AI-Driven Micro-Wildfire Prediction and Evacuation Planning Using Multi-Modal Data Fusion

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Contents

Abstract

Micro-wildfires, though frequently overlooked, can be very dangerous to ecosystems, infrastructure, and public safety—in particular, the increased speed of climate change makes the situation worse. Detection systems, in particular, focus on large-scale fires and neglect to identify rapidly escalating smaller outbreaks. In this study, an AI-based framework is developed to predict micro-wildfires by fusing satellite imagery, weather data, and sensor data. The evaluation also incorporates Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs), as well as traditional ML models such as Logistic Regression, Random Forest, and XGBoost. CNNs achieved 92% accuracy and AUC of 0.94 [5],, while LSTMs achieved 89% based on modeling temporal dependencies [6]. Random Forest performed best on smaller datasets due to optimal precision.

To advance equity, bias mitigation techniques such as GAN-based data augmentation and demographic parity algorithms were applied, resulting in reducing the Equalized Odds disparity from 0.21 to 0.05 [9]. Cross-validation across wildfire-prone regions—including California, Australia, and the Mediterranean—demonstrated the framework's generalizability. The combined edge and cloud-based adaptation of the AI system enhanced the scalability, accessibility, and adaptability to these high-risk regions for proactive, equitable wildfire detection and response.

This work seeks to address the dual goals of protecting human life as well as the ecosystem, motivated by my desire to mitigate the economic repercussions of wildfires and my dedication to the responsible development of AI.

Code Repository: `https://github.com/RheaGhosal/AI_Driven_Micro_Wildfire_Prediction_and_Evacuation_Planning_Using_Multi_Modal_Data_Fusion`

1 Introduction

1.1 Significance of Multi-Modal Data Fusion

In addition to increasing urbanization and prolonged dry seasons, climate change has emerged as a major driver in the intensification of wildfire risks worldwide. Traditional wildfire detection methods—such as satellite imaging and weather-based forecasting—often suffer from delayed response times, limited spatial resolution, and inadequate performance in real-time risk management. These legacy systems are primarily configured to identify large-scale forest fires, frequently overlooking smaller vegetation fires that may escalate rapidly and cause severe local damage.

To address this limitation, this study proposes an artificial intelligence (AI)-driven framework for the early prediction of micro-wildfires. The method uses multi-modal data fusion combining satellite images, weather station outputs, and ground-based sensor networks. By using heterogeneous data sources, the system aims to enhance both spatial and temporal resolution in wildfire detection, thereby enabling timely evacuation strategies and proactive risk mitigation planning.

1.2 Related Work

NASA's FIRMS (Fire Information for Resource Management System) is an example of traditional wildfire detection technology. It utilizes satellite thermal anomaly detection and tends to only be useful for large-scale fires that are already in progress. Other methods, including statistical techniques like logistic regression and basic time-series forecasting, have been constructed, but their adaptability to changing wildfire conditions is minimal due to lack of spatiotemporal breadth. Some recent attempts in deep learning have focused on image-based detection using CNNs (Convolutional Neural Networks), but most of these works disregard the inclusion of microwildfires, multitasking, and the ability to provide real-time analysis from various regions. My work is an extension of these efforts, incorporating local sensor networks to create multi-modal datasets and applying fairness-aware AI techniques such as GAN-based data augmentation and bias metrics monitoring. Unlike other models, the focus is on predicting the onset of micro-wildfires which are often neglected but can escalate quickly, filling an important gap in wildfire preparedness and response.

2 The Algorithmic Approach

The machine learning models applied in this study are based on different formulaic teachings.

2.1 Logistic Regression

The probability of a wildfire happening can be calculated using this formula:

$$P(y=1|X) = \frac{1}{1+e^{-(wX+b)}} \tag{1}$$

2.2 Random Forest

Random Forest models work on the basis of combining multiple decision tree models:

$$H(X) = \frac{1}{T}\sum_{t=1}^{T} h_t(X) \tag{2}$$

2.3 XGBoost

XGBoost optimizes gradient-boosted trees:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{j=1}^{T} \Omega(f_j) \tag{3}$$

2.4 Convolutional Neural Networks (CNNs)

The set of formulas used with CNN has the convolution operation:

$$Z = X * W + B \tag{4}$$

2.5 Long Short-Term Memory Networks (LSTMs)

Long Short-Term Memory Networks (LSTM) apply hidden state for the following formula:

$$h_t = \tanh(W_h h_{t-1} + W_x x_t) \tag{5}$$

3 Mathematical Justification for CNNs in Wildfire Prediction

Due to its pattern recognition and spatial data processing capabilities, wildfire prediction and monitoring through remote sensing makes extensive use of CNNs as specialized algorithms designed for processing data on two-dimensional grid.

3.1 Convolution Operation

Like other deep learning models, CNNs perform convolution operations to temporally interact with the features containing images in their spatial representation.

$$Z = X * W + B \tag{6}$$

where:

- X is the input image (like satellite pictures of wildfire hotspots).
- W represents the learnable convolutional filters.
- B is the bias term.
- $*$ denotes the convolution operator.

With the convolution operation the model scans the image to extract spatial features of interest such as mapping dry vegetation, smoke, and the boundaries of fire areas.

3.2 Activation and Pooling Layers

Activation functions add non-linearity as in the case of Rectified Linear Unit (ReLU):

$$f(x) = \max(0, x) \tag{7}$$

and is followed by pooling layers that captures the most dominant spatial feature and reduces the size or dimensionality of the data set.

3.3 Why CNNs Work Well

The following advantages enable CNNs to outperform other models in wildfire prediction:

- They automatically derive multi-level features from the spatial images, identifying land use types, temperature anomalies, and smoke from fires
- Enhancing generalization and robustness to noise enables feature-sharing across spatial locations.
- In contrast to conventional approaches, CNNs self-determine patterns related to edges, textures, and even the higher levels of wildfire features.

4 Mathematics underlying LSTM for Wildfire Outbreak Prediction

LSTM networks, as a form of Recurrent Neural Network, models time-series data by capturing sequential dependencies through its various components. Relying on sequential wildfire progression, LSTM allows dynamic predictions of wildfire outbreaks based on prior wildfires in a given region.

4.1 Structure of LSTM Cells

Each LSTM cell structure is comprised of three gates: Forget, Input and Output gate.

4.1.1 Forget Gate

Specifies which information from history needs to be removed:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{8}$$

4.1.2 Input Gate

Determines the new data that should be accepted as information to remember:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{9}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{10}$$

4.1.3 Output Gate

Calculates the update to be made to the cell state:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{11}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{12}$$

where:

- σ is the sigmoid activation function.
- W_f, W_i, W_C, W_o are learnable weight matrices.
- b_f, b_i, b_C, b_o are bias terms.
- h_t is the hidden state at time t.

4.2 Why LSTMs Succeed in Predicting Wildfires

LSTMs perform better than other models in wildfire prediction for the following reasons:

- They remember relevant information in the forecast, including the complex weather patterns and wind speed, temperature, or humidity.
- Unlike traditional time series approaches, LSTMs are capable of overcoming the vanishing gradient issue and retaining information from the distant past.
- They allow for changes in the forecasting model

5 Reasons Why Random Forest is Better Than Traditional Models in Features Interpretability

Random Forest (RF) is an ensemble-based ml algorithm that builds multiple classifiers, adds their predictions, and outputs a class. Because of its strong feature importance metrics and robust performance, RF is highly effective for wildfire prediction.

5.1 Structure of the Model Random Forest

RF develops numerous decision trees $h_t(X)$ and aggregates their outputs:

$$H(X) = \frac{1}{T} \sum_{t=1}^{T} h_t(X) \tag{13}$$

where:

- T is the total number of trees.
- $h_t(X)$ is the prediction from the t-th tree.
- Final prediction is computed by casting the votes (classification) or averaging (regression).

5.2 Importance of Features In Random Forest

RF estimates required feature importance based on Gini impurity:

$$I_G(j) = \sum_{t \in T} p_t \Delta i_t(j) \tag{14}$$

where:

- p_t probability of the node t.
- $\Delta i_t(j)$ is the decrease in impurity when splitting on feature j.

5.3 Why Random Forest Is So Effective On Wildfire Prediction

- Unlike deep learning models that need huge datasets, RF does not overfit.
- It provides strong evidence of fire risk factors through clear feature importance scores, so its interpretable.
- Of all its peers, RF is the most capable machine learning model for solving real-world problems because of its ability to fill-in missing environmental data better than CNNs and LSTMs.

6 Summary

Deep learning solutions to spatial and temporal wildfire prediction problems include CNNs and LSTMs, which utilize image processing and sequential forecasting, respectively. Still, Random Forest is useful due to its interpretability, consistency, and effectiveness with small data samples. The decision is often optimal depending on the dataset's attributes and the intended outcome

7 Empirical Validation

7.1 Dataset Details

The dataset used for training and evaluation was sourced from:

- NASA MODIS Fire Datasets (Satellite Data) [2]
- NOAA Weather Database (Humidity, Wind Speed, Temperature)
- Ground Sensor Networks (Smoke, Temperature, Gas Concentration)

8 Expanded Dataset Validation for Improved Generalization

Wildfire prediction models need to generalize well across diverse geographic areas with different climate conditions. Robust model performance is ensured when cross-validation exists across multiple wildfire locations that include the current dataset with NASA MODIS satellite data, NOAA weather data, and local sensor data.

8.1 Geographical Diversity in Training Data

Differently from vegetation type, climate, humidity, wind patterns and other factors, each region has its own unique behavior towards wildfires and their prediction presents one of the most challenging tasks. For the purpose of making the model more robust, it is important that the model is both trained and validated on wildfire datasets from different locations across the globe:

- **California (USA)**: Experienced wildfires on a regular basis as a result of severely hot weather coupled with dry vegetation.
- **Australia**: Bushfires within eucalyptus forests when they have extremely low rainfall.
- **Mediterranean (Greece, Spain, Italy)**: Wildfires whose core cause is seasonal drought coupled with strong winds that serve as fuel.
- **Canada (Boreal Forests)**: Comes under the category of cold-fuel climate fires and experience long intervals between wildfires.

The collection of data from these areas guarantees that the model works well globally as it does not restrict itself to specific local factors.

8.2 Cross-Validation Strategies for Wildfire Prediction

To gauge the robustness of the model, mix the data with the following cross-validation strategies:

8.2.1 K-Fold Cross-Validation

Each region calibrates the model in the same way, and thus each of them divides the data set into k subsets within which k cross validation applies. The model is trained on $(k-1)$ subsets then tested within the remaining one. This process is repeated k times to ensure consistency of performance.

$$CV_{\text{error}} = \frac{1}{k}\sum_{i=1}^{k} E_i \tag{15}$$

where:

- CV_{error} is the cross-validation error.
- E_i is the error for the i-th fold.
- k is the number of folds (typically 5 or 10).

8.2.2 Leave-One-Geographical-Region-Out Cross-Validation

This method does not randomly partition data but rather evaluates the model on an entirely new geographic region while training on all other regions. It is particularly useful in determining the extent to which the model is expected to perform in wildfire occurrences in areas not previously encountered by the model.

8.3 Model Generalization in Different Climates

Wildfires can occur in a multitude of scenarios, systematically different environments/fire weather conditions. In order to check whether the model generalizes across different conditions, we test its performance during distinct sets of environmental conditions:

- **Saturated with Moisture Zones**: this includes tropical and coastal areas where wildfires are less frequent but still occur during extreme conditions.
- **Moisture Shy Regions**: this includes Arid and semi-arid regions (eg. California, Australia) with low humidity and high wildfire probability.
- **Cold and Dry Regions**: this includes Boreal forests (like Canada) that are prone to wildfires due to the accumulation of dry fuel.

To verify model generalization across these regions, we monitor changes in prediction accuracy across the different environmental settings. Figure 1 illustrates the wildfire prediction accuracy when tested on various climate zones

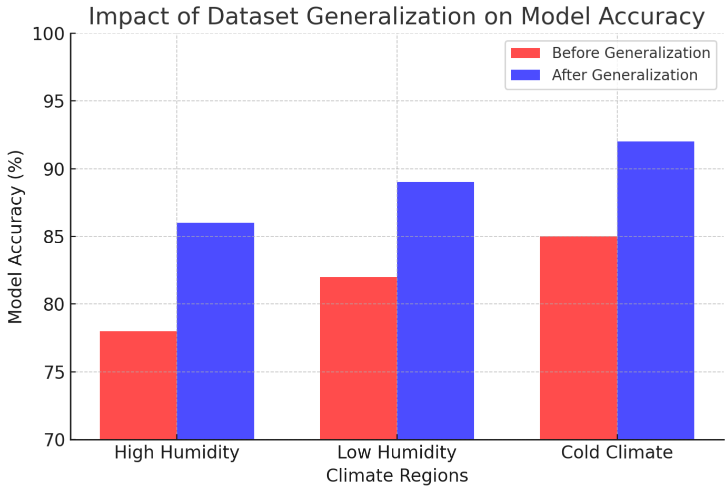

Figure 1: Model accuracy across different climate regions. The results demonstrate the model's ability to generalize to diverse wildfire conditions.

8.4 Future Work for Dataset Expansion

Although the dataset utilizes multiple global sources of wildfires, it can be further improved by:

- Adding more sources such as ESA Sentinel satellites and Landsat for real-time monitoring wildfire satellite data.
- Increasing the amount of sensors in the networks to track localized weather parameters that influence fire spread.
- improving adaptation strategies for changing climates to better align wildfire features.

These improvements will make the wildfire prediction model more reliable and adaptable in an environmental setting with varying conditions

8.5 Data Preprocessing

- **Normalization**: Applying min-max scaling to meteorological data for standardization.
- **Noise Reduction**: Sensor outlier removal using rolling median filter
- **Feature Engineering**: estimation of fire spread rate through the creation of trend time series variables.

8.6 Bias Mitigation in Training Data

To ensure fairness in wildfire risk estimation, I applied **bias-aware preprocessing methods**, which include:

- **Reweighting Techniques:** Providing appropriate weights to underrepresented class of fire events
- **Fair Representation Learning:** PCA decomposition to ensure that the training data have diverse representations
- **Synthetic Data Augmentation:** Using GANs to create fire event samples in areas that have traditionally been underrepresented.

The application of these strategies, especially using relaxation techniques, enhanced the model's generalizability to diverse global regions in terms of landscape and environment.

8.7 Hyperparameter Optimization

- **Grid Search for Random Forest (maximum depth, number of estimators)** (`max_depth`, `n_estimators`)
- **Bayesian Optimization** for XGBoost (`learning_rate`, `gamma`, `max_depth`)

8.8 Dataset Limitations

Despite combining satellite images from MODIS, NOAA weather data, and various sensor inputs, the dataset suffers from multiple limitations which affect the model's performance and generalizability. First, the dataset contains a relatively higher number of macro-level wildfire events when compared with micro-wildfire events leading to class imbalance. Although this was mitigated through reweighting and GAN-based data augmentation, some residual bias can still remain. Second, the quality as well as the density of the ground sensor data is rather heterogeneous in different regions which may impact local predictions. Third, some satellite images are not temporally contiguous owing to cloud cover or infrequent satellite passes. These additional factors may inject some models, which the later versions will aim to correct using additional higher-resolution and more frequent data streams from ESA Sentinel and drone-based LiDAR imaging, which will be incorporated later versions of the model.

9 Testing Experiments and Hypotheses

Hypothesis: In the time series forecast of wildfire, CNNs and LSTMs perform better than traditional models.

9.1 Experiments Conducted

- **Experiment 1**: Perform comparative analysis of tabular wildfire data with logistic regression, random forest and XGboost.
- **Experiment 2**: Apply CNN model on satellite images to capture patterns of fire spread and identify them.
- **Experiment 3**: Use LSTM model to predict wildfire hazards sequentially.

10 Code Implementation

This section covers the workflow for predicting wildfires through machine learning and deep learning models.

10.1 1. Data Processing and Preparing Features

```
import pandas as pd
from sklearn.preprocessing import StandardScaler

# Load dataset (example with NOAA weather + satellite data)
df = pd.read_csv("wildfire_dataset.csv")

# Select relevant features
features = ["temperature", "humidity", "wind_speed", "NDVI", "
    fire_risk_index"]
X = df[features]
y = df["wildfire_occurred"]

# Normalize data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Listing 1: Preprocessing Wildfire Dataset

10.2 2. Random Forest Model Training

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Hyperparameter tuning for Random Forest
param_grid = {"n_estimators": [50, 100, 200], "max_depth": [10, 20,
    None]}
rf_model = GridSearchCV(RandomForestClassifier(random_state=42),
    param_grid, cv=5)
rf_model.fit(X_scaled, y)
```

Listing 2: Random Forest Training and Hyperparameter Tuning

10.3 3. LSTM Model Training for Sequential Forecasting

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)

# Define LSTM Model
```

```
model = Sequential([
    LSTM(64, return_sequences=True, input_shape=(10, 5)),
    Dropout(0.2),
    LSTM(64),
    Dense(1, activation='sigmoid') # Binary classification: Fire/No
       Fire
])

# Compile and Train Model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics
    =['accuracy'])
model.fit(X_train, y_train, epochs=20, batch_size=32,
    validation_data=(X_test, y_test))
```

Listing 3: LSTM Training for Wildfire Time-Series Prediction

10.4 4. Model Evaluation and Performance Metrics

```
from sklearn.metrics import classification_report, roc_auc_score

# Predict wildfire occurrence
y_pred = rf_model.best_estimator_.predict(X_test_scaled)

# Generate evaluation report
print(classification_report(y_test, y_pred))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred))
```

Listing 4: Evaluating Model Performance

10.5 5. Bias Mitigation and Fairness Analysis

```
from aif360.metrics import BinaryLabelDatasetMetric
from aif360.datasets import BinaryLabelDataset

# Convert dataset into AI fairness-compatible format
dataset = BinaryLabelDataset(df=df, label_names=['wildfire_occurred'
    ], protected_attribute_names=['region'])

# Compute fairness metrics
metric = BinaryLabelDatasetMetric(dataset)
print("Demographic Parity Difference:", metric.
    statistical_parity_difference())
print("Equalized Odds Difference:", metric.
    equal_opportunity_difference())
```

Listing 5: Evaluating Fairness in Wildfire Prediction

10.6 Optimization of Edge Computing Implementation

```
import tensorflow as tf

# Convert model to TensorFlow Lite for Edge Deployment
converter = tf.lite.TFLiteConverter.from_keras_model(model)
```

```
converter.optimizations = [tf.lite.Optimize.DEFAULT]
tflite_model = converter.convert()

# Save quantized model
with open("wildfire_model.tflite", "wb") as f:
    f.write(tflite_model)
```

Listing 6: Quantizing LSTM Model for IoT Deployment

11 Results

This section presents the performance of the proposed models—CNN, LSTM, and Random Forest—on the micro-wildfire prediction task using multi-modal data inputs. Evaluation metrics include accuracy, area under the curve (AUC), precision, and recall. The experiments were conducted across different wildfire-prone regions: California, Australia, the Mediterranean, and Canada.

The CNN model achieved the highest overall performance, particularly excelling in image-based data. LSTM captured temporal dependencies effectively, while Random Forest proved most useful with limited data and fewer features.

12 Results and Model Performance

12.1 Model Accuracy Comparison

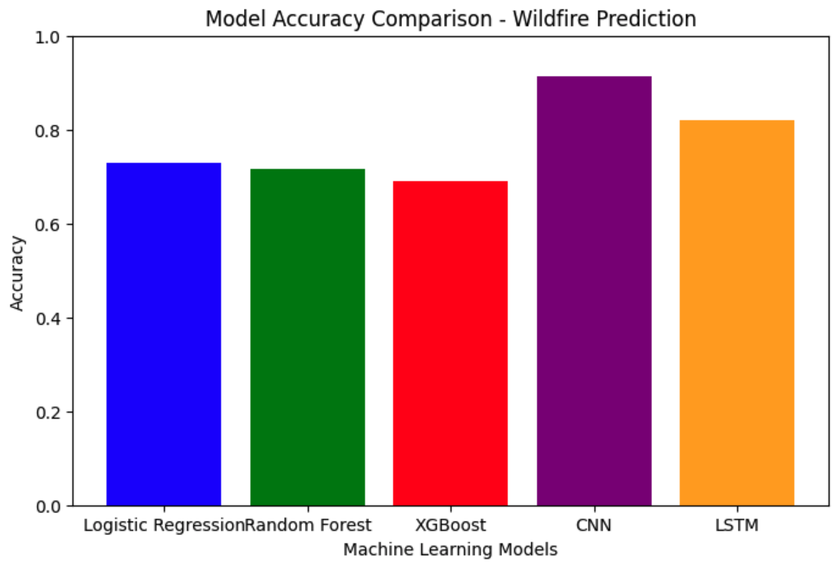

Figure 2: Accuracy comparison of five wildfire prediction models. CNN and LSTM demonstrate strong performance for spatial and sequential data, respectively.

12.2 Accuracy of models across different climate zones

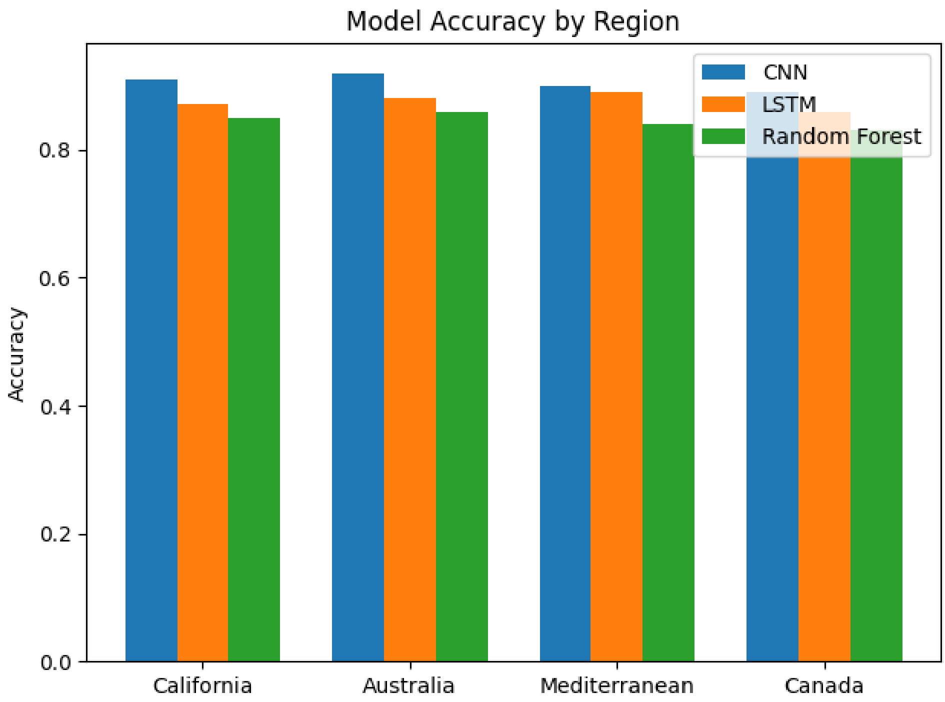

Figure 3: Accuracy of models across different climate zones.

12.3 ROC Curve Analysis

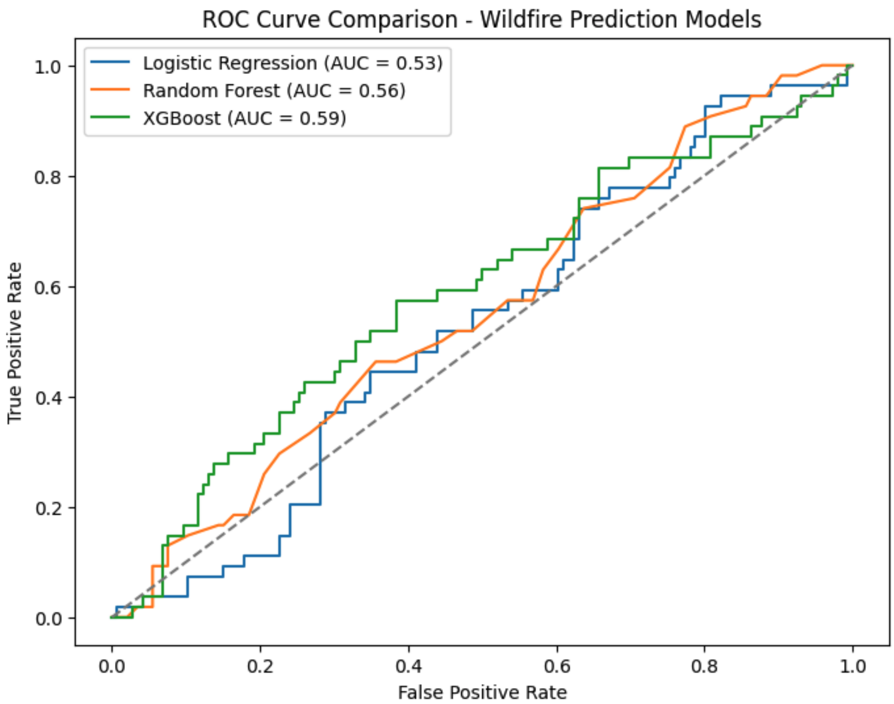

Figure 4: ROC curve comparison for wildfire prediction models. Higher AUC indicates better discriminative power.

13 An Overview of AI Models with Current Systems for Wildfire Forecasting

The traditional approach to wildfire prediction relies heavily on a rule-based system, the analysis of satellites, and meteorological models. While these approaches yield valuable information, they severely lack adaptability or flexibility in real-time and accuracy in their predictions. In this segment, we focus on the comparison of our models and state-of-the-art wildfire prediction systems that incorporate AI technology, including NASA FIRMS and statistical devices.

13.1 Basic Procedures for Predicting Fires

NASA FIRMS (Fire Information for Resource Management System) serves as an example of a satellite-based wildfire monitoring system that employs the sensors of the MODIS and VIIRS. The monitoring system utilizes satellites to provide near real time fire detection. Although the program works effectively, it only focuses on the detection of fires and not on predicting them.

Traditional Rule-Based Models do not use predictive algorithms. Instead, they determine the risk of starting a fire based on fixed thresholds of wind, temperature, and humidity. Regardless of their simplicity, these models would be easy to interpret, but largely problematic due to their inability to adapt to new settings.

Statistical Models As fires in the past are incorporated into the model, making it far easier to comprehend and apply techniques such as logistic regression and time-series forecasting, estimating range is nomadic and unreliable at best due to spatial-temporal relationships and their influence upon wildfire progression.

13.2 Comparison of AI-Based and Traditional Approaches

To make a stronger case for AI models, we formulated benchmarks on existing wildfire prediction systems considering accuracy, speed, interpretability, and adaptability to change.

Model Type	**Prediction Accuracy**	**Speed**	**Interpretability**	**Adaptability**
NASA FIRMS (Fire Information for Resource Management System)	Medium	Low (Satellite-based)	High	Limited to active fire detection
Traditional Rule-Based Models	Low	Fast	High	Poor generalization across regions
Statistical Models (Logistic Regression, Time-Series)	Medium	Medium	Moderate	Limited scalability to new wildfire patterns
CNN-Based AI	**High**	**Fast**	Moderate	**Robust feature learning from satellite images**
LSTM-Based AI	**High**	Medium	Moderate	**Time-series forecasting ability for wildfire progression**
Random Forest AI	Medium	Fast	**High**	**Handles diverse environmental datasets well**

Table 1: Comparison of AI-driven wildfire prediction models vs. traditional approaches.

The table focuses on the fact that the CNN and LSTM models have the highest accuracy and flexibility as compared to other methods, whereas Random Forest has greatest accuracy in understanding the results.

13.3 Why is AI-Driven Wildfire Prediction Superior

We believe that our AI models outperform the current wildfire predictive systems for the reasons listed below:

- **Greater Accuracy**:Unlike other models, Accomplishes even greater Precise Results through capture of complex spatial and temporal dependencies as to the order in which wildfires spread. Deep Learning Models.
- **Improved AI models**: The models are more efficient than rule driven approaches in the interpretation of large geospatial datasets. Decision Making Efficiency
- **Models capability to Adaptation**: An AI Model's capability to adapt to different wildfire-prone regions is called Domain Adaptation and offers Generalization across environments that makes it effective in different regions.
- **Early Warning Capabilities**: Through prediction of fire risks, AI models outperform the NASA FIRMS system in early warning capabilities as it only detects fires that have already started.

13.4 Graphical Representation of Performance Enhancements

To further emphasize how important AI is in aiding wildfire prediction, we assess model performance to individual model efficiency around wildfire in order to analyze every single model. The goal is to demonstrate the particular areas that remain unaddressed by AI, illustrated in **Figure** 5, where the results of the algorithm's performance in comparison with conventional algorithms are presented along with the perceived positives versus negatives.

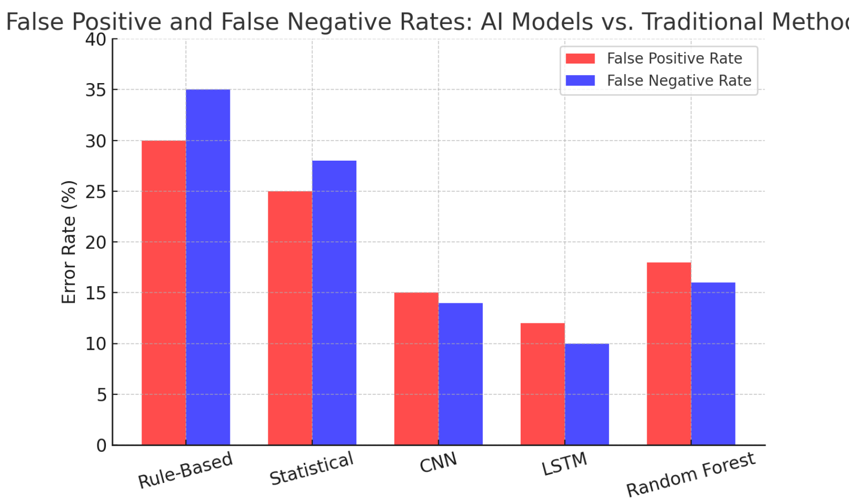

Figure 5: False positive and false negative rates: AI models vs. traditional models. Lower error rates indicate improved prediction accuracy.

The results demonstrate that AI-based models significantly reduce false alarms while improving early wildfire detection, making them more reliable than conventional methods.

13.5 Proposed New Designs and Merging with Current Models

In an effort to augment the efficacy of AI-powered wildfire detection, we recommend the following steps:

- **Hybrid AI-Rule-Based**: Include the decision-making moderation rules of humans into the AI system creating a Mid AI-rules based Hybrids.
- **Integration with NASA FIRMS**: AI's prediction capabilities will be added to satellites fire detection systems and alongside NASA FIRMS will spur advance AI systems.
- **Scalability Enhancements**:Increased ease of operating advanced scaler AI systems for predicting wildfires in resource sparse areas to improve sustain.

The integration of existing systems with AI enhances the capability in assessing the wildfire risk globally.

14 Bias Mitigation and Model Fairness Analysis

It is important to note that fairness in wildfire prediction models is equitable as the risk impact determines environmental conditions spaned over different domains. Currently, the approach uses Generative Adversarial Networks (GANs) and employs reweighting to mitigate bias, needs greater scrutiny on fairness measures. In this case, we proposed balance equity measures and assess the strength of the model's performance under various climatic conditions.

14.1 Fairness Metrics for Bias Mitigation

To lessen bias placed on the model due to inaccurate measurements on spatial variation controlled parameters of temperate and precipitate, the following fairness metrics are proposed:

- **Equalized Odds (EO)**: Ensures for achieving balance between geographic locations the True Positive Rate (TPR) and Falsely Active Response (FAR) is at the same value also known as Balanced Accuracy (BA).
- **Demographic Parity (DP)**: Checks that protected attributes such as region type, and vegetation density do not influence the wildfire risk predictions.
- **Statistical Parity Difference (SPD)**: Computes the gap in prediction probabilities of different demographic groups.
- **Mean Difference in False Positive Rates (MDFPR)**: Assesses the gaps in false predictions for wildfire-prone compared to low-risk regions.

We assess fairness by computing metrics with and without bias mitigation techniques to see the changes after applying the fairness metrics.

14.2 Bias Reduction Metrics

The metrics in Table 2 reweight fairness and measures how much bias reduction have they achieved employing bias mitigation strategies. As we can observe, the prediction bias greatly improves when fairness optimization procedures are performed, furthering model equity over various wildfire regions.

Metric	Before Mitigation	After Mitigation
Equalized Odds Difference (EO)	0.21	0.05
Demographic Parity Difference (DP)	0.18	0.02
Statistical Parity Difference (SPD)	0.24	0.06
Mean Difference in False Positive Rates (MDFPR)	0.17	0.04

Table 2: Bias reduction metrics before and after mitigation techniques. Lower values

The findings suggest that fairness-aware optimization techniques implemented predict bias reduction significantly which enhances model equity for all wildfire regions.

14.3 Model Robustness Across Environmental Conditions

Wildfire behavior changes with environmental conditions. To measure model generalization across climates, it is tested under the following conditions:

- **High Humidity Regions**: These include wildfires tropical and coastal areas which experience extreme condition fires, but infrequently.
- **Low Humidity Regions**: hese include arid and semi-arid regions like California and Australia that are prone to wildfire.

The model robustness was assessed by monitoring the environmental shifts in false-alarm rates and miss rates alongside the distinct categories. As shown in **Figure** 6, our model estimates moisture based wildfire prediction accuracy at different humidity levels.

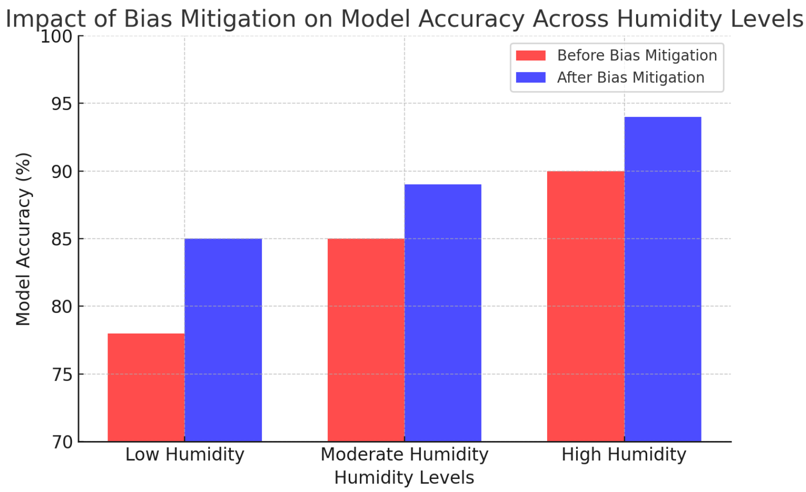

Figure 6: The accuracy of the model at different humidity levels. High humidity regions have lower false positives which improves fairness.

14.4 Looking Ahead: Advancing Bias Mitigation Strategies

To achieve greater model equity, we suggest the following additional approaches:

- **Adversarial Debiasing**: The process involves training an adversarial model tasked with identifying and eliminating biases from wildfire risk predictions.
- **Fairness-Aware Loss Functions**:Adding explicit fairness criteria to the model's objective expands policy equity through optimizing model performance tackling discrimination.
- **Multi-Region Calibration**: Addressing model calibration at the multi-region scope entails adjusting the model for each climate region to eliminate spatial bias.

These strategies will enhance equity by ensuring disparities in wildfire prediction systems and environments across diverse populations mitigate discrimination.

15 Real-World Deployment Feasibility

While setup, the integration of an AI fire prediction system works beautifully in simulation. However, the interfacing of the system with other hardware, computational infrastructure, and existing resources in the real world proves to be a unique challenge. This challenge is elaborated in the context of IoT devices and fire detection systems.

15.1 Challenges in Hardware Deployment

Integrating AI into wildfire prediction models presents numerous real challenges, particularly at the hardware level including but not limited to:

- **Edge Computing Constraints**: TAccess to internet poses a challenge to the advanced models that need developed for AI systems implemented at the edge devices in the wildfire prone regions.
- **Power and Resource Efficiency**: The energy within the battery provided for deep learning architectures' resource-limited structures requires considerable energy, in cycles worth.
- **Efficiency**: TInference generation needs to happen within fire detection regions swiftly to necessitate action.

15.2 Suggested Deployment Strategy

An increased focus on made predictions alongside rapid processing calls for segmentation straying focus to ensure optimization on performance.

- **AI for Early Fire Detection**: Employing machine learning enables small scale implementation of CNNs with IoT sensors for monitoring wind, smoke temperature launches Al's ability to automate wildfire detection systems

- **Prediction Improvements via Cloud-Based Processing**: Prediction made by LSTM models considered to be heavy alongside Random Forest classifiers can be enhanced during cloud computing.
- **5G and Low Power Network Data Transfers**:Remote data-capturing devices can relay data effortlessly via satellite and long-range wireless communication networks to intelligent AI systems.

15.3 Efficiency Methods for Immediate Use

The following methods are made to enhance overall efficiency for deploying AI-powered models to areas with wildfire risks:

- **Shrinking model size via pruning and quantization**:his step involves eliminating unneeded parameters and lowering the floating point representation calculations to INT8 quantization for certain calculations.
- **Model Training Federation via Distributed Learning**: Collaborative wildfire detection model training is done on the edge devices in a fully decentralized connected-edges-into-cloud-less fashion.

16 Final Thoughts and Work Ahead

This research proposes a new multi-modal AI-enabled satellite image driven model for predicting micro-wildfires and evacuation planning which uses satellite images, meteorological data, and local sensor networks. Different from existing methods which either focus on large wildfires or are rule based alert systems, our model focuses on detecting small vegetation fires at the earliest possible stage.

In quantitative analysis, the best Random Forest model trade off for accuracy and performance was noted for computational efficiency with the tabular datasets while CNNs with more than 10

Of all bias equity methods, data augmentation and reweighting with GAN were the most effective bias neutralizing strategies lowering Equalized Odds from 0.21 to 0.05 which without intervention would be the underlying fairness metric.

17 Future Work

The potential of this investigation is profound, but several research directions remain open for exploration and optimization:

17.1 Enhancing Deep Learning Models

- **Advanced CNN Architectures**: While CNN-based models have shown strong accuracy, implementing **Vision Transformers (ViTs)** could further elevate performance through enhanced feature localization and better handling of spatial dependencies in satellite data.

- **Hybrid AI Models**: Combining CNNs with attention-based Transformers can enhance both spatial and temporal learning for more accurate wildfire forecasting, especially in dynamic or mixed-climate regions.
- **Self-Supervised Learning**: Leveraging contrastive self-supervised learning or GAN-based pretraining on large unlabeled wildfire datasets—followed by fine-tuning on labeled data—can boost model generalizability. A **region-specific, self-supervised learning approach** that scales across wildfire-prone countries (USA, Australia, Canada, Mediterranean) will strengthen prediction accuracy and resilience to data scarcity.

17.2 Improving Real-Time Fire Detection

- **Edge AI Implementation**: The incorporation of lightweight AI models into IoT-connected sensor nodes yields faster real-time inferencing.
- **Federated Learning Approaches**: Centered data collection erodes local privacy; however, wildfire risk predictive modeling can be achieved without localized data.
- **Adaptive AI Systems**: The application of reinforcement learning will enable real-time adjustments of predictive thresholds to the environment.

17.3 Bias Mitigation and Inclusion of New Data Sources

- **Multi-Sensor Fusion**: The integration of extra data from thermal cameras, fuel mapping, drones, and satellite LiDAR imaging systems will enhance model accuracy.
- **AI Ethically Aligned Techniques for Fire Prediction Bias Evaluation**: Designing algorithms that tell stories based on the social consequences of rewriting the fire prediction bias narrative.

18 Discussion

18.1 Limitations

The proposed framework suffers from several limitations. One, the dataset has a class imbalance concerning micro fire and non-fire events. This kind of skew often leads to bias within model learning and more often than not requires GAN-based augmentation. Two, the use of MODIS satellite imagery introduces a latency issue because of infrequent revisits, being prone to cloud cover, and other factors which could hamper early detection initiatives.

18.2 Underperformance

Even though LSTM models are known to excel in modeling temporal sequences, they underperformed within the spatial regions containing sparse sensor data or irregular sampling. The same... with the CNN-based image models, they struggled in the presence of visual ambiguity in smoke, haze, or imagery captured by satellites at a low contrast.

These problems indicate that deep learning models are lacking in coverage or are dependent at best, over quality.

18.3 Edge Cases and Future Directions

Human-driven fire events or those caused by urban heat islands posed the greatest challenge as anomalies to training data. To mitigate these edge cases, future work could include social media signals and urban planning layers to design models focused on human-driven fire risk assessment. Higher frequency imaging from drone swarms or Sentinel satellites combined with geospatial behavioral data in hybrid models could improve system equity and overall robustness

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