California Fire Predictor Model

Purpose / Objective

- Build a machine learning model that predicts whether a **wildfire will start on a given day**, using historical weather conditions.
- Understand which environmental factors (temperature, wind, precipitation, seasonality, lagged conditions) influence wildfire risk the most.
- Use **time-aware evaluation** to avoid data leakage and simulate real-world forecasting.
- Provide interpretable visualizations (correlation heatmaps & feature importance)

Dataset

- Gathered from NOAA Climate Data Online with fire incident data from CAL FIRE.

Each row includes:

- Precipitation, Max / Min / Avg Temperature, Avg Wind Speed, Season, Lagged weather metrics (previous day's wind & precipitation), Derived features (temperature range, wind–temperature ratio), **fire_start_day** (True = fire occurred)

After cleaning: **~15,000 usable rows**
Class distribution:

- **No Fire:** 10005
- **Fire:** 4971

CA_Weather_Fire_Dataset_1984-2025_new.csv > data

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date,precipitation,max_temp,min_temp,avg_wind_speed,fire_start_day,year,temp_range,wind_temp_ratio,month,season,lagged_precipitat
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Methodology

Overview

- Encode FIRE-START-DAY as binary target (1 = risk of fire, 0 = no risk of fire)
- Perform a 90/10 train-test split while maintaining class balance (risk of fires = rare)

Models Evaluated

- Decision Tree – non-linear patterns, interpretable structure
- Random Forest – robust non-linear modeling, provides feature importance

Analysis Techniques

- Feature importance – identify key environmental drivers of fire occurrence
- Ablation Testing – assess the impact of removing specific variables

Preprocessing

One-Hot Season Encoding: Improved model understanding of seasonal fire patterns.

Data Cleaning: Removed corrupt rows to maintain consistent numeric input (missing values).

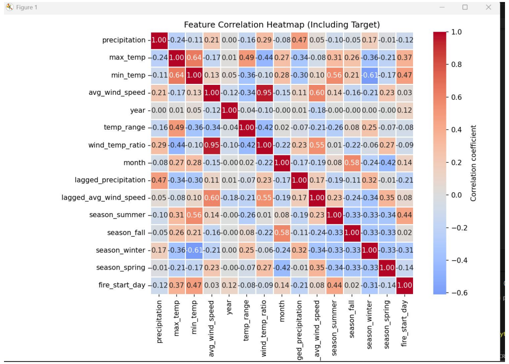
Feature Name Construction: Generated readable names (season_summer, season_fall, ...) for interpretability.

Correlation Analysis

Constructed heatmaps to identify which features correlate with fire occurrence.

Strongest correlations:

- High temperatures
- Low precipitation
- Seasonal patterns
- Lagged weather conditions



Preprocessing Continued

Feature Additions: Engineered several new weather-based features designed to capture patterns that the raw dataset could not represent.

- Features added: a 3 day rolling average of maximum temperature, 3 day rolling average of wind speed, a 7 day cumulative precipitation sum, number of dry days within the last 7 days (precipitation = 0), and the interaction of temperature and wind (max_temp * avg_wind_speed).
- Interaction between temperature and wind + max temperature proved to have a top 5 feature importance.
- 3 day average temperature also made it in the top 5 features, for feature importance.

Features Removed: Removed low-importance features in order to reduce noise in the data set and improve the model's ability to focus and find true patterns and variables that may influence fire risk.

- Trained the random forest model using all features, and after training we printed out the feature importance.
- Defined a cutoff, any feature with an importance less than .025 would be removed.
- The following values were removed: precipitation, lagged_precipitation, number of dry days.

Machine Learning

Class Balance:

- No fire risk (0) = 9999
- Fire risk (1) = 4971

Addressing the class imbalance:

- Weight for No: 0.7486
- Weight for Yes: 1.5057
- Improves recall for fire days, which is the most important objective
- We calculated class weights using scikit-learn tools, which assign higher weight to the minority class (fire days) so the model does not ignore rare fire events.

Model Used

RandomForestClassifier

- 300 trees
- Handles nonlinear relationships
- Provides built-in feature importance
- Robust to noise and real-world variability

Evaluation Metrics

- Accuracy
- Precision, Recall, F1-Score

Post-Processing / Results

Model Performance:

- Accuracy: 71.2%
- Fire Risk Precision 0.5419
- Fire Risk Recall: 0.6360
- Fire Risk F1-Score: 0.5862

The model correctly identifies ~63% of real

fire-start days

Top 5 Important Features:

- Min_temp, temp_3day_avg, year, lagged_avg_wind_speed, wind_3day_avg

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Number of instances with fire_start_day = 0 (No) and 1 = (Yes)
No:  9999
Yes:  4971
Class weights:
Weight for No: 0.7486
Weight for Yes: 1.5057
Classification report:
              precision    recall  f1-score   support

           0     0.8141    0.7478    0.7795      1019
           1     0.5419    0.6360    0.5852       478

    accuracy                         0.7121      1497
   macro avg     0.6780    0.6919    0.6824      1497
weighted avg     0.7272    0.7121    0.7175      1497


Top 5 features by importance:
                feature  importance
               min_temp    0.137239
          temp_3day_avg    0.117377
                   year    0.084914
 lagged_avg_wind_speed    0.083779
          wind_3day_avg    0.075930
```

Takeaways / Future Improvements

- Wildfires are often anomalies
    - Had to implement class weights
    - SMOTE wouldn't be possible because these had chronological order
        - Can't synthesize a fire day on a non-fire day

- Weather variables are consistently **top predictors**
    - Things related to temperature, humidity, and wind were always on top

- Possible Additional Features
    - Adding human factors (population density, proximity to roads/power lines)
    - Vegetation moisture
    - Find actual areas of California instead of an overall estimate

- Pick a data set that has a defined class
    - The model only predicts if the day is at high risk for a fire
        - High Risk Fire Day *does not equal* an actual fire