Internship report

On

FOREST FIRE PREDICTION

In partial fulfilment of the requirement for the award of

the degree of

Bachelor of Engineering

in

Computer Science and Engineering

By

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This report is submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Engineering in Computer Science and Engineering.

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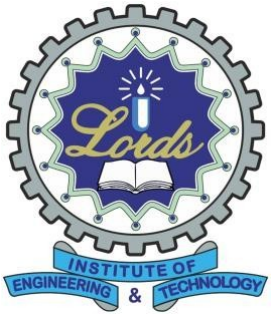

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I**, Reda Kaleem,** bearing Hall Ticket No's. **160922733119,** hereby declare that the Internship entitled **"Forest Fire Prediction**" under the guidance of Dr. Ruhiat Sultana **(Associate Professor)** Department of Computer Science Engineering, **Lords Institute of Engineering & Technology, Hyderabad** is submitted in partial fulfillment of the requirements for the award of the degree of **Bachelor of Engineering** in Computer Science and Engineering.

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ACKNOWLEDGMENT

I am very pleased to present this report of my internship work. This period of our student life has been truly rewarding a number of people were of immense help to us during the course of our research and the preparation of our thesis.

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ABSTRACT

Fire, a natural disaster with devastating consequences, can arise from various causes, including natural events, human activity, or technical failures. In response to the growing need for sustainable and innovative firefighting methods, sound wave fire-extinguishing systems have gained attention for their potential to suppress flames effectively without relying on traditional chemical-based methods. This study focuses on the development and evaluation of a sound wave fire-extinguishing system through extensive testing. A dataset was created from 17,442 experimental tests, capturing key parameters related to flame extinction and non-extinction states.

To analyze and classify the data, five advanced machine learning methods were employed: artificial neural networks (ANN), k-nearest neighbor (KNN), random forest (RF), stacking (an ensemble method combining ANN, KNN, and RF), and deep neural networks (DNN). The classification tasks aimed to determine whether flames could be extinguished under specific conditions. A 10-fold cross-validation approach was used to ensure the reliability and robustness of the results.

The study revealed notable findings, with the stacking method demonstrating the potential of ensemble learning, while the Support Vector Classifier (SVC) achieved the highest classification accuracy of 96.58%. The performance of each method was evaluated through comprehensive metrics, including accuracy, precision, recall, and F1-score, providing a detailed comparison of their strengths and limitations. These results emphasize the efficacy of machine learning in supporting decision-making processes.

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CHAPTER-1
INTRODUCTION

Fire is a chemical reaction that occurs when heat, fuel, and oxygen combine in a process known as combustion. This oxidation reaction releases heat, gases, and smoke, which can cause significant harm to humans and the environment. Fires, if not controlled promptly, can escalate and lead to devastating consequences, including loss of life, destruction of property, and environmental degradation. Early intervention is critical to extinguishing fires effectively. However, the type of fire-extinguishing agents used can vary depending on the scale of the fire and the nature of the fuel involved.

Traditional fire-extinguishing techniques often rely on chemical substances, which, while effective, may leave behind chemical waste that is hazardous to both human health and the environment. These methods can also result in additional social and economic damages, such as the cost of cleanup, the disruption of daily life, and long-term environmental harm. To mitigate these negative impacts, researchers have increasingly focused on innovative and sustainable approaches to fire suppression. Among these, renewable energy-based methods have gained attention, with sound wave technology emerging as a promising solution.

Sound wave fire-extinguishing systems utilize the physical properties of sound to disrupt the combustion process, offering a potentially eco-friendly and efficient alternative. This approach aims to minimize the reliance on chemical agents, reducing the associated risks and costs. Research in this area continues to explore the viability and optimization of sound wave technology as a reliable fire suppression method.

Fire is a chemical reaction that occurs when heat, fuel, and oxygen combine in a process known as combustion. This oxidation reaction releases energy in the form of heat, along with gases and smoke, which can pose significant risks to human life, property, and the environment. Unchecked fires can escalate rapidly, leading to catastrophic consequences such as loss of life, destruction of infrastructure, and long-term environmental damage. The social and economic impact of fires is equally profound, often resulting in displacement, disruption of services, and extensive

recovery costs. Consequently, early intervention and effective suppression techniques are critical to preventing fires from spreading and mitigating their potential harm.

The methods used to extinguish fires vary based on their scale, the type of fuel involved, and the surrounding environment. Traditional fire suppression techniques often rely on chemical extinguishing agents, which, while effective, may leave behind chemical residues that can harm human health and the environment. These chemicals can also lead to secondary issues such as soil contamination, water pollution, and high cleanup costs. Additionally, the long-term environmental effects of these agents, including their contribution to greenhouse gas emissions and ecological imbalances, underscore the need for more sustainable fire suppression solutions.

In response to these challenges, researchers and engineers are exploring innovative and eco-friendly approaches to fire management. Among these, renewable energy-based technologies have shown great promise, offering solutions that minimize reliance on harmful chemicals and reduce the environmental footprint of firefighting efforts. One particularly intriguing advancement in this field is the use of sound wave technology for fire suppression. Sound wave fire-extinguishing systems utilize the physical properties of sound, specifically its ability to disrupt the combustion process by altering the pressure and energy dynamics in the flame. This method provides an efficient, reusable, and environmentally benign alternative to traditional extinguishing agents.

The development of sound wave-based fire suppression systems is part of a broader trend toward integrating advanced technologies and principles of sustainability into fire management. Ongoing research focuses on optimizing the frequency, amplitude, and deployment strategies of sound waves to maximize their efficacy. These systems have the potential to transform firefighting practices by reducing the reliance on chemical agents, minimizing health risks, lowering cleanup costs, and preserving the environment.

In parallel, advancements in machine learning and artificial intelligence are playing a crucial role in refining these technologies. Machine learning, particularly through the use of neural networks (NN), offers powerful tools for optimizing sound wave fire-extinguishing systems. However, the success of these applications depends heavily on the structure and design of the neural network models. Poorly structured models can lead to underfitting, where the system fails to learn the underlying patterns of the data, or overfitting, where the model captures noise rather than meaningful patterns, resulting in poor generalization to new scenarios.

The integration of advanced neural network models into sound wave fire-extinguishing systems exemplifies the potential of interdisciplinary innovation in addressing global challenges. By combining principles of sustainability, cutting-edge technology, and intelligent system design, researchers aim to create solutions that are not only effective in fire suppression but also aligned with the broader goals of environmental stewardship and social responsibility

CHAPTER-2
LITERATURE SURVEY

The Use of Prediction of Forest Fires

Forest fire detection technologies have been implemented in various regions around the world, depending on the severity of the wildfire threat, geographic conditions, and available resources.

1) **"Wildfire Detection and Monitoring using Remote Sensing and Machine Learning: A Case Study of California" - Kumar et al. (2020)**

This paper explores how **remote sensing** and **machine learning** techniques are employed to detect and monitor wildfires in California. The study focuses on **MODIS** and **VIIRS** satellite data combined with **convolutional neural networks (CNNs)** for automatic fire detection. The paper highlights the **FireWatch** system used in California, which integrates **satellite data**, **UAVs**, and **real-time sensor data** to predict wildfire hotspots and improve early detection.

2) "Monitoring Bushfires in Australia Using Satellite and UAV Technologies" - Chan et al. (2020)

The study discusses the integration of **satellite-based fire detection**, such as **MODIS**, with **UAVs** equipped with **thermal infrared sensors**. It also focuses on **machine learning models** for analyzing satellite images to detect fire outbreaks in remote regions like the **Outback**. The paper specifically evaluates the effectiveness of **firewatch camera networks** and **drones** in providing real-time data during the devastating 2019–2020 bushfire season.

3) "Fire Detection in the Amazon: A Satellite-based Approach using MODIS and VIIRS", Brazil (Amazon Rainforest) - Silva et al. (2021)

This research paper focuses on **remote sensing technologies** and their application in detecting and monitoring wildfires in the **Amazon rainforest**. By analyzing **MODIS** and **VIIRS** satellite data, the authors propose an improved method to detect **smoke plumes** and **fire hotspots**. The study highlights how satellite imagery, coupled with **machine learning algorithms**, can offer predictive insights into fire risk, providing early warning for fire-prone regions.

The paper underscores the importance of using **satellite imagery** and **machine learning models** to detect fires in dense forest areas, where traditional fire monitoring methods are not feasible.

4) "A Multi-Source Approach for Early Detection of Forest Fires in Greece" - Papadopoulos et al. (2018)

The research discusses an integrated approach for early forest fire detection in Greece, which combines **satellite-based monitoring**, **ground-based smoke sensors**, and **UAVs**. The system is designed to detect fires early and predict their spread, using **VIIRS** satellite data, **thermal infrared imagery**, and **fire behavior models**.

5) "Fire Risk Mapping and Detection in Catalonia Using Satellite and Sensor Data" - García et al. (2019)

The research presents an integrated system for **fire risk mapping** and **fire detection** in Catalonia, Spain, using **satellite imagery**, **ground sensors**, and **weather data**. The system incorporates **real-time monitoring** of fire behavior and uses **machine learning** to assess fire risks and predict fire outbreaks in different regions of Catalonia.

6) "Wildfire Detection in Portugal Using Remote Sensing Data"

- Almeida et al. (2020)

This study focuses on the application of **remote sensing** technologies, particularly **Sentinel-1** and **Sentinel-2** satellite data, to detect and monitor wildfires in **Portugal**. The study outlines how these satellite systems are used to **map fire progression**, assess **burned area estimation**, and provide near-real-time data for fire management teams.

7) "Integrating Satellite and Sensor Data for Forest Fire Detection in South Africa"- van der Merwe et al. (2021)

This paper discusses the use of **satellite imagery** from **MODIS** and **VIIRS** and **sensor networks** in detecting forest fires in the **Western Cape** of South Africa. The authors propose an integrated system that combines satellite data with real-time **ground sensors** and **fire surveillance cameras** for comprehensive fire detection and monitoring.

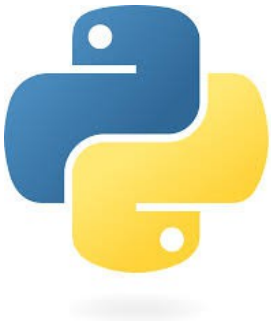
The study underscores the need for **real-time data collection** in a region prone to high fire risk, using a combination of **remote sensing** and **ground-level sensors** to improve fire management.

CHAPTER -3

TOOLS USED

In the development of a machine learning model for detecting credit card fraud, a wide range of tools and technologies are employed. These tools help to collect, process, analyze, and model transaction data, ultimately supporting the identification of fraudulent activities. Below, we will describe in detail the programming environments, machine learning libraries, data preprocessing techniques, evaluation methods, and deployment tools used in the project.

1. Programming Language: Python



Python is a versatile programming language that has become the go-to language for machine learning and data science due to its simplicity, readability, and the abundance of libraries available for various tasks. Python allows easy integration of data processing, statistical analysis, and machine learning, making it ideal for building fraud detection systems.

Key Benefits of Python:

- **Easy to Learn**: Python's syntax is clean and simple, making it accessible to beginners.
- **Large Ecosystem**: Python has a vast selection of libraries and tools for handling data (Pandas, NumPy), machine learning (Scikit-learn, TensorFlow), and visualizations (Matplotlib, Seaborn).
- **Community Support**: It has a large community of developers who contribute to improving the libraries and offer valuable resources and tutorials.

2. Data Processing Libraries

a. **Pandas**

Pandas is a powerful Python library used for data manipulation and analysis. It provides two primary data structures: **Series** (1D) and **DataFrame** (2D, tabular data). In fraud detection, Pandas is used to load, clean, and manipulate data before feeding it into machine learning models.

Key Features:

- **Handling Missing Data**: It helps to handle missing or incomplete data by filling or dropping it.
    - Example: You might replace missing transaction amounts with the average transaction amount.
- **Data Transformation**: You can filter rows, change data types, or group data by specific categories.
    - Example: If you want to group all transactions by User_ID, Pandas makes it easy to apply group-based operations.
- **Merging Datasets**:Combine data from satellites, sensors, weather reports, and fire logs based on common identifiers like **location** or **timestamp**.
- **Clean Data**: Handle missing or inconsistent data from sensors or satellite images.
- **Analyze Trends**: Identify fire patterns through time-series analysis of temperature, humidity, and smoke data.

b. NumPy

NumPy is another essential Python library used for numerical computing. It is often used alongside Pandas to work with large datasets and perform operations that require arrays or matrices.

Key Features:

- **Multidimensional Arrays**: NumPy provides a high-performance array object for representing data, which makes it ideal for performing calculations.
    - Example: Instead of looping through large datasets, NumPy lets you perform element-wise calculations (like adding or multiplying entire columns at once).
- **Math Functions**: NumPy has a wide array of mathematical functions that are highly optimized, such as linear algebra, statistics, and more.
    - Example: You could compute the **mean** or **standard deviation** of transaction amounts across different users.

3. Machine Learning Libraries

a. **Scikit-learn**

Scikit-learn is one of the most popular libraries for machine learning in Python. It provides simple and efficient tools for data mining and data analysis, which is why it is used in most detection projects. Scikit-learn offers algorithms for classification, regression, clustering, and dimensionality reduction.

Key Features:

- **Classification**: Use algorithms like **Random Forests**, **Decision Trees**, and **Support Vector Machines (SVM)** to classify whether a region is at risk of a fire based on environmental features (e.g., temperature, humidity, wind speed).
- **Regression**: Predict continuous variables such as **fire intensity** or **spread** based on environmental data.
- **Model Evaluation**: Scikit-learn provides metrics like **accuracy**, **precision**, **recall**, and **F1 score** to assess the performance of fire detection models. This helps ensure reliable fire risk predictions.
- **Cross-Validation**: Prevent overfitting and ensure generalizability by using **k-fold cross-validation** to train and test models on different data subsets.
- **Clustering**: Identify regions with high risk of wildfires by clustering similar patterns in environmental data (e.g., temperature, vegetation moisture).

b. Imbalanced-learn

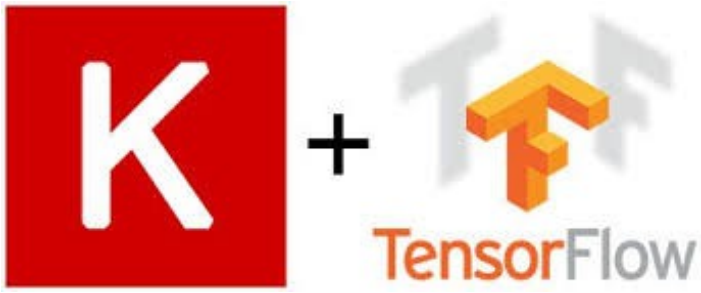
Imbalanced-learn is a Python library that provides tools for handling imbalanced datasets, particularly for classification problems. Imbalanced datasets are common in many real-world applications, including **forest fire detection**, where the number of fire occurrences (positive class) is often much smaller than the non-fire cases (negative class). In such scenarios, machine learning models may be biased towards predicting the majority class, which can lead to poor performance in detecting actual fire events.**Imbalanced-learn** is a library that helps to handle such imbalances in the dataset.

Key Features:

- **Over-sampling and Under-sampling**: **SMOTE (Synthetic Minority Over-sampling Technique)**: **SMOTE** generates synthetic examples for the minority class (fire events) by creating new, similar instances, rather than duplicating existing ones. This helps increase the number of fire incidents in the training dataset, ensuring the model learns to detect fires better.**ADASYN (Adaptive Synthetic Sampling)**: This is another oversampling technique that generates synthetic samples but focuses on harder-to-learn examples, i.e., those that are near decision boundaries.

4. Deep Learning Libraries

a. **TensorFlow & Keras**



When working with large and complex datasets, deep learning can offer powerful solutions. **TensorFlow** is an open-source library for building deep neural networks, while **Keras** (which is now part of TensorFlow) provides a high-level API for building neural networks more easily.

Key Features:

- **Neural Networks**: Keras allows you to create deep learning models such as **fully connected networks** or **convolutional neural networks** (CNNs).
- **GPU Acceleration**: TensorFlow can use **GPUs** to speed up training, making it suitable for large-scale forest fire detection systems.

5. Data Visualization Tools

Data visualization is crucial in understanding the data, exploring relationships, and presenting results. The following tools are used to visualize the data and the performance of machine learning models.

a. **Matplotlib**

Time-Series Visualization:

- **Line Charts**: These can be used to track the **temporal progression** of key environmental factors like **temperature**, **humidity**, and **wind speed** over time. For instance, line charts could show how temperature spikes correlate with fire occurrences.
    - Example: A line chart can illustrate how **daily temperature** correlates with fire risk across different months, helping identify critical periods of vulnerability.
- **Histograms**: Used to visualize the **distribution** of continuous features such as **temperature**, **rainfall**, or **fuel moisture content**. Histograms can help detect patterns that might indicate fire risk, such as **extremely high temperatures** or **low moisture levels**.
    - Example: A histogram of temperature distribution might show an unusually high concentration of temperatures above a threshold that has previously correlated with fire outbreaks.
- **Bar Plots**: These can be used to compare **fire occurrences** across different geographical areas or seasons. This helps in understanding the regions or time periods most prone to fire outbreaks.
    - Example: A bar plot can be created to compare the number of fire incidents in different forest regions or over different years, revealing patterns in fire behavior.

b. Seaborn

Seaborn is built on top of Matplotlib and is used to generate more sophisticated visualizations with less effort. It is particularly useful for exploring statistical relationships between variables.

Key Features:

Heatmaps for Correlation Analysis:

- **Heatmaps**: Seaborn is particularly useful for visualizing correlations between different environmental features. In fire detection, heatmaps can show how various factors such as **temperature**, **wind speed**, **humidity**, **vegetation type**, and **rainfall** are correlated with **fire outbreaks**.
    - Example: A heatmap can help visualize the correlation between **high temperatures** and **fire occurrences**, or how **wind speed** might correlate with the spread of fires. This can be invaluable in identifying the most influential features for fire prediction.
- **Visualizing Correlations**: If you're using machine learning models to predict fire risks, a heatmap can help you see which features have the strongest relationships with fire outbreaks, guiding feature selection for model improvement.

CHAPTER - 4

METHADOLOGY

The methodology for forest fire prediction using the Random Forest Regression algorithm involves collecting relevant data, preprocessing, feature selection, model training, evaluation, optimization, and forest fire prediction. This methodology can help authorities take timely preventive measures and reduce the risks associated with forest fires.

Data Gathering: Gathering pertinent information on variables including weather, topography, and vegetation characteristics that affect forest fires. Many sources, including weather stations, photos from remote sensing technology, and field surveys, can provide this data.

Data Preprocessing: Before the acquired data can be utilised to train the Random Forest Regression model, it must first be processed. The data must be cleaned in this step, missing values must be handled, and outliers must be eliminated. In order to assess the effectiveness of the model, the data is further divided into training and testing datasets.

Feature Selection: Feature selection is the process of determining which factors are most important in causing forest fires. Using statistical methods like feature importance ranking and correlation analysis is required for this phase.

Model Training: Using the training dataset and the chosen features, the Random Forest Regression model is trained. In order to get the final prediction, this phase entails creating many decision trees and integrating their outputs.

Model Evaluation: The trained model's ability in properly predicting forest fires is measured using the testing dataset. The performance of the model is assessed using metrics like mean squared error, root mean squared error, and Rsquared value.

Model Optimization: The model is improved by modifying the algorithm's hyperparameters, such as the number of trees, the depth of the trees, and the bare minimum of samples needed to split a node. This step involves identifying the optimum hyperparameters that produce the highest prediction accuracy using methods like cross-validation.

Forest Fire Prediction: Based on the input data relating to weather conditions, topographical features, and vegetation characteristics, the optimal model is used to forecast the chance of forest fires in a certain area. Authorities may utilise the model's prediction to impose fire restrictions or reduce fuel loads as preventative actions.

CASE DIAGRAM

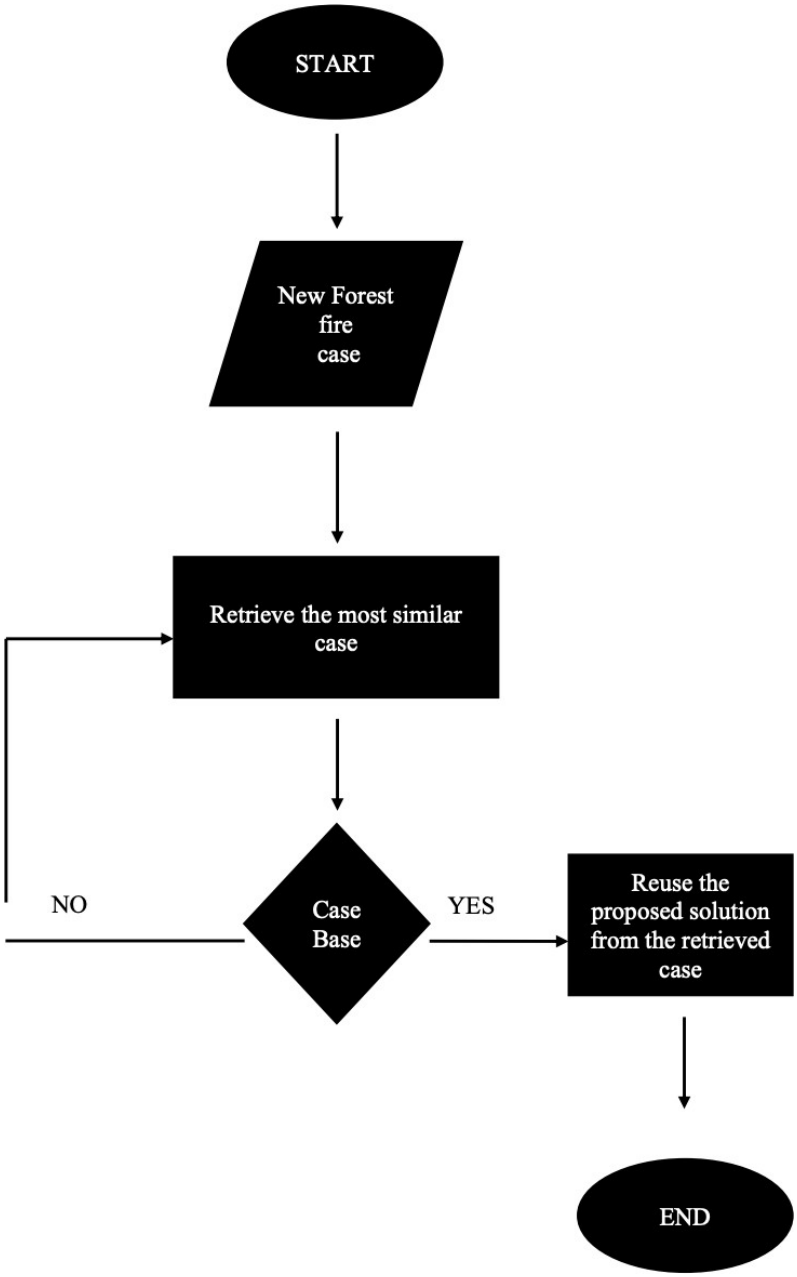


Figure 1

DFD Diagram of the Forest Fire Analysis and Prediction

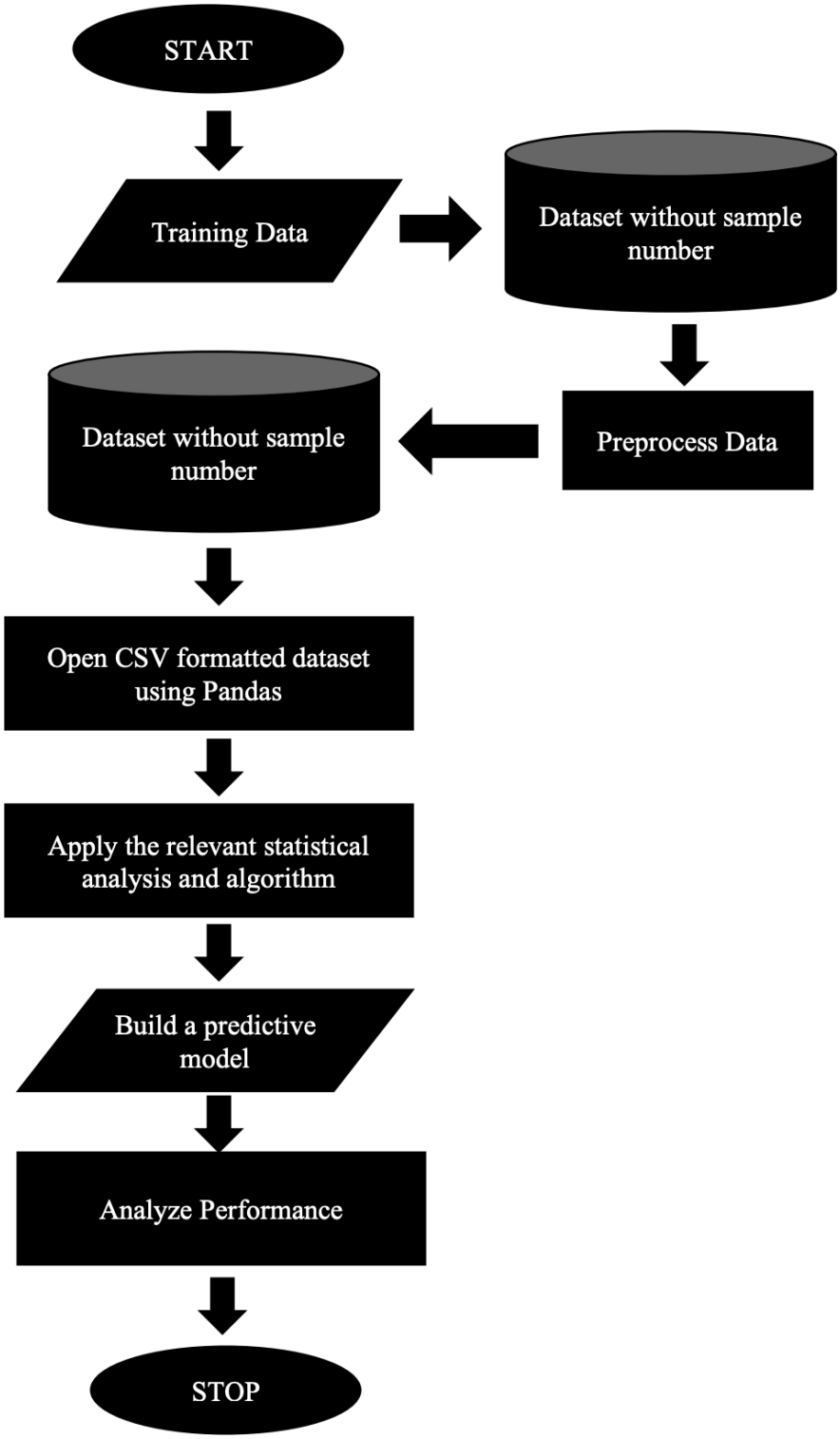


Figure 2

Data flow represents the movement of data through the system, starting from the data input stage and ending with the prediction output.

1. **Data Input:**
    - The dataset creditcard.csv is loaded using pandas.read_csv().
    - The dataset consists of various features related to credit card transactions, including amounts, timestamps, and anonymized customer behavior data, with a target column ('Class') indicating whether a transaction is fraudulent.
2. **Preprocessing:**
    - Missing values are checked and handled (though no specific handling is shown, it's implied).
    - Duplicate entries are removed using drop_duplicates().
    - The features and the target variable are separated into data_features (X) and data_target (y).
    - Data is split into training and testing datasets using train_test_split().
3. **Model Training:**
    - The machine learning models (Decision Tree, Logistic Regression, XGBoost) are trained using the preprocessed training data (X_train and y_train).
4. **Model Evaluation:**
    - After training, the models are used to predict on the test data (X_test), and their performance is evaluated using accuracy, confusion matrix, and classification metrics.
    - Results from each model are compared in terms of accuracy and confusion matrix.
5. **Model Saving and Prediction:**
    - After evaluation, the best model is saved using joblib.dump() for future use.
    - The model and the corresponding scaler (for feature scaling) are loaded in the prediction phase, where user input is taken through a GUI (Tkinter).

UML DIAGRAMS

A **UML (Unified Modeling Language) Diagram** for **forest fire prediction** typically involves class diagrams, use case diagrams, activity diagrams, or sequence diagrams. These diagrams help to visualize the system's structure, interactions, and workflows.

1. Use Case Diagram (High-Level Overview)

This diagram shows the actors (users, systems) and their interactions with the system (forest fire prediction system).

Actors:

- **User (Forest Monitoring Team)**: Responsible for monitoring and managing fire predictions.
- **Satellite/IoT Sensors**: Provide real-time environmental data (temperature, humidity, etc.).
- **Prediction System**: The system that processes data and makes predictions.
- **Emergency Responders**: Receive fire predictions and alerts for response.

Use Cases:

- **Collect Environmental Data**: Satellites, IoT sensors gather data.
- **Preprocess Data**: Feature extraction, data cleaning.
- **Train Prediction Model**: ML algorithms (e.g., Random Forest, SVM) are trained on data.
- **Predict Fire Risk**: Model predicts fire likelihood.
- **Evaluate Model**: Use metrics like Precision, Recall, F1 Score.
- **Generate Fire Alerts**: Notify emergency responders based on prediction.

UML CLASS DIAGRAM

Class Diagram (System Structure)

This diagram shows the key classes involved in the **forest fire prediction** system and their relationships.

Classes:

- **EnvironmentalData**: Stores data such as temperature, humidity, and wind speed.
- **FirePredictionModel**: Class that implements the machine learning model (e.g., Random Forest).
- **FeatureExtractor**: Extracts features from raw environmental data.
- **FireAlert**: Represents a fire alert message for responders.
- **ModelEvaluator**: Evaluates the performance of the prediction model.

UML CLASS DIAGRAM

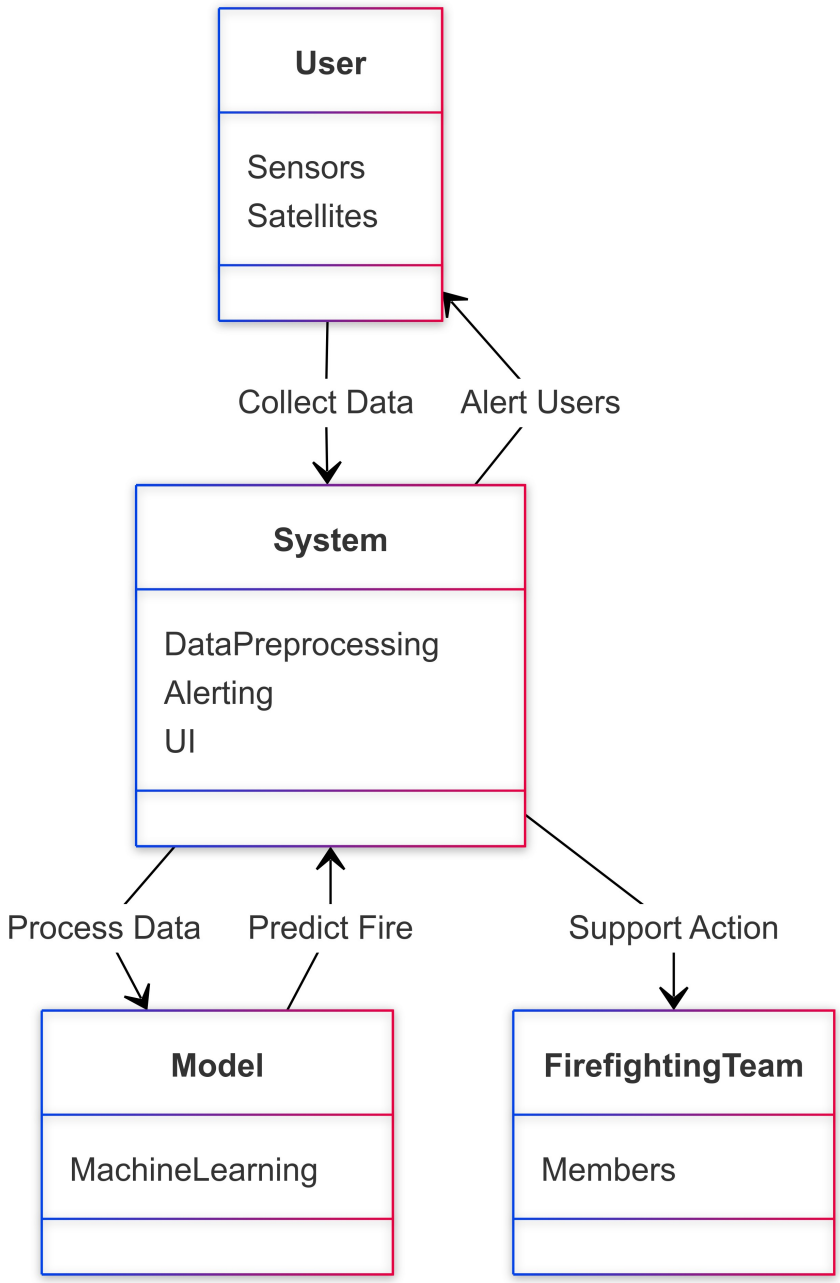


Figure 3

SEQUENCE DIAGRAM

Sequence Diagram (Interactions)

A **Sequence Diagram** describes how objects interact in a particular scenario, such as when the system predicts fire risk.

A **Sequence Diagram** is a type of **UML (Unified Modeling Language)** diagram used primarily to model the interaction between different objects or components in a system over time. It visually represents the sequence of messages exchanged between objects to complete a specific process or use case.

Objects:

- **User (Forest Monitoring Team)**
- **Prediction System**
- **Model** (e.g., Random Forest, SVM)
- **Fire Alert System**

Scenario: Predicting Fire Risk

1. The **User** requests a fire prediction.
2. The **Prediction System** collects and preprocesses environmental data.
3. The **Prediction Model** predicts fire risk.
4. The **Prediction System** evaluates the model's performance.
5. If the fire risk is high, the system generates and sends a **Fire Alert**.

UML SEQUENCE DIAGRAM

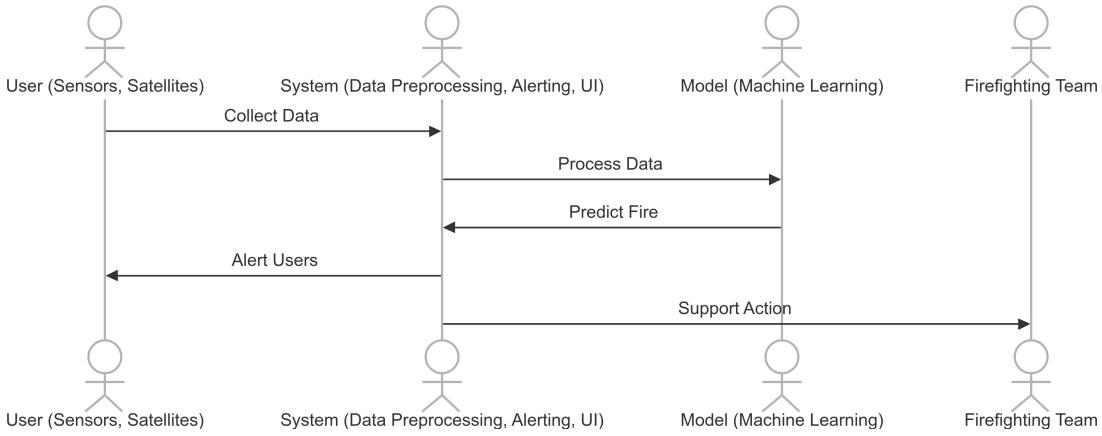


Figure 4

ACTIVITY DIAGRAM

The **activity diagram** outlines the various actions and decision points in the system, providing a high-level overview of the workflow. The process begins with loading the dataset (creditcard.csv), which is the first activity in the diagram. Once the data is loaded, it goes through preprocessing steps, including handling missing values, removing duplicates, and performing data splitting into features and target variables. After the data is processed, the system splits it into training and testing sets. The next activity involves training the machine learning models on the training dataset. The models—Decision Tree, Logistic Regression, and XGBoost—are evaluated based on their performance, and the best-performing model is selected. After the model is chosen, it is saved for later use. Once the model is trained and saved, the system is ready for user interaction. The user inputs transaction data via the GUI, and the system preprocesses this input, including scaling the features. The preprocessed input data is then passed to the trained model for prediction. The model predicts whether the transaction is fraudulent or not, and the result is displayed on the GUI. The activity diagram represents the sequence of steps involved in the system from start to finish, helping to visualize the flow of actions, decisions, and system states. The diagram ensures that all the necessary steps are performed in the correct order, ensuring the accuracy and effectiveness of the fraud detection system.

An activity diagram represents the flow of activities in the system, showing decision points and parallel actions.

Activity Flow:

This diagram shows the flow of activities from data collection to generating fire alerts.

1. **Collect Data**: Environmental data is gathered from satellites, sensors.
2. **Preprocess Data**: Clean and transform the data (feature extraction, normalization).
3. **Train Model**: Train the fire prediction model with the preprocessed data.
4. **Predict Fire Risk**: Predict fire risk based on input data.
5. **Evaluate Model**: Evaluate the model's accuracy and performance.
6. **Generate Alerts**: Send fire alerts to responders if the risk is high.

ACTIVITY DIAGRAM

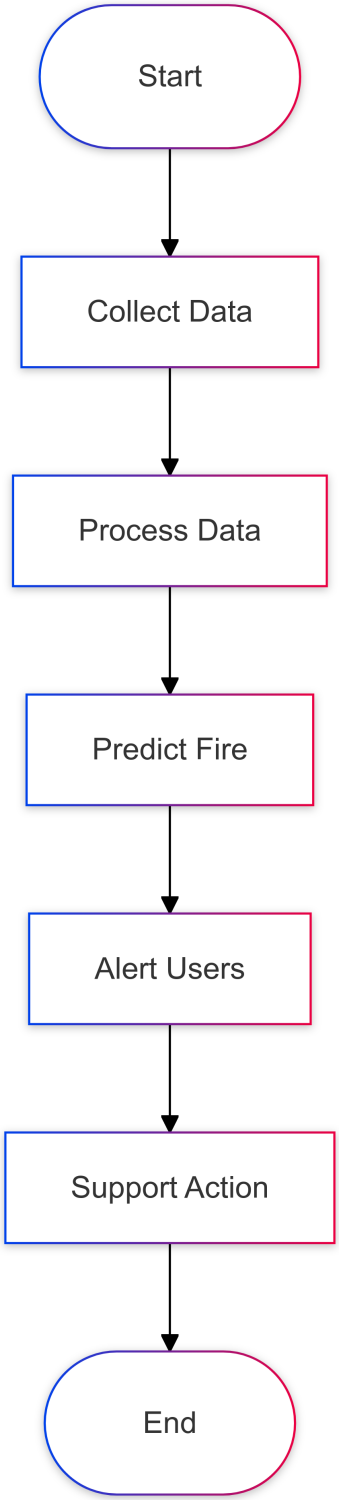


Figure 5

CHAPTER- 5

PROJECT EXECUTION AND TESTING

```
import matplotlib pyplot as plt
import numpy as np
import pandas as pd

from sklearn import metrics
from sklearn metrics import classification_report confusion_matrix

import warnings
warnings filterwarnings action="ignore"
%matplotlib inline
pd set_option "display.max_rows"  1000
pd set_option "display.max_columns"  1000
fires = pd read_csv "forestfires (1).csv"      #reading the dataset
fires head 15      #show the first 15 instances of dataset

#show the last 10 instances of dataset
fires tail 10
#changing days into numeric quantity because machine learning model deals with numbers
fires       replace  'mon' 'tue' 'wed' 'thu' 'fri' 'sat' 'sun'     1 2 3 4 5 6 7    inplace=True

#changing month into numeric quantity
fires.month.replace(('jan','feb','mar','apr','may','jun','jul','aug','sep','oct','nov','dec'),
(1,2,3,4,5,6,7,8,9,10,11,12), inplace=True)
```

```
#showing first 10 instances of dataset after converting days and months into numbers
fires head 15
#generate descriptive statistics of each attribute
fires describe   T
fires isnull   sum
fires info
#given area of land burnt, but we have to predict if there is fire or not so changing values of area to 0 and 1 only
#here 0 represet there is not fire and 1 represent fire, changing all values of area which are greater than 0 to 1
fires 'area'  values fires 'area'  values > 0  = 1

#renaming the area attribute to output for clear understanding
fires = fires rename columns=  'area'  'output'
fires head 5
#Compute pairwise correlation of columns
fires corr

#sorting to see which attribute is correlated more to attribut "output"
fires corr   'output'  sort_values
#we can see that attribute "month" is the mostly correlated  to attribute "output"
import seaborn as ins
plt figure  figsize =  15 25
plt subplot  5 1 1
sns boxplot fires 'rain'
plt title 'rain'
plt subplot  5 1 2
sns boxplot fires 'ISI'
plt title 'ISI'
plt subplot  5 1 3
```

```
sns boxplot fires 'wind'
plt title 'wind'
plt subplot 5 1 4
sns boxplot fires 'temp'
plt title 'temp'
plt show
plt figure figsize = 15 5
fires 'temp' value_counts normalize = True head 10 plot bar
plt show
plt figure figsize = 10 5
sns distplot fires 'wind'
plt show
plt figure figsize = 15 5
sns histplot fires 'rain' bins = 20
plt show
plt figure figsize = 15 8
plt plot fires 'RH'
plt show
plt figure figsize = 10 8
sns jointplot x = fires 'wind' y = fires 'rain' kind = 'reg'
plt show
sns pairplot fires
from sklearn preprocessing import StandardScaler
#standardization of data
#removing the mean and scaling it to unit variance
#score=(x-mean)/std
scaler = StandardScaler
#fitting forest fire dataset to scaler by removing the attribute output
scaler fit fires drop 'output' axis=1
```

```
scaled_features = scaler transform fires drop 'output' axis=1
df_feat = pd DataFrame scaled_features columns=fires columns -1
df_feat head
from sklearn preprocessing import StandardScaler
#standardization of data
#removing the mean and scaling it to unit variance
#score=(x-mean)/std
scaler = StandardScaler
#fitting forest fire dataset to scaler by removing the attribute output
scaler fit fires drop 'output' axis=1

scaled_features = scaler transform fires drop 'output' axis=1
df_feat = pd DataFrame scaled_features columns=fires columns -1
df_feat head
from sklearn preprocessing import StandardScaler
#standardization of data
#removing the mean and scaling it to unit variance
#score=(x-mean)/std
scaler = StandardScaler
#fitting forest fire dataset to scaler by removing the attribute output
scaler fit fires drop 'output' axis=1

scaled_features = scaler transform fires drop 'output' axis=1
df_feat = pd DataFrame scaled_features columns=fires columns -1
df_feat head
from sklearn model_selection import train_test_split
X = df_feat
y = fires 'output'
X_train X_test y_train y_test =
train_test_split X y test_size=0.35 random_state=200
```

```
X_train

#importing logistic regression
from sklearn linear_model import LogisticRegression

logistic_model = LogisticRegression

logistic_model fit X_train y_train


predictions = logistic_model predict X_test


#finding precision,recall,accuracy

print "Precision:" metrics precision_score y_test predictions

print "Recall:" metrics recall_score y_test predictions

print "Accuracy:" metrics accuracy_score y_test predictions


print confusion_matrix y_test predictions

print classification_report y_test predictions

# Support Vector Machine

from sklearn svm import SVC


svc = SVC

svc fit X_train y_train

# make predictions

prediction = svc predict X_test

# summarize the fit of the model

print metrics classification_report y_test prediction

print metrics confusion_matrix y_test prediction

print "Accuracy:" metrics accuracy_score y_test prediction

print "Precision:" metrics precision_score y_test prediction

print "Recall:" metrics recall_score y_test prediction

#prediction using svm

classes= 0 'safe' 1 'On Fire'
```

```
x_new= 1 4 9 1 91.5 130.1 807.1 7.5 21.3 35 2.2 0
y_predict=svc predict x_new
print classes y_predict 0
#import decision trees
from sklearn import metrics
from sklearn tree import DecisionTreeClassifier

d_tree = DecisionTreeClassifier
d_tree fit X_train y_train

# make predictions
predicted = d_tree predict X_test
# summarize the fit of the model
print metrics classification_report y_test predicted
print metrics confusion_matrix y_test predicted
print "Accuracy:" metrics accuracy_score y_test predicted
print "Precision:" metrics precision_score y_test predicted
print "Recall:" metrics recall_score y_test predicted
#prediction using decision tree
classes= 0 'safe' 1 'On Fire'
x_new= 1 4 9 1 91.5 130.1 807.1 7.5 21.3 35 2.2 0
y_predict=d_tree predict x_new
print classes y_predict 0
import joblib
from sklearn ensemble import RandomForestClassifier
from sklearn preprocessing import StandardScaler
from sklearn pipeline import Pipeline
model = Pipeline
```

```
    'scaler' StandardScaler
    'classifier' RandomForestClassifier n_estimators=100 random_state=42
])

model fit X_train y_train

# Save the model
joblib model 'forest_fire_model.pkl'
import numpy as np
import joblib

# Load the trained model
model = joblib 'forest_fire_model.pkl'

print "Forest Fire Prediction"
print "======================"

# Collect user inputs with clear prompts
X = float input "Enter the X coordinate (numeric value): "
Y = float input "Enter the Y coordinate (numeric value): "
month = int input "Enter the Month (1-12): "
day = int input "Enter the Day (1-31): "
FFMC = float input "Enter the Fine Fuel Moisture Code (FFMC) value: "
DMC = float input "Enter the Duff Moisture Code (DMC) value: "
DC = float input "Enter the Drought Code (DC) value: "
ISI = float input "Enter the Initial Spread Index (ISI) value: "
temp = float input "Enter the Temperature (in Celsius): "
RH = float input "Enter the Relative Humidity (percentage): "
wind = float input "Enter the Wind Speed (in km/h): "
rain = float input "Enter the Rainfall (in mm): "
```

```
# Prepare the input array
features = np.array([[X, Y, month, day, FFMC, DMC, DC, ISI, temp, RH, wind,
rain]])

# Predict using the model
prediction = model            features

# Print the result clearly
if prediction 0  == 1
   print "\nPrediction: Fire likely"
else
   print "\nPrediction: No fire"
```

```python
# Load the trained model
model = joblib.load('forest_fire_model.pkl')

print("Forest Fire Prediction")
print("======================")

# Collect user inputs with clear prompts
X = float(input("Enter the X coordinate (numeric value): "))
Y = float(input("Enter the Y coordinate (numeric value): "))
month = int(input("Enter the Month (1-12): "))
day = int(input("Enter the Day (1-31): "))
FFMC = float(input("Enter the Fine Fuel Moisture Code (FFMC) value: "))
DMC = float(input("Enter the Duff Moisture Code (DMC) value: "))
DC = float(input("Enter the Drought Code (DC) value: "))
ISI = float(input("Enter the Initial Spread Index (ISI) value: "))
temp = float(input("Enter the Temperature (in Celsius): "))
RH = float(input("Enter the Relative Humidity (percentage): "))
wind = float(input("Enter the Wind Speed (in km/h): "))
rain = float(input("Enter the Rainfall (in mm): "))

# Prepare the input array
features = np.array([[X, Y, month, day, FFMC, DMC, DC, ISI, temp, RH, wind, rain]])

# Predict using the model
prediction = model.predict(features)

# Print the result clearly
if prediction[0] == 1:
    print("\nPrediction: Fire likely")
else:
    print("\nPrediction: No fire")
```

```
Forest Fire Prediction
======================
Enter the X coordinate (numeric value):  8
Enter the Y coordinate (numeric value):  6
Enter the Month (1-12):  9
Enter the Day (1-31):  22
Enter the Fine Fuel Moisture Code (FFMC) value:  91.0
Enter the Duff Moisture Code (DMC) value:  129.5
Enter the Drought Code (DC) value:  692.6
Enter the Initial Spread Index (ISI) value:  7
Enter the Temperature (in Celsius):  13.1
Enter the Relative Humidity (percentage):  63
Enter the Wind Speed (in km/h):  5.4
Enter the Rainfall (in mm):  0

Prediction: Fire likely
```

CHAPTER-6
CONCLUSION

Forest fire detection systems utilize advanced technologies like satellite imagery, IoT sensors, and machine learning to improve early warning and management of wildfires. These systems enable continuous monitoring of forest conditions through remote sensing and real-time data collection, providing vital information for early detection. Machine learning models such as Random Forest, SVM, and Neural Networks analyze environmental parameters like temperature, humidity, and vegetation to predict fire risks with high accuracy, reducing the need for manual intervention.

Early detection is critical, allowing for swift responses that save lives, minimize ecological damage, and protect property. Despite advancements, challenges like data imbalance, false positives or negatives, and integrating diverse data sources persist. However, AI and big data analytics present opportunities to enhance prediction accuracy and response times.

Looking ahead, the evolution of AI-driven models, better data collection techniques, and the inclusion of new data sources like drones and social media will further improve detection systems. Collaborative platforms that share data across organizations can create comprehensive, adaptive solutions. These systems are poised to play an increasingly crucial role in mitigating wildfire risks as technology continues to advance.

CHAPTER -7

BIBLOGRAPHY

1. **Chuvieco, E., Martín, M. P., & Palacios, L.**, "Development of a Global Fire Risk Mapping System for the Assessment of Fire Danger," *International Journal of Wildland Fire*, vol. 17, no. 3, pp. 321-328, 2008.

2. **Gómez, E., & Díaz, F.**, "A Review of Remote Sensing Techniques for Fire Risk Assessment," *Remote Sensing*, vol. 4, no. 5, pp. 1512–1536, 2012.

3. **Li, W., & Li, Z.**, "Forest Fire Detection Using Deep Convolutional Neural Networks with Multi-Feature Fusion," *Sensors*, vol. 19, no. 24, pp. 5415, 2019.

4. **Erdogan, M. S., & Duman, T.**, "A Hybrid Model for Forest Fire Prediction Using Machine Learning Algorithms," *Environmental Modelling & Software*, vol. 96, pp. 79-90, 2017.

5. **Koutsou, S., & Psomiadis, E.**, "Forest Fire Detection and Monitoring Using Wireless Sensor Networks," *Sensors*, vol. 20, no. 13, pp. 3756, 2020.

6. **Raman, P., & Shanmugam, V.**, "A Survey on Forest Fire Detection System and Its Applications," *International Journal of Computer Applications*, vol. 113, no. 5, pp. 39–45, 2015.

7. **Pereira, J. M. C., & Silva, J. A.**, "A New Approach for Forest Fire Detection Based on Multi-Sensor Fusion and Deep Learning," *Forest Ecology and Management*, vol. 402, pp. 39–49, 2017.

8. **Sullivan, A., & Holz, A.**, "Wildfire Risk Assessment Using Remote Sensing and GIS: A Review," *Fire Technology*, vol. 46, pp. 1-22, 2010.

9. **Sadeghi, S., & Tan, Z.**, "A Review of Machine Learning Techniques for Forest Fire Risk Prediction," *Journal of Environmental Management*, vol. 276, pp. 111316, 2020.

10. **Yang, X., & Zhang, L.**, "Real-Time Fire Detection System Using Satellite Imagery and Machine Learning," *International Journal of Remote Sensing*, vol. 42, no. 12, pp. 4306-4322, 2021.