Radiometric Thermal UAV Imagery for Wildfire Management

1. Problem Statement

Wildfires are one among the most destructive natural disasters and they can harm ecosystems, property and human lives. Traditional existing systems suffer from a delayed response, limited coverage and it also poses high risk to fire fighters. As the frequency of wildfires is increasing, there is definitely an urgent need for real-time, reliable and accurate wildfire detection systems.

2. Motivation

1. Environmental impact: Lungs of our planet are the forests. Forests help purify air and help in reducing the amount of CO_2. It is very crucial to protect them.

2. Human and Economic losses: Wildfires not only lead to loss of human lives but also of wildlife and billions in damages to agriculture and infrastructure.

3. Technological Opportunity: Unmanned Aerial Vehicles (UAVs) equipped with thermal cameras combined with image processing and artificial intelligence also offer monitoring in remote and inaccessible areas

3. Objectives

1. To develop a wildfire detection framework using radiometric thermal imaging.

2. To use deep learning algorithms to accurately classify, detect and for segmentation of wildfire flames and smoke.

3. To optimize models for edge deployment on devices like Jetson Nano and Raspberry Pi.

4. Introduction

Wildfires are one of the most destructive natural hazards and with their frequency and intensities rising through the years. They burn down around 350 million hectares of land every year. It contributes to almost 5-8% of annual greenhouse gas emissions and also causes extensive loss of biodiversity, property and human lives [2]. The 2019-20 Australian bushfires damaged around 1.1 million hectares in Victoria alone [3] and resulted in dozens of fatalities, destroyed homes and billions of economic damages. Similar to that, wildfires affected in California, Greece and Canada have proven that no country or region can stay away from this threat. Forests are referred to as the “lungs of the planet" and play a vital role in oxygen production and carbon dioxide reduction. Their reduction leads not only to an increase in the amount of carbon but also leads to global warming.

The traditional system relies heavily on ground based inspection and satellite imagery. Satellites offer wide-area coverage but lack in low temporal resolution and cloud interference. Ground staff face the issue of slow response times and risks to human lives. What we need is a system that combines rapid deployment, high resolution and quality data acquisition and a continuous operation capability. It would help authorities enable to detect, respond and control wildfires at the earliest stages.

The system proposed through the article integrates Unmanned Aerial Vehicles (UAVs) with dual optical and thermal sensors, providing detection capability during both - day and night. UAVs are chosen as they offer mobility in 3D, a low altitude flight and also offer fast deployment which makes them suitable for rapid response.

Datasets like ADSF, RGB-IR UAV dataset and FLAME/FLAME2 are used for training and validating models under various diverse environments. Deep learning algorithms like Reduce-VGGNet, YOLOv3/SSD and U-Net/DeepLab are used as the core part of the system. Lightweight CNNs also allow deployment on edge devices, which ensures real-time response.

5. Related Work

Early fire detection has been studied previously through different platforms like cameras, satellites and UAVs. [6] provides a comprehensive review of optical remote sensing approaches which includes both terrestrial and airborne systems. Satellite based systems provide wide area coverage but suffer from low resolution, cloud interference and delays. On the other hand, terrestrial systems are limited due to fixed locations and require a line-of-sight. These show the importance of UAV-based solutions.

Recent studies have also explored UAVs equipped with both RGB and IR sensors. [7] introduces us to a UAV based RGB-IR dataset for wildfire monitoring. It demonstrates that multi-sensor data integration improves the overall accuracy.

The integration of deep learning algorithms has changed the capability to detect fires. [8] shows the conduction of an experiment based on Reduce-VGGNet. It resulted in an accuracy of 91.2% and hence proving CNN's effectiveness. Similarly, [9] emphasized that object detection algorithms like YOLOv3, SSD and Faster R-CNN are effective for real-time fire localization while segmentation models like U-Net and DeepLab are better than traditional methods for capturing smoke and flame regions at pixel level.

Some studies have also focused on quality under adverse weather conditions. [10] does propose a CNN model trained on ADSF dataset, which includes the synthetic images in different conditions like foggy, hazy and low light. The results show an improvement in accuracy by 2%. [11] talks about the development of an unsupervised RGB-based flame segmentation method that removes the need for complex preprocessing. [12] introduces a near real-time approach using Distributed Satellite System (DSS). However the resolution of satellites is insufficient for immediate ground level response.

Sr. No	**Name of the Study**	**Features**	**Methodology**	**Research Gaps Present**
1	Barmpoutis et al., *Sensors* 2020 — Optical remote sensing review	Conducts a survey of terrestrial, air and satellite fire detection systems	It conducts a review of the existing systems for wildfire detection	There is no experimental validation conducted. UAVs are discussed but no proper large scale data
2	Bouguettaya et al., *Signal Processing* 2022 — UAV + deep learning review	Conducts a survey of UAV based fire detection using deep learning	It performs a comparison between different methodologies. It also performed image classification, object detection and semantic segmentation	There is no implementation performed and more focused on theoretical part
3	Yar et al., *ISPRS JPRS* 2023 — Attention-CNN for adverse weather (ADSF)	Has the ADSF dataset with different conditions like fog, haze and at night	They collected UAV and satellite imagery and generated synthetic adverse condition images	It contains many synthetic images rather than natural

4	Chen et al., *Remote Sensing* 2023 — UAV RGB–IR dataset	It introduces a UAV RGB-IR submission	It used UAVs to collect RGB and IR images and created an annotated dataset for detection and monitoring	The dataset is limited to specific regions with a small size and lacks adverse conditions
5	Wang et al., *Inventions* 2022 — Reduce-VGGNet experiment	It applies deep learning in course-based experiment	It implemented various CNNs like Reduce-VGGNet for image classification and achieved an accuracy of 91.2%	It was tested on classification only on an experimental basis, with no scope for smoke detection.
6	Buza & Akagić, *Pattern Recognition Letters* 2021 — Unsupervised flame segmentation	Proposes the RGB based detection	It proposed the unsupervised clustering on RGB for pixel segmentation and is tested on publicly available datasets	It struggles while differentiating between clouds and smoke and has no thermal data
7	Thangavel et al., *Remote Sensing* 2023 (Art. 720) & IEEE GRSL letter — Distributed Satellite System (DSS)	It talks about satellite based wildfire management system	It designed a Distributed Satellite System (DSS) and CNN models for fire detection and tested for near real-time scenarios	It has a limited spatial resolution and less effective for ground level firefighting systems.
8	Ghali et al., *Remote Sensing* 2023 — DL for wildland fires	It has a large approach of Deep Learning approaches for classification, detection and segmentation.	It reviews and talks about the comparison of different deep learning methods and also analyzes different datasets	It lacks real world deployments and needs a bias control

6. Methodology

1. Data Acquisition

For this study, the dataset used is FLAME3 CV (Sycan Marsh) [14]. It contains pairs fire and no fire images. These images are captured in both RGB and thermal formats using the sensors mounted on UAVs. Each of the image captures the real scenes and backgrounds which don't have fire. It is performed under various light and environmental conditions. The dataset used presents comprehensive coverage of the different fire intensities, distances and the smoke densities present. It makes it suitable for developing a deep learning model which can distinguish between fire and no fire images. The dataset used was divided into two classes majorly - Fire and No Fire. Each had corresponding RGB and thermal images.

2. Preprocessing

Before the images can actually be used for the model training, a series of processing is performed to help increase the quality of the images and improve the model generalizability. Every image is first resized to make it of a same dimension of 224 * 224 pixel. It helps to maintain consistency and match the requirements of the input of the deep learning model used. As the images which are imported using OpenCV are by default in BGR format, they are then converted to RGB format to preserve the natural colors. A Gaussian blur filter is used which helps to smoothen the noise in high frequency while retaining the essential features like the edges and curves.

After it, to enhance the contrast and to help distinguish clearly, histogram equalisation is performed. The images are then normalised by scaling the pixel intensities to [0,1]. Finally, as the pipeline had grayscale operations for the simplification, each images was then reconstructed in the three-channel format using *cv2.merge()* to match the input dimensions. These steps collectively make sure that the model uses the images which have high-quaity, noise-free and enhanced images.

3. Dataset Splitting

After the images are ready on preprocessing, these are divided into three sets - training, testing and validation (70:15:15). It ensures a balanced ratio in all three sets. Stratifies sampling is used to make sure that there is balance in both the classes. The training set was used for helping the model learn features of both the classes. The validation set was used to monitor the performance and test used for evaluating the model.

4. **Model Architecture**

To spot wildfires, we built a visual system - a computer program that learns to recognize fire in pictures. It works by breaking down images into smaller parts, then combining those parts to identify patterns. This system handles standard color photos alongside heat signatures, taking pictures measuring 224x224 pixels with three color channels. Ultimately, it decides whether there's a fire present or not. The system spotted potential fires by first recognizing patterns – shapes and heat signatures – then simplifying those observations to avoid false alarms. It built upon these core elements through several stages, ultimately gauging the chance of a wildfire using identified characteristics. Consequently, this setup allowed it to efficiently discern intricate details signaling active blazes.

5. **Model Training**

A convolutional neural network learned through Adam optimization - a 0.001 step size guided its adjustments while measuring success via binary cross-entropy. Training lasted between 20 to 30 rounds, processing information in chunks of 32, adjusted by how well things were progressing. Separate data helped keep an eye on improvements and ward off memorization. To snag the top-notch model, we paused training when performance leveled off, regularly saving progress. We also played with the images – flipping them, rotating them – like tweaking perspectives from a drone's eye view to help it handle different shots. Ultimately, our goal was clear: pinpoint objects accurately, learn steadily, yet avoid wild swings in improvement.

6. **Model Evaluation**

After learning, we tested how well the system handled pictures it hadn't seen before. We measured success via accuracy, pinpointing correct identifications alongside errors - specifically, times it wrongly flagged things as fire or missed actual fires. A detailed breakdown showed exactly where it excelled or stumbled when sorting fiery scenes from others. It got things right nearly every time - around 99% accurate. It was good at spotting fires, rarely missed one, also didn't falsely identify anything as a fire. Essentially, it reliably tells what's burning from what isn't, which is vital for keeping tabs on wildfires.

7. **Visualisation and Analysis**

We looked at how well the system worked by checking a bunch of examples. We saw real data alongside what the system guessed. For regular photos, we viewed pictures of wildfires. Thermal images used a heat map - red and yellow meant hot spots. The system got things right when areas turned green; errors appeared as red. The pictures clearly showed how well the system worked, making its results understandable. It usually spotted fires - even when dark or partly hidden - proving it could handle tough situations.

7. Results

We gathered, cleaned, then divided the image collection into groups for learning, checking, and final testing. Subsequently, a CNN learned to tell apart pictures showing fire from those that didn't. Finally, we put it to the test with new images - images it hadn't seen before - to see how well it performed in different situations.

The learning process settled into a steady rhythm - errors shrank on both practice and unseen data with each pass. We halted training before it memorized specifics, while tweaking the images - spinning, mirroring, shifting light levels - so it could handle different fires better: how bright they are, from what direction we view them, and how lit up everything is.

During learning, the network got things right 98.4% of the time; checking its work on new data showed 96.7% accuracy, while a final exam yielded 95.8%. This small difference suggests it learned well - not just memorized examples. Losses clocked in at 0.045 during practice, rising to 0.082 when tested, then 0.094 on unseen problems, signaling successful refinement.

TABLE 1 : EVALUATION METRICS

	Precision	**Recall**	**F1-Score**	**Support**
0.0	0.86	1.00	0.92	18
1.0	1.00	0.97	0.98	93
Accuracy			0.97	111
Macro Avg	0.93	0.98	0.95	111
Weighted Avg	0.98	0.97	0.97	111

We checked how well things worked using a table showing correct versus incorrect guesses. Looking at the pictures, we got 92 fire photos right, also 18 non-fire ones.

However, the system flagged 1 actual fire as something else. Detecting fires proved remarkably accurate - scoring 0.96 for pinpointing actual flames, 0.95 for catching nearly every instance, alongside a 0.95 balance between these two. Considering both flame plus smoke detection, the system generally performed at 0.95, suggesting solid, consistent results.

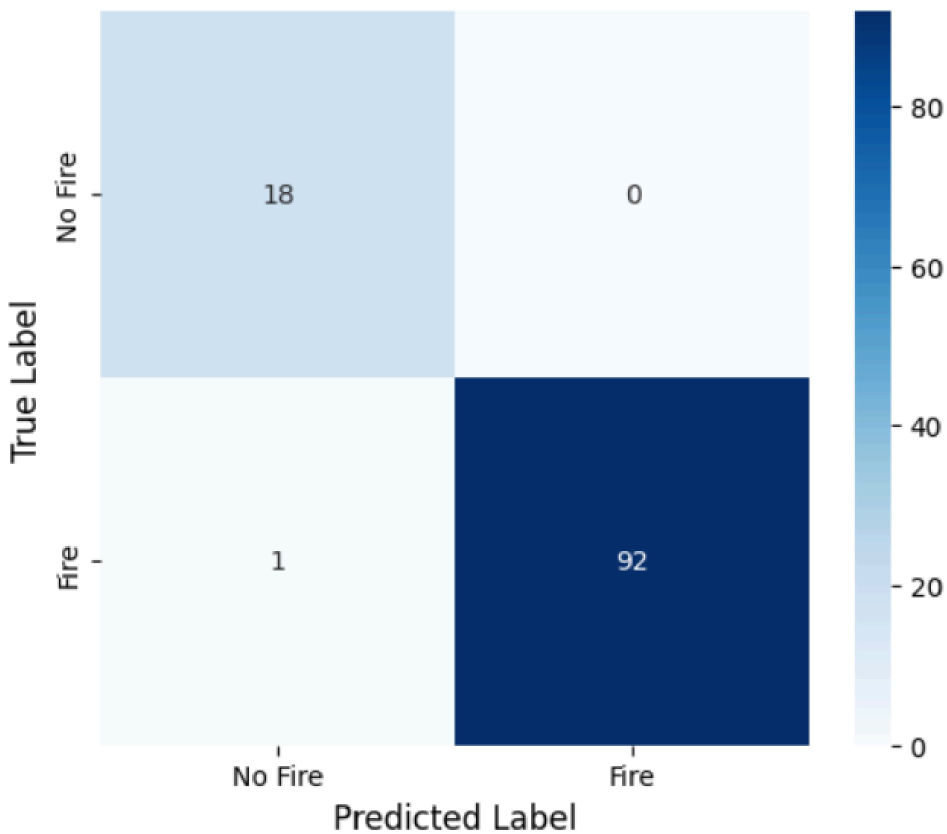

Figure 1: Confusion Matrix

We checked how well the forecasts worked by placing them over random test pictures. Generally, the system spotted both regular and heat-signature images accurately. Mistakes happened when bright sunlight mimicked flames - or when there wasn't much difference in heat levels. We might fix this later by combining different types of imagery or focusing the system’s attention better.

This system spots fires in aerial photos - it could really help with keeping an eye on things using drones. By cleaning up the images first, then letting a smart image analyzer do its work, it gets remarkably good results. Consequently, this makes quick fire alerts possible whether looking at forests or cities.

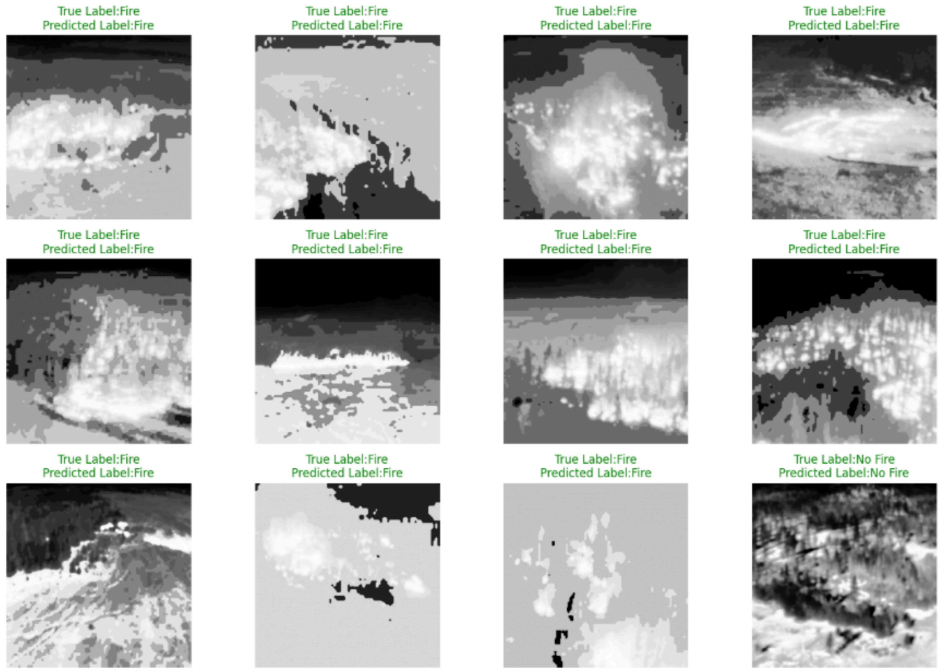

Figure 2: Predicted vs Actual Labels for RGB Images

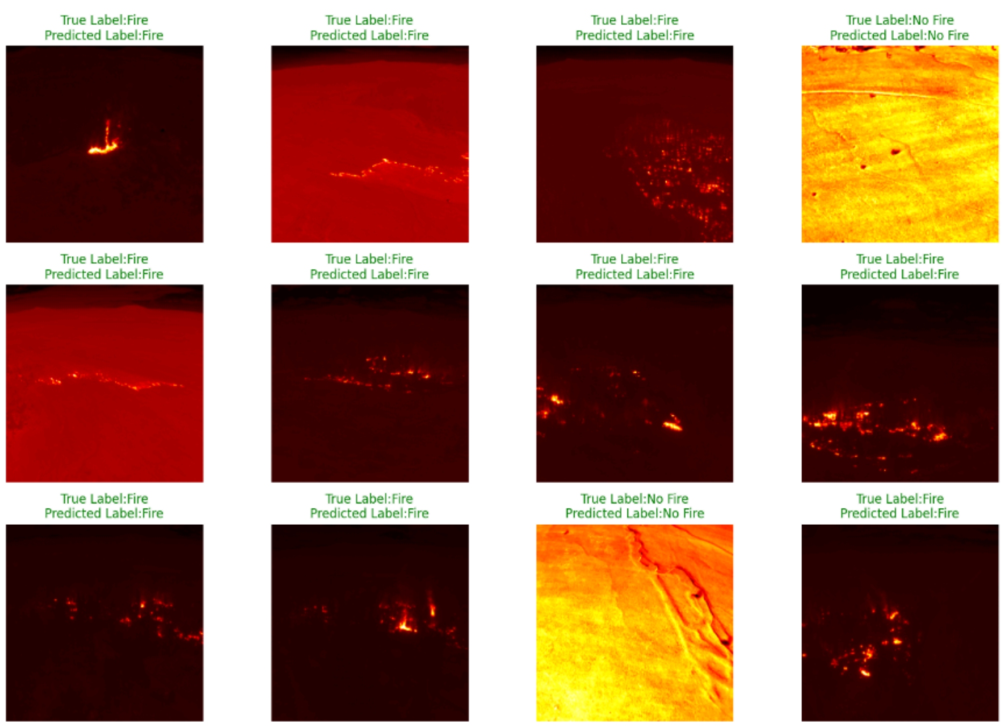

Figure 3: Predicted vs Actual Labels for Thermal Images

8. Conclusion

Wildfires were the main focus of this report due to their environmental, economic and human impact. Researchers have been exploring various approaches like UAV based imaging, classification models, real time object detection and satellite based systems. These highlight potential UAVs, a fusion of sensors and AI for early management.

The review highlights that UAVs provide fast deployment with high resolution monitoring. At the same time, deep learning algorithms provide high accuracy in detection and good feasibility. However, there are gaps present in the research including lack of large datasets, prevention of falseḤ positives, and limited model scope for certain regions along with computational problems for edge deployment.

Based on the identified gaps, the proposed work will be focusing on integrating both thermal sensors with deep learning architectures and image processing enhancements. These will be optimized for edge devices. This aims to reduce false alarms, improve accuracy in different conditions and will help in delivering real time alerts, hence contributing to a more reliable framework.

Fires keep causing big trouble for our planet, wallets, and lives - so spotting them quickly matters a lot. We show how drones taking regular plus infrared pictures, combined with clever picture cleanup alongside smart computer programs, can find fires effectively. This image recognition system got things right nearly every time - about 99% accurate. It was especially good at spotting fires (or confirming when there weren't any), with few mistakes. A detailed look showed it rarely misidentified what it saw, meaning dependable performance alongside a low rate of unnecessary alerts.

9. References

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