# FireFinder

## A Feature-Centric Pipeline for Robust Fire Detection in Images

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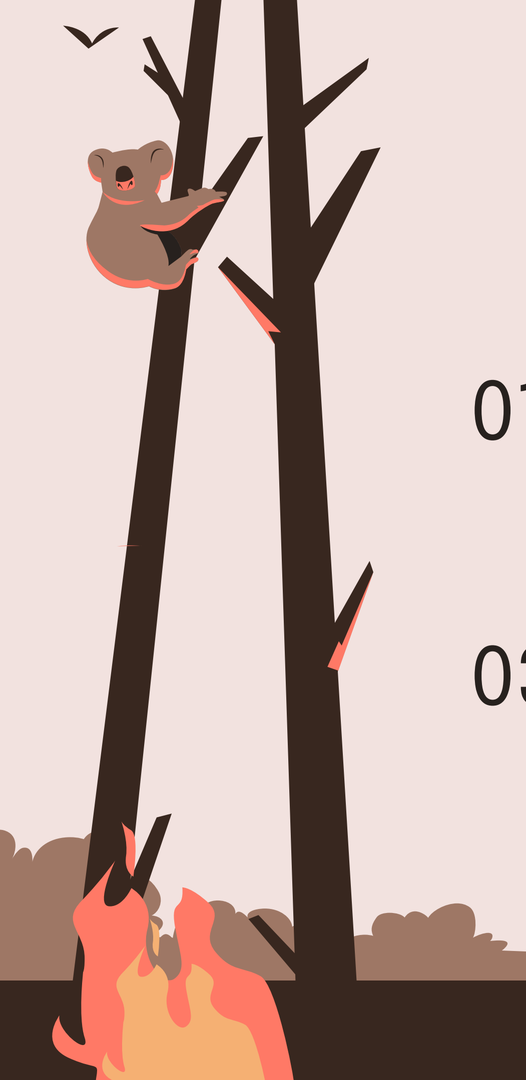

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# Relevant Background Information

- Computer Vision & Fire Detection:
  - Computer vision enables machines to analyze visual data, crucial for applications like wildfire detection.
  - Increased wildfire frequency due to climate change necessitates reliable, fast detection methods.
- Fire Monitoring Systems:
  - Ground sensors: Limited spatial coverage, prone to errors.
  - Satellites: Broad coverage, but low temporal resolution.
  - UAVs: Balanced approach with high-resolution, real-time imaging.
- Vision-Based Fire Detection:
  - Analyzes images/videos using color, shape, texture, and motion.
  - Challenges:
    - Variable fire appearances.
    - Non-fire objects with fire-like colors.
    - Noise from illumination, haze, complex backgrounds.

# The Problem

- Variability in fire appearance due to environmental conditions.
- Distinguishing fire from non-fire objects with similar colors (e.g., sunlit surfaces).
- Impact of noise factors: variable illumination, haze, complex backgrounds.
- The Limitation of using only color based fire detection.

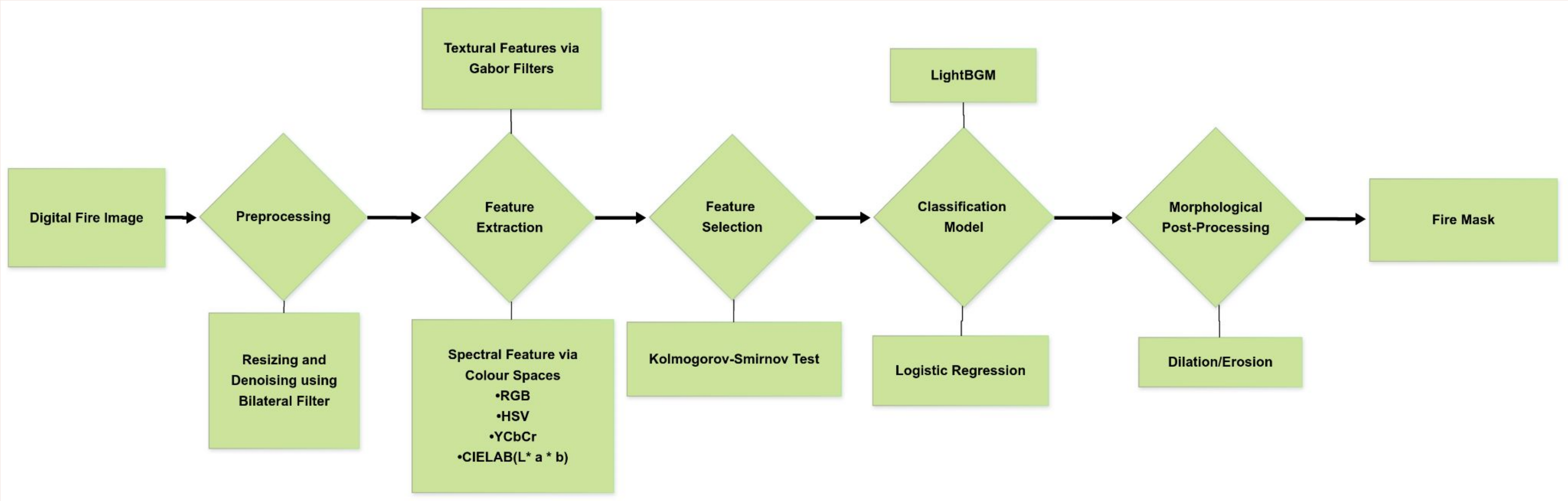
# Enter: FireFinder

- Pixel-wise fire detection in images
- Integrates both **Color information** and **Spatial Texture Analysis**
  - Fire has characteristics colors (Red/Yellow)
  - AND unique **texture patterns** (chaotic, flickering) that simple colored objects lack
- Combining these features leads to more reliable detection
  - **Lower false positive rate**

# Our pipeline

| | |
|---|---|
| 1. Preprocessing | Reduce noise while preserving edges (**Bilateral Filter**) |
| 2. Feature Extraction | Captures **Color Spaces** (YCbCr, L*a*b) and applies **Gabor filters** to capture textural features |
| 3. Feature Selection | **Kolmogorov–Smirnov** (KS) test and **PCA** for color features |
| 4. Classification | Train models (**Logistic Regression** & **LightGBM**) on selected features. |
| 5. Post-processing | Refine the output mask (**Morphological Operations**) |

# Pipeline



Textural Features via Gabor Filters
LightBGM
Digital Fire Image
Preprocessing
Feature Extraction
Feature Selection
Classification Model
Morphological Post-Processing
Fire Mask
Resizing and Denoising using Bilateral Filter
Spectral Feature via Colour Spaces
•RGB
•HSV
•YCbCr
•CIELAB(L* a * b)
Kolmogorov-Smirnov Test
Logistic Regression
Dilation/Erosion

# The Features

## Color Features

- Extracted from **RGB, HSV, YCbCr, L*a*b** (12 total initially)
- KS Test showed Cb, R, Cr, V, b are most discriminative (Highest separation between fire/non-fire pixels)

## Texture Features

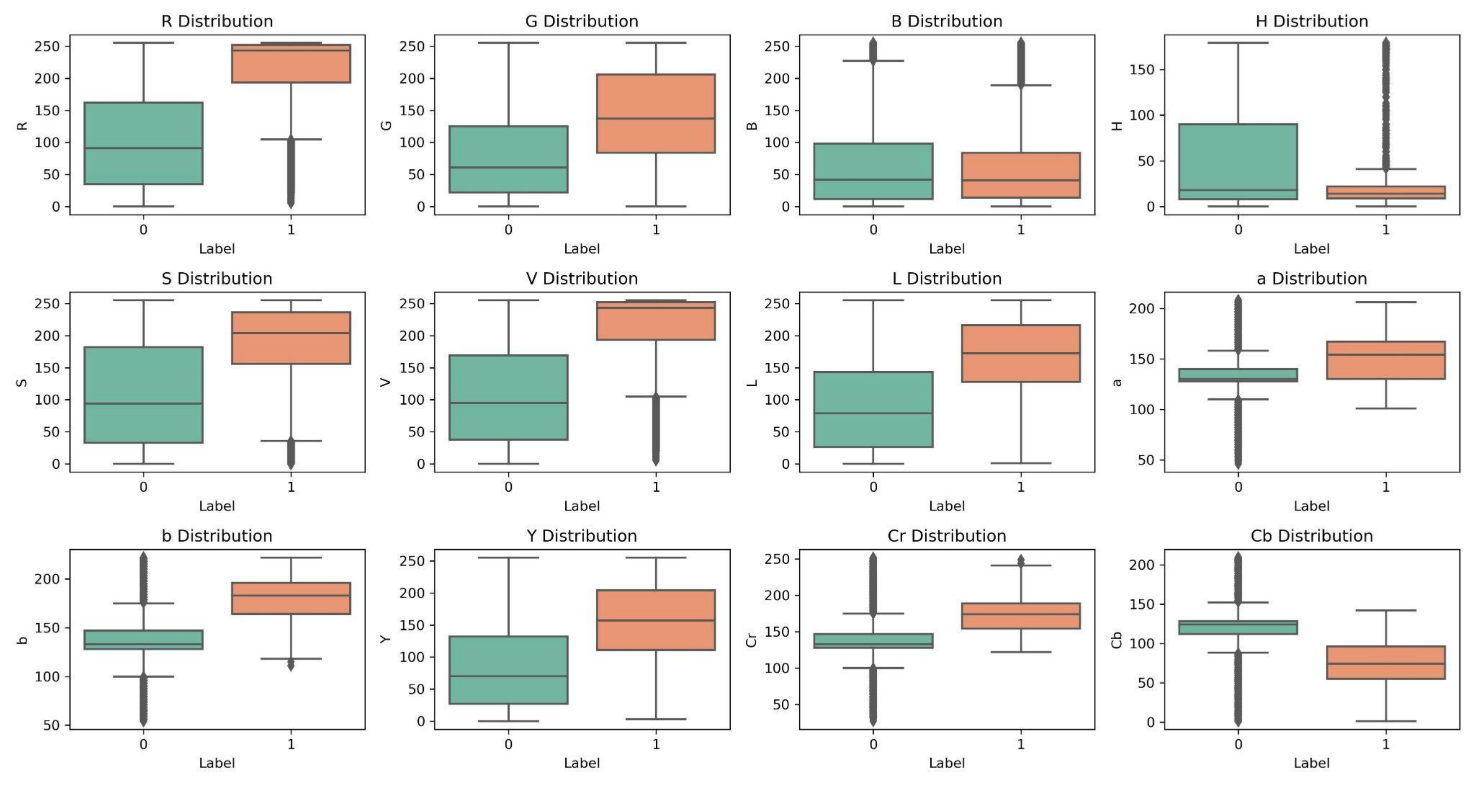
- 16 Gabor responses generated (**different orientations/scales**)
- KS test confirmed discriminative power (~0.43 KS). Top 4 selected.

# Best Color Channels

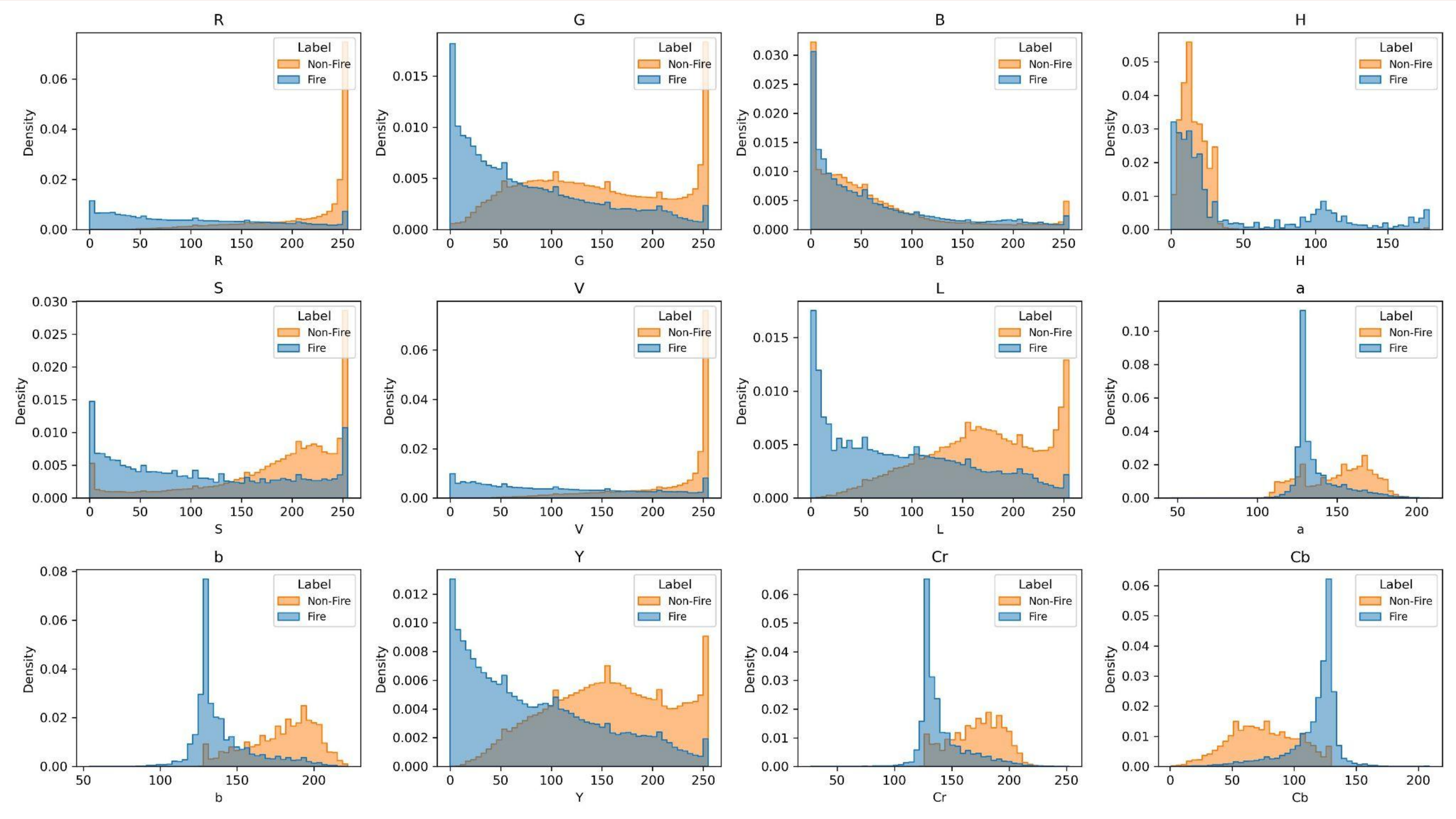
Table 1: KS Test Results for Color Channels

| Channel | Non-Fire Mean | Non-Fire Std | Fire Mean | Fire Std | Abs Mean Diff | KS Statistic |
|---|---|---|---|---|---|---|
| Cb | 116.8 | 20.2 | 75.5 | 26.2 | 41.3 | 0.7 |
| R | 102.8 | 74.9 | 215.6 | 48.8 | 112.8 | 0.6 |
| Cr | 140.5 | 20.4 | 171.0 | 21.9 | 30.5 | 0.6 |
| V | 106.8 | 76.1 | 215.7 | 48.8 | 108.9 | 0.6 |
| b | 114.4 | 21.4 | 84.2 | 21.7 | 30.2 | 0.6 |
| S | 108.5 | 81.7 | 184.3 | 65.6 | 75.8 | 0.4 |
| Y | 85.3 | 66.3 | 155.3 | 57.9 | 70.0 | 0.4 |
| L | 84.5 | 69.0 | 147.3 | 60.6 | 62.8 | 0.4 |
| G | 80.2 | 67.4 | 142.6 | 69.4 | 62.4 | 0.4 |
| H | 44.4 | 51.8 | 16.1 | 11.0 | 28.3 | 0.3 |
| a | 131.7 | 11.8 | 132.5 | 21.4 | 0.9 | 0.3 |
| B | 65.5 | 66.4 | 62.2 | 64.2 | 3.3 | 0.0 |

# Best Color Channels



# Best Color Channels

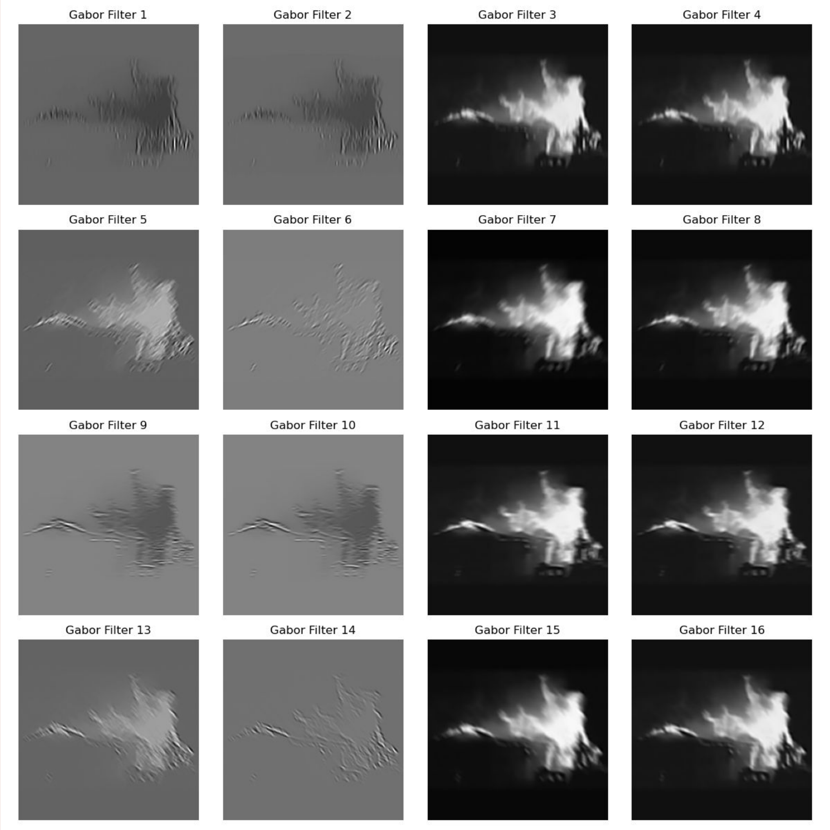


# Best Gabor Features

Table 3: Descriptive Statistics and KS Test for Gabor Features

| Feature | Non-Fire Mean | Non-Fire Std | Fire Mean | Fire Std | Abs Mean Diff | KS Statistic |
|---|---|---|---|---|---|---|
| gabor_14 | 768.2 | 587.8 | 1381.1 | 508.7 | 612.9 | 0.43 |
| gabor_6 | 768.2 | 587.8 | 1381.0 | 509.0 | 612.8 | 0.43 |
| gabor_2 | 726.8 | 558.3 | 1312.6 | 485.5 | 585.8 | 0.43 |
| gabor_10 | 727.1 | 558.8 | 1307.4 | 482.9 | 580.4 | 0.43 |
| gabor_3 | 393.4 | 304.9 | 714.2 | 265.9 | 320.8 | 0.43 |
| gabor_15 | 393.5 | 305.0 | 713.9 | 265.6 | 320.4 | 0.43 |
| gabor_7 | 393.5 | 305.0 | 713.9 | 265.6 | 320.4 | 0.43 |
| gabor_11 | 393.4 | 305.0 | 713.3 | 265.3 | 319.9 | 0.43 |
| gabor_12 | 321.4 | 248.2 | 580.6 | 216.7 | 259.2 | 0.43 |
| gabor_4 | 321.4 | 248.2 | 580.5 | 217.0 | 259.1 | 0.43 |
| gabor_0 | 287.4 | 226.1 | 525.1 | 201.2 | 237.7 | 0.43 |
| gabor_8 | 287.7 | 226.7 | 520.6 | 196.4 | 232.9 | 0.43 |
| gabor_1 | 155.6 | 123.9 | 286.0 | 111.2 | 130.5 | 0.43 |
| gabor_13 | 155.8 | 123.4 | 285.4 | 109.3 | 129.6 | 0.43 |
| gabor_5 | 155.8 | 123.4 | 285.4 | 109.4 | 129.5 | 0.43 |
| gabor_9 | 155.7 | 124.2 | 284.3 | 108.7 | 128.6 | 0.43 |

# Best Gabor Features



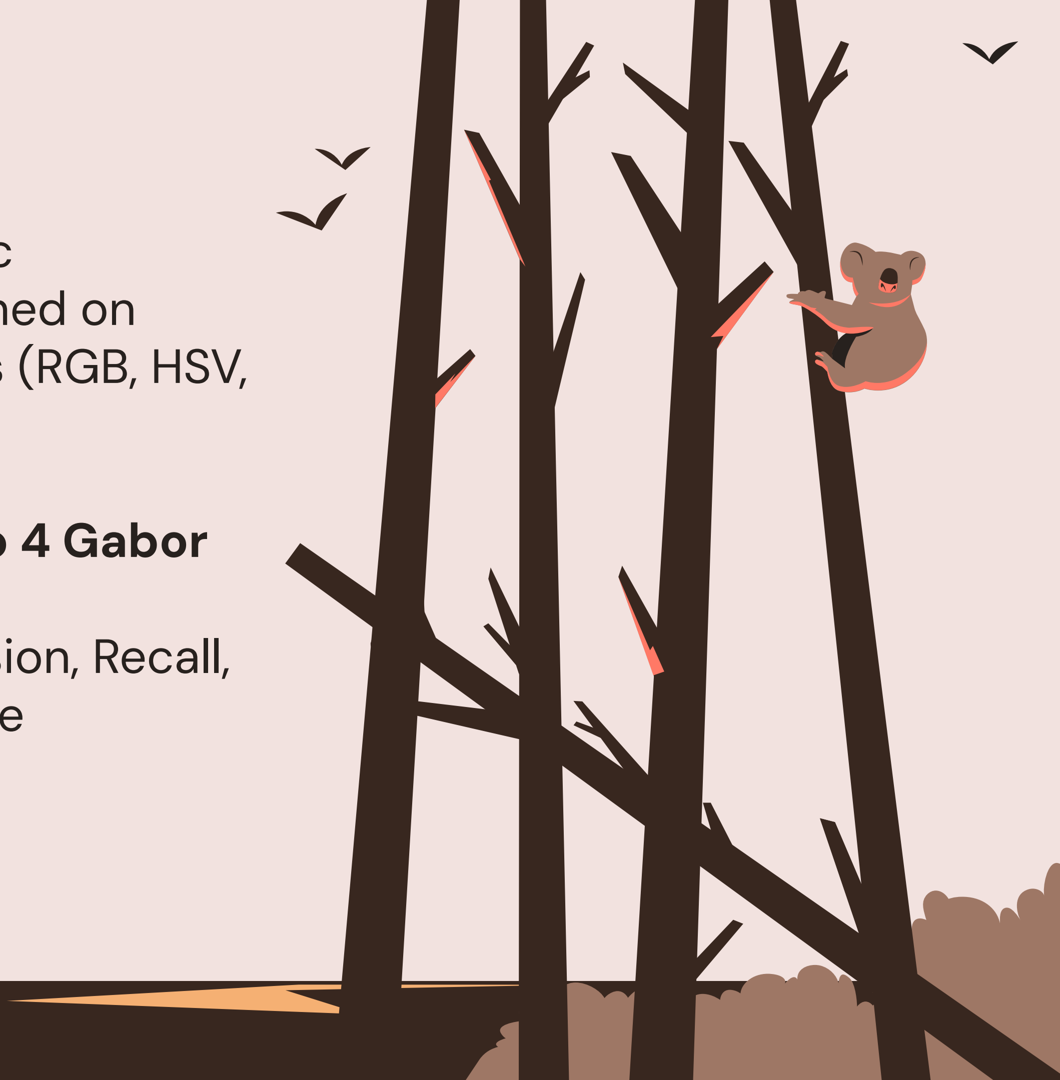
# The Dataset

- 226 diverse real-world images (fire/non-fire) including challenging negatives
- **Processing:**
  - 80/20 training/testing split
  - Balanced training set by undersampling non-fire pixels


Live
Demo
Time!

# Evaluation

- Compared models (Logistic Regression, LightGBM) trained on
  - Individual color spaces (RGB, HSV, etc.)
  - Combined features
- Selected **Top 5 Color** + **Top 4 Gabor** using KS Test Results
- Evaluated: Accuracy, Precision, Recall, F1-Score, False Positive Rate



# Highlight

LightGBM achieved:

**90.68%** accuracy

**91.09%** F1-Score

**13.92%** FPR

# Next Steps

- Exploring real-time implementation on UAVs or embedded systems.
- Investigating more advanced texture features or deep learning integration.
- Expanding the dataset to include more diverse fire scenarios.
- Optimizing the pipeline for speed and efficiency.
- Testing the system in real life scenarios.

# Thanks!

## Question time

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