INFOSYS SPRINGBOARD VIRTUAL INTERNSHIP

FWI PREDICTOR

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MILESTONE 1

Dataset Source : Kaggle

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import
LabelEncoder, StandardScaler
from sklearn.model_selection import
train_test_split, GridSearchCV
from sklearn.linear_model import
LinearRegression, Ridge, Lasso
from sklearn.metrics import
mean_absolute_error, mean_squared_error,
r2_score
import pickle
```

This code imports all the required Python libraries for data handling, visualization, preprocessing, model training, evaluation, and saving the trained model.
It prepares the environment for performing EDA, feature scaling, regression modeling (Ridge), performance evaluation, and model serialization.

```python
df = pd.read_csv("FWI Dataset.csv")
if 'Region' in df.columns:
df['Region'] =
df['Region'].astype('category').cat.codes
```

Dataset is loaded using pandas.
The following information is displayed:
Entire dataset
Dataset structure (df.info())
Statistical summary (df.describe())
First & last 5 rows
Converts the Region column from strings to numerical category codes. Useful for machine learning algorithms that accept numeric inputs.

```python
numeric_df =
df.select_dtypes(include=['int64',
'float64'])
```

Extracts only numerical features for later analysis.

```python
print(df.shape)
print(df.columns)
```

To ensure the dataset structure is correct.

```
df.isnull().sum()
df[df.isnull().any(axis=1)]
df.columns = df.columns.str.strip()
```

Identifies missing values in each column.
Displays rows containing incomplete data.
Removes extra spaces in column names (common in raw CSV files).

```
for col in df.columns:
if df[col].dtype == 'object':
df[col] = df[col].astype(str).str.strip()
```

Removes unnecessary spaces in string values.
Ensures uniform data format.

```
for col in df.columns:
if df[col].dtype == 'object':
df[col] = df[col].str.replace(" ", " ")
if df[col].str.contains(" ").any():
df[col] = df[col].str.split(" ").str[0]
```

This ensures numeric columns convert cleanly.

```
numeric_cols =
['Temperature','RH','Ws','Rain','FFMC','D
MC','DC','ISI','BUI','FWI']
for col in numeric_cols:
```

```
df[col] = pd.to_numeric(df[col],
errors='coerce')
```

Converts corrupted strings into numeric format.
Non-convertible values become Nan.

```
df['Region'] =
df['Region'].fillna(df['Region'].mode()[0
])
df['Classes'] =
df['Classes'].fillna(df['Classes'].mode()
[0])
```

Uses mode (most frequent value) for categorical features.
Prevents ML models from failing due to null values.

<u>Label Encoding Categorical Columns</u>

```
le_region = LabelEncoder()
df['Region_encoded'] =
le_region.fit_transform(df['Region'])
le_class = LabelEncoder()
df['Classes_encoded'] =
le_class.fit_transform(df['Classes'])
```

Convert string labels to numeric classes for ML model training.

Encoding All Remaining Categorical Columns

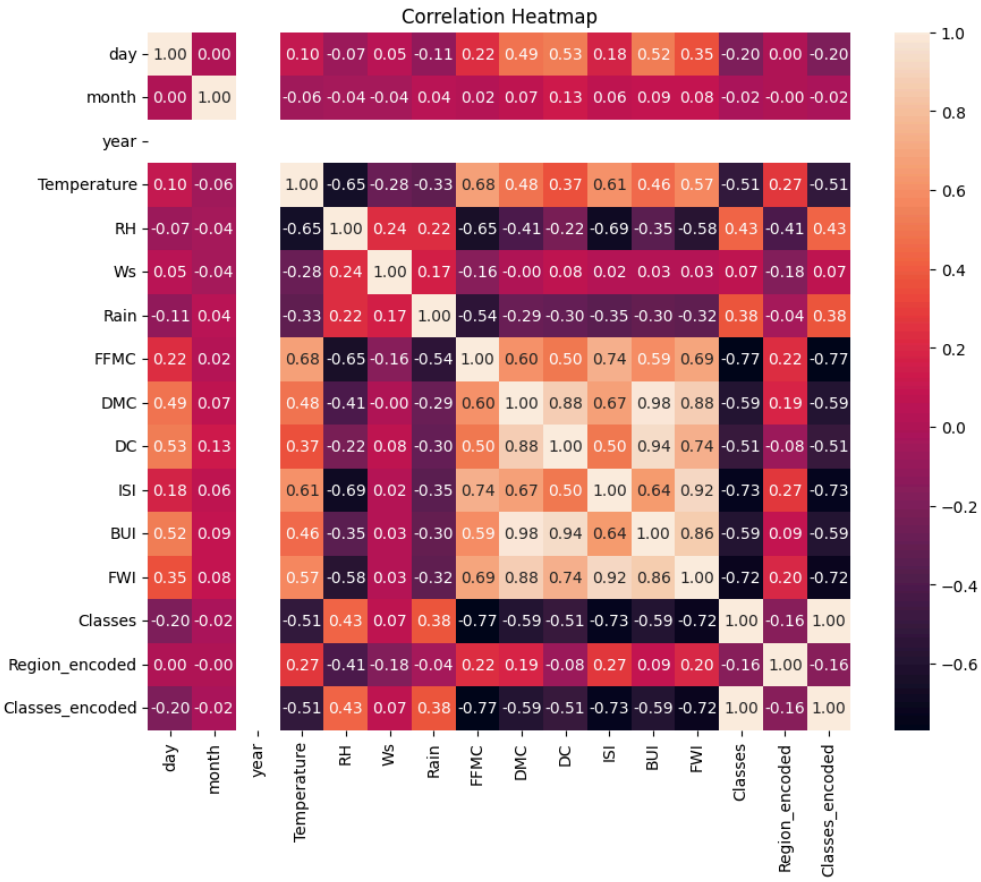
```
df_encoded = df.copy()
label_encoders = {}
for col in df_encoded.columns:
if df_encoded[col].dtype == 'object':
le = LabelEncoder()
df_encoded[col] =
le.fit_transform(df_encoded[col].astype(s
tr))
label_encoders[col] = le
```

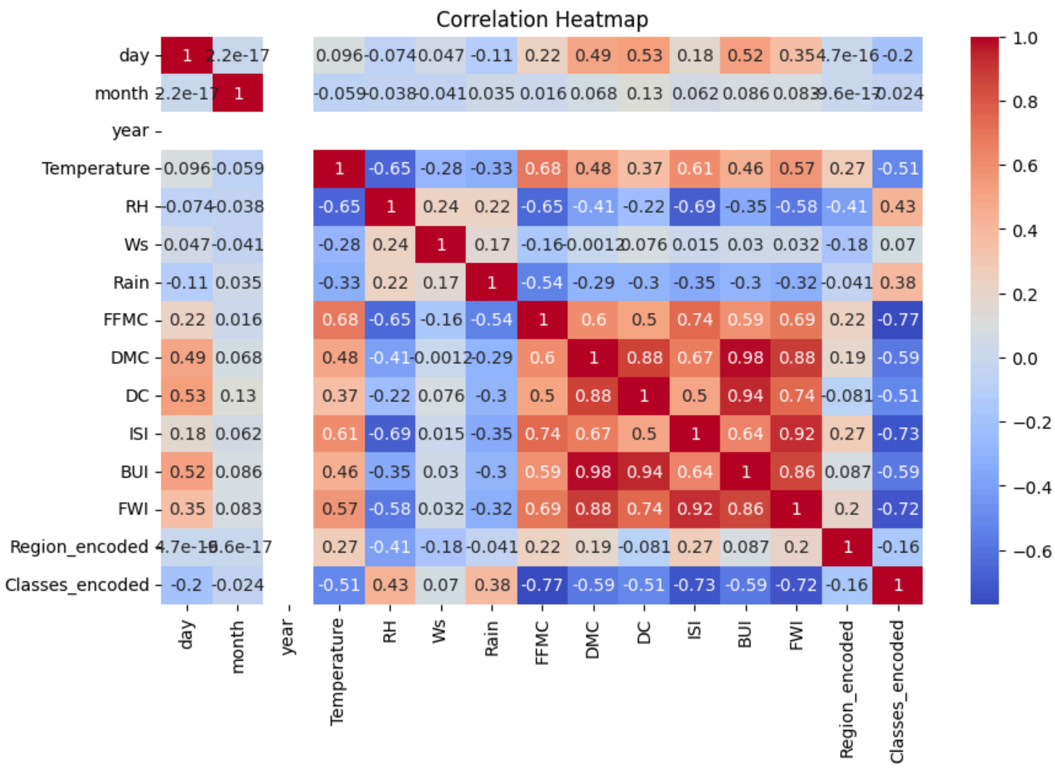
This ensures all non-numeric features are usable in correlation analysis.

Correlation Heatmap

```
plt.figure(figsize=(10,8))
sns.heatmap(numeric_df.corr(),
annot=True)
plt.show()
```

Used to understand:
Feature relationships
Which variables strongly influence FWI
Multicollinearity issues

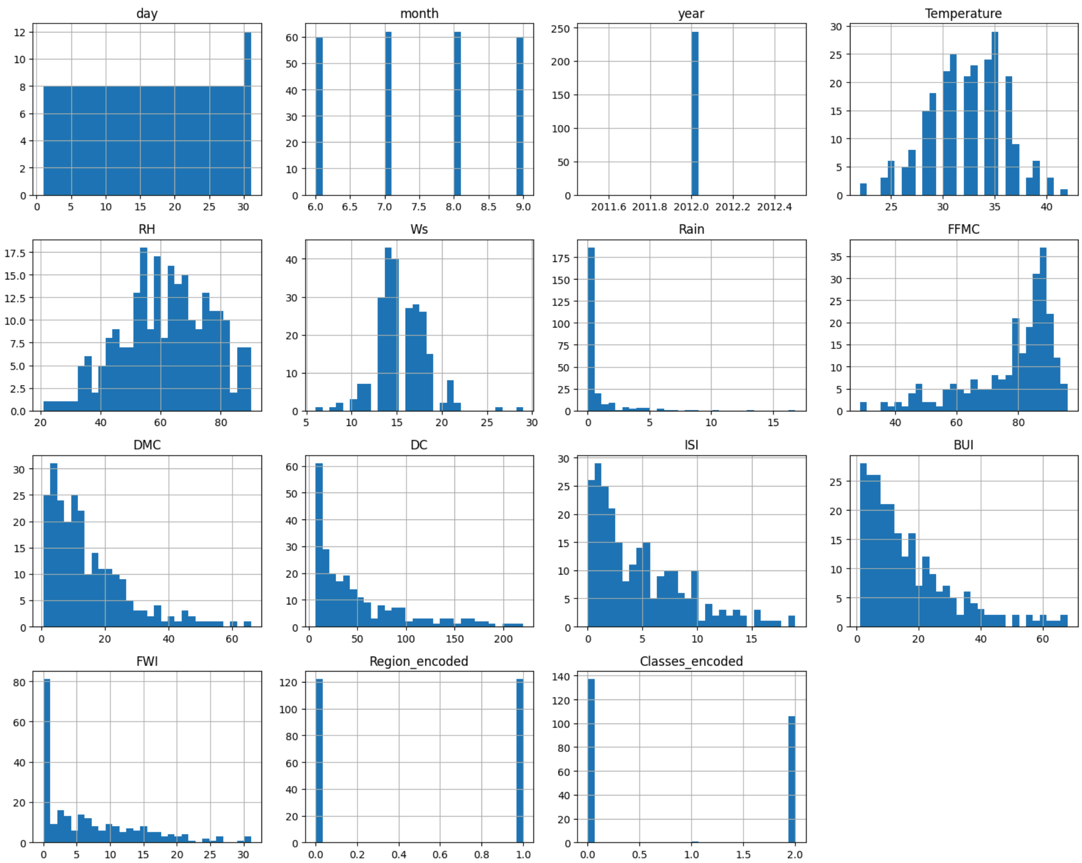

Correlation Heatmap
day
month
year
Temperature
RH
Ws
Rain
FFMC
DMC
DC
ISI
BUI
FWI
Classes
Region_encoded
Classes_encoded
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6


Correlation Heatmap
day
month
year
Temperature
RH
Ws
Rain
FFMC
DMC
DC
ISI
BUI
FWI
Region_encoded
Classes_encoded
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

Histogram Plots

```
numeric_df.hist(figsize=(15, 12),
bins=30)
plt.show()
```

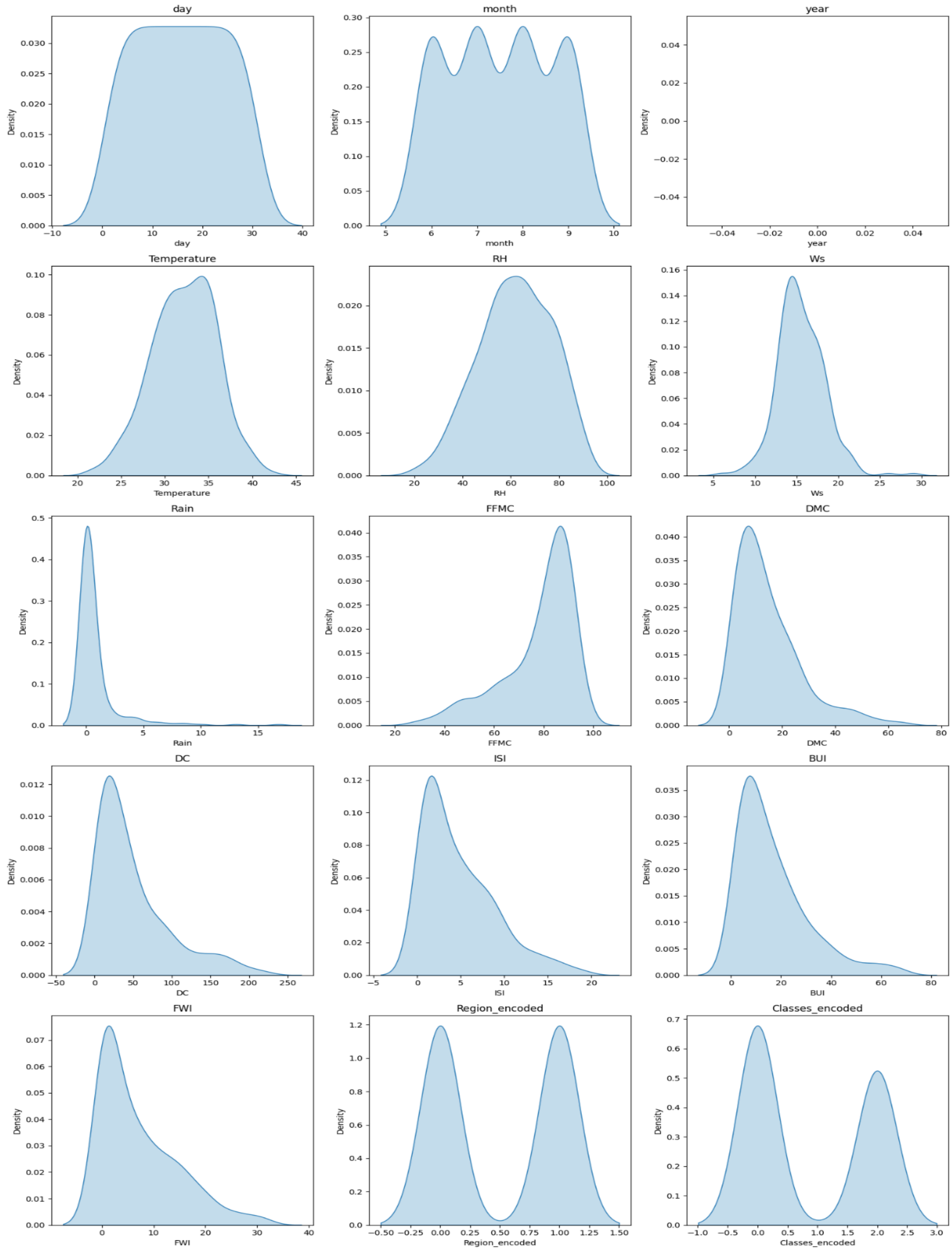
Shows distribution of each numeric feature:
Normal , Skewed, Outliers



Density (KDE) Plots

```
sns.kdeplot(numeric_df[col], fill=True)
```

These help understand:
Probability distribution, Spread of data, Detecting skewness

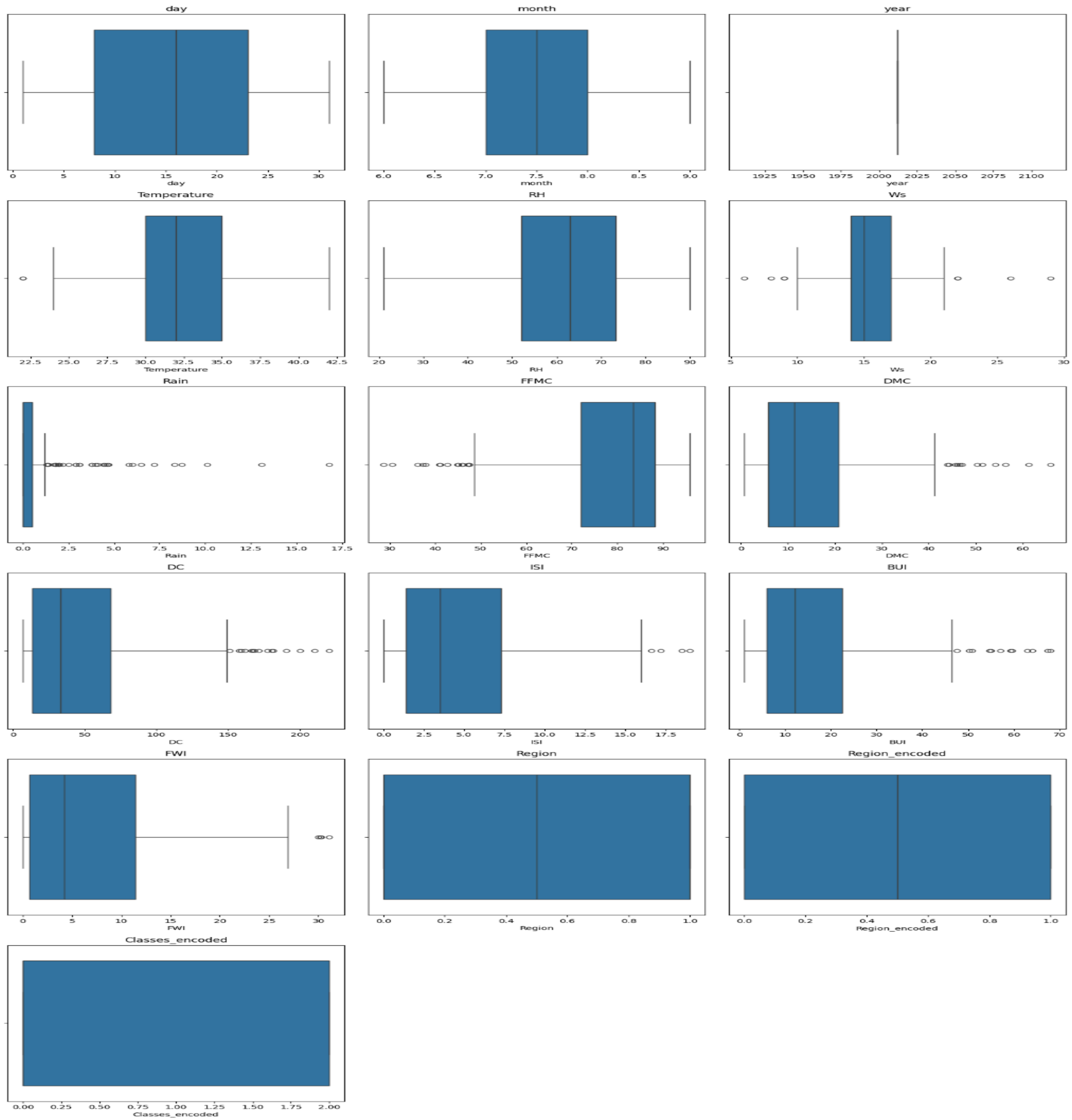


<u>Boxplots for Outlier Detection</u>

```
sns.boxplot(x=df[col])
```

Used to visually identify:

Outliers, Data spread, Extreme values



Outlier Treatment using IQR

```
Q1 = numeric_df[col].quantile(0.25)
Q3 = numeric_df[col].quantile(0.75)
IQR = Q3 - Q1
df[col] = df[col].clip(lower, upper)
```

Purpose:

Removes extreme values

Prevents model distortion

Makes distributions more stable

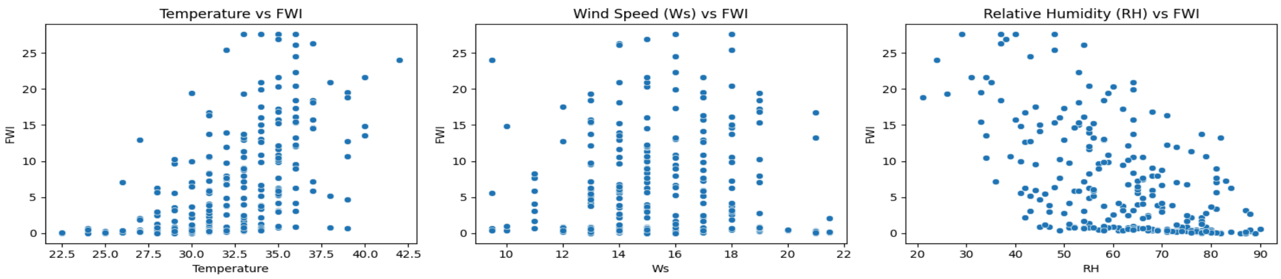
Scatter Plots

```
sns.scatterplot(x=df['Temperature'],
y=df['FWI'])
sns.scatterplot(x=df['Ws'], y=df['FWI'])
sns.scatterplot(x=df['RH'], y=df['FWI'])
```

Shows:

How individual features impact FWI

Linear / non-linear trends and Data clusters



To save the cleaned dataset.

```
df.to_csv("FWI Cleaned.csv", index=False)
```

Milestone 1 Outcome Summary

- Fire Weather Index (FWI) dataset successfully loaded and inspected
- Dataset structure, data types, and summary statistics analyzed
- Missing values identified and handled using appropriate imputation techniques
- Categorical variables encoded for machine learning compatibility
- Data type casting applied to ensure numerical consistency
- Outliers detected using boxplots and distribution analysis
- Exploratory Data Analysis (EDA) performed using histograms, KDE plots, and scatterplots
- Correlation analysis conducted to understand feature relationships
- Cleaned and processed dataset saved as FWI Cleaned.csv for model development

MILESTONE 2

```
df = pd.read_csv("FWI Cleaned.csv")
```

The cleaned Fire Weather Index dataset prepared in Milestone 1 was loaded for model development.

```
df = df.dropna(subset=["FWI"])
```

Rows with missing target values were removed to avoid errors during model training.

```
features =
["Temperature","RH","Ws","Rain","FFMC","D
MC","DC","ISI","BUI"]
X = df[features]
y = df["FWI"]
```

Relevant meteorological and fire index features were selected based on correlation and domain relevance, with FWI chosen as the target variable.

```
train_test_split(X, y, test_size=0.2,
random_state=42)
```

The dataset was split into 80% training and 20% testing data to ensure model generalization.

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

StandardScaler was applied to normalize feature values and ensure uniform scale across all input variables.

```
pickle.dump(scaler, f)
```

The trained scaler was saved as `scaler.pkl` to maintain consistency during model deployment.

```
LinearRegression(), Ridge(), Lasso()
```

Linear, Ridge, and Lasso regression models were trained to compare performance and select the best model.

```
MAE, RMSE, R2 Score
```

Model performance was evaluated using MAE, RMSE, and R^2 score to measure prediction accuracy and variance explanation.

```
results_df.sort_values(by="R2 Score")
```

A comparison table was created to objectively identify the best-performing regression model.

```
GridSearchCV(estimator=Ridge(),
param_grid={"alpha":[0.01,0.1,1,10,100]})
```

GridSearchCV was used to tune the alpha parameter to balance bias and variance.

```
best_ridge.predict(X_test_scaled)
```

The optimized Ridge model was evaluated on test data to confirm its performance.

```
pickle.dump(best_ridge, f)
```

The final trained Ridge Regression model was saved as `ridge.pkl` for deployment.

"Ridge Regression was selected..."

Ridge Regression was chosen due to its ability to handle multicollinearity among correlated weather features and its superior cross-validation performance.

Milestone 2 Outcome Summary

- Feature selection completed using correlation and domain knowledge
- Data normalized using StandardScaler
- Train–test split applied for generalization
- Multiple regression models evaluated
- Ridge Regression selected as the best model
- scaler.pkl and ridge.pkl successfully saved