Assessment Task 1 – Image Processing and Pattern Recognition

Project Requirements and Specifications

Project Group 38

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Executive Summary

This project proposes the development of an automated two-stage image classification system for the early detection of bushfires. Bushfires represent one of the most severe natural hazards facing Australia and other parts of the world, with escalating impacts on human health, ecosystems, and the economy. Climate change has intensified their frequency and severity, highlighting the urgent need for improved early detection methods. Traditional approaches, such as satellite monitoring and lookout towers, remain constrained by human oversight, cloud interference, and delayed response times. An automated, image-based system provides a scalable alternative that can operate continuously with minimal human intervention.

We propose to achieve this with a two-stage classification schema in the interests of efficiency and economy of operation in its expected context. In Stage 1, a lightweight classifier determines whether an image contains a hazard, distinguishing fire or smoke from non-fire conditions. By prioritising recall, this stage ensures that potential hazards are not overlooked. If a hazard is identified, Stage 2 is activated to categorise the type of hazard as either smoke or fire. This additional classification supports emergency response planning, as visible flames typically demand immediate suppression, whereas smoke may indicate a smaller or hidden ignition requiring verification patrols. The staged approach ensures that computational resources are conserved under normal, non-hazardous conditions, while more detailed analysis is triggered only when necessary.

The system will be trained and evaluated using the publicly available Forest Fire, Smoke, and Non-Fire Image Dataset (Minha, 2023), which provides a balanced and curated foundation for reliable experimentation. Classical feature extraction methods such as LBP, GLCM, HOG, and colour ratios, paired with lightweight classifiers like SVM and kNN, will form the core of the pipeline, with performance assessed through metrics including recall, precision, F1-score, and confusion matrices. By combining efficiency, transparency, and reproducibility, this project aims not only to demonstrate the feasibility of automated bushfire detection but also to highlight its potential role in enhancing early warning systems, reducing false alarms, and ultimately safeguarding communities and ecosystems in the face of escalating climate-driven fire risks.

Introduction

The Project consists of a two-stage image classification system that supports automated bushfire monitoring. In Stage 1, the system identifies if there is a hazard by telling apart SMOKE or FIRE from non-fire images. In Stage 2, if a hazard is identified, the system assesses its severity as either SMOKE (indicating a possible or early-stage ignition) or FIRE (indicating an active, high-heat event). Under normal conditions, the system should generate no warnings. However, if a real or potential fire is detected, the system will issue an alert and label the type to help guide an appropriate response. This two-stage design offers efficiency. Stage 1 delivers a quick decision at the image level, giving just one label per frame without the need for tracking or localisation. This streamlined first step acts as a filter, allowing only potential hazards to trigger the more resource-intensive Stage 2, which focuses on differentiating fire from smoke.

We will build the system in Python using clear, explainable pipelines. These will include normalising light and contrast, extract texture and gradient features, and using simple colour ratios to tell flame cores apart from smoke plumes. For classification, we will test models like Linear SVM and kNN, adjusting threshold as needed. The dataset is the Forest Fire, Smoke, and Non-Fire Image Dataset (Minha, 2023), which has three classes: FIRE, SMOKE, and NON-FIRE. In Stage 1, FIRE and SMOKE are grouped as the positive class against NON-FIRE. In Stage 2, we compare FIRE and SMOKE directly. Ambiguous cases like fog, steam, or glare will be left out of training and reserved for error analysis. To ensure reproducibility, we will standardise resolution, fix train/validation/test splits, and evaluate performance with confusion matrices, ROC and PR curves for Stage 1, and class-specific precision, recall, and F1 scores for Stage 2. A small failure gallery will highlight common misclassifications.

Problem Importance

Bushfires are destructive natural hazards, causing devastating impacts on ecosystems and human lives. Recently, climate change and rising global temperatures have contributed to an increase in the frequency, intensity and severity of bushfires (EPA, 2024). Bushfires spread rapidly to surrounding bushland until the fire's boundary encounters a shortage of either heat, fuel and/or oxygen (CSIRO, 2015). Critically, the earlier a bushfire can be identified and assessed, the more manageable it is for responders. Early detection is therefore critical, the ability to recognise smoke or fire in its early stages, can help prevent small ignitions developing into more uncontrolled catastrophes (Bugarić et al., 2025). Traditional bushfire detection methods, such as lookout towers or satellite monitoring, are limited to human attention, cloud cover and long response times. A pre-positioned, automated image-based system provides a scalable and efficient alternative that can operate continuously with minimal human intervention.

In 2019-2020, Australia experienced an unprecedented scale of bushfires across New South Wales, with at least 1 billion animals killed and 33 lives tragically lost (Australian Academy of Science, 2020). Thick smoke cloaked many cities and neighbourhoods, causing an 86% spike in respiratory-related presentations at the Batlow emergency department and the sale of inhalers increased by 144% at pharmacies along the Mid North Coast (Australian Institute of Health and Welfare, 2020). Furthermore, the small particulate matter that makes up bushfire smoke has also been found to act as triggering factor for acute coronary events such as cardiac arrests (Haikerwal et al., 2015). These short-term effects of bushfire smoke have been heavily studied for their impact, however limited longer term studies have been performed to study the effect on individuals exposed to prolonged periods of smoke inhalation, conditions that were present in the 2019-2020 bushfires (Department of Health, Disability and Ageing, 2022). An automated detection system for bushfires could alert authorities earlier giving them more time to limit the scale of future bush fires, saving lives and minimising longer term health impacts.

In addition to human health concerns, bushfires can impose considerable ecological and economic impacts. When they do occur, they can inflict substantial reduction in habitat availability for dependent fauna (Baranowski et al., 2021), with the magnitude of affected habitat scaling directly with the extent of a bushfire. Between the loss of potential shelter and dependable food sources, bushfires cause significant disruption to native wildlife and their food chains (Rijksen & Dickman, 2014). Bushfires can also negatively affect aquatic species and ecosystems in the affected area, with the large-scale bushfires of 2019-2020 noted to have had an adverse impact on water quality in applicable regional areas, posing concerns both for the health of affected aquatic ecosystems and complicating water purification processes for human consumption (Jackson et. al., 2024). Moreover, these fires also burnt over twelve million hectares of bushland and destroyed more than three thousand homes (WWF, 2020), contributing to an estimated AUD 2.3bn of direct insurance costs and a total of AUD 100bn in indirect costs relating to lost tourism and broader economic decline (Ahmed & Ledger, 2023).

Therefore, Australian bushfires have historically had devastating impacts on public health, the environment and the economy and climate change is expected to increase the frequency and severity of future bushfires. An automated early detection system will mitigate human error and give authorities greater response time, preventing small fires from becoming uncontrolled. Furthermore, the implementation of a successful system will reduce the likelihood of Australia experiencing another catastrophic bushfire, which will save lives and livelihoods.

Dataset

Source and licensing

We will use the Forest Fire, Smoke, and Non-Fire Image Dataset (Minha, 2023). This dataset is a curated collection from multiple sources, including Kaggle, Yandex, and public forest-fire galleries. It is public and suitable for coursework. We will cite the author and keep the original license and attribution.

Scope for this project

This project aims to design and evaluate a two-stage image classification system for early bushfire detection. The system will operate on static images captured by monitoring devices in forested environments. The primary objective is to distinguish between hazardous and non-hazardous conditions to classify the hazard type and for a prioritised response.

First Stage

The first stage addresses the fundamental operational requirements of public safety, identifying whether the image contains a potential hazard or no hazard, in this case being FIRE/SMOKE or NON-FIRE/SMOKE. The emphasis on this stage is on high recall, since missing a fire hazard can have severe real-world consequences.

Second Stage

Once a hazard has been identified, the second stage classifies the hazard into smoke or fire. This classification helps emergency response teams determine the urgency and type of intervention needed. Visible flames generally demand urgent and robust suppression measures on the affected site/s, while smoke absent flames presume a greater emphasis on on-site verification to allay concerns of early or hidden ignition.

Dataset Scope

The system will be trained and evaluated on the Forest Fire, Smoke, and Non-Fire Image Dataset (Minha, 2023) which contains 42,900 images across 3 classes. The datasets are already split into training and testing sets, which will allow us to fairly benchmark the different methods. There are an even split of images across the three classes in the test and train sets and there is a 75/25 split between the training and test sets which will allow the model to generalise well and avoid overfitting. Within the training set, 20% of the data will be held out as a validation set to fine-tune hyperparameters and monitor overfitting. This ensures that the model is reliable and reproducible, while also reducing the risk of overtraining. By using the curated dataset, the model can provide meaningful insights into the strengths and weaknesses of various classification systems in the context of real-world bushfire detection

Curation & Preprocessing

Effective dataset preparation is essential for creating strong and reproducible classifiers. Before training, we carried out a careful curation and preprocessing process to clarify labels, reduce noise, and standardise inputs.

Curation

Curation begins with checking the clarity and accuracy of labels. We exclude ambiguous or misleading samples like fog, steam, industrial emissions, or strong sun glare from training but keep them for error analysis. This way, classifiers learn from clear examples of FIRE, SMOKE, and NON-FIRE. We can still evaluate their robustness against real-world challenges. We also remove duplicate and corrupted files to avoid bias and redundancy. Research shows that label and duplicate errors can distort results and obscure true model performance (Northcutt et al., 2021).

After curation, we preprocess the dataset for machine learning pipelines. All images are resized to a fixed resolution to ensure consistency and efficient computation across models. We convert images to a uniform RGB colour space, and we apply normalisation for light colour, contrast, and saturation to reduce variability from different devices and environments. This normalisation helps minimise overfitting to irrelevant details, like uneven lighting. We follow common practices in wildfire imagery by standardising inputs and applying mild, label-preserving augmentations to improve generalisation (e.g., El-Madafri et al., 2024).

To ensure reproducibility, we divide the dataset into training, validation, and test subsets using stratified sampling. This keeps the proportions of FIRE, SMOKE, and NON-FIRE consistent. As a result, the model does not favour larger classes, and evaluation reflects the actual class balance. To enhance generalisation, we augment the training set with small rotations, horizontal flips, and slight brightness adjustments. This helps the model adapt to natural variations in viewpoint and lighting while preserving the labels (El-Madafri et al., 2024).

We standardise labels for consistency. Any image showing visible open flames is labelled FIRE, even if smoke is present. Images with smoke plumes or haze, without a flame, are labelled SMOKE. NON-FIRE images show forested areas without smoke or fire. Clear labelling rules reduce confusion during training and evaluation, supporting interpretability and transparent reporting.

Through careful curation and preprocessing, we transform the dataset from a raw collection of images into a reliable, structured basis for developing and accessing our two-stage classification system.

Preprocessing (Implementation Details)

We revised all images to 256x256, applied basic colour balance and contrast normalisation, and used light label-preserving augmentations like small rotations, brightness shifts, and horizontal flips. These steps follow standard practice in wildfire images work, which standardises preprocessing and uses mild augmentations to improve generalisation (e.g., El-Madafri et al., 2024). We used the Forest Fire Smoke and Non-Fire Image dataset as our data source (Minha, 2023) and created stratified splits to keep class balance: 75/25 train/test, with 20% of the training set held out for validation (effective 60% train / 15% val / 25% test, stratified by class). We fixed the random seed to ensure reproducibility. The validation split is used exclusively for hyperparameter and threshold selection; the final model is retrained on train+val and evaluated once on the held-out test set.

Why This Matters

By organising confusing images that resemble fires into specific subclasses and applying the same preprocessing to all images, we created a dataset that is clean and realistic. This helps ensure that performance metrics reflect true classification ability instead of dataset artifacts such as label noise or confounding negatives (El-Madafri et al., 2024; Northcutt et al, 2021). This is particularly important in safety-critical domains like wildfire monitoring (EPA, 2024).

Methods & Alternatives

Conceptually, the target system can be divided into two related tasks. Stage 1 determines if a fire hazard appears in the image. If Stage 2 is activated, it classifies the severity of the hazard as either SMOKE or FIRE. This two-stage design combines efficiency and operational logic: a lightweight hazard filter runs continuously while the heavier classifier activates only when an anomaly is detected. An alternative would be a single-stage multi-class classifier (FIRE, SMOKE, NON-FIRE). However, this would increase the computational load under normal conditions and raise the risk of misclassification (Gragnaniello et al., 2024; Cheknane et al., 2024).

In Stage 1 (Hazard vs Non-Hazard), the positive class is defined as both FIRE and SMOKE, with NON-FIRE as the negative class. Here, a lean classifier (e.g. logistic regression) is suitable, since continuous operation demands efficiency. The evaluation emphasises recall, as missing a hazard is more critical than a false alarm (Yuan et al., 2015; Jin et al., 2023).

Formula (Saito & Rehmsmeier, 2015; Davis & Goadrich, 2006; Powers, 2020):

$$Recall = \frac{TP}{TP + FN}$$

This approach ensures that even rare fire or smoke events are not missed. Precision, accuracy, and the F1 score are also reported for balance (Saito & Rehmsmeier, 2015; Davis & Goadrich, 2006; Powers, 2020):

Formula (Saito & Rehmsmeier, 2015; Davis & Goadrich, 2006; Powers, 2020

$$Precision = \frac{TP}{TP + FP} \qquad Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

In Stage 2 (Smoke vs Fire), we differentiate between visible flames and smoke-only scenes. Any image showing a visible flame is labelled FIRE, even if smoke is also present. Plumes or haze without flames are labelled SMOKE. The pipeline normalizes colour and contrast, extracts texture and gradient cues such as GLCM, LBP, and HOG, and applies colour-based rules to capture flame colour characteristics. For example, high Y/Cr and low Cb in YCbCr indicate bright flame cores, while red-yellow dominance in RGB/HSV helps separate these from the more diffuse and lower-saturation look of smoke (Haralick et al., 1973;et al., 2002; Dalal & Triggs, 2005; Çelik & Demirel, 2009; Yuan, 2008). Classifiers such as Linear SVM and kNN will be used, with decision thresholds fine-tuned against a validation set. Both precision and recall are crucial for guiding resource allocation; a confusion matrix reveals misclassifications (e.g., smoke misidentified as fire in poor lighting) (Yang et al., 2024).

Alternatively, we could create a binary-only system that stops at Stage 1. This would reduce computation and minimise the risk of fire/smoke misclassification, but it would shift triage decisions back to human operators and diminish the benefits of automation. Therefore, the two-stage framework is more compelling for real-world deployment.

To ensure reproducibility, all models will be trained and validated on the Forest Fire, Smoke, and Non-Fire Dataset (Minha, 2023). We will use a fixed resolution of 256x256, with stratified splits (75/25 for validation) and controlled augmentations. We will summarise performance using ROC curves (plotting TPR vs FPR) and Precision-Recall curves, which are particularly suitable for imbalanced datasets (Saito & Rehmsmeier, 2015).

Alternative Methodology

While the proposed system focuses on a two-stage design for efficiency and operational strength, we need to consider backup options. A minimum viable approach would be to implement only Stage 1 (Hazard vs Non-Hazard) as a binary classifier. This design would still provide early warning capability by separating hazardous from non-hazardous conditions. However, it would require human operators to handle the more detailed classification of FIRE vs SMOKE. This fallback cuts down on computational demands and keeps the system feasible if Stage 2 turns out to be too complicated or time-consuming.

While our design emphasises a two-stage framework, we also understand the need for practical feasibility. If Stage 2 turns out to be too demanding in terms of computation or time with the full 42.9k-image dataset, a binary-only Stage 1 classifier could still give a reliable early warning by distinguishing between hazardous and non-hazardous conditions. In these situations, human operators would make triage decisions, such as smoke versus fire, which keeps things safe while reducing the computational load. We could also test lighter classifiers, such as Naïve Bayes or Random Forest, or use dataset sampling strategies to manage training time and costs. These backup options help ensure that the system can be delivered within project limits while allowing space for future improvements.

Evaluation Methodology

To assess the performance of our bushfire detection system, we use a structured, multi-metric evaluation method. The system operates in two distinct stages, consistent with fire-detection research that separates fire region proposal from recognition and classification (Gragnaniello et al., 2024; Cheknane et al., 2024). The main goal of stage 1 is to reliably identify hazardous images (SMOKE or FIRE) versus non-hazardous one. In this stage, we prioritise recall because missed hazards can lead to serious outcomes, and early detection is crucial (Yuan et al., 2015; Yang et al., 2024). Stage 2 aims to differentiate smoke from fire once a hazard s detected, for example, systems trained to recognise both classes (Cheknane et al., 2024). We measure performance using precision, recall, and F1-scores for each class. Precision and recall are standard metrics reported in fire and smoke studies, while F1 is commonly used to balance them (Yang et al., 2024; Gragnaniello et al., 2024).

Stage 1: Hazard vs Non-Hazard (Fire/Smoke vs Non-Fire).

The main objective of Stage 1 is safety assurance. We want to ensure that we do not miss any real hazards. Therefore, we focus on recall more than other metrics. Missing a hazard can have serious consequences, which is more critical than falsely identifying a hazard (Yuan et al., 2015; Jin et al., 2023). In addition to recall, we report precision, F1-score, and overall accuracy to evaluate the balance between detecting hazards and minimising false alarms (Yang et al., 2024). We further produce ROC and Precision–Recall (PR) curves, which are widely used to analyse classifier performance under different thresholds, particularly in safety-critical tasks (Gragnaniello et al., 2024; Deshpande et al., 2025).

Stage 2: Smoke vs Fire (Hazard Classification)

After detecting a hazard, the system must decide between SMOKE and FIRE. In this stage, both precision and recall matter equally because they affect response planning. For instance, mistaking FIRE for SMOKE could delay urgent action, while mislabelling SMOKE as FIRE might waste resources. Therefore, we report class-specific precision, recall, and F1-scores (Cheknane et al., 2024; Yang et al., 2024). We summarise outcomes with a confusion matrix to show patterns of misclassification, such as smoke being misidentified as fire in low light conditions (Gragnaniello et al., 2024).

Overall Evaluation

Our evaluation focuses on Stage 1 hazard recall and accuracy. We use ROC and PR analysis to determine appropriate thresholds. For Stage 2, we assess the quality of triage decisions by examining per-class precision, recall, and F1. This two-stage evaluation makes sure the system reliably flags hazards and categorises their severity meaningfully. The pipelines are lightweight and transparent, allowing for deployment on edge devices and supporting auditability in safety-critical situations. Using a curated public dataset makes our work ethical and reproducible, and documenting known failure modes keeps human oversight central in unclear cases.

Conclusion

This project set out to design and evaluate a two-stage image classification system for the early detection of bushfires. The motivation for this work arises from the increasing frequency, intensity, and severity of wildfires worldwide, trends that have been strongly linked to climate change and global warming. Traditional detection methods, such as satellite imaging and lookout towers, remain constrained by cloud cover, long revisit times, and human attention spans. Consequently, there is an urgent need for scalable, automated, and accurate systems capable of identifying fire hazards in their earliest stages. By developing and benchmarking a lightweight image-based classification pipeline, this project aims to contribute toward reducing the catastrophic human, environmental, and economic impacts of bushfires.

The system is built around a two-stage design that mirrors how fire authorities must make operational decisions in practice. In Stage 1, the system distinguishes between hazardous (FIRE or SMOKE) and non-hazardous images. Here, recall is prioritised because missing a hazard could delay suppression activities and result in severe outcomes. In Stage 2, once a hazard is detected, the system classifies whether the threat is smoke or visible flame. This stage directly supports triage, where smoke may indicate an early ignition requiring verification patrols, while visible flames typically demand urgent suppression. This two-stage framework reflects real-world firefighting needs: it first establishes whether action is necessary at all, then guides the urgency and scale of that action.

A key strength of the project is the use of the Forest Fire, Smoke, and Non-Fire Image Dataset (Minha, 2023). This curated dataset contains 42,900 balanced images across three categories, ensuring that the model is not biased toward any single class. The dataset is split into training and testing subsets, with additional validation sets carved out to fine-tune parameters and prevent overfitting. Balanced class representation, clear labelling rules, and reproducibility make the dataset especially suitable for evaluating and comparing alternative methods. By excluding ambiguous samples such as fog or glare from training, yet retaining them for error analysis, we ensured both the integrity of the models and insights into their limitations.

Beyond the technical aspects, this project also underscores the societal and environmental importance of wildfire detection. Bushfires in Australia and elsewhere have led to tragic loss of life, widespread destruction of ecosystems, and severe public health consequences from smoke inhalation. Automated detection systems cannot replace human decision-makers, but they can act as a critical first layer of defence, alerting authorities earlier and enabling faster, more efficient deployment of firefighting resources. By keeping the pipelines transparent, reproducible, and lightweight, the project addresses both the ethical and practical considerations of deploying technology in safety-critical contexts.

Ultimately, this project has demonstrated a structured and comprehensive approach to designing, implementing, and evaluating a bushfire detection system using image classification. It has been shown that a two-stage framework, supported by curated data, thoughtful preprocessing, lightweight feature extraction, and robust evaluation, can provide a reliable foundation for real-world applications. While there are limitations such as the exclusion of localisation and temporal tracking the insights gained here open pathways for future work, including integration with video data, thermal imagery, and more advanced neural models. Ultimately, the project highlights not only the feasibility of automated bushfire detection but also its necessity in an era of escalating climate-driven fire risks.

References

Ahmed, I., & Ledger, K. (2023). Lessons from the 2019/2020 "Black Summer Bushfires" in Australia. International Journal of Disaster Risk Reduction, 96(1). https://doi.org/10.1016/j.ijdrr.2023.103947

Australian Academy of Science. (2020, February 3). The Australian bushfires—why they are unprecedented. Www.science.org.au. https://www.science.org.au/news-and-events/news-and-media-releases/australian-bushfires-why-they-are-unprecedented

Australian Institute of Health and Welfare. (2020). Australian bushfires 2019–20: exploring the short-term health impacts. Australian Institute of Health and Welfare. https://www.aihw.gov.au/reports/environment-and-health/short-term-health-impacts-2019-20-bushfires/contents/summary

Baranowski, K., Faust, C.L., Eby, P., Bharti, N. (2021). Quantifying the impacts of Australian bushfires on native forests and gray-headed flying foxes. *Global Ecology and Conservation, 27*(2021). https://doi.org/10.1016/j.gecco.2021.e01566

Bugarić, M., Krstinić, D., Šerić, L., & Stipaničev, D. (2025). Current Trends in Wildfire Detection, Monitoring and Surveillance. Fire, 8(9), 356. https://doi.org/10.3390/fire8090356

Çelik, T., & Demirel, H. (2009). Fire detection in video sequences using a generic color model. Fire Safety Journal, 44(2), 147–158. https://doi.org/10.1016/j.firesaf.2008.05.005

Cheknane, M., Bendouma, T., & Boudouh, S. S. (2024). Advancing fire detection: two-stage deep learning with hybrid feature extraction using faster R-CNN approach. Signal, Image and Video Processing, 18(6–7), 5503–5510. https://doi.org/10.1007/s11760-024-03250-w

CSIRO. (2015, December 17). *Bushfire basics: what you need to know*. https://www.csiro.au/en/news/all/articles/2015/december/bushfire-basics

Dalal, N., & Triggs, B. (2005). Histograms of oriented gradients for human detection. 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), 1, 886–893 vol. 1. https://doi.org/10.1109/CVPR.2005.177

Davis, J., & Goadrich, M. (2006). The relationship between Precision-Recall and ROC curves. ICML 2006 : Proceedings, Twenty-Third International Conference on Machine Learning, 233–240. https://doi.org/10.1145/1143844.1143874

Department of Health, Disability and Ageing. (2022, July 25). enHealth guidance – Bushfire smoke and health. Australian Government Department of Health and Aged Care. https://www.health.gov.au/resources/publications/enhealth-guidance-bushfire-smoke-and-health-summary-of-the-current-evidence?language=en

Deshpande, U. U., Michael, Araujo, S., Srinivasaiah, S. H., Harshel Malawade, Kulkarni, Y., & Desai, Y. (2025). Real-time fire and smoke detection system for diverse indoor and outdoor industrial environmental conditions using a vision-based transfer learning approach. Frontiers in Computer Science, 7. https://doi.org/10.3389/fcomp.2025.1636758

El-Madafri, I., Peña, M., & Olmedo-Torre, N. (2024). Real-Time Forest Fire Detection with Lightweight CNN Using Hierarchical Multi-Task Knowledge Distillation. Fire (Basel, Switzerland), 7(11), 392. https://doi.org/10.3390/fire7110392

Gragnaniello, D., Greco, A., Sansone, C., & Vento, B. (2024). Fire and smoke detection from videos: A literature review under a novel taxonomy. Expert Systems with Applications, 255, Article 124783. https://doi.org/10.1016/j.eswa.2024.124783

Haikerwal, A., Akram, M., Del Monaco, A., Smith, K., Sim, M. R., Meyer, M., Tonkin, A. M., Abramson, M. J., & Dennekamp, M. (2015). Impact of Fine Particulate Matter (PM 2.5) Exposure During Wildfires on Cardiovascular Health Outcomes. Journal of the American Heart Association, 4(7). https://doi.org/10.1161/jaha.114.001653

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural Features for Image Classification. IEEE Transactions on Systems, Man, and Cybernetics, SMC-3(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314

Jackson, R., Krishna, K.C.B., Li, M., Sathasivan, A., Senevirathna, L. (2024). The influence of recent bushfires on water quality and the operation of water purification systems in regional NSW. *Scientific Reports, 14*(2024). https://doi.org/10.1038/s41598-024-66884-3

Jin, C., Wang, T., Alhusaini, N., Zhao, S., Liu, H., Xu, K., & Zhang, J. (2023). Video Fire Detection Methods Based on Deep Learning: Datasets, Methods, and Future Directions. Fire (Basel, Switzerland), 6(8), 315. https://doi.org/10.3390/fire6080315

Minha, A. (2023). *Forest fire, smoke, and non-fire image dataset* [Data set]. Kaggle. https://www.kaggle.com/datasets/amerzishminha/forest-fire-smoke-and-non-fire-image-dataset

Northcutt, C. G., Athalye, A., & Mueller, J. (2021). Pervasive Label Errors in Test Sets Destabilize Machine Learning Benchmarks. https://doi.org/10.48550/arxiv.2103.14749

Ojala, T., Pietikainen, M., & Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(7), 971–987. https://doi.org/10.1109/TPAMI.2002.1017623

Powers, D. M. W. (2020). Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. https://doi.org/10.48550/arxiv.2010.16061

Rijksen, E. & Dickman, C. (2014, December 12). *Predators get the advantage when bushfires destroy vegetation.* The Conversation. https://theconversation.com/predators-get-the-advantage-when-bushfires-destroy-vegetation-32821

Saito, T., & Rehmsmeier, M. (2015). The Precision-Recall Plot Is More Informative than the ROC Plot When Evaluating Binary Classifiers on Imbalanced Datasets. PloS One, 10(3), e0118432. https://doi.org/10.1371/journal.pone.0118432

U.S. Environmental Protection Agency (EPA). (2024, June). *Climate change indicators: Wildfires.*https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires

WWF. (2020). Australian Bushfires of 2019/2020 | Australian Bushfires | WWF Australia. Wwf.org.au. https://wwf.org.au/what-we-do/australian-bushfires/

Yang, M., Qian, S., & Wu, X. (2024). Real-time fire and smoke detection with transfer learning based on cloud-edge collaborative architecture. IET Image Processing, 18(12), 3716–3728. https://doi.org/10.1049/ipr2.13187

Yuan, C., Youmin Zhang, & Zhixiang Liu. (2015). A survey on technologies for automatic forest fire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques. Canadian Journal of Forest Research, 45(7), 783–792. https://doi.org/10.1139/cjfr-2014-0347

Yuan, F. (2008). A fast accumulative motion orientation model based on integral image for video smoke detection. Pattern Recognition Letters, 29(7), 925–932. https://doi.org/10.1016/j.patrec.2008.01.013

Appendix

Contribution Table

Name	Student Number	Contribution
Raymond Hsu		Curation (foundation)
Jun Hyun Lim		Introduction (foundation & revision), Problem Importance (revision) Dataset (Source and Licensing & Curation & Preprocessing (all the part) & Why This Matter) (foundation & revision), Methods & Alternatives (foundation & revision), Alternative Method (revision) Evaluation Methodology (foundation & revision), Document control
Hani Motassam		Project scope (Drafted and finalised), Problem Importance (Researched and structured with citations), evaluation methodology (expanded and aligned with rubric), Wrote the executive summary based on foundation written by William and Refined the Conclusion.
Thisuni Rupatunge		**DID NOT CONTRIBUTE**
William Tran		Executive Summary (foundation), Introduction (revision), Problem Importance (environmental impacts and project rationale), Methods & Alternatives (foundation)
Benjamin White		Dataset Scope- sourced dataset and wrote about its train/test split and class balance Problem Importance- Heavily researched health, environmental, and economic effects of bushfires, re-structured the section, and wrote conclusion Alternate Methodology- brainstormed potential

		alternative methods if issues occur References- Collated numerous references, ensuring alphabetical order