Group 73 Progress Report:
Wildfire Detection Classification Plan

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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

We are training our model with the splits gathered from Kaggle. We have 1887 data points for training, 402 for validation, and 410 for test. This roughly corresponds to a 70-15-15 split of our dataset.

The dataset is composed of images mainly depicting forests, fields, and rural areas. Images are sorted into two categories; "fire" and "nofire". These categories constitute the labels we use during training.

The images are of different resolutions and quality. Some images are considerably higher resolution than others, and it is apparent that the images are from different time periods and were taken by different devices. This presents a minor challenge in training our model, where we need to ensure our model can use each and every one of these data points. We tacke this by normalizing our data as outlined in the Features section.

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

Our model is a feedforward classification model. It is composed of TODO Conv2D layers of size TODO with ReLu activation, followed by a Dense layer with TODO units. The model has TODO parameters in total, taking up about TODO MB in total.

Before training, we optimized various parameters empirically. We set out certain augmentations and resolutions to be tested, then trained a model on every dimension of this space via nested for loops that can be found in our code. This process is further outlined in the Features section. The size of layers and the number of layers were determined by manual empirical testing.

6 Results and Evaluation

Our model evaluation process focuses on comparing different image preprocessing and augmentation configurations to identify the combination that offers the best trade-off between computational efficiency and classification accuracy. The array of pixel sizes we are testing includes pixelsizes TODO Each configuration was trained for five epochs, and both validation accuracy and average computation time per epoch were recorded to measure performance. The system automatically stops iterating over new resolutions when accuracy improvements fall below 3%, reducing unnecessary computation.

Initial experiments at lower resolutions (128x128) with standard augmentation (rotation, brightness, and zoom variations) achieved validation accuracies around 57 - 58%.

Larger image resolutions are currently being evaluated to determine whether higher spatial detail leads to significant accuracy gains. The best configuration identified so far will be used to train the final CNN model, which is then validated and tested on separate data subsets.

The final architecture employs a four-block convolutional neural network (Conv2D-MaxPooling layers) with dropout for regularization, compiled with binary cross-entropy loss, a metric of accuracy, and the Adam optimizer. Model performance is monitored across epochs using accuracy and loss curves saved as visual outputs. Test performance will be reported once all preprocessing configurations finish executing. For baselines, the model without augmentation and at lower resolutions serves as the control, while subsequent tests compare the impact of increasing image size and data augmentation strength.

Our current best model uses no augmentation and normalizes images to 224x224. This model achieves a training accuracy of 83.73% and a validation accuracy of 79.85%. However, this model is an early experiment and many areas of improvement were raised during the experimentation process. as outlined in the Feedback and Plans section.

To evaluate model performance, the following classification metrics are computed on the test set:

Metric	Fire	No Fire	Weighted Avg.	Support
Precision	xxx	xxx	xxx	xxx
Recall	xxx	xxx	xxx	xxx
F1-Score	xxx	xxx	xxx	xxx
Accuracy			xxx	

Table 1: Model performance metrics on the test set (placeholders to be updated after full training).

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

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