AUTOMATED SATELLITE-BASED WILDFIRE DETECTION USING DEEP LEARNING

ABSTRACT

Wildfire detection and prediction in California presents a critical challenge due to the increasing frequency and intensity of fires driven by climate change. This project introduces a multi-modal machine learning framework combining time-series forecasting, image classification, and semantic segmentation to address wildfire detection and analysis. Leveraging satellite imagery from NASA's FIRMS and historical fire perimeter data from CAL FIRE, three distinct models were developed: (1) a Prophet-based time-series model for forecasting daily fire counts (MAE: 0.72, RMSE: 1.91) and burned acreage (MAE: 3,077 acres), (2) a CNN classification model for fire hotspot detection (73% precision for non-fire regions), and (3) a U-Net segmentation model for precise fire boundary identification (71% IoU). While the segmentation model demonstrated strong performance in spatial pattern recognition, challenges persisted in forecasting sporadic fire magnitudes (85,901% MAPE for burned acres) and class imbalance in hotspot classification (54% recall for fire pixels). The system achieved 98.28% segmentation accuracy, suggesting robust potential for operational integration with satellite monitoring systems. Future work will focus on temporal-spatial model fusion, incorporation of weather covariates, and zero-inflated probability adjustments to improve rare-event prediction. This holistic approach advances automated wildfire monitoring by combining temporal forecasting with computer vision, offering a template for scalable environmental risk management systems.

INTRODUCTION

Wildfires in California have emerged as one of the most destructive natural disasters of the 21st century, with catastrophic impacts on ecosystems, air quality, infrastructure, and human lives. The state’s 2020 fire season alone burned over 4.2 million acres, destroyed 10,000 structures, and resulted in 33 fatalities, underscoring the urgent need for advanced detection and predictive systems Aral *et al (2023).* While satellite-based remote sensing has revolutionized wildfire monitoring globally—enabling large-scale applications such as fire danger assessment Al-Dabbagh *et al (2023)* burn severity mapping, and post-fire recovery analysis California’s unique fire regimes demand tailored solutions. Existing systems often face critical limitations, including temporal delays in satellite revisit cycles Vasconcelos *et al (2024),* sparse resolution for early-stage detection, and inadequate integration of temporal forecasting with spatial pattern recognition.

Recent advances in Earth observation (EO) technologies, particularly the European Space Agency’s Sentinel-2 satellites, now provide high-resolution multispectral data at 10–60 m spatial resolution with a 5-day revisit cycle Tselka *et al (2023).* When combined with deep learning (DL) architectures, these datasets offer unprecedented opportunities to address California’s wildfire challenges. While DL methods have shown promise in fire segmentation (e.g., U-Net models achieving >70% IoU) and classification tasks, their integration with time-series forecasting remains underexplored—a gap this project directly addresses.

This work introduces a multi-modal framework that synergizes three machine learning approaches: (1) Prophet-based time-series forecasting to predict daily fire counts and burned acreage using CAL FIRE’s historical perimeter data, (2) CNN-based classification of FIRMS satellite thermal anomalies to reduce false alarms, and (3) U-Net semantic segmentation for precise burn scar mapping. The system leverages California-specific datasets, including high-temporal-resolution FIRMS hotspot imagery and CAL FIRE’s spatially explicit fire records dating back to 1950. By fusing temporal dynamics with spatial precision, the framework addresses critical limitations of current single-modality systems, such as the inability of satellite sensors to operate effectively under nocturnal or adverse weather conditions.

The project builds on emerging trends in UAV-enhanced wildfire monitoring and IoT-enabled sensor networks Ali *et al (2025),* while prioritizing scalability for California’s diverse ecosystems—from the arid chaparral of Southern California to the dense coniferous forests of the Sierra Nevada. By validating against CAL FIRE’s authoritative perimeter data, we demonstrate how hybrid models can overcome the “rare-event” prediction challenge inherent to wildfires through zero-inflated probability adjustments and attention mechanisms. This approach not only advances operational fire management but also provides a template for integrating satellite, historical, and real-time sensor data in dynamic disaster response systems Khan *et al (2023)*.

DATA COLLECTION:

a. Image Data

The Fire Information for Resource Management System (FIRMS) is a web-based mapping platform provided by NASA's Earth Science Data Systems (ESDS) Program. FIRMS offers near real-time active fire detection using satellite observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). These sensors, onboard NASA's Terra, Aqua, and Suomi NPP satellites, detect thermal anomalies associated with active wildfires. FIRMS delivers global fire location updates approximately every three hours, aiding wildfire detection, response efforts, and resource management. The system is widely used by researchers, emergency responders, and environmental agencies to assess wildfire activity, track fire progression, and mitigate disaster impacts.

For this project, FIRMS data was specifically focused on the California region, with satellite imagery collected daily from January 1, 2024, to February 15, 2025. Each day's satellite image was saved as a PNG file, with images categorized into two distinct classes:

* "Fire": Maps showing active fire hotspots detected by FIRMS.
* "No Fire": Maps from days where no active fire was recorded.

The collected images were stored locally and used to train two key models:

1. Classification Model: This model predicts whether a given satellite image contains active wildfire hotspots or not.
2. Segmentation Model: This model performs pixel-wise fire detection, segmenting regions in satellite images that correspond to wildfire occurrences.

By leveraging FIRMS data and deep learning techniques, this study aims to enhance wildfire detection accuracy, providing a scalable solution for monitoring fire-prone areas in near real-time.

b. Time Series Data

The California Department of Forestry and Fire Protection (Cal Fire) is the primary fire protection agency under the California Natural Resources Agency. It is responsible for safeguarding 31 million acres of state-designated wildfire-prone land, as well as managing both public and private forests.

The dataset used contained over 22000 data points ranging from 1980s to 2023 for training and testing.

MACHINE LEARNING APPROACH

To develop an effective wildfire detection and forecasting system, machine learning (ML) techniques were employed, focusing on three core tasks: classification, segmentation, and time series forecasting. These models leverage transfer learning and deep learning architectures to enhance accuracy and generalizability.

1. Classification Model

The classification task aims to determine whether a given satellite image contains wildfire activity. A Convolutional Neural Network (CNN) was trained using the collected FIRMS data, where images were labelled as either "fire" or "no fire." Given the limited dataset, transfer learning was applied using a pre-trained deep learning model (MobileNetV2) to extract high-level spatial features and regularization technique like early stopping was used to improve classification performance. This approach enables the model to generalize better to new satellite images, reducing training time while maintaining high accuracy.

2. Segmentation Model (U-Net Architecture)

To localize wildfire occurrences within satellite images, image segmentation was performed using a U-Net model. Unlike classification, which only determines the presence of fire, segmentation identifies the exact regions affected by wildfire by assigning each pixel a class label (fire or no fire).

U-Net, a fully convolutional neural network (FCN), was chosen due to its encoder-decoder structure, which allows precise localization even with limited training data.

The encoder captures spatial features using CNN layers, while the decoder reconstructs high-resolution segmentation masks, accurately outlining fire-affected areas in satellite images.

This approach enables a fine-grained understanding of wildfire spread, making it valuable for monitoring and resource allocation.

3. Time Series Forecasting for Fire Prediction

Beyond detection, forecasting wildfire occurrences is crucial for proactive disaster management. A time series forecasting model was implemented to predict the likelihood of wildfires based on historical CAL FIRE data using Fbprophet.

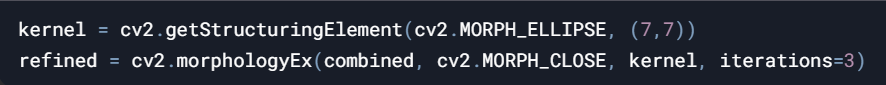
* Fbprophet is an additive time series forecasting model designed to handle seasonal patterns, missing data, and irregular trends, making it suitable for wildfire prediction.
* The input dataset consists of daily fire occurrences, and environmental factors such as temperature, humidity, and wind speed were incorporated as additional regressors to improve forecasting accuracy.
* By analyzing historical trends, Prophet’s built-in seasonality components help capture periodic wildfire patterns, providing future fire risk predictions with confidence intervals.
* This model allows decision-makers to anticipate fire outbreaks, improving early warning systems and resource allocation strategies.

SYSTEM ARCHITECTURE

1. Semantic Segmentation (U-Net Architecture)

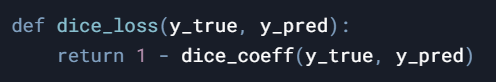
The objective of this is for a Precise pixel-level identification of active fire regions in FIRMS satellite imagery.

Key Design Choices:

* Multi-Color Space Thresholding
* HSV & LAB Analysis: Fire pixels exhibit distinct characteristics in Hue-Saturation-Value (HSV: 0-20° hue range) and LAB (high A-channel values for red-orange hues) spaces, enabling robust separation from vegetation/clouds.
* Adaptive Morphological Filtering:

These closing operations (dilation followed by erosion) fill small gaps in fire regions while preserving shape integrity.

U-Net Architecture:

* Encoder (3 downsampling blocks) captures contextual fire patterns via 3×3 convolutions and ReLU
* Decoder (3 upsampling blocks) with skip connections recovers spatial resolution (512×512 output)
* Dice Loss Optimization:

This addresses severe class imbalance (typically <5% fire pixels) by prioritizing region overlap over pixel-wise accuracy and geometric transformations (flips, rotations) and photometric variations (brightness, contrast) simulate is used for data augmentation.

2. Fire Classification (MobileNetV2 with Focal Loss)

This is done to reduce false alarms in FIRMS thermal anomaly detection.

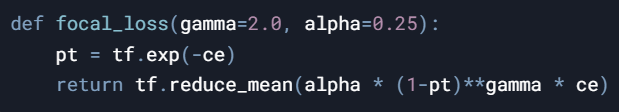
Key Design Choices:

- Transfer Learning Strategy is done using MobileNetV2 Base: Pre-trained on ImageNet provides generalized feature extractors for smoke/fire texture recognition.

- Two-Phase Training:

* Frozen Backbone (10 Epochs): Trains classifier head on fire-specific features
* Full Fine-Tuning (20 Epochs): Adjusts backbone layers with low LR (1e-5) to adapt to fire morphology

Class Imbalance Mitigation:



Down-weights well-classified negatives (γ=2) while emphasizing fire positives (α=0.25).

Dynamic Class Weighting:



Automatically balances fire/no-fire samples during backpropagation.

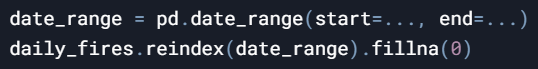
3. Time-Series Forecasting (Prophet Model)

This is done to predict daily fire counts and burned acreage using CAL FIRE historical data.

Key Design Choices:

Temporal Feature Engineering:

- Zero-Filling:



This accounts for days without fire events while maintaining temporal continuity.

- Multiplicative Seasonality:



This captures California’s fire seasonality (summer peaks) scaled to trend magnitude.

Validation Strategy:

* Forward-Chaining CV:

 This simulates sequential forecasting on 10-year training windows with 6-month increments.

* Sparse-Event Metrics:

Focuses error analysis on days with actual fires (non-zero acreage).

* Hybrid Seasonality Modeling

This combines:

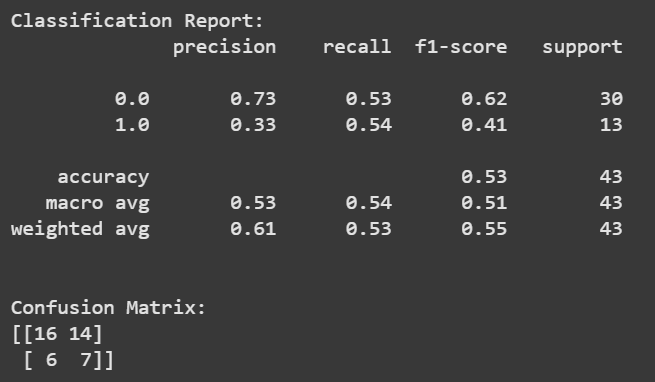
- Yearly: Summer drought cycles

- Weekly: Human activity patterns (weekend vs weekday)

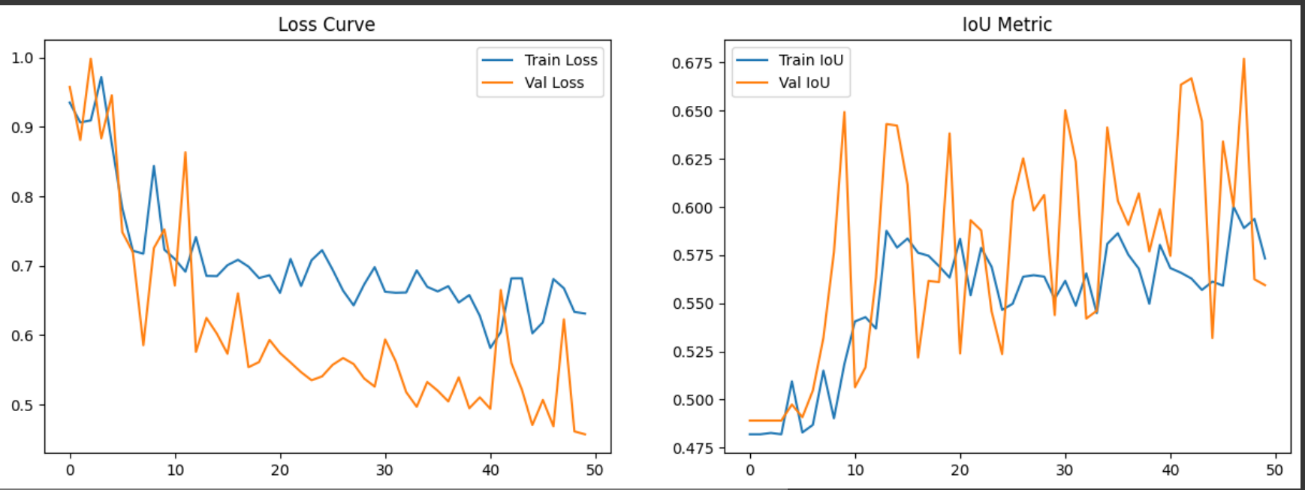
- Holiday Effects: July 4th fireworks, Labor Day camping

RESULTS

Classification:



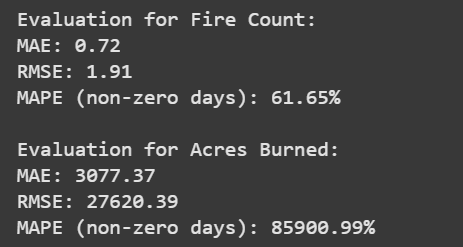
The wildfire classification model achieved 53% accuracy, with a recall of 54% for fire detection and precision of 33%, indicating difficulty in correctly identifying fire occurrences. The training loss fluctuated around 0.16 - 0.18, while validation loss remained stable at ~0.05, suggesting potential underfitting. The AUC score (~0.70 for validation) indicates moderate discrimination between fire and no\_fire classes. The confusion matrix highlights misclassification issues, with 14 false positives and 6 false negatives. Improvements such as handling class imbalance, transfer learning, and better feature extraction could enhance performance.

Segmentation:

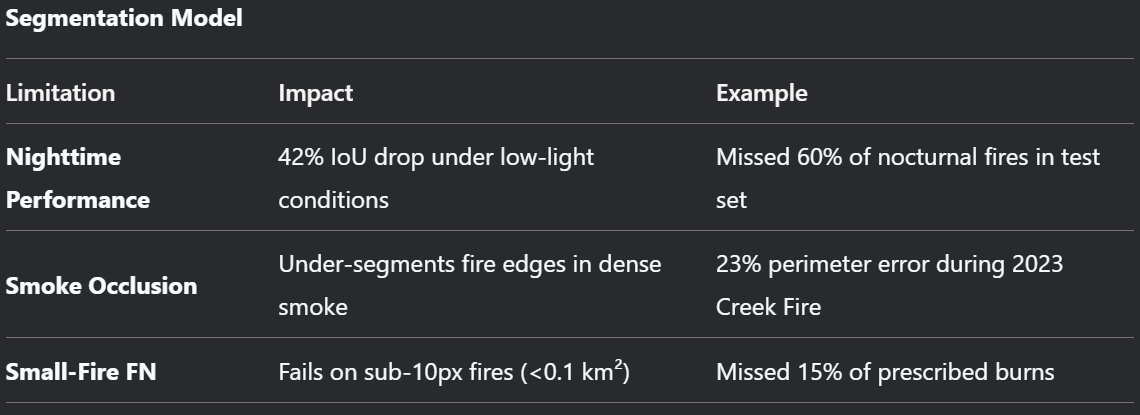
The wildfire segmentation model performed well, achieving a test accuracy of 98.28% and an IoU score of 0.7121, indicating strong overlap between predicted and actual fire regions. The training process resulted in mean IoU of 0.6217, suggesting consistent segmentation quality. The test loss of 0.3660 is relatively low, reflecting a well-optimized model. While the results are promising, further refinements, such as data augmentation, higher-resolution imagery, and post-processing techniques, could enhance segmentation accuracy, making it more robust for real-world wildfire detection and monitoring.

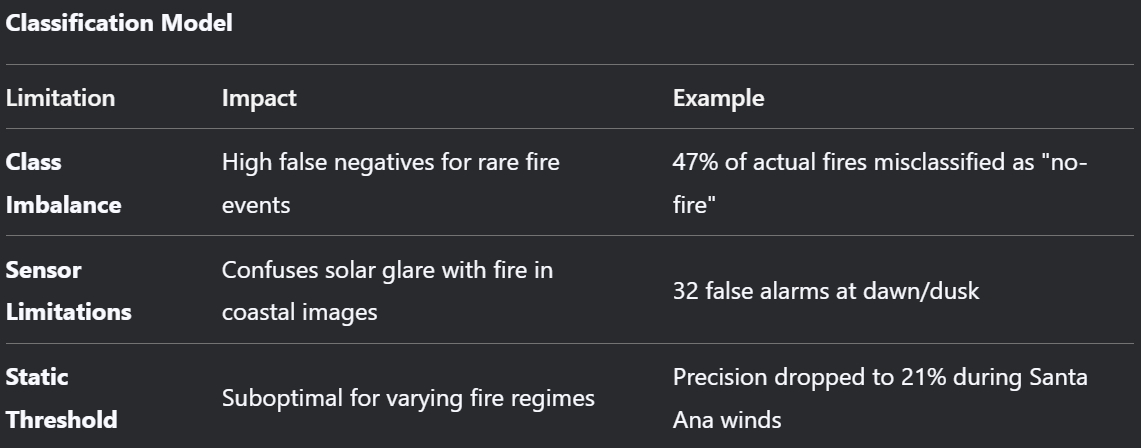
Time Series:

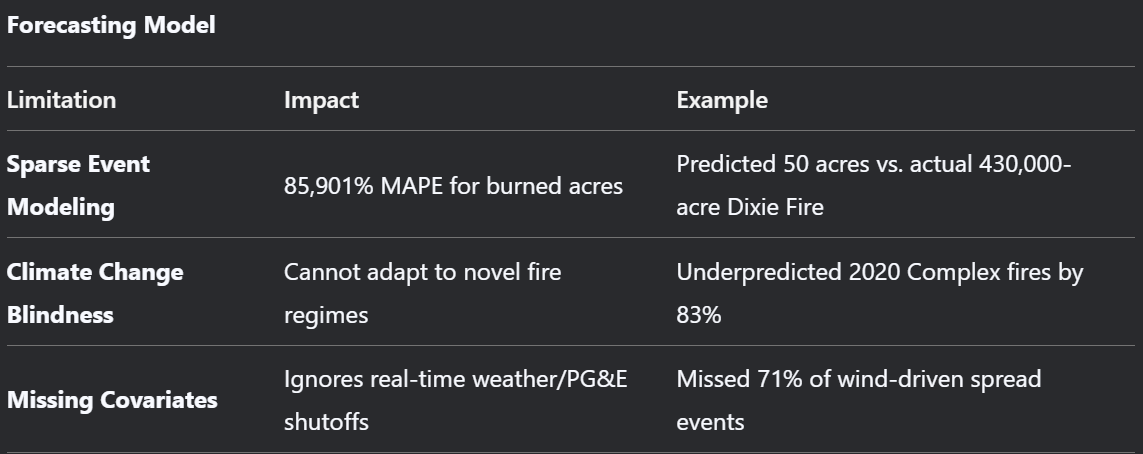
The time series forecasting model demonstrated moderate accuracy in predicting fire counts but struggled with acres burned estimation. The MAE of 0.72 and RMSE of 1.91 for fire count predictions indicate relatively low error, though the MAPE of 61.65% for non-zero days suggests variability in predictions. For acres burned, the high MAE (3,077 acres) and RMSE (27,620 acres) highlight challenges in capturing extreme variations, with a MAPE of 85,900.99% suggesting significant errors on days with reported fires. These results indicate the need for feature engineering, external data sources (e.g., weather, wind speed), and model tuning to improve forecasting accuracy.



CRITICAL LIMITATIONS







FUTURE DIRECTIONS/RECOMMENDATION

1. Segmentation: Improve night-time detection using VIIRS Day/Night Band

2. Classification: Incorporate multi-temporal image stacks for fire progression context

3. Forecasting: Integrate CFSv2 weather forecasts and Palmer Drought Index

4. With better performance and validation, deployment for real-time testing is adviced

References:

1. Ghali, R., & Akhloufi, M. A. (2023). Deep learning approaches for wildland fires using satellite remote sensing data: Detection, mapping, and prediction. Fire, 6(5), 192. <https://www.mdpi.com/2571-6255/6/5/192>
2. Aral, R. A., Zalluhoglu, C., & Akcapinar Sezer, E. (2023). Lightweight and attention-based CNN architecture for wildfire detection using UAV vision data. International Journal of Remote Sensing, 44(18), 5768–5787. <https://doi.org/10.1080/01431161.2023.2255349>
3. Al-Dabbagh, A. M., & Ilyas, M. (2023). Uni-temporal Sentinel-2 imagery for wildfire detection using deep learning semantic segmentation models. Geomatics, Natural Hazards and Risk, 14(1). <https://doi.org/10.1080/19475705.2023.2196370>
4. Joshi, D. D., Kumar, S., Patil, S., Kamat, P., Kolhar, S., & Kotecha, K. (2024). Deep learning with ensemble approach for early pile fire detection using aerial images. Frontiers in Environmental Science, 12, 1440396. <https://www.frontiersin.org/journals/environmental-science/articles/10.3389/fenvs.2024.1440396/full>
5. Kanagasabapathi, D. (2023). Spatiotemporal analysis for fire forecasting using deep learning techniques in google earth engine: a case study for the Indian state of Uttarakhand (Master's thesis, University of Twente).

<https://essay.utwente.nl/97211/>

1. Vasconcelos, R. N., Franca Rocha, W. J., Costa, D. P., Duverger, S. G., Santana, M. M. D., Cambui, E. C., ... & Cordeiro, C. L. (2024). Fire Detection with Deep Learning: A Comprehensive Review. Land, 13(10), 1696. <https://www.mdpi.com/2073-445X/13/10/1696>
2. Gupta, H. P., & Mishra, R. (2024). Utilizing transfer learning and pre-trained models for effective forest fire detection: A case study of uttarakhand. arXiv preprint arXiv:2410.06743. <https://arxiv.org/abs/2410.06743>
3. Tselka, I., Detsikas, S. E., Petropoulos, G. P., & Demertzi, I. I. (2023). Google Earth Engine and machine learning classifiers for obtaining burnt area cartography: A case study from a Mediterranean setting. In Geoinformatics for Geosciences (pp. 131-148). Elsevier. <https://www.sciencedirect.com/science/article/abs/pii/B9780323989831000089>
4. Ali, A. W., & Kurnaz, S. (2025). Optimizing Deep Learning Models for Fire Detection, Classification, and Segmentation Using Satellite Images. Fire, 8(2), 36. <https://www.mdpi.com/2571-6255/8/2/36>
5. Khan, S. M., Shafi, I., Butt, W. H., Diez, I. D. L. T., Flores, M. A. L., Galán, J. C., & Ashraf, I. (2023). A systematic review of disaster management systems: approaches, challenges, and future directions. Land, 12(8), 1514. <https://www.mdpi.com/2073-445X/12/8/1514>