This Project is about Wildfire Detection

```
# import required library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.feature_selection import RFE
```

Step 1: Data Overview

```
# Load your dataset
df = pd.read_csv('/content/synthetic_wildfire_data.csv')  # Adjust path if needed
```

```
# Basic Info
print("Shape:", df.shape)
```

```
Shape: (7999, 17)
```

```
print("Columns:", df.columns.tolist())
```

```
Columns: ['latitude', 'longitude', 'timestamp', 'ir_band_1', 'ir_band_2', 'ir_band_3', 'temperature', 'vegetation_index', 'wind_spee
```

```
print("Data Types:\n", df.dtypes)
```

```
Data Types:
 latitude             float64
longitude            float64
timestamp             object
ir_band_1            float64
ir_band_2            float64
ir_band_3            float64
temperature          float64
vegetation_index     float64
wind_speed           float64
wind_direction       float64
humidity             float64
elevation            float64
slope                float64
land_use              object
distance_to_urban    float64
cloud_cover          float64
fire_detected          int64
dtype: object
```

```
print("Basic Statistics:", df.describe(include='all'))
```

```
Basic Statistics:            latitude    longitude         timestamp    ir_band_1    ir_band_2  \
count   7999.000000  7999.000000              7999  7999.000000  7999.000000
unique          NaN          NaN              7937          NaN          NaN
top             NaN          NaN  28-03-2022 23:27          NaN          NaN
freq            NaN          NaN                 2          NaN          NaN
mean      -0.365650    -1.288231               NaN    36.510214    64.605959
std       52.231873   103.781112               NaN    32.126231    46.106082
min      -89.990491  -179.982675               NaN     0.014488     0.015774
25%      -46.247262   -91.846694               NaN    15.065296    28.733460
50%       -0.969044    -2.490751               NaN    29.669511    58.041002
75%       45.565455    88.030582               NaN    44.304869    88.400523
max       89.977297   179.963886               NaN   149.991198   199.753763

          ir_band_3  temperature  vegetation_index   wind_speed  \
count   7999.000000  7999.000000       7999.000000  7999.000000
unique          NaN          NaN               NaN          NaN
top             NaN          NaN               NaN          NaN
freq            NaN          NaN               NaN          NaN
mean      97.995506   577.111069          0.000814     9.990877
std       68.750806   245.346532          0.576340     5.784680
min        0.021865   200.084317         -0.999768     0.000111
25%       44.800171   373.888782         -0.496420     4.957317
50%       89.136274   555.339394         -0.007965    10.037231
75%      132.498607   732.415748          0.500914    14.991883
max      299.929850  1199.959168          0.999503    19.995045
```

```
        wind_direction     humidity    elevation        slope land_use  \
count      7999.000000  7999.000000  7999.000000  7999.000000     7999
unique             NaN          NaN          NaN          NaN        5
top                NaN          NaN          NaN          NaN    urban
freq               NaN          NaN          NaN          NaN     1636
mean        178.714646    49.902679  1978.391861    45.032205      NaN
std         103.635932    28.687563  1148.986980    26.106159      NaN
min           0.100089     0.000843     0.315015     0.008394      NaN
25%          88.138358    25.358771   981.859052    22.463321      NaN
50%         180.159990    49.762007  1967.373879    45.460505      NaN
75%         267.436572    74.898952  2970.752133    67.519698      NaN
max         359.972938    99.997597  3999.297675    89.990151      NaN

        distance_to_urban  cloud_cover  fire_detected
count         7999.000000  7999.000000    7999.000000
unique                NaN          NaN            NaN
top                   NaN          NaN            NaN
freq                  NaN          NaN            NaN
mean         25118.989026    49.809635       0.152269
std          14369.044974    28.556395       0.359304
min              6.441237     0.040154       0.000000
25%          12710.570250    25.376844       0.000000
50%          25076.488520    49.700527       0.000000
75%          37498.555155    74.433834       0.000000
max          49988.104330    99.983132       1.000000
```

```
# check null value
print(" Null Values:", df.isnull().sum())
```

```
 Null Values: latitude             0
longitude            0
timestamp            0
ir_band_1            0
ir_band_2            0
ir_band_3            0
temperature          0
vegetation_index     0
wind_speed           0
wind_direction       0
humidity             0
elevation            0
slope                0
land_use             0
distance_to_urban    0
cloud_cover          0
fire_detected        0
dtype: int64
```

Step 2: Data Preprocessing

Data Cleaning

```
# Drop timestamp as it's not useful for prediction
df.drop(columns=['timestamp'], inplace=True)

# Convert land_use (categorical) to numerical using category encoding
df['land_use'] = df['land_use'].astype('category').cat.codes
```

Outlier Treatment

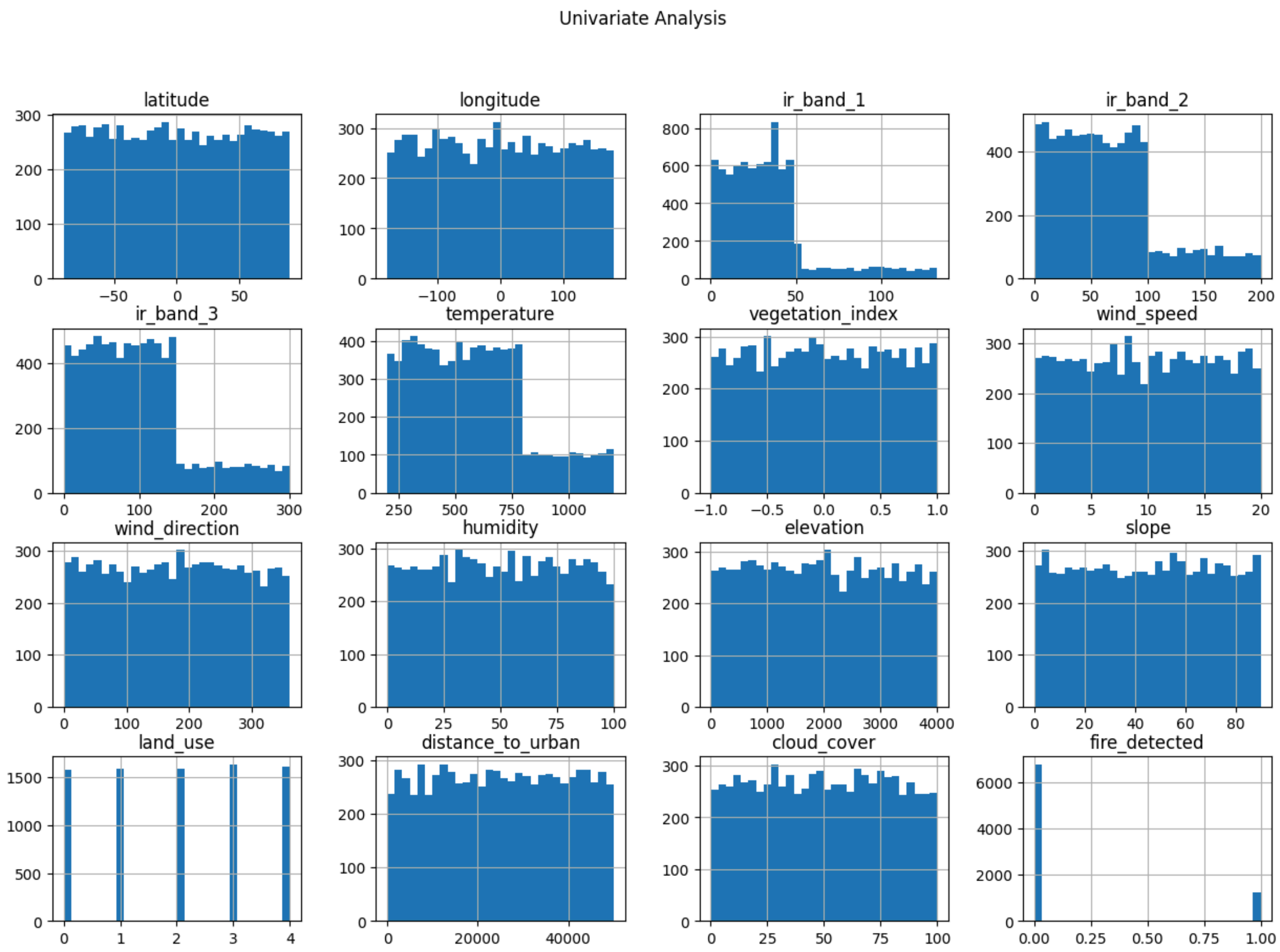
```
# Replace extreme values with column mean
for col in df.select_dtypes(include='number').columns:
    mean = df[col].mean()
    std = df[col].std()
    upper = mean + 3 * std
    lower = mean - 3 * std
    df[col] = np.where((df[col] > upper) | (df[col] < lower), mean, df[col])
```

Step 3: Exploratory Data Analysis (EDA)

Univariate Analysis

```
df.hist(bins=30, figsize=(15, 10))
plt.suptitle("Univariate Analysis")
```

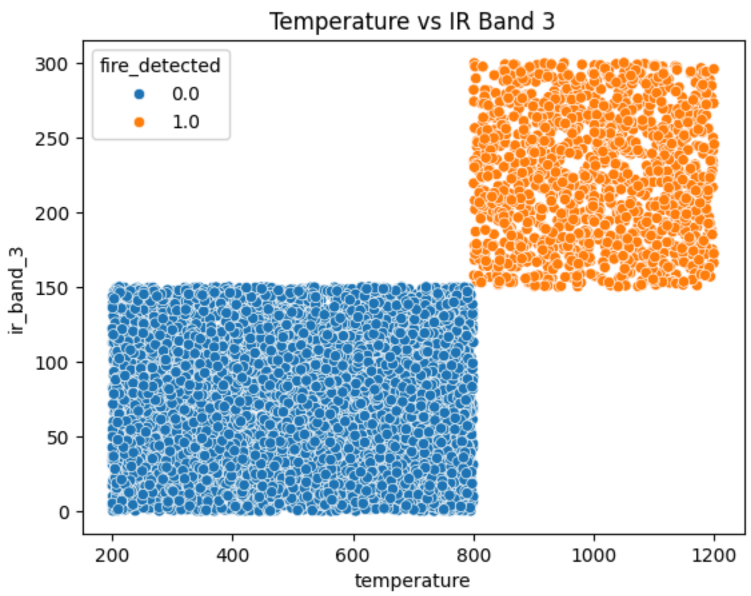
```
plt.show()
```

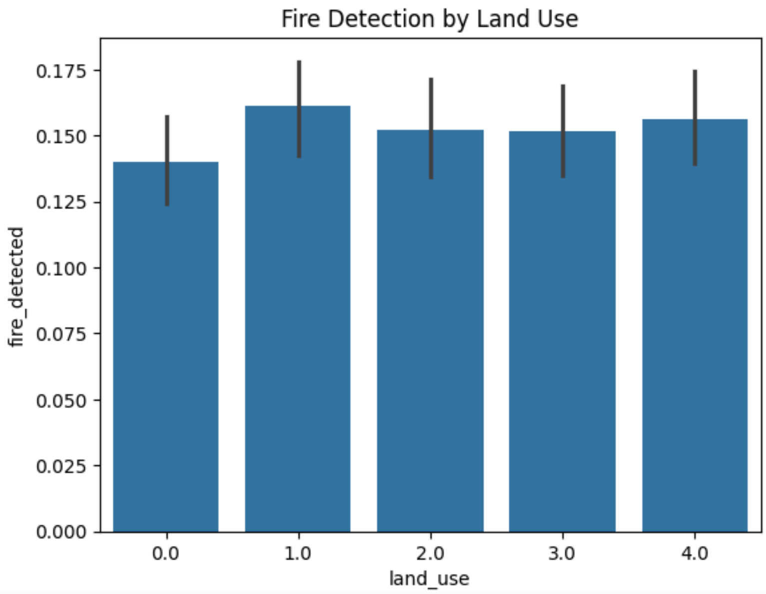


Bivariate Analysis

```
# Scatter for numerical-numerical
sns.scatterplot(data=df, x='temperature', y='ir_band_3', hue='fire_detected')
plt.title("Temperature vs IR Band 3")
plt.show()

# Bar plot for categorical-numerical
sns.barplot(data=df, x='land_use', y='fire_detected')
plt.title("Fire Detection by Land Use")
plt.show()
```

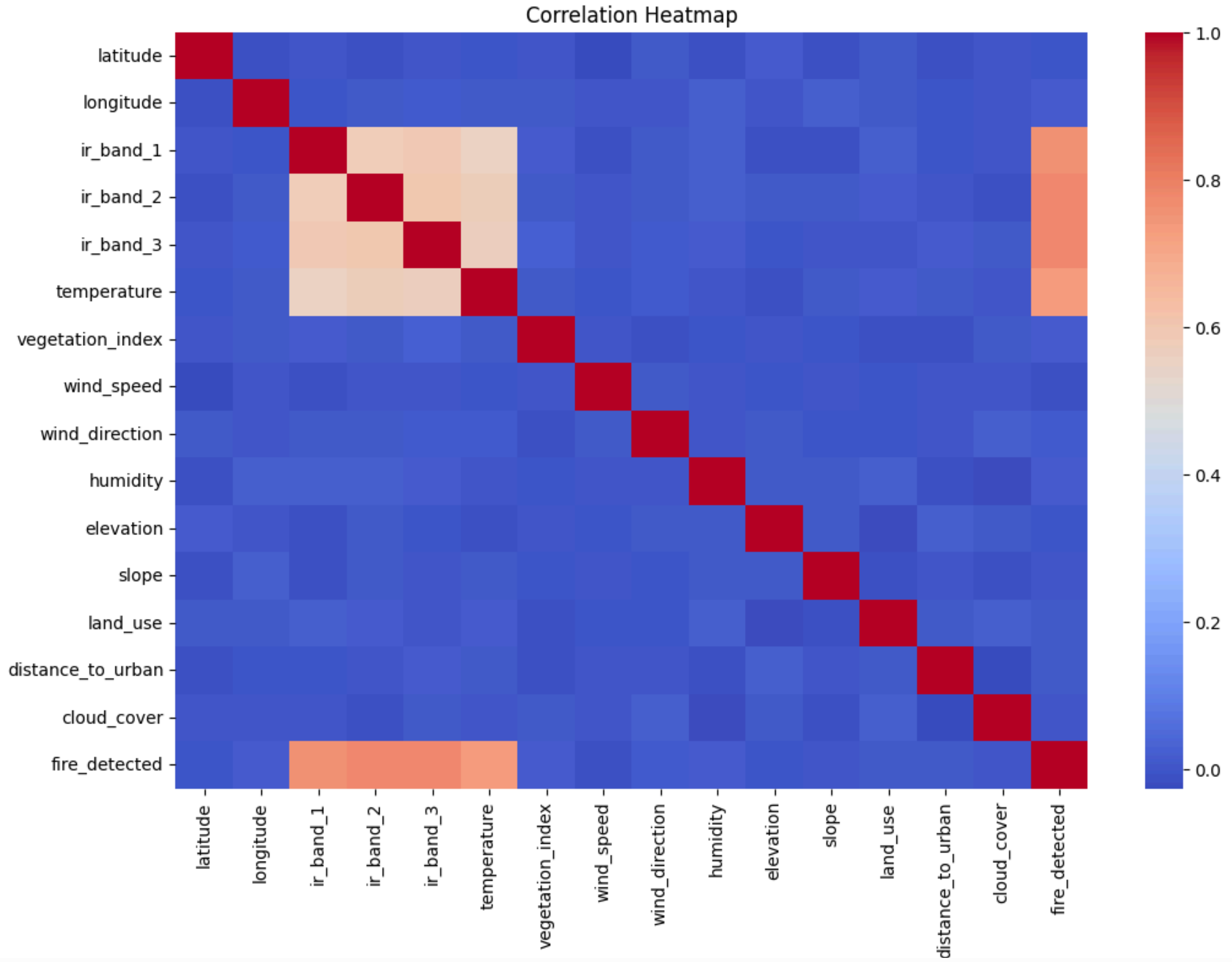




Correlation Matrix

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), cmap='coolwarm')  # removed annot=True
plt.title("Correlation Heatmap")
plt.show()
```



Step 4: Data Preparation for ML

Splitting Features and Target

```
X = df.drop('fire_detected', axis=1)
y = df['fire_detected']
```

Train-Test Split

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Feature Scaling

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Step 5: Base Model Training

```
model = RandomForestClassifier(random_state=42)
model.fit(X_train_scaled, y_train)

y_pred = model.predict(X_test_scaled)

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[1336    0]
 [   0  264]]
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1336
         1.0       1.00      1.00      1.00       264

    accuracy                           1.00      1600
   macro avg       1.00      1.00      1.00      1600
weighted avg       1.00      1.00      1.00      1600
```

Start coding or generate with AI.

step-6 perform hyper perameter tunning using cross validation

```
from sklearn.model_selection import GridSearchCV

param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'max_features': ['sqrt', 'log2']
}

grid = GridSearchCV(RandomForestClassifier(random_state=42), param_grid, cv=5, scoring='f1')
grid.fit(X_train_scaled, y_train)

print("Best Parameters:", grid.best_params_)
best_model = grid.best_estimator_
```

```
Best Parameters: {'max_depth': None, 'max_features': 'sqrt', 'n_estimators': 100}
```

Step 7: Feature Selection using RFE

```
selector = RFE(RandomForestClassifier(), n_features_to_select=8)
selector.fit(X_train_scaled, y_train)

selected_features = X.columns[selector.support_]
print("Selected Features:\n", selected_features)
```

```
Selected Features:
 Index(['latitude', 'ir_band_1', 'ir_band_2', 'ir_band_3', 'temperature',
       'wind_speed', 'elevation', 'slope'],
      dtype='object')
```

```
# Example: replace values with user input (must match original column order)
new_data = [[
    12.5,          # latitude
    77.5,          # longitude
    35.5,          # ir_band_1
    62.3,          # ir_band_2
    90.1,          # ir_band_3
    550.2,         # temperature
    0.12,          # vegetation_index
    10.0,          # wind_speed
    180.0,         # wind_direction
    45.0,          # humidity
    1000.0,        # elevation
    20.0,          # slope
    1,             # land_use (use encoded number)
    25000.0,       # distance_to_urban
    50.0           # cloud_cover
]]
```

```
# Scale the new input
new_data_scaled = scaler.transform(new_data)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but Star
  warnings.warn(
```

```
# Predict
prediction = model.predict(new_data_scaled)
probability = model.predict_proba(new_data_scaled)

# Output
print("Fire Detected (1 = Yes, 0 = No):", prediction[0])
print("Probability [No Fire, Fire]:", probability[0])
```

```
Fire Detected (1 = Yes, 0 = No): 0.0
Probability [No Fire, Fire]: [1. 0.]
```