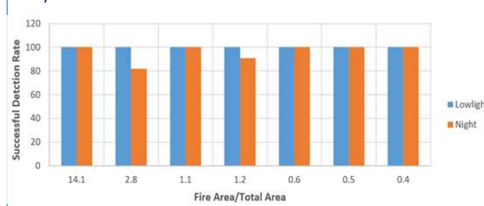

Fig. 6. Detection results from the experiment

Fig. 7. Picture of finished device

CONCLUSION

Based on our research and experimental results for power consumption, fire detection, and internet connectivity, we are confident in the viability of our automatic wildfire detection system and network. Our devices are made to be easily deployable and usable in a variety of areas, thanks to their wireless internet and independent power sources. Our machine learning algorithm shows promising accuracy that can be improved with further training and more varied datasets. Alongside that, our website's ability to store, organize, and display fire images from multiple devices makes it seamless to add new units quickly. These aspects together create a system of automatic wildfire detection that future implementations can scale very efficiently in all kinds of areas.

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References

[1] CALFIRE. "2020 Incident Archive." CalFire Incidents, www.fire.ca.gov/incidents/2020/.
[2] "About: Nevada Seismological Lab." About ALERTWildfire.org, ALERTWildfire, www.alertwildfire.org/about.html.
[3] Fire-smoke detection dataset: https://github.com/gengyanlei/fire-detect-yolov4
[4] Landscape Pictures Dataset: www.kaggle.com/arnaud58/landscape-pictures.