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# Multimodal Machine Learning and Uncertainty-Aware Simulation of Wildfire Occurrence, Severity, and Spread

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***Abstract*** - Facing the increasing frequency and severity of wildfires, the need for advanced predictive systems for wildfire occurrence, severity, and spread has grown significantly in recent years. Wildfires pose threats to the environment, economy, and communities, including the destruction of infrastructure, ecosystems, and human health. Traditional models often rely on simplified assumptions and are limited to specific conditions, making it difficult to generalize across large spatial and temporal scales. This project addresses the challenge of wildfire prediction using a multimodal machine learning framework that combines satellite imagery, weather data, and terrain information. An attention-enhanced LSTM network is integrated with XGBoost and Random Forest models using a stacked ensemble architecture to predict wildfire ignition probabilities. The proposed model demonstrates strong predictive performance, achieving an overall accuracy of 92% and a minority class recall of 97% for wildfire ignition events. The reliability of the predicted probabilities is supported by a Brier Score of 0.0616, indicating good calibration for real-world decision support. Feature importance analysis identifies the Burning Index (BI) and Energy Release Component (ERC) as the most influential predictors, consistent with established fire science principles. Future work will focus on incorporating uncertainty estimation through Bayesian methods to further enhance robustness for operational wildfire risk assessment.

***Keywords*:** Wildfire prediction, Machine learning, Uncertainty quantification, Risk modeling

## 1. Introduction

The impact of climate change [1] on wildfire behavior has become increasingly evident, with rising temperatures and shifting environmental conditions contributing to more frequent and severe fire events. The rapid growth of deadly, destructive wildfires has led to many negative impacts, including damaged infrastructure, poor air quality, and loss of life. Wildfire survivors often are at risk of instability and homelessness, as the rebuilding process often takes years [2]. These wildfires also have a major impact on health [3], especially for humans and certain populations. Overall, wildfires pose a threat to ecosystems, infrastructure, and public health, demonstrating the necessity of precise prediction to effectively prevent these detrimental effects.

Current approaches include the Rothermel surface fire spread model, a mathematical and physics-based model used to predict wildfires [4]. While traditional models have limited predictive capability to predict wildfire events, machine learning approaches have been proven to demonstrate superior efficiency and accuracy due to the ability to take in multiple diverse datasets [5]. Traditional models are also unable to take into account more complicated factors like human activity, road density, and agricultural activity. Recent studies have demonstrated the effectiveness of integrating meteorological, vegetation, and terrain information to improve wildfire prediction; however, challenges remain in capturing temporal dependencies, fusing distinct data sources, and maintaining predictive performance for relatively rare wildfire events [6].

This paper presents a multimodal machine learning-based framework for predicting wildfire occurrence in Los Angeles, California, by integrating diverse environmental data sources. By leveraging environmental datasets and advanced machine learning techniques, this work aims to improve wildfire occurrence prediction and produce probabilistic forecasts to support early wildfire risk assessment and resource allocation in fire-prone regions.

## 2. Methodology

### 2.1. Study Area and Data Sources

The study area comprises a forested region within Los Angeles County, California, selected due to its history of recurring wildfire activity and the availability of multi-modal environmental data. The temporal coverage spans 2000–2020. All datasets were accessed and preprocessed using Google Earth Engine (GEE) and custom Python scripts. Fire occurrence data were obtained from MODIS fire products and converted to binary wildfire labels. Meteorological variables were obtained from gridMET and included temperature, humidity, precipitation, wind speed, solar radiation, vapor pressure deficit (VPD), Burning Index (BI), and Energy Release Component (ERC). Vegetation information was derived from Landsat imagery using NDVI, while terrain variables were obtained from the SRTM digital elevation model. All datasets were spatially and temporally harmonized to produce a final dataset containing 15,330 daily observations.

### 2.2. Feature Engineering

Base features included meteorological, vegetation, terrain, and fire danger variables. To capture antecedent conditions, 30-day and 90-day cumulative precipitation were calculated, and a fire spread score was derived from wind speed, slope, and vegetation characteristics. Temporal dependencies were modeled using a 7-day sliding window. Lagged variables and anomaly features were included for key meteorological variables. Continuous features were normalized using Min-Max scaling, with scaling parameters fitted exclusively on the training set.

### 2.3. Model Development and Evaluation

The prediction task was formulated as binary wildfire occurrence forecasting. A sequence of observations from days (t-6) to (t) was used to predict wildfire occurrence at day (t+1), with an additional 4-day forecasting horizon evaluated for comparison. An 80/20 chronological train-test split was adopted to preserve temporal ordering. To address class imbalance, SMOTE and class weighting were applied to the training data. The proposed model consists of an Attention-LSTM network combined with XGBoost and Random Forest classifiers in a stacked ensemble framework. Predicted probabilities from the base models were integrated using a logistic regression meta-learner. Model performance was evaluated using accuracy, precision, recall, AUC-ROC, and probability calibration metrics. Feature importance analysis was additionally conducted to assess the influence of environmental variables on wildfire ignition.

## 3. Results and Discussion

### 3.1. Predictive Performance

The multi-level stacking ensemble was evaluated using the hold-out chronologically structured test set, which constitutes 20% of the time-stamped dataset. The model obtained an overall accuracy of 92%. A confusion matrix was generated at the optimal decision threshold of 0.8.

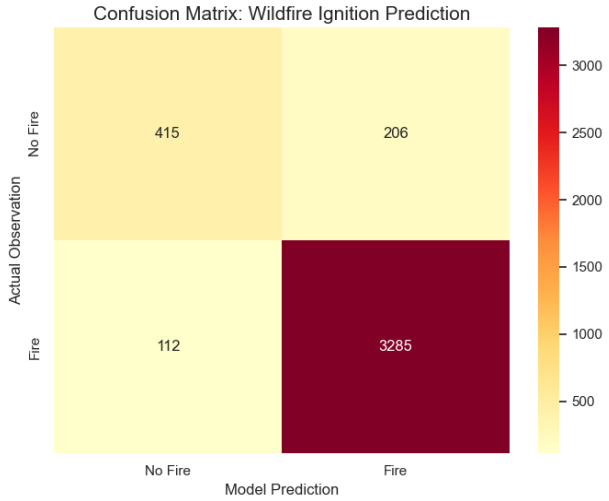


Fig. 1: Confusion matrix for binary wildfire ignition prediction at a 0.8 decision threshold.

According to Fig. 1, the model predicted most of the wildfires correctly, achieving 3,285 true positives and 112 false negatives. This demonstrates a recall of 97% for wildfire ignitions.

### 3.2. Discriminative Power and Probability Calibration

To evaluate the classifier independent of the decision threshold, performance was measured using the Receiver Operating Characteristics (ROC) curve (Figure 2). The model yielded an Area Under the ROC curve (AUC-ROC) of 0.94, demonstrating strong class separability between fire and non-fire conditions.

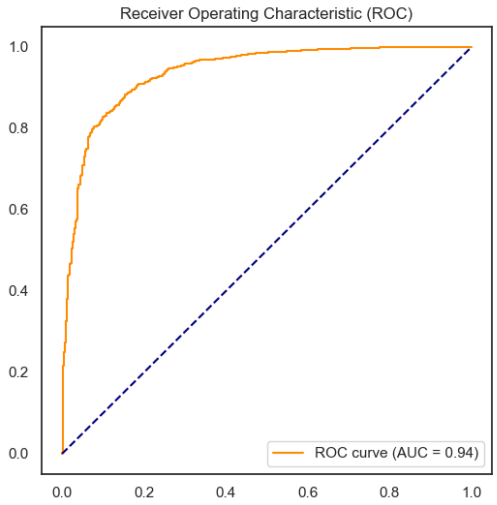


Fig. 2: Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) for the stacking ensemble model.

### 3.3. Temporal Sequence Dynamics

The Attention-LSTM architecture analyzes antecedent time-series patterns within the 7-day sliding window. Figure 3 displays the predicted wildfire ignition probabilities compared to the observed binary outcomes across the first 100 observations in the test dataset.

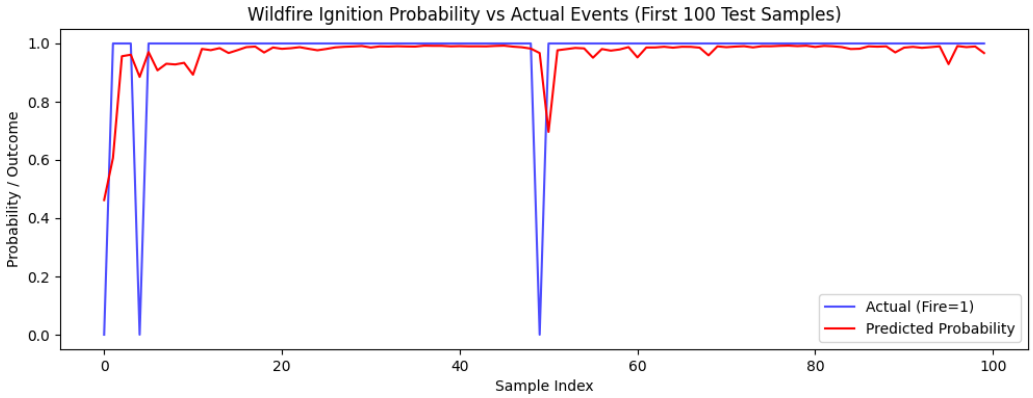


Fig. 3: Comparison of predicted wildfire ignition probabilities against actual fire occurrences over 100 sequential test samples.

The estimated probability function follows the downward movement and rapid peaks of the actual fire indicators. These results suggest that the attention mechanism captures sequential weather and fuel patterns associated with wildfire ignitions.

### 3.4. Feature Importance

To assess the relationships between environmental factors and wildfire ignition risk, an out-of-fold feature importance analysis was performed within the ensemble framework (Figure 4).

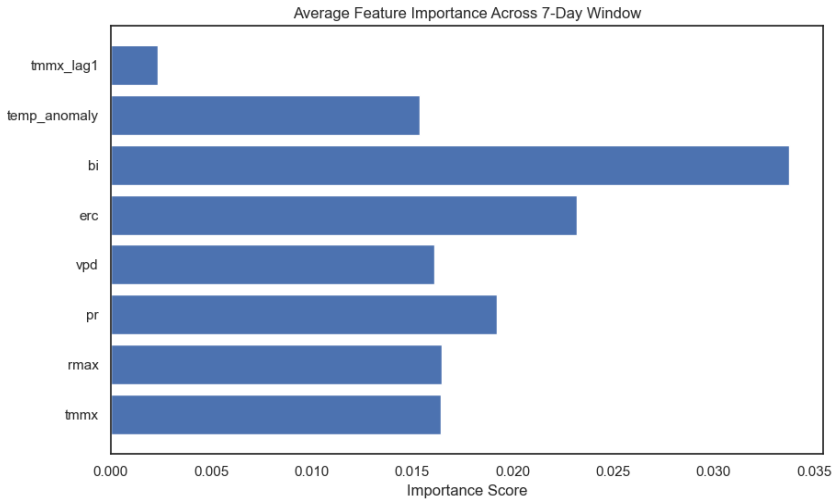


Fig. 4: Stacking ensemble feature importance scores aggregated over the 7-day antecedent observation window.

The Burning Index (BI) was the dominant predictor, with the highest importance score of approximately 0.034. Energy Release Component (ERC) and daily precipitation (pr) were the second and third most important predictors. Vapor pressure deficit (vpd), maximum relative humidity (rmax), and maximum temperature (tmmx) exhibited moderate importance scores. Lagged variables, such as tmmx_lag1, had limited utility, suggesting that the LSTM captured temporal relationships more effectively than manually engineered lag features.

## 4. Conclusion

In conclusion, this study developed a multimodal machine learning framework for wildfire occurrence prediction by integrating weather, vegetation, terrain, and fire danger data into a unified spatiotemporal model. By combining an attention-based LSTM network with XGBoost and Random Forest models in a stacked ensemble architecture, the framework captures temporal environmental patterns and nonlinear relationships associated with wildfire ignition.

The proposed approach demonstrated strong predictive performance, achieving an overall accuracy of 92%, a wildfire-event recall of 97%, and a Brier score of 0.0616. These results indicate that multimodal data fusion and temporal learning can effectively identify wildfire-prone conditions while producing well-calibrated probability estimates suitable for risk assessment. Feature importance analysis showed that the Burning Index (BI) and Energy Release Component (ERC) were the most influential predictors, consistent with established wildfire science.

Despite these results, wildfire prediction remains challenging due to event rarity and environmental complexity. While class-balancing techniques such as SMOTE improved detection performance, limitations remain regarding synthetic data generation and missing human-related factors such as infrastructure and ignition sources. The study was also limited to Los Angeles County, and further validation is needed across different geographic regions.

Future work will focus on improving model robustness and extending the scope of the current framework. Key directions include incorporating uncertainty quantification methods to better characterize prediction reliability, such as Bayesian modeling approaches and ensemble-based confidence estimation. Additional improvements will explore the integration of real-time human activity data, including infrastructure proximity, population density, and ignition source indicators, to better capture anthropogenic wildfire drivers that are not represented in the current dataset. Model development will also consider more advanced deep learning architectures, particularly transformer-based models, to further enhance long-range temporal dependency modeling beyond recurrent networks. Furthermore, future work will investigate coupling ignition probability forecasting with fire spread and severity simulation models to provide a more complete wildfire risk assessment pipeline. Expanding the dataset to include multiple geographic regions and diverse fire regimes will also be essential for evaluating model generalizability. Finally, improvements to data balancing strategies beyond SMOTE, including more realistic synthetic sampling or cost-sensitive learning approaches, may further enhance model reliability under extreme class imbalance conditions.

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