Group 73 Progress Report: Wildfire Detection Classification Plan

Andy Huynh, Berk Yilmaz, Tanisha Tasnin
huynha3@mcmaster.ca, **yilmag1@mcmaster.ca**, **tasnint@mcmaster.ca**

1 Introduction

Wildfires are becoming increasingly prevalent and devastating due to climate change [1]. This poses a growing threat to both human safety and the environment, causing billions of dollars in damages each year and severely affecting air quality and biodiversity [4], [9], [8]. Early detection of wildfires is crucial for effective response and mitigation efforts. However, detecting wildfires at an early stage can be challenging. Subtle indicators such as light smoke or small flames can be obscured by dense vegetation, clouds, or varying terrain, often making traditional monitoring methods unreliable [13]. In an attempt to address this issue, our project explores the use of Convolutional Neural Networks (CNNs) for automatic wildfire detection from images [12], [10]. Our project formulates the task as a binary classification problem: given an RGB image of an area, the model identifies it as a "fire" or "no fire" scenario using 'The wildfire dataset' by El Madafri on kaggle [5].

2 Related Work

Advancements in wildfire research have led to the use of deep learning to enhance prediction, monitoring, and detection capabilities [10]. There are several existing solutions that use a combination of various CNN architectures and other neural networks for wildfire prediction. Popular models include **FirePred** and **WFNet**. *FirePred* is a hybrid multi-temporal CNN model for wildfire spread prediction and *WFNet* is a hierarchicalCNN for wildfire spread prediction [7], [6]. However these models, like most renowned ones, focus on modeling wildfire spread and spatiotemporal dynamics rather than direct detection from visual data which our project addresses. For direct wildfire detection from images, the paper **Advanced Wildfire Detection Using Deep Learning Algorithms: A Comparative Study of CNN Variants** is a notable example [2]. This study evaluates models such as InceptionV3, Xception, and NASNetMobile on over 25,000 images, achieving accuracies above 98%. While this study focuses on benchmarking CNN architectures for accuracy, our project differs by optimizing image preprocessing and augmentation pipelines to balance accuracy with computational efficiency for real-time detection. There are however other CNN projects such as Malaria Detection using TensorFlow's malaria dataset that resemble our project's workflow more closely [11], [3]. Similar to our approach, they emphasize image preprocessing, model training, and performance optimization for efficient binary classification.

3 Dataset

4 Features

Since convolutional neural networks (CNNs) learn features automatically, our "feature engineering" focuses on transformations that enhance spatial learning rather than on hand-crafted variables.

5 Implementation

6 Results and Evaluation

7 Feedback and Plans

The primary feedback focused on improving the reproducibility and interpretability of the results. Specifically, the TA recommended implementing a more consistent validation split across all preprocessing configurations to ensure that performance differences are not influenced by random sampling. Additionally, they advised that the baseline model should be clearly defined and quantitatively compared against augmented configurations to emphasize the measurable impact of each experimental change. Another key piece of feedback was to include computational metrics—such as average training time per epoch and resource utilization—in the results table. This would clearly demonstrate trade-offs between model accuracy and computational efficiency, which is key to optimizing performance under limited resources. The TA also suggested monitoring for potential overfitting by tracking training and validation accuracy curves more closely and introducing early stopping or dropout adjustments if the validation loss diverges.

For the remainder of the project, we plan to incorporate these recommendations by (1) locking a fixed random seed for reproducibility, (2) ensuring the dataset splits are stratified, (3) expanding the evaluation metrics to include F1-score and confusion matrices for a more detailed performance assessment, and (4) introducing a systematic summary table comparing all tested resolutions and augmentation levels. We will also document the data preprocessing pipeline in greater detail to improve transparency and ensure that results are easily replicable. Finally, once the best-performing configuration is identified, we will retrain the model for additional epochs and evaluate it on a held-out test set to provide final quantitative results and visualizations.

Team Contributions

References

[1] National Aeronautics and Space Administration. 2025. Wildfires and climate change. Web page. Available at https://science.nasa.gov/earth/explore/wildfires-and-climate-change/. Accessed: 2025-11-09.

[2] Abhila O. Anju, M. Jayasree, S. Yashica, K. S. Vishali, M. Yuvaraj, and K. Suresh Babu. 2025. Advanced wildfire detection using deep learning algorithms: A comparative study of cnn variants. *International Research Journal on Advanced Science Hub (IRJASH)*, 7(02):79–86.

[3] Bnsreenu. 2023. Malaria binary classification using tensorflow lite. https://github.com/bnsreenu/python_for_microscopists/tree/master/237_tflite_using_malaria_binary_classification. GitHub repository, accessed on 2025-11-10.

[4] Health Canada. 2024. Human health effects of wildfire smoke — report summary. Web document. Available at https://www.canada.ca/en/services/health/healthy-living/environment/air-quality/wildfire-smoke/human-health-effects-report-summary.html. Accessed: 2025-11-09.

[5] I. El-Madafri, M. Peña, and N. Olmedo-Torre. 2023. The wildfire dataset – enhancing deep learning-based forest fire detection with a diverse evolving open-source dataset. https://www.kaggle.com/datasets/elmadafri/the-wildfire-dataset?resource=download. Kaggle dataset, accessed on 2025-11-10.

[6] Wenyu Jiang, Yuming Qiao, Guofeng Su, Xin Li, Qingxiang Meng, Hongying Wu, Wei Quan, Jing Wang, and Fei Wang. 2023. Wfnet: A hierarchical convolutional neural network for wildfire spread prediction. *Environmental Modelling & Software*, 170:105841.

[7] Mohammad Marjani, Seyed Ali Ahmadi, and Masoud Mahdianpari. 2023. Firepred: A hybrid multi-temporal convolutional neural network model for wildfire spread prediction. *Ecological Informatics*, 78:102282.

[8] NBC News. 2025. Billion-dollar disasters: The economic toll of wildfires, severe storms and earthquakes is soaring. Web document. Available at https://www.nbcnews.com/science/climate-change/billion-dollar-disasters-economic-toll-wildfires-severe-

[9] Laxita Soontha and Mohammad Younus Bhat. 2026. Global firestorm: Igniting insights on environmental and socio-economic impacts for future research. *Environmental Development*, 57. Accessed: 2025-11-10.

[10] Dario Spiller, Andrea Carbone, Stefania Amici, Kathiravan Thangavel, Roberto Sabatini, and Giovanni Laneve. 2023. Wildfire detection using convolutional neural networks and prisma hyperspectral imagery: A spatial-spectral analysis. *Remote Sensing*, 15(19):4855.

[11] TensorFlow Datasets. 2023. Malaria dataset. https://www.tensorflow.org/datasets/catalog/malaria. Contains 27,558 thin blood-smear cell images with parasitized/uninfected labels.

[12] Eleni Tsalera, Andreas Papadakis, Ioannis Voyiatzis, and Maria Samarakou. 2023. Cnn-based, contextualized, real-time fire detection in computational resource-constrained environments. *Energy Reports*, 9:247–257.

[13] Berk Özel, Muhammad S. Alam, and Muhammad U. Khan. 2024. Review of modern forest fire detection techniques: Innovations in image processing and deep learning. *Information*, 15(9):538.