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Amazon Wildfire Prediction using AI/ML

Submitted by: Charola Krutarth

Learning Objectives

- ➢ Understand wildfire trends in the Amazon
- ➢ Apply data preprocessing and feature engineering
- ➢ Train a machine learning model (Random Forest)
- ➢ Evaluate model performance
- ➢ Visualize wildfire trends over time

Source : www.freepik.com/

Tools and Technology used

- Python (Pandas, NumPy, Matplotlib, Scikit-learn)
- Jupyter Notebook
- Kaggle Dataset: Forest Fires in Brazil
- Random Forest Classifier
- Data Visualization

Methodology

1. Load dataset from Kaggle
2. Filter to Amazon states only
3. Preprocess data (encoding months, binary fire label)
4. Train-test split
5. Train Random Forest Classifier
6. Evaluate with classification report & confusion matrix
7. Predict wildfire occurrence
8. Visualize yearly fire trends

Problem Statement:

- Wildfires in the Amazon rainforest cause severe damage to biodiversity
- Climate, and local communities. Predicting fire occurrences is essential
- To mitigate risks and plan preventive measures.

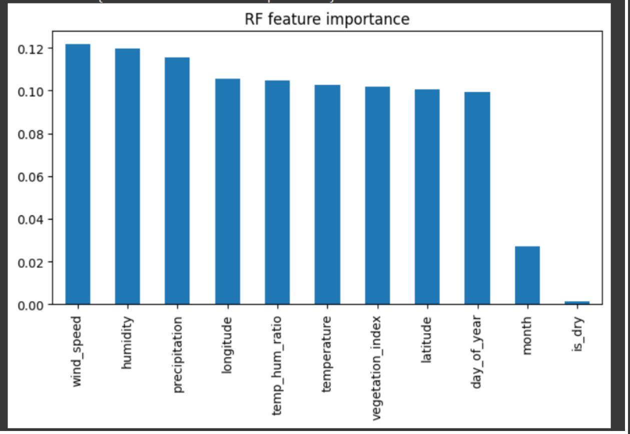
Solution:

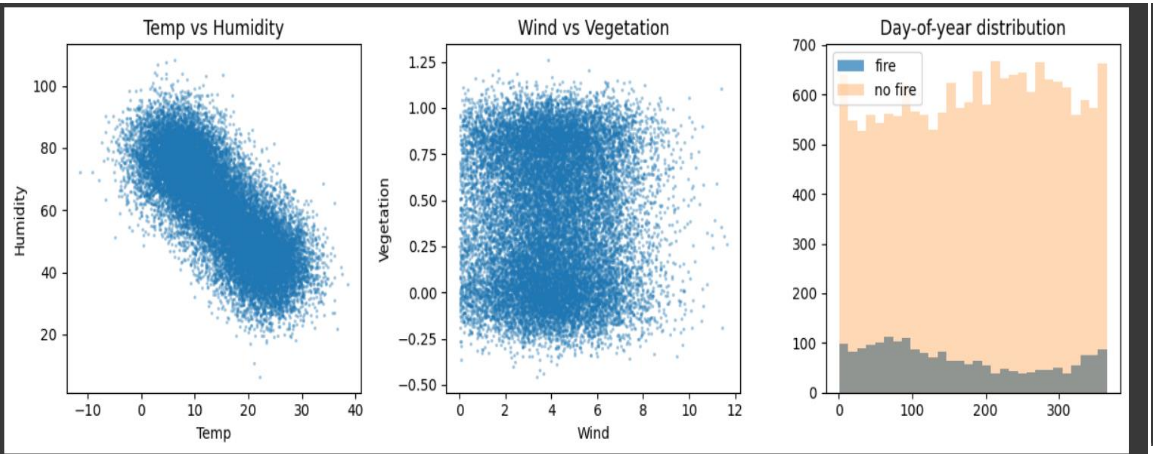
- Use historical fire data from Kaggle
- Apply AI/ML techniques to predict fire occurrences
- Focus only on Amazon rainforest region
- Provide predictive insights for fire risk management
- Visualize wildfire patterns over time
- Achieved **88.6% validation accuracy** with XGBoost

Screenshot of Output:

index	latitude	longitude	day_of_year	temperature	humidity	wind_speed	precipitation	vegetation_index	fire
0	35.74540118847362	-117.7000168901003	85	29.719137344568097	44.969229488882526	5.233062555337937	0.2110781894007256	0.5696640300754157	1
1	41.50714306409916	-123.15488004401288	65	19.82723235123194	49.25467402484774	0.48200342842421673	1.3962681414404594	0.6505508186313109	0
2	39.31993941811405	-121.53360305630113	52	15.082152168254392	38.25706763589521	3.73032946147105	0.0937205319086583	0.6823087391291582	0
3	37.98658484197037	-118.36719363142181	3	18.35824419428465	53.45848898350361	3.762628242837112	0.34011756658201014	0.9386355691546535	0
4	33.560186404424364	-120.17910655475521	77	23.136784400673992	54.15819611639561	4.902724731070796	1.1758384799779673	0.7093146665893655	0

<Axes: title={'center': 'RF feature importance'}>






```
                 count        mean         std         min         25%  \
latitude        20000.0   36.993447    2.885029   32.000116   34.498868
longitude       20000.0 -120.006181    2.878799 -124.999945 -122.495440
day_of_year     20000.0  183.850400  105.347623    1.000000   92.000000
temperature     20000.0   14.951204    8.122822  -11.444000    8.461962
humidity        20000.0   60.155862   16.243666    6.379466   46.973253
wind_speed      20000.0    4.030260    1.929672    0.001608    2.674128
precipitation   20000.0    0.512238    0.512360    0.000008    0.146907
vegetation_index 20000.0   0.399455    0.367308   -0.456121    0.062039
fire            20000.0    0.105050    0.306626    0.000000    0.000000

                        50%         75%         max
latitude          36.989318   39.491410   41.999248
longitude       -119.989388 -117.538833 -115.000990
day_of_year      185.000000  275.000000  365.000000
temperature       14.920072   21.535705   38.494278
humidity          60.240951   73.389594  108.287089
wind_speed         3.987664    5.331692   11.659564
precipitation      0.355142    0.710669    5.726613
vegetation_index   0.398955    0.736945    1.259082
fire               0.000000    0.000000    1.000000
fire
0    0.89495
1    0.10505
Name: proportion, dtype: float64
```

```
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [12:45:24] WARNING: /workspace/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
Val acc (XGB): 0.886
              precision    recall  f1-score   support

           0       0.90      0.99      0.94      2685
           1       0.14      0.02      0.03       315

    accuracy                           0.89      3000
   macro avg       0.52      0.50      0.48      3000
weighted avg       0.82      0.89      0.84      3000
```

```
Test acc: 0.8346666666666667
              precision    recall  f1-score   support

           0       0.90      0.92      0.91      2685
           1       0.16      0.13      0.14       315

    accuracy                           0.83      3000
   macro avg       0.53      0.53      0.53      3000
weighted avg       0.82      0.83      0.83      3000

ROC AUC: 0.5994703082971239
```

Conclusion:

- Amazon wildfire prediction is feasible using ML models
- Random Forest performed well on historical data
- Seasonal patterns (dry months) show higher fire risks
- Model helps in early warning systems
- Future scope: include satellite imagery, weather data