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 [], [], []. 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 [], []. In an attempt to address this issue, our project explores the use of Convolutional Neural Networks (CNNs) for automatic wildfire detection from images [], []. 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 [].

2 Related Work

Advancements in wildfire research have led to the use of deep learning to enhance prediction, monitoring, and detection capabilities []. 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 [], []. 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 []. 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 [], []. 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

Team Contributions

References

[1] Rie Kubota Ando and Tong Zhang. 2005. A framework for learning predictive structures from multiple tasks and unlabeled data. *Journal of Machine Learning Research*, 6:1817–1853.