ARDC

Enhancing Wildfire Management
By
Team 3 (Pyro Vision)

Good evening to all respected tutors and other team members.

- We are ***'Pyro Vision',*** a group of passionate individuals, committed to utilizing machine learning and data science to address the critical environmental issue related to wildfires.
- Today, we'll take you on a journey through our project, sharing our insights and strategies.
- We believe that by the end of this presentation, you'll gain a deep understanding of our project's significance and the direction we're heading.
- The topic of our project is ***"Enhancing wildfire management".*** A case study of Greece.
- Our group consists of four team members: Ahmed, Ashutosh, Nutan, and Shivani; all of them are full-time students at UTS.

Wildfire: A Global Concern

- The phenomenon of wildfires is not new to our planet. However, recent years have witnessed an alarming increase in the frequency and intensity of these fires across the globe.
- From the vast rainforests of the Amazon to the bushlands of Australia, no region has remained untouched. The consequences are multifaceted, affecting the environment, economy, and human settlements.

- Tree cover loss from fire over the past 20 years is shown in dark. Time-lapse provided by *World Resources Institute (WRI) via GFW.*

Why Choose Greece ?

Greece: A Nation Under Siege

- Greece, with its Mediterranean climate and extensive forested areas, has always been susceptible to wildfires.
- However, the past decade (2013-2023) has seen an unprecedented surge in these destructive events.
- Each year, news headlines relay harrowing tales of villages evacuated, ancient forests reduced to ash, and sadly, lives lost.
- Notably, in August 2023, Greece faced the largest wildfire in the European Union.


Greece
Greece wildfire declared largest ever recorded in EU
Eleven planes and helicopter from bloc sent to tackle fire that has burned more than 300 sq miles of land
The wildfire at Dadia national park is still out of control, according to the Greek fire service. Photograph: Alexandros Avramidis/Reuters
Agence France-Presse
Wed 30 Aug 2023 00.22 AEST

- This recent development in August 2023 is a key reason why our group, Pyro Vision, has chosen Greece as the focal point for our wildfire research efforts.

Wildfire Prediction Model

The primary objective of this model is to ascertain the likelihood of wildfire incidents transpiring across Greece on a monthly basis, spanning from January 2022 to August 2023.

Wildfire Data

Data Collection

- NASA Firms provides access to data originating from various satellite observations, our data follow satellite observations conducted by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Aqua and Terra Satellites.
- Wildfire Data from NASA Firms.

	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	confidence	version	bright_t31	frp	daynight	type
0	41.0920	22.2347	303.4	1.0	1.0	2013-01-03	1133	Aqua	MODIS	56	6.03	282.8	7.4	D	0
1	40.5030	21.1837	325.7	1.1	1.0	2013-01-08	1151	Aqua	MODIS	84	6.03	277.0	30.9	D	0
2	40.6681	22.6679	313.0	1.2	1.1	2013-01-08	1151	Aqua	MODIS	73	6.03	278.7	20.0	D	0
3	40.6697	22.6823	318.3	1.2	1.1	2013-01-08	1151	Aqua	MODIS	78	6.03	278.9	26.2	D	0
4	40.5687	22.6940	301.7	1.2	1.1	2013-01-08	1151	Aqua	MODIS	48	6.03	277.3	10.7	D	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1922	40.6628	22.6989	322.8	1.1	1.0	2013-12-19	1145	Aqua	MODIS	82	6.03	283.4	25.3	D	0
1923	40.6394	22.5875	300.6	1.1	1.0	2013-12-19	1145	Aqua	MODIS	39	6.03	284.5	6.2	D	0

Wildfire Prediction Model

Wildfire Data.

Processing Wildfire Data.

- The initial wildfire data provided to be used consists of 15 columns: latitude, longitude, brightness, scan, track, acq_date, acq_time, satellite, instrument, confidence, version, bright_t31, frp, daynight, and type. But all these columns were not required.
- Relevant columns were selected by filtering the wildfire data to include records within specified latitude (34 to 42) and longitude (19 to 29) ranges. The latitudes and longitudes were rounded off to two decimal places.
- The data was organised into groups based on latitude, longitude, acquisition date, satellite, and instrument. Within each group, the maximum confidence value was retained. Records with low confidence (confidence < 50) were excluded from the dataset. The resulting dataset consisted of aggregated daily fire records.
- Then nine columns were removed from dataset and remaining columns are latitude, longitude, acq_date, satellite, instrument and confidence.

Wildfire Prediction Model

Wildfire Data.

Creating new feature columns in Wildfire Data.

- The first step in this process was the conversion of the 'acq_date' column into a datetime format in order to have a year and month column.
- The dataset after having month and year column was grouped based on 'latitude,' 'longitude,' 'year,' and 'month,' summarizing wildfire occurrences within these specific temporal and spatial dimensions. The resulting dataset included columns denoting 'latitude,' 'longitude,' 'year,' 'month,' and 'fire_cnt' (indicating wildfire incident counts).
- The second column created was the 'fire' column, which served as a binary indicator. This column was determined based on the comparison of 'fire_cnt' (fire incident count) against a predefined minimum threshold, denoted as 'MIN_FIRE_RECORDS.'
- Apart from this, using these two columns, six other new columns were created.
- The final wildfire data with all required columns was created.

Wildfire Prediction Model

Final Wildfire Dataset.

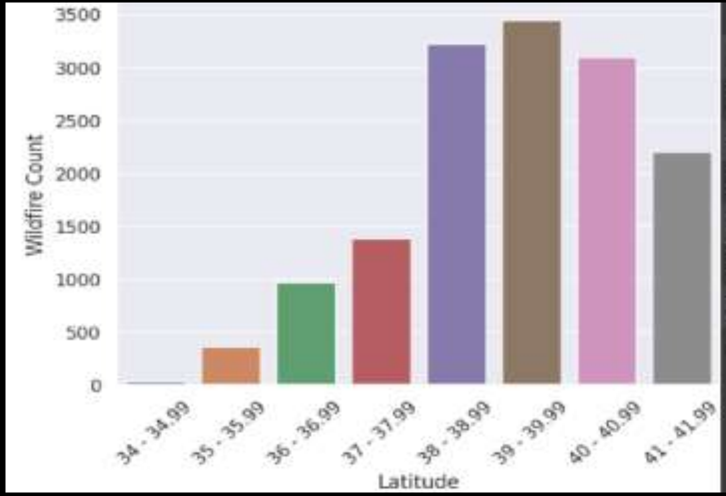
latitude	longitude	year	month	fire_cnt	fire	fire_cnt_before	fire_before	fire_cnt_last_year	fire_last_year	fire_cnt_last_year_same_month	fire_last_year_same_month
35.0	25.7	2013	7	0.0	0	0.0	0.0	0.0	0.0	0.0	0.0

Columns	Description
Latitude	Angular distance north or south of earth equator.
Longitude	Angular distance of place east or west of Greenwich meridian.
Month	Month of wildfire predict period.
Fire Report count Before	Number of fire report in past for specific latitude – longitude pair.
Fire count (Before)	The number of fires with probability with probability of occurring in the past for a specific latitude – longitude pair.
Fire Report (last year)	Number of fire report in last year for specific latitude – longitude pair.
Fire Count (last year)	The number of fires with probability of occurring in the last year for a specific latitude – longitude pair.
Fire Report (Same month last year)	Number of fire report in same month of the last year for specific latitude – longitude pair.
Fire Count (Same month last year)	The number of fires with probability of occurring in same month of last year for a specific latitude – longitude pair.

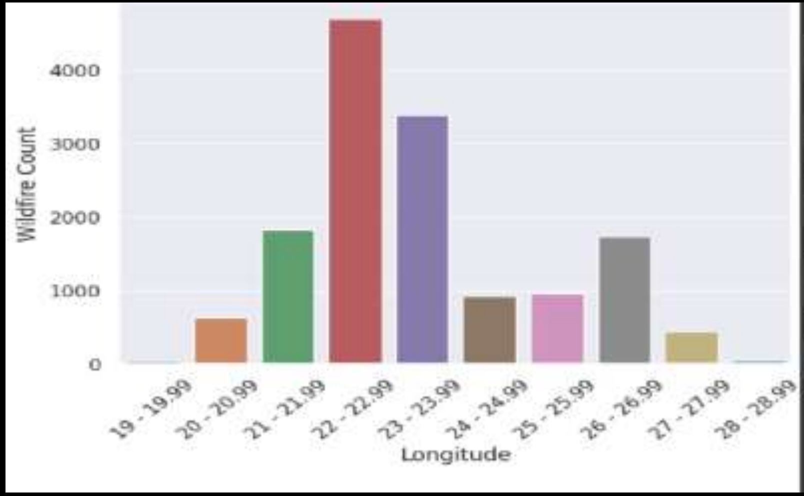
Wildfire Prediction Model

Data Analysis

➢ Total Wildfire counts for latitude and longitude intervals.

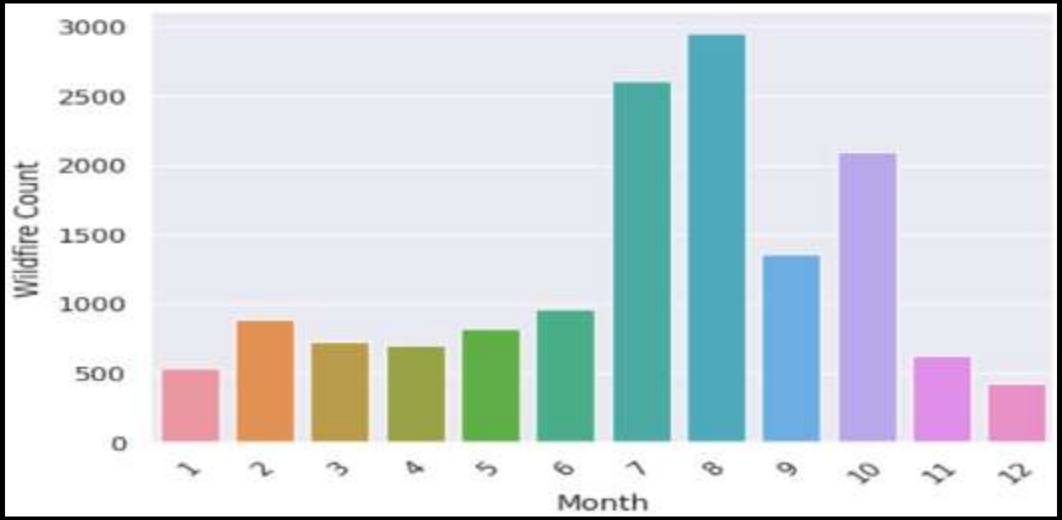


	Latitude	Wildfire Count
0	34 - 34.99	29
1	35 - 35.99	364
2	36 - 36.99	972
3	37 - 37.99	1387
4	38 - 38.99	3222
5	39 - 39.99	3450
6	40 - 40.99	3098
7	41 - 41.99	2204



	Longitude	Wildfire Count
0	19 - 19.99	46
1	20 - 20.99	630
2	21 - 21.99	1826
3	22 - 22.99	4699
4	23 - 23.99	3400
5	24 - 24.99	925
6	25 - 25.99	960
7	26 - 26.99	1735
8	27 - 27.99	449
9	28 - 28.99	56

➢ Total wildfire count by month.



Wildfire Prediction Model

Temperature Dataset

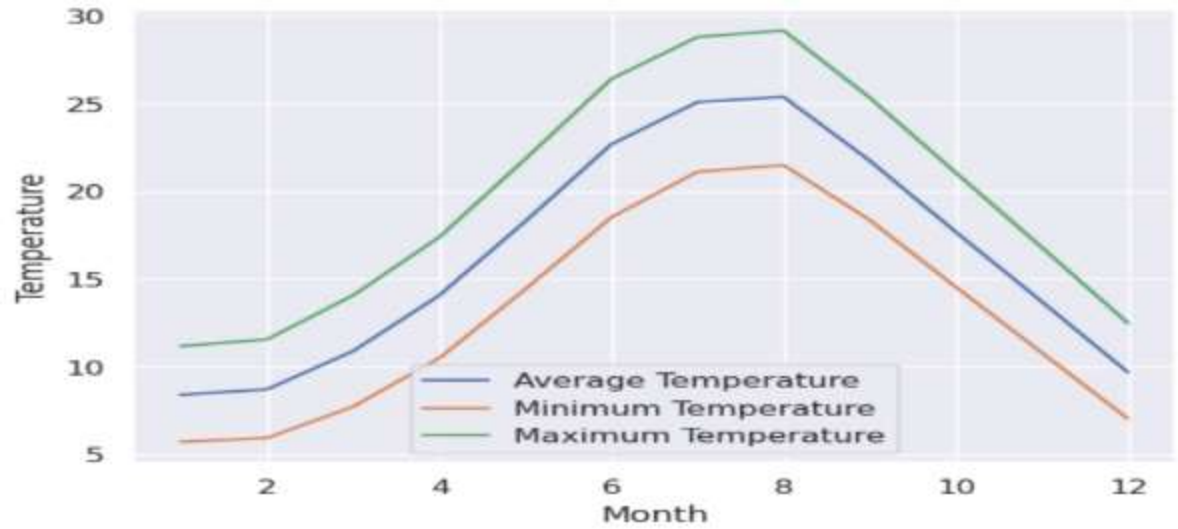
Data Collection Temperature dataset (Scrapped from European Climate Assessment and Dataset + Weather and

Climate + Berkeley Earth)

latitude	longitude	month	year	temperature_min	temperature_avg	temperature_max
38.6	21.4	1	2014	4.3	7.5	11.0
39.2	22.8	1	2013	0.4	4.1	8.6
38.1	20.5	1	2013	9.2	10.5	11.5
35.5	24.0	1	2013	8.5	10.1	12.4

Data Analysis.

- Minimum, maximum and average temperatures for each month



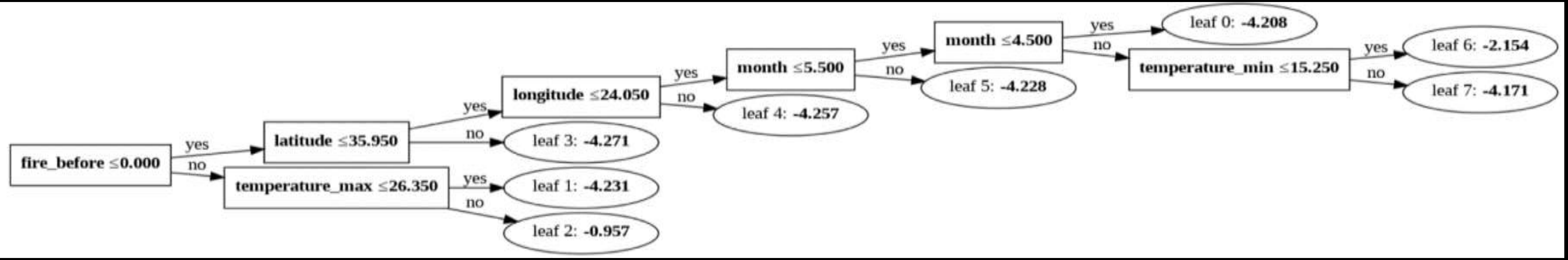
Wildfire Prediction Model

Model Training

LightGBM Model Configuration

- Dataset objects were created for the LightGBM model (an advance decision tree alogrithm), using the defined features and target variable.
- Optimized hyperparameters for the LightGBM model were set. These hyperparameters were obtained through the optimization process described earlier and included parameters for binary classification, regularization terms (reg_alpha and reg_lambda), and the number of leaves in decision trees (num_leaves).
- Early stopping was enabled during training to prevent overfitting, with a maximum of 20 rounds without improvement.

Decision Tree Visualization of LightGBM Model



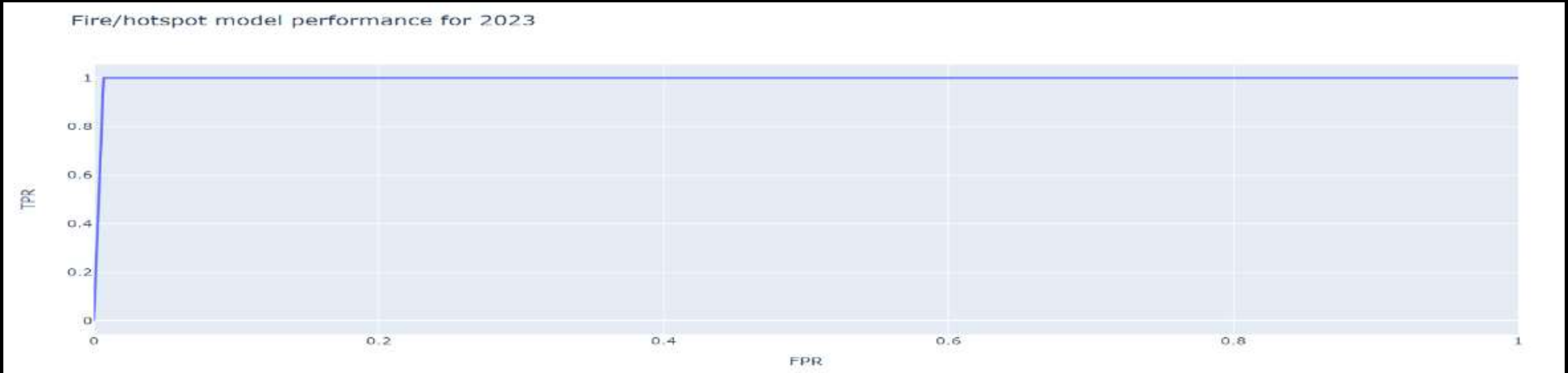
Wildfire Prediction Model

Model Evaluation

A classification report was presented, providing detailed metrics such as precision, recall, and F1-score for both "fire" and "not fire" classes.

	precision	recall	f1-score	support
not fire	1.00	0.99	1.00	13240
fire	0.25	1.00	0.41	31
accuracy			0.99	13271
macro avg	0.63	1.00	0.70	13271
weighted avg	1.00	0.99	1.00	13271

- The ROC-AUC score was calculated to assess the model's ability to distinguish between positive and negative classes which was found to be 0.9965.
- An ROC/AUC curve was plotted to visualize the trade-off between true positive rate and false positive rate.



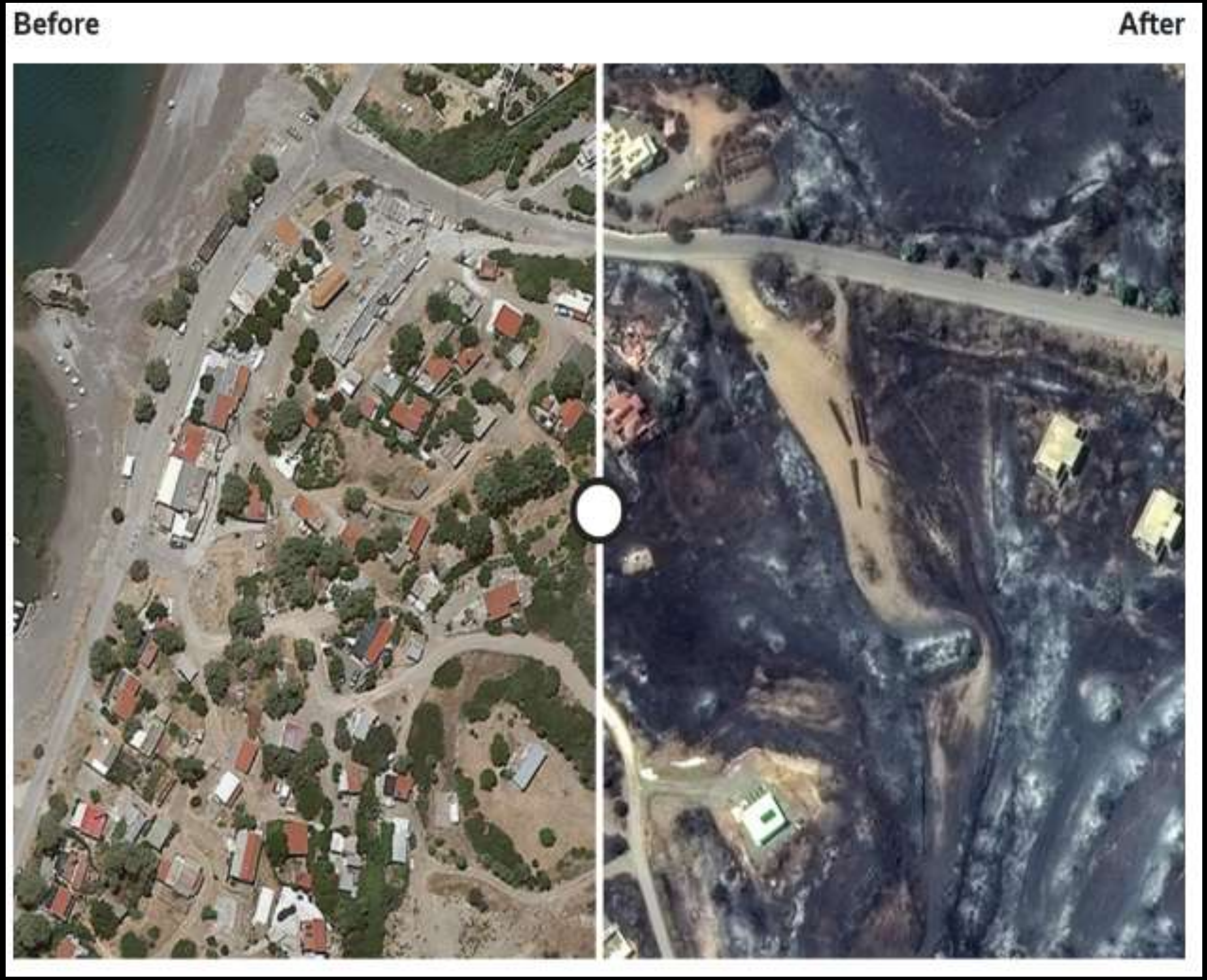
Smoke & Fire Detection

Smoke and fire Detection is crucial to provide rapid response in detecting wildfires in forest areas, large campuses, and communities.

Why???

Early Detection and suppression saves precious forests, natural resources, assets,

Saves lives, and fire control costs.



DATA COLLECTION

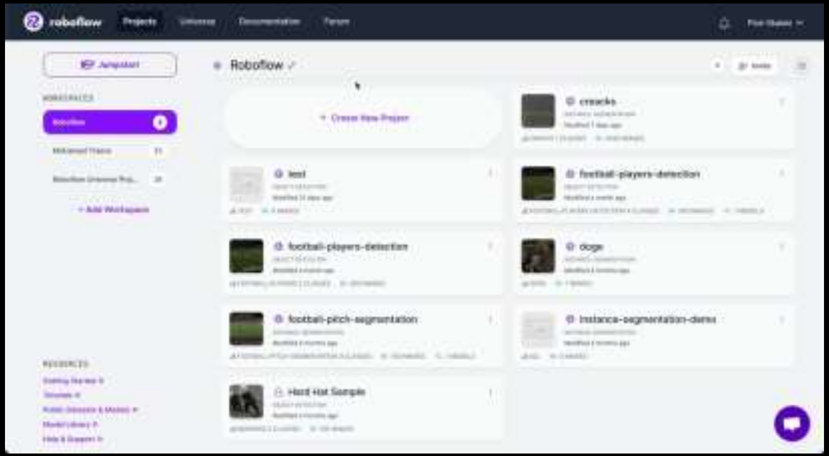
- Data were collected from various sources such as Kaggle, Google,etc.

FIRE

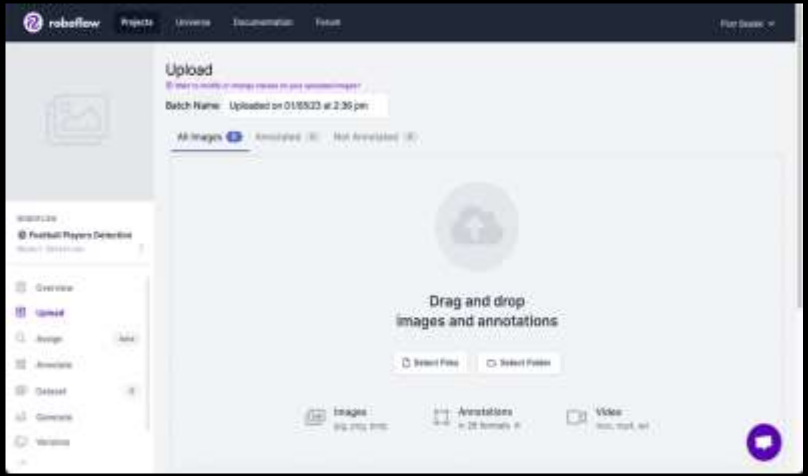
SMOKE

PREPARING THE DATA

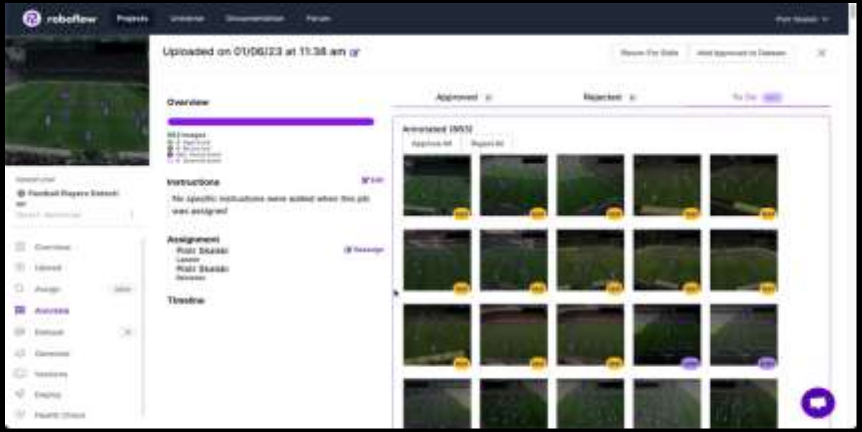
1. Creating the project



2. Uploading the images



3. Labelling

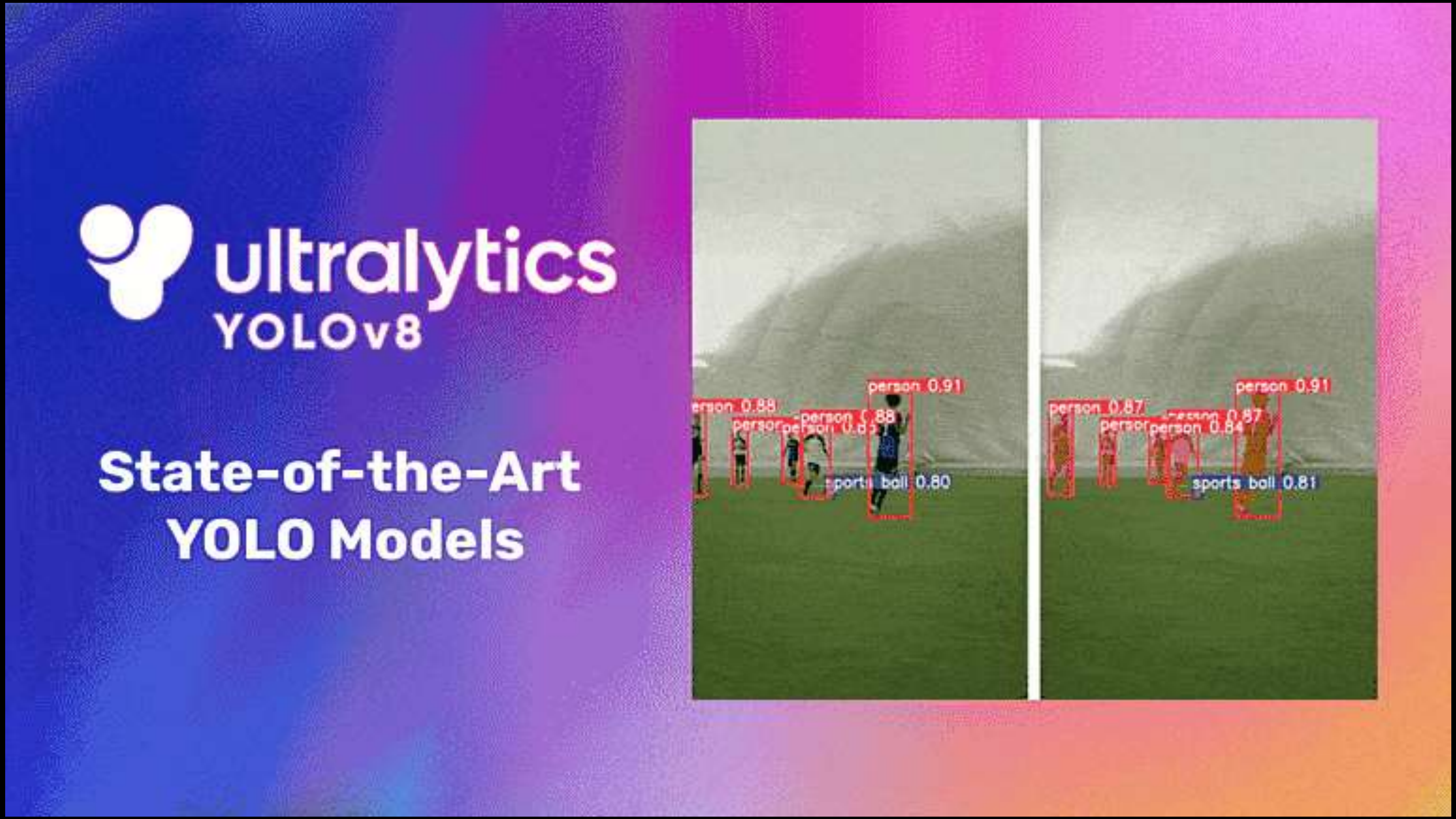


4. Generating the required version

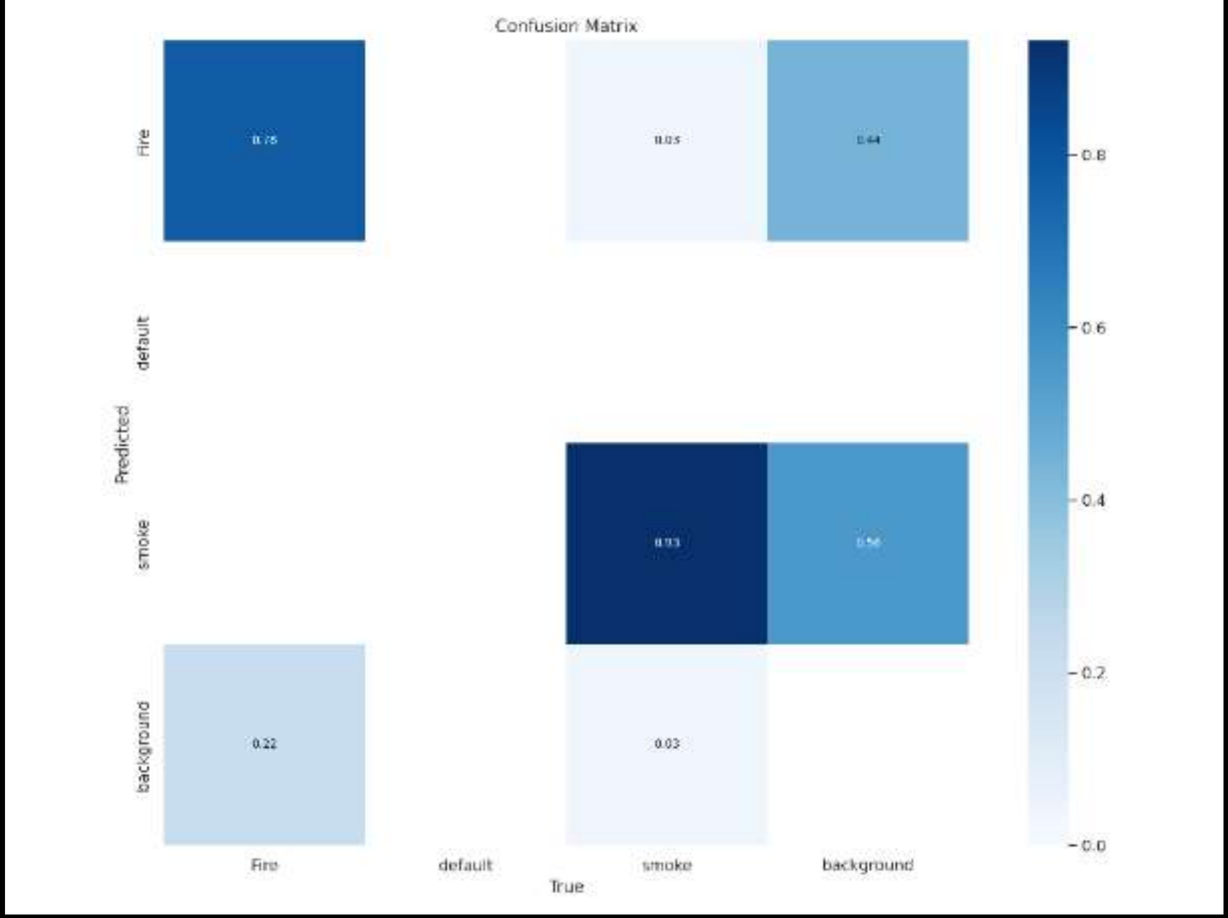
MODEL SELECTION

- YOLOv8 by Ultralytics:

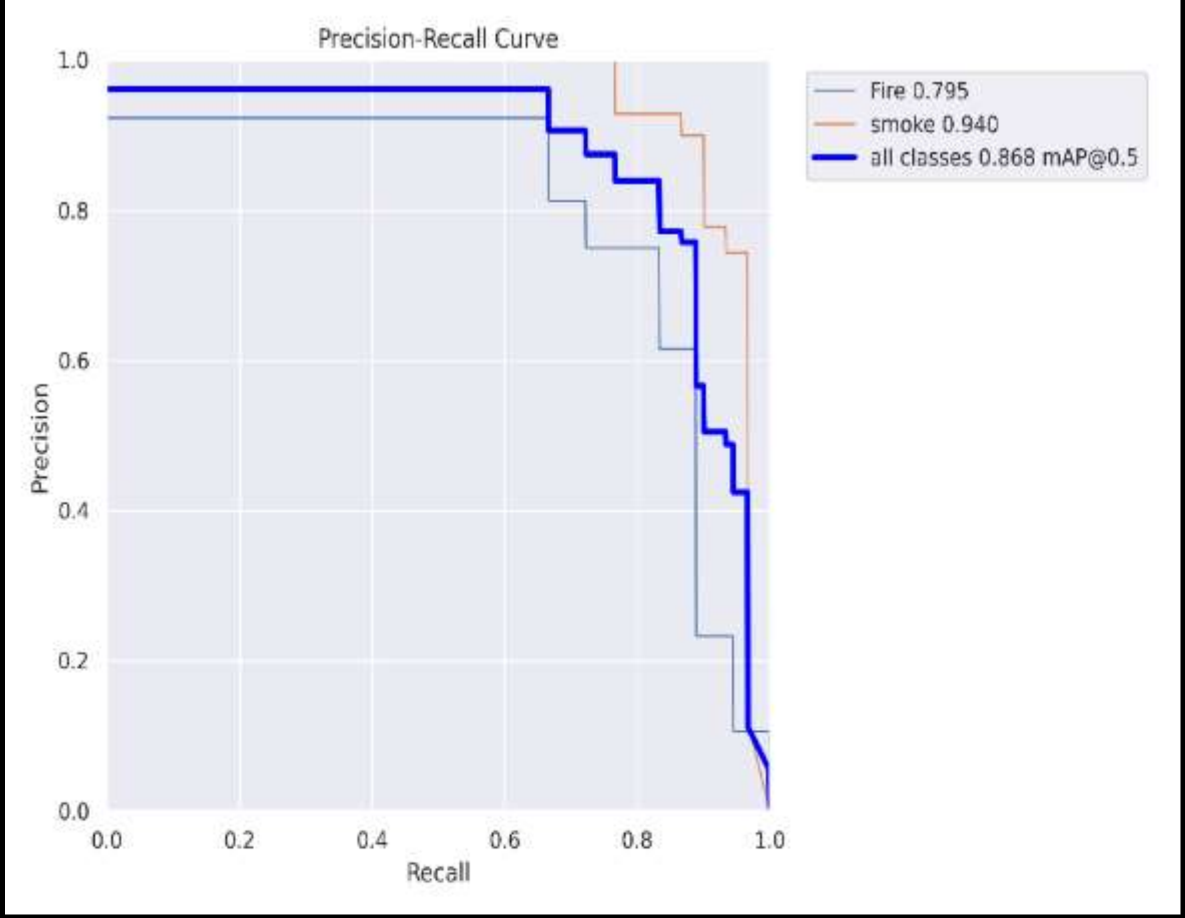
- What is it? The latest version of "You Only Look Once" (YOLO) series for object detection.
- Advantage: Unlike traditional models which segment an image and analyze parts, YOLOv8 detects objects across the whole image in a single pass.
- Why Choose YOLOv8? It's fast and efficient, making it ideal for real-time applications.



MODEL PERFORMANCE



CONFUSION MATRIX

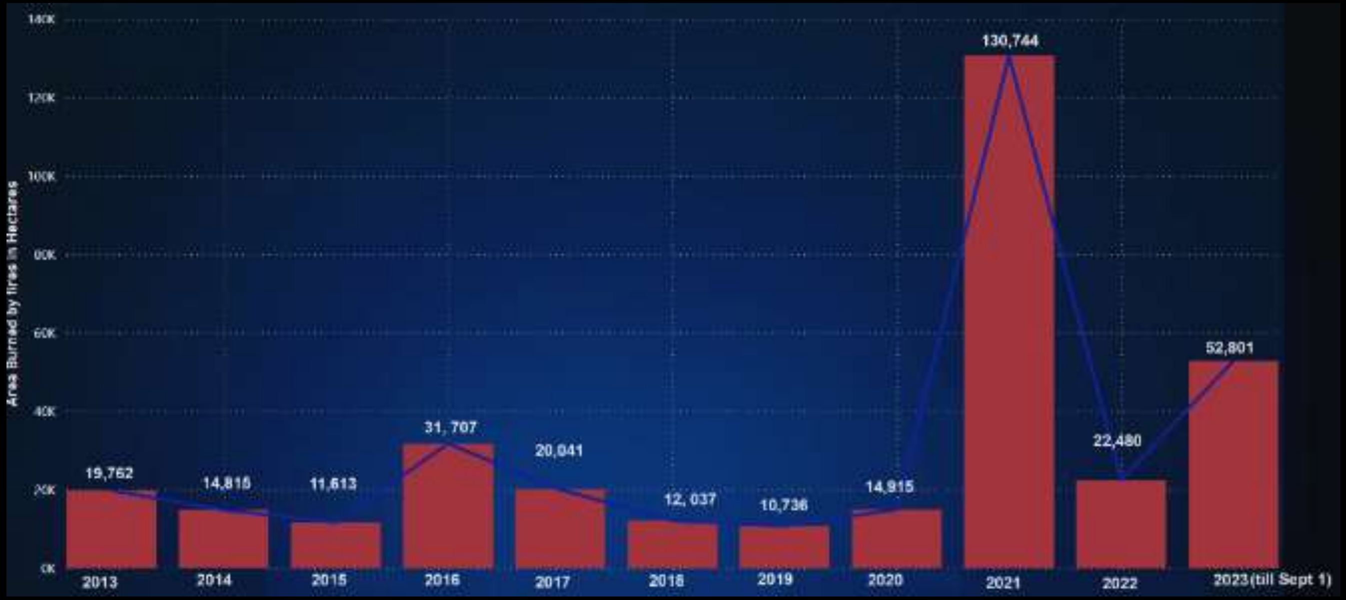


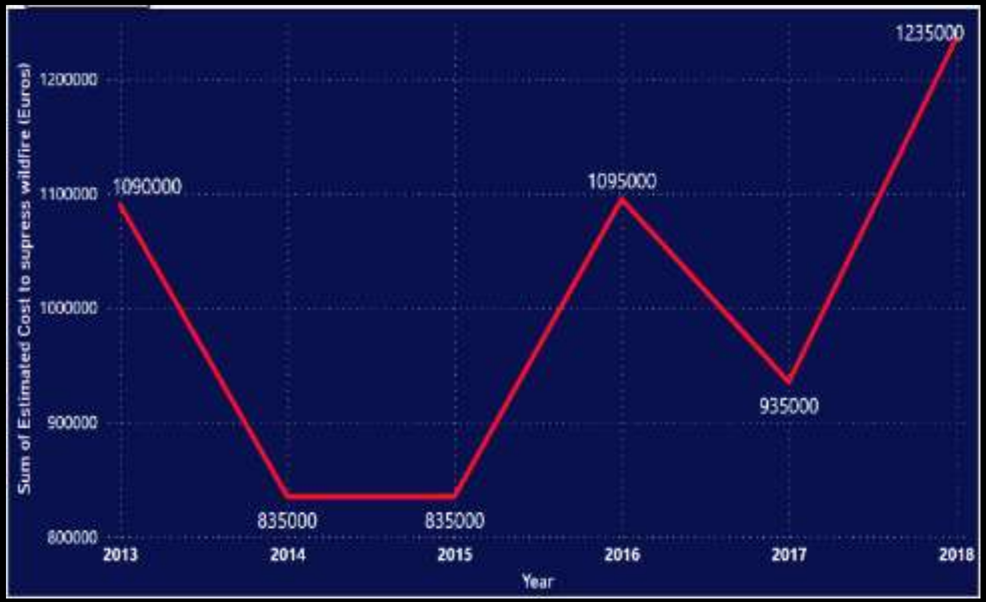
P-R CURVE with 0.868

RESULTS

Wildfire Impact Visualization in Greece

Visualising Area Burned by Wildfires (2013-2023) in Greece and Estimated cost to suppress wildfires per fire in Greece from 2011 to 2018 (in euros).





Recommended Strategies

Wildfire Preparation

- It has been determined that the latitude range of **39 - 39.99** and the longitude range of **22 - 22.99** have the highest wildfire counts, underscoring the need for heightened monitoring and preventative measures in these specific geographic zones.
- It is notable that temperature is at its highest in **August**, coinciding with the highest wildfire counts during this month. This highlights the critical connection between temperature patterns and wildfire risk, emphasizing the need for proactive measures during August to mitigate the potential for wildfire outbreaks.
- Recognizing August as a peak wildfire month underscores the importance of heightened preparedness during this period. Authorities can allocate additional resources, manpower, and firefighting equipment in advance.

Recommended Strategies

Smoke Detection Response

- **High Precision for Fire Detection**: The model's accuracy in identifying fire incidents enables swift response. It can trigger alerts to relevant authorities, leading to the rapid dispatch of response teams to the location of the fire.
- **Slightly Lower Fire Detection Precision**: While fire detection precision is slightly lower, it still contributes to early fire identification. The model can assist in distinguishing fire from other objects, facilitating a quicker response.
- **High Precision for Smoke Detection**: Exceptional precision in detecting smoke is vital for rapid response. Accurate smoke detection can trigger alerts and help responders assess the situation effectively.
- **Balanced Average Precision Across All Classes**: The model's balanced performance across all classes ensures its versatility in handling different object detection tasks during a wildfire response. It can provide real-time decision support to responders, aiding in containment and suppression efforts.

Recommended Strategies

Recovery Strategies from Wildfire

A report on Euro news claims that environmentalists who advocate stronger international action to kerb climate change have accused Greek authorities of spending more funds on extinguishing fires than on prevention.

So, the requirement for recovery is to save money by stopping the wildfire causes, which can result from factors like extreme temperatures or human negligence. By addressing the root causes of wildfires, authorities can save significant amounts of euros, which could be redirected to more effectively manage and mitigate wildfires. These saved funds can be utilized in the following ways to complete the recovery process effectively:

1. Invest in Prevention	**2. Enhance Preparedness**	**3. Ecological Rehabilitation**
4. Community Support	**5. Education and Awareness**	**6. Long-Term Resilience**

By taking these steps, authorities can not only recover from the devastating impact of wildfires but also create a more resilient, prepared, and sustainable environment for the future.

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Future Scope

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Wildfire Prediction Model

- Utilization of additional datasets, specifically for features like relative humidity, wind speed, and flora.
- Extracting features suitable for time-series analysis, including metrics such as autocorrelation and seasonality, to gain deeper insights into wildfire occurrences.
- Implementing advanced hyper-parameter optimization techniques, such as Optuna or Hyperopt, to fine-tune the model's performance.
- Exploring the potential of different machine learning models beyond LightGBM, including CatBoost, XGBoost, neural networks, and ensemble methods, to determine which one offers the best performance for wildfire prediction.

Smoke and Fire Detection

1. Real-time Deployment on Surveillance Cameras	2. Public Awareness and Integration	
3. Continuous Feedback Loop	4. Model Improvements	6. Additional Feature Integration


THANK YOU