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Master's Thesis

Models and Algorithms in Analysis and Prediction of Ground Fires

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Abstract

Ground fires, particularly in forested and grassland areas, pose growing challenges to both environmental protection and public safety. Predicting fire occurrences and their behavior is critical for efficient resource management, early intervention, and risk reduction. This research explores the potential of ensemble machine learning techniques, specifically Stacking and Voting methods, to improve the forecasting of ground fire events, including fire intensity patterns and intensity.

In this study, various machine learning models, including Decision Trees, Random Forests, Support Vector Machines (SVM), and ensemble approaches such as Stacking and Voting classifiers, are compared for both classification and regression tasks. The classification models aim to predict the likelihood of a fire occurring in a specific region, while the regression models estimate the intensity in terms of direction and intensity. The experiments were based on real-world data, which included meteorological variables, vegetation types, topographic features, and historical fire data.

The results indicate that ensemble learning models, particularly the Stacking method, outperform individual models by a significant margin. The Stacking Classifier achieved the highest classification accuracy and F1 score, while the Stacking Regressors showed the lowest prediction error and the most accurate projections of fire intensity. Additionally, hyperparameter tuning techniques, such as Grid Search and Random Search, further optimized the performance of models, especially for Random Forests and SVM.

These findings highlight the effectiveness of ensemble models, especially Stacking, for both fire occurrence prediction and behavior forecasting. The increased accuracy of these models offers valuable insights for fire management, aiding in risk assessment, resource distribution, and emergency planning. However, challenges related to the interpretability of the models and the quality of the input data remain. Future research could address these issues by enhancing model transparency and robustness.

The study also proposes several directions for future research, such as the integration of real-time data, the exploration of deep learning approaches, and the enhancement of model explainability through techniques like SHAP and LIME. Moreover, future work should focus on expanding the models to predict fires across different regions and implementing these approaches within real-world fire management systems.

Keywords

Ground fire prediction, ensemble learning, Stacking Classifier, Voting Classifier, machine learning, fire intensity forecasting, hyperparameter tuning, real-time data, model explainability, wildfire management

Contents

1. Introduction

1.1 Background of Ground Fire Prediction

As global temperatures rise and climate change accelerates, ground fires have emerged as a significant environmental and public safety concern. Over recent decades, the frequency, intensity, and geographic spread of wildfires have increased substantially, leading to severe ecological damage and property losses. Specifically, ground fires, which occur in forested areas or grasslands, present unique challenges due to their complex spread patterns and the difficulty in accurately predicting both their occurrence and behavior.

Ground fires can be initiated by various factors, including weather conditions, human activities, and natural events. The key factors that influence fire behavior include temperature, humidity, wind speed, and the type of fuel available. Given that these factors are dynamic and often interrelated, traditional fire prediction methods, which are based on physical models or heuristic rules, often fall short in dealing with the unpredictable nature of fire intensity[1]. Therefore, there is a pressing need for improved fire prediction models that can integrate multiple data sources and accurately forecast fire behavior under varying conditions.

Recent advancements in machine learning (ML) offer promising solutions to these challenges. By utilizing large datasets and advanced predictive algorithms, machine learning techniques can enhance the accuracy of real-time fire occurrence predictions and behavior forecasts, even in complex and rapidly changing environments. This research specifically investigates the application of ensemble machine learning methods, such as Stacking and Voting, to improve the prediction accuracy of ground fire occurrences and

their behavior.

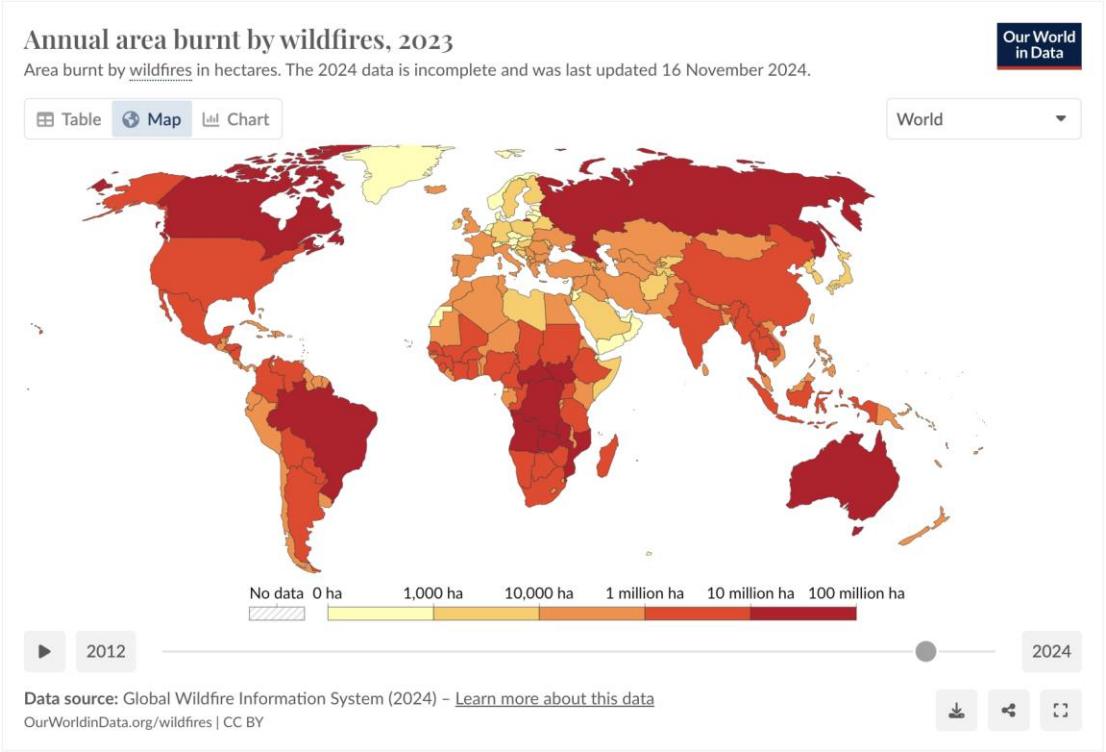

Figure 1.1: The figure shows the increase in ground fire incidents worldwide, highlighting the growing threat posed by wildfires[2].

1.2 Problem Statement

Predicting the occurrence and intensity of ground fires is a challenging task due to the multitude of variables that influence fire behavior. Traditional fire prediction models, which rely on empirical rules or physical simulations, have demonstrated limitations in terms of both adaptability and accuracy[3]. While machine learning (ML) techniques have shown success in other predictive domains, their application to fire prediction remains relatively underexplored.

One of the main difficulties in predicting ground fires is the integration of diverse and heterogeneous data sources, such as meteorological conditions, vegetation types, and historical fire events. These data must be effectively utilized to generate precise predictions. Additionally, models must be capable of generalizing across various geographical regions and climatic conditions. Existing models often struggle to balance accuracy and robustness in fire intensity predictions, with issues such as overfitting or underfitting arising, depending on the nature of the training data[4].

This study aims to fill the gap in current fire prediction models by exploring the potential of ensemble machine learning techniques, such as Stacking and Voting, which combine multiple base models to enhance prediction accuracy and generalization. Specifically, the research focuses on evaluating the effectiveness of these ensemble methods in predicting fire occurrence, spread direction, and intensity across different climatic and geographical contexts.

1.3 Study Aims and Objectives

The main goal of this study is to design and assess an ensemble machine learning framework that combines multiple base models to predict the occurrence and behavior of ground fires. The specific objectives of this research are as follows:

1. To compare the performance of individual machine learning models (such as Decision Trees, Random Forests, and Support Vector Machines) with ensemble methods (including Stacking and Voting) in predicting fire-related outcomes.
2. To evaluate the accuracy of these models in forecasting fire occurrence, spread, and intensity across different geographical regions and under varying environmental conditions.
3. To enhance model performance through hyperparameter optimization techniques, such as Grid Search and Random Search, aiming to increase the reliability of fire predictions.
4. To examine the practical application of the developed models by testing them in real-world fire prediction scenarios, incorporating real-time weather data and fire risk information from diverse sources.

1.4 Motivation for the Study

This research is motivated by the increasing global prevalence of ground fires and their significant ecological and economic consequences. Traditional fire prediction methods have struggled to keep up with the growing complexity of fire behavior, particularly under the combined effects of climate change and urbanization. Improving fire prediction accuracy can greatly enhance the efficiency of resource allocation, optimize emergency response strategies, and reduce both human and property losses associated with wildfires.

By developing a more precise prediction system through machine learning techniques, this study aims to advance wildfire management practices. Ensemble methods, known for improving the generalization ability of machine learning models, are particularly effective in enhancing their reliability in practical, real-world situations. Additionally, the integration of real-time data with predictive modeling holds great potential for transforming fire management strategies

1.5 Research Significance

This research holds both theoretical and practical significance:

1. Theoretical Contribution: This study makes a valuable contribution to the application of machine learning in environmental sciences, with a focus on utilizing ensemble learning techniques for addressing complex, real-world problems. It advances existing wildfire prediction research by exploring innovative uses of ensemble methods, which combine multiple base models to enhance predictive accuracy and performance.
2. Practical Implications: The outcomes of this study have direct relevance to fire management systems, enabling agencies to make more informed, data-driven decisions regarding fire prevention, resource allocation, and emergency response strategies. By improving fire prediction accuracy, this research can help mitigate ecological damage and reduce the risks wildfires pose to human populations.

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1.6 Scope, Limitations, and Delimitations

While this study concentrates on developing and evaluating machine learning models for ground fire prediction, its scope is constrained by the available data. The accuracy of the models is influenced by the quality and comprehensiveness of the input data, which includes meteorological variables, vegetation types, and historical fire records. Furthermore, the study mainly analyzes data from regions with accessible historical fire data, meaning the results may not be fully applicable to areas with distinct fire dynamics or limited data availability.

This chapter introduced the problem of ground fire prediction, the objectives of the study, and the motivation behind using machine learning, particularly ensemble methods,

to improve prediction accuracy. It highlighted the practical significance of improving fire prediction models for better resource management and disaster mitigation. The next chapter will provide a theoretical background on ground fire prediction and a literature review of relevant machine learning techniques.

2. Theoretical Framework and Literature Review

2.1 Overview of Ground Fires

Ground fires, which burn beneath the surface layer of the soil, are distinct from surface fires that consume vegetation at the forest floor and crown fires that spread through the upper canopy[5].These fires typically occur in areas with deep organic soils, such as peatlands, grasslands, and certain forest types[6]. Ground fires are characterized by a slow-burning process that can persist for months, even smoldering under wet or snowy conditions, which makes their detection and management particularly difficult[7].

The behavior of ground fires is shaped by a variety of factors, including fuel type, moisture content, climatic conditions, and topography[8]. For example, in peat bogs, high moisture content may inhibit the spread of ground fires. However, during drought conditions, these fires can spread quickly and become much harder to control[9]. Research indicates that ground fires in forest ecosystems pose significant risks because they can persist for extended periods, with the potential to reignite under favorable conditions[10].

Figure 2.1: this figure compares the characteristics of ground fires, surface fires, and crown fires, highlighting key differences in their intensity and behavior[11].

2.2 Key Factors Influencing Ground Fires

Ground fires are influenced by a range of environmental, climatic, and human-induced factors:

1. Climatic Conditions

Temperature, humidity, and wind speed are pivotal in determining fire behavior[12]. Elevated temperatures and low humidity levels reduce vegetation moisture content, thereby heightening the likelihood of ignition. Wind, in particular, can intensify fires and accelerate their spread[13].

2. Vegetation and Fuel Types

The nature and condition of vegetation are critical factors in fire intensity[14]. Forests with thick underbrush, as well as grasslands and peat bogs, provide abundant

fuel for ground fires[15]. Particularly, dry, organic-rich materials can sustain long-lasting smoldering, even after visible flames have diminished[16].

3. Topography

The landscape significantly affects fire dynamics[17]. Fires spread faster on slopes due to the pre-heating effect, which dries and ignites fuel uphill[18]. Conversely, flatter terrain may impede rapid fire progression[19].

4. Human Activity

Human interventions, such as land clearing, agriculture, and the misuse of fire, are key drivers of ground fire ignition and spread[20]. These actions alter the landscape, increase fuel availability, and can create conditions that facilitate fire spread[21].

Factor	Description	Impact on Fire Behavior
Climatic Conditions	Temperature, humidity, wind speed, precipitation	Affects fuel moisture and ignition
Vegetation	Type of vegetation, moisture content	Determines fire intensity and spread
Topography	Slope, elevation, aspect	Affects spread rate and direction
Human Activity	Land use changes, agricultural practices	Increases fuel load and ignition risk

Table 2.2: Factors Influencing Ground Fire Behavior

2.3 Ground Fire Behavior and Prediction

Predicting the behavior of ground fires is a complex task due to the many variables that interact in a given fire event[22]. Traditional fire behavior models, like the Rothermel fire spread model, provide essential insight into the physical processes that govern fire spread, including the influence of weather, fuel type, and terrain[23]. These models, however, are limited in their capacity to handle the dynamic and non-linear aspects of real-world fire behavior[24].

With the rise of machine learning (ML) techniques, newer prediction models are able to process large, complex datasets and better account for the variability of real-world conditions[25]. ML methods can adaptively learn from past fire data to improve prediction accuracy over time[26]. Recent advances have integrated deep learning and other sophisticated algorithms into fire prediction systems, offering promising results for more accurate real-time fire forecasting[27].

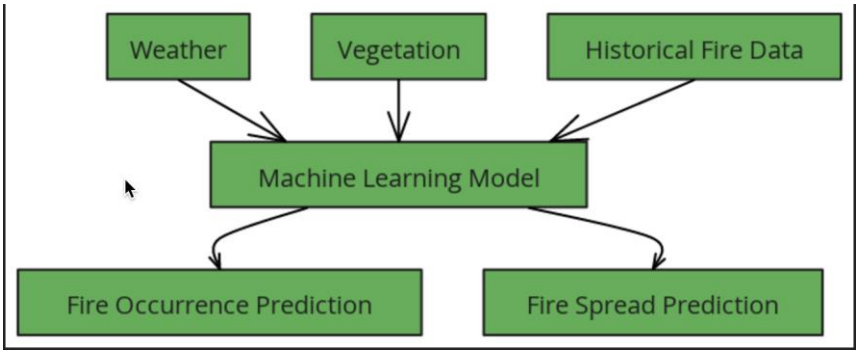

Figure 2.3: This diagram illustrates the integration of various input features (weather, vegetation, historical data) into a machine learning model to predict fire occurrence and intensity.

2.4 Ground Fires in the Southwest United States: A Comprehensive Analysis

Ground fires, which occur beneath the surface layer of the soil, present serious ecological, environmental, and socio-economic challenges, especially in regions prone to frequent and severe wildfires. The southwestern United States, with its diverse landscapes, varying climatic conditions, and a range of vegetation types, offers an excellent setting to investigate the dynamics of ground fires. This chapter discusses the feasibility and rationale for utilizing data-driven approaches, specifically machine learning, to predict and analyze ground fire behavior in this region. By examining factors such as geography, climate, ecology, vegetation, and historical fire events, we highlight the accessibility and wealth of data that make this region an ideal candidate for ground fire research.

2.4.1 Geographical and Climatic Features of the Southwestern U.S.

The southwestern U.S. is characterized by a highly diverse terrain, including deserts, grasslands, and forested areas with mountainous highlands. These landscapes, combined with a highly variable climate, contribute to a fire-prone environment. The region experiences extreme weather conditions, such as high temperatures, low humidity, and periodic droughts, which significantly increase the risk of fire ignition. The presence of dry vegetation and lack of moisture make the region highly susceptible to wildfires, including ground fires.

Temperature plays a critical role in fire behavior. During the summer months, temperatures can soar, while low humidity further dries out vegetation, making it highly flammable. Wind is another crucial factor that can amplify the intensity and spread of fires. When wind speeds are high, fires can travel faster and burn more intensely, adding a layer of unpredictability to fire behavior in the region. Additionally, the region's varied topography, including steep slopes and flat plains, causes fire spread to behave differently in different areas. For example, fires are more likely to move quickly uphill due to a phenomenon known as the pre-heating effect, while they may spread more slowly on flat landscapes.

Given these complex climatic and geographical features, understanding how fires behave in this region is crucial for effective fire management, as different landscapes may require different approaches to fire prediction and mitigation.

2.4.2 Vegetation and Ecological Factors Influencing Fire Behavior

The ecological diversity of the southwestern U.S. is reflected in the variety of vegetation types that dominate the region, each influencing fire behavior in different ways. Grasslands, deserts, forests with dense underbrush, and peat bogs provide different types of fuel that can sustain fires. Ground fires often spread in areas where the fuel is abundant, especially in regions with dense grass or dry, organic material, such as peat bogs and forested areas.

In particular, dry vegetation and organic material, rich in carbon content, are more prone to smoldering for extended periods. Even when visible flames may no longer be present, the fire can continue to burn underground, making detection and suppression difficult. Dense vegetation like that found in Arizona's forests, composed of juniper, ponderosa pine, and other tree species, provides ideal conditions for ground fires to persist and spread. These types of vegetation, particularly in areas where moisture levels are low, can create prolonged burning events that may last for days or even weeks, challenging fire management efforts.

Understanding the role of different vegetation types and their condition—whether dry or moist—helps predict how fires will behave under various conditions. By incorporating data on vegetation health and type, fire prediction models can better estimate fire spread and intensity, ensuring that fire management strategies are tailored to specific landscapes.

Figure 2.4: Vegetation pictures of the Southwest region of the United States[28]

2.4.3 The Importance of Historical Fire Data

An important factor in predicting and analyzing ground fires in the southwestern U.S. is the wealth of historical fire data available. Over the past several decades, this region has experienced a rise in the frequency, intensity, and scale of wildfires, leading to a substantial collection of data related to past fire events. This data, which includes records of fire locations, sizes, durations, and the environmental conditions surrounding each fire, is collected by organizations such as the U.S. Forest Service, the National Interagency Fire Center (NIFC), and NOAA.

The availability of such historical data is invaluable for building machine learning models that can accurately predict fire occurrences and behavior. By analyzing historical fire patterns and trends, researchers can identify fire-prone areas and assess which factors—such as temperature, humidity, wind speed, and vegetation types—are most strongly correlated with fire intensity. This information can be used to train predictive models, which are crucial for real-time fire forecasting and early warning systems.

Furthermore, integrating historical fire data with other sources of environmental data, such as current meteorological information and satellite-based observations, allows for more accurate, timely predictions. This approach can significantly improve the accuracy of fire predictions by taking into account the latest weather conditions and fire behavior, helping fire management agencies better prepare for and respond to fires.

2.4.4 Rationale for Data-Driven Models in Fire Prediction

Data-driven models, especially those employing machine learning techniques, are particularly well-suited for predicting ground fires in the southwestern U.S. The region's diverse terrain, climatic variability, and the availability of large datasets make it an ideal environment for the application of these advanced techniques. Machine learning models, such as ensemble methods (e.g., Stacking and Voting), can process vast amounts of data from multiple sources to provide highly accurate predictions of fire behavior.

The advantage of machine learning in fire prediction lies in its ability to handle complex, nonlinear relationships between various factors—such as weather, vegetation, and topography—that influence fire intensity. Unlike traditional fire prediction models, which rely on physical simulations or empirical rules, machine learning models can adapt to the complexities and variability of real-world conditions. These models can be trained on large datasets to improve their generalization, ensuring that they perform well not just on historical data but also in real-time fire prediction scenarios.

Additionally, machine learning models can integrate data from various sources, including satellite imagery, meteorological stations, and historical fire records, providing a comprehensive view of fire dynamics. This ability to synthesize diverse

datasets makes machine learning techniques highly effective for predicting fire occurrence, intensity, and spread, even in regions with changing fire regimes.

2.4.5 Conclusion: Feasibility and Potential of Data-Driven Fire Prediction in the Southwest

The southwestern U.S. provides a unique and highly relevant setting for studying ground fires. The region's diverse geography, complex climatic conditions, and range of vegetation types make it a challenging but critical area for fire prediction research. The availability of historical fire data, combined with real-time meteorological and satellite-based observations, provides a robust foundation for building accurate, data-driven models.

Given the abundance of data and the complexity of fire behavior in this region, machine learning models offer a promising approach for improving fire prediction accuracy. By leveraging diverse data sources and applying advanced modeling techniques, researchers can develop models that better predict fire occurrence, spread, and intensity. These models can ultimately assist fire management agencies in making more informed decisions about fire preparedness, resource allocation, and emergency response.

As the frequency and intensity of wildfires continue to rise, particularly in the context of climate change, the need for sophisticated, data-driven fire prediction models becomes more urgent. The southwestern U.S. offers an ideal testing ground for developing and validating these models, which have the potential to transform fire management practices and reduce the impacts of wildfires on both human populations and the environment.

3. Research Methodology

3.1 Data Acquisition and Processing

To develop accurate fire prediction models, it is essential to use high-quality data that comprehensively captures the key factors influencing fire behavior. In this study, we incorporated a range of data sources, such as meteorological conditions, vegetation types, historical fire occurrences, and topographical features. Proper preprocessing of these datasets is vital to ensure that the models are trained on clean, pertinent, and well-organized data. The following section provides an overview of the data collection and preprocessing steps.

3.1.1 Data Collection

The primary data sources for this study were obtained from various trusted and authoritative platforms, ensuring the accuracy and relevance of the information used in the fire prediction models. The key data sources include:

Meteorological Data:The meteorological data, including temperature, humidity, wind speed, and precipitation, were sourced from multiple weather stations and national weather agencies. Key sources included:

- National Oceanic and Atmospheric Administration (NOAA): Provides real-time weather data and long-term climate data across various regions[29].
- European Space Agency (ESA) – Copernicus Atmosphere Monitoring Service (CAMS): Offers global atmospheric data including temperature, wind speed, and humidity, which are essential for fire risk modeling[30].
- World Meteorological Organization (WMO): Coordinates the global exchange of weather data between meteorological institutions, which is useful for cross-regional fire risk modeling[31].

Vegetation Data: Satellite imagery and remote sensing data were used to classify vegetation types and assess fuel availability. These data are critical for

understanding the combustibility of different vegetation types, which is essential for predicting fire intensity. Key sources of vegetation data include:

- NASA's MODIS (Moderate Resolution Imaging Spectroradiometer): Provides near-real-time satellite imagery for monitoring vegetation types, fuel load, and fire activity[32].
- Landsat Program (USGS): Landsat satellites capture high-resolution imagery, which can be used for land cover classification and vegetation mapping, helping to estimate fuel density and fire-prone areas[33].
- FAO Global Forest Resources Assessment (FRA): This database provides information on global forest resources, including vegetation types, biomass, and fuel characteristics, which is useful for fire behavior modeling[34].

Fire History Data: Historical fire data, such as fire locations, dates, and affected areas, were sourced from fire management agencies, government bodies, and academic institutions. These records provide insight into patterns of fire occurrence, helping to identify high-risk areas and estimate future fire probability. Primary sources included:

- National Interagency Fire Center (NIFC): Collects and distributes data on wildfires in the United States, including detailed records on fire locations and sizes[35].
- Global Wildfire Information System (GWIS): Offers global wildfire data, including information on fire locations, areas burned, and wildfire trends over time[36].
- European Forest Fire Information System (EFFIS): Provides historical fire data for Europe, including detailed records on past fires, fire occurrence, and burned areas[37].

Topographical Data: Topographical data were collected using digital elevation models (DEMs) to assess the terrain’s impact on fire spread. Slope, elevation, and other terrain features are critical for fire behavior, particularly in mountainous or hilly areas. The main sources for this data include:

- NASA’s Shuttle Radar Topography Mission (SRTM): Provides global elevation data with a resolution of 30 meters, which is essential for fire spread modeling in hilly and mountainous regions[38].

- United States Geological Survey (USGS) National Elevation Dataset (NED): Supplies high-resolution DEMs for the United States, which are useful for assessing terrain influence on fire behavior[39].
- OpenTopography: A free, online portal that provides access to topographical data, including DEMs, lidar data, and other terrain features. This data helps in creating detailed models of fire spread based on slope and elevation[40].

3.1.2 Data Preprocessing Techniques

Data preprocessing is a critical step in machine learning that involves preparing raw data for model building by cleaning, transforming, and organizing it. The goal is to ensure that the data fed into machine learning models is accurate, well-structured, and relevant to the specific problem at hand. This section outlines the essential preprocessing steps undertaken in this study, with a particular focus on the techniques employed in Python.

Step 1: Data Importation and Exploration

The first phase of preprocessing is data collection. For ground fire prediction, this involves gathering data from various sources, such as environmental monitoring systems, satellite imagery, weather data, and historical fire records. The data is typically stored in formats like CSV files, databases, or APIs, and Python's Pandas library is commonly used to manage these datasets. Pandas provides a powerful DataFrame structure that supports heterogeneous data types, making it easy to read, write, and explore datasets.

After importing the data, an initial exploration is conducted to better understand its structure and quality. This step includes inspecting the first few rows of the dataset, checking the data types of each variable, and identifying any potential issues, such as missing or inconsistent values. A key focus at this stage is to understand the relevance of the collected data to the prediction of ground fires, ensuring that it reflects environmental factors like temperature, humidity, fuel types, and historical fire incidents.

Step 2: Handling Missing Data

Missing values are a common challenge in real-world datasets, and ground fire data is no exception. Gaps in the data may arise from various factors, such as

incomplete records, sensor malfunctions, or errors during data collection. In this study, two main strategies were adopted to address missing data:

Imputation: For numerical variables, missing values were filled with the mean or median of the respective columns. For categorical data, the most frequent value (mode) was used to replace missing entries, ensuring the distribution of categories remained consistent. This method helps to maintain the integrity of the dataset without losing valuable information.

Removal: In cases where a significant portion of data was missing, particularly for crucial features or target variables, rows with missing values were removed. Additionally, columns with a high proportion of missing data (exceeding a predefined threshold) were discarded to prevent skewing the analysis and ensure the dataset's relevance for model training.

For imputation tasks, the SimpleImputer class from Python's Scikit-learn library was employed, as it offers an efficient way to fill in missing values with statistical measures like the mean, median, or mode. For more advanced cases, techniques such as interpolation or custom imputation models may be considered, particularly when dealing with time-series data or complex datasets with spatial dependencies, as is often the case with ground fire prediction.

```
# Remove columns with more than 50% missing values
threshold = len(merged_data) * 0.5
merged_data.dropna(axis=1, thresh=threshold, inplace=True)

# Separate numeric and non-numeric columns
numeric_cols = merged_data.select_dtypes(include=['number']).columns
non_numeric_cols = merged_data.select_dtypes(exclude=['number']).columns
# Impute missing values
imputer_numeric = SimpleImputer(strategy='mean')
merged_data[numeric_cols] = imputer_numeric.fit_transform(merged_data[numeric_cols])
imputer_non_numeric = SimpleImputer(strategy='most_frequent')
merged_data[non_numeric_cols] = imputer_non_numeric.fit_transform(merged_data[non_numeric_cols])
# Remove duplicate rows
cleaned_data = merged_data.drop_duplicates()
```

Step 3: Feature Engineering for Ground Fire Prediction

Feature engineering is a critical step in the machine learning pipeline, as it involves the creation of new features that can better capture the underlying patterns in the data, ultimately improving the performance of predictive models. In the context of ground fire prediction, this process becomes even more significant due to the complex interactions between various environmental factors that influence fire behavior.

In this study, a variety of new features were generated from the raw data to enhance model accuracy and better reflect the conditions under which ground fires are likely to occur. The raw data collected for ground fire prediction includes environmental variables such as temperature, humidity, wind speed, fuel type, and historical fire records. By combining and transforming these variables, we were able to generate more informative features.

These new features were then incorporated into the dataset, with the goal of providing machine learning models with more relevant and predictive information. By capturing the complex relationships between these environmental factors, the feature engineering process plays a crucial role in improving the overall predictive power of the models:

Fire Weather Index (FWI): This feature was derived by combining weather variables, such as temperature, wind speed, and humidity, to assess fire risk. By multiplying temperature and wind speed and dividing by humidity, we created an index that better reflects the danger of fire under specific weather conditions.

Slope and Elevation: Using Digital Elevation Models (DEMs), features related to the terrain's slope and elevation were computed. These features are vital because the steepness of the land significantly influences fire behavior. Slope was calculated based on the elevation change over a defined distance .

Vegetation Classification: Vegetation types, such as forests, grasslands, and shrublands, were classified using satellite imagery. To make these categorical labels compatible with machine learning algorithms, they were converted into numerical values through encoding techniques.

The Pandas library was utilized for these transformations, with functions such as apply() and map() being employed to perform mathematical operations and categorical encoding.

Step 4: Data Normalization and Scaling

Scaling ensures that all features are comparable in magnitude, which prevents certain features with larger numerical ranges from disproportionately influencing the model's performance. In ground fire prediction, environmental variables such as temperature, humidity, and elevation can vary widely in their values, and unscaled data may lead to biased model outcomes.

Two common techniques for scaling data are:

Normalization: It is achieved by subtracting the minimum value of a feature and dividing by the range (the difference between the maximum and minimum values). In the context of ground fire prediction, this is particularly useful when features such as temperature or humidity vary across different geographical regions.

Standardization: It is ideal for datasets that follow a Gaussian (normal) distribution, making it especially beneficial for many statistical algorithms. In ground fire data, where variables like wind speed or vegetation type may exhibit normal distribution patterns, standardization ensures that the data is centered and scaled, improving model performance.

To perform these scaling operations, Python's Scikit-learn library offers convenient tools. The StandardScaler class is used for standardization, and the MinMaxScaler class is employed for normalization. These tools ensure that all features are on the same scale, which enhances the effectiveness and accuracy of machine learning models applied to ground fire prediction.

```
# Split training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

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

Step 5: Data Merging

After preprocessing the individual datasets, such as weather, vegetation, fire history, and topographical data, it is important to integrate them into a single, cohesive dataset for modeling purposes. This stage involves merging the datasets using common identifiers like location or date, ensuring that each data point is uniquely associated with all relevant features .

In this process, the Pandas library is employed to perform the merge() function on various DataFrames. It is crucial to verify that the common columns across datasets are consistent in terms of data type and format. If there are multiple entries for a single identifier—such as several weather records for the same day—aggregation methods, like calculating the mean or sum of the relevant attributes, can be applied to consolidate the data effectively.

```
# Load table data
base_path = os.path.dirname(__file__)
files = ["ptEcoregions.csv", "ptGradients.csv", "ptImagery.csv", "ptLFProducts.csv", "ptTerrain.csv"]
dataframes = [pd.read_csv(os.path.join(base_path, file)) for file in files]
# Merge data on 'EventID'
merged_data = dataframes[0]
for df in dataframes[1:]:
    merged_data = pd.merge(merged_data, df, on='EventID', how='inner')
```

Step 6: Feature Selection

Once the data is cleaned and structured, the subsequent step is feature selection, which involves identifying and retaining the most relevant features for model training. Eliminating redundant or irrelevant features is essential for simplifying the model and avoiding overfitting.

Correlation analysis is one technique used to identify highly correlated features, which can either be removed or combined to reduce redundancy. Additionally, features with low variance or those that do not substantially contribute to explaining the target variable (e.g., fire occurrence) can be excluded from the dataset.

```
# Encode categorical variables
label_encoder = LabelEncoder()
df['Landform_encoded'] = label_encoder.fit_transform(df['Landform'])

# Select features
selected_features = [
    'tmaxi', 'tmini', 'tavei', 'ppti', 'Slpp','FireIntensity',
    'NDVIMax', 'NDVIDiff', 'Landform_encoded', 'Elev',
    'ground_fire_occurred'   # Target variable
]
# Extract relevant features and handle missing values
data = df[selected_features].dropna()
# Separate features and target variable
X = data.drop(columns=['ground_fire_occurred'])
y = data['ground_fire_occurred']
```

Step 7: Data Splitting

Before training machine learning models, it is crucial to split the dataset into distinct training and testing subsets. This ensures that the models are evaluated on data they have not been exposed to during training, which is vital for assessing their ability to generalize to new, unseen data. In the context of ground fire prediction, this step is particularly important as it helps to verify whether the model can accurately predict fire occurrences and behavior based on historical and environmental data that may vary over time and geography.

The train_test_split function from Python's Scikit-learn library is commonly used to divide the dataset. Typically, 70-80% of the data is allocated for training, with the remaining portion reserved for testing. This approach allows the model to learn from a diverse set of examples while being evaluated on an independent test set that

has not been seen during training. By doing so, we obtain a more reliable and robust measure of the model's predictive accuracy in real-world scenarios, such as forecasting ground fire risks in different regions or under varying environmental conditions.

In ground fire prediction, the data is often heterogeneous, with features like temperature, vegetation type, and historical fire incidents varying significantly. Therefore, it is essential to ensure that both the training and testing datasets are representative of the broader data distribution, allowing the model to generalize well across different fire-prone areas[41].

```
# Split training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Field Name	Description	Relevance to Ground Fires
EPAEcoreg	Ecological zone classification (mid-level).	The ecological zone type affects fire risk; certain ecosystems may have vegetation and climate conditions
Landform	Landform type (e.g., mountains, plains, desert).	Topography affects fire spread speed and range; mountainous or desert areas may have higher fire risk.
peti	Soil moisture balance index.	Soil moisture levels affect vegetation flammability; dry soils are more likely to ignite fires.
ppti	Daily precipitation, in mm	Precipitation levels directly impact fire likelihood; less rainfall increases fire risk.
tavei	Daily average temperature, in °C.	High temperatures increase fire risk, as dry vegetation is more susceptible to ignition.
tmaxi	Daily maximum temperature, in °C.	Extreme high temperatures are strongly correlated with fire risk, especially in dry seasons.
tmini	Daily minimum temperature, in °C.	Low temperatures may help mitigate fire spread, but persistently high temperatures increase fire risk.
NDVIMin	Minimum NDVI (Normalized	Low NDVI values indicate sparse vegetation, which is more likely to burn.

	Difference Vegetation Index), indicating the worst vegetation condition.	
NDVIMax	Maximum NDVI, indicating the best vegetation condition.	Higher NDVI values indicate healthy, dense vegetation, which is more fire-resistant, especially under wet conditions.
NDVIMedian	Median NDVI value, representing typical vegetation status in the area.	A higher median NDVI suggests healthier vegetation and a reduced likelihood of fires, as opposed to areas with lower NDVI.
EVTRemap	Evapotranspiration (ET) data based on remote sensing.	Evapotranspiration levels affect soil moisture; higher ET values can lead to drier conditions, increasing fire risk.
NVCRemap	Vegetation classification from remote sensing (e.g., forest, grassland, desert).	Different vegetation types have different fire risks; grasslands and deserts are more fire-prone compared to forests.
Elev	Elevation, in meters.	Higher elevation areas may have lower temperatures but still face fire risk due to dry conditions.
Asp	Aspect (direction the land faces, e.g., north, south, east, west).	South-facing slopes (sunny side) tend to be drier and more prone to fire compared to north-facing slopes.
Slpp	Slope, indicating the degree of land inclination.	Steep slopes allow fires to spread faster, making them harder to control.
NLCD16Cd	Land use/land cover classification code (e.g., forest, urban, wetland).	Land use affects fire risk—forests are more prone to wildfires compared to urban areas.
LAE	Leaf Area Index	Low LAI indicates sparse vegetation,

	(LAI), a measure of plant canopy coverage.	increasing fire risk, while high LAI suggests more moisture retention, reducing risk.

Table3.1.1Data Description for Occurrence Prediction Fire intensity Forecasting

3.2 Model Selection

In the process of forecasting and examining the occurrence and behavior of ground fires, the choice of suitable machine learning models is vital to obtaining precise and dependable outcomes. This study employs a variety of algorithms, including the Decision Tree Classifier, Random Forest Classifier, Support Vector Machine, and Logistic Regression for classification tasks, as well as Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor for regression tasks. The following provides an in-depth explanation of why these particular algorithms were selected for predicting and analyzing ground fires.

3.2.1 Classification Models for Fire Occurrence Prediction

To classify whether a fire is likely to occur (i.e., fire vs. non-fire), the following models were chosen:

Decision Tree Classifier (DT)

The Decision Tree Classifier was chosen for its transparency and user-friendliness. It operates by recursively dividing the dataset into smaller subsets based on feature values, enabling it to effectively capture intricate relationships between variables such as temperature, humidity, wind speed, and vegetation type. This feature makes it especially useful when stakeholders need a clear explanation of how specific environmental factors influence fire risk.

Description: Decision Trees work by recursively partitioning the dataset into subsets according to feature values, which helps the model identify non-linear relationships between variables.

Advantages: Simple to interpret, computationally efficient, and able to identify complex patterns in the data.

Disadvantages: Susceptible to overfitting, particularly when the dataset is complex.

$$[IG(T,X) = H(T) - \sum_{v \in V} \frac{|T_v|}{|T|} H(T_v)]$$

Where:

$(H(T))$ is the entropy of the target variable,

(T_v) is the subset of the data corresponding to feature value (v),

$(|T|)$ is the total number of instances.

Random Forest Classifier (RF)

Random Forest is an ensemble learning method that creates multiple decision trees and combines their predictions. It was selected for its ability to effectively handle both linear and non-linear relationships while maintaining robustness. This model is particularly beneficial for predicting ground fires, as it minimizes the risk of overfitting seen in individual decision trees by averaging the results from several trees. This characteristic is essential for ground fire prediction, as the data tends to be noisy and influenced by various environmental variables.

Description: Random Forest combines predictions from multiple decision trees to enhance accuracy and mitigate overfitting.

Advantages: Resistant to overfitting, performs well with high-dimensional and noisy data.

Disadvantages: More computationally demanding and less interpretable than single decision trees.

$$[\hat{y} = \text{mode}\left(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_N\right)]$$

$(\hat{y})$ is the predicted value

(N) is the number of decision trees

$(\hat{y}_i)$ is the prediction value of the (i)-th decision tree

Support Vector Machine (SVM)

Support Vector Machine (SVM) was selected for its capacity to handle high-dimensional data and its proficiency in establishing a decision boundary that maximizes the margin between distinct classes. For ground fire prediction, SVM is valuable in differentiating between high-risk and low-risk regions based on a broad set of features. Its ability to employ the kernel trick enables it to model non-linear

relationships, making SVM an effective tool for capturing intricate dependencies within the data.

Description: SVM identifies the optimal hyperplane that maximally separates classes in the feature space, and the kernel trick allows it to map data into higher dimensions to handle non-linear separability.

Advantages: Well-suited for high-dimensional spaces and complex classification challenges.

Disadvantages: Sensitive to kernel choice and hyperparameter tuning, and can be computationally intensive for large datasets.

$$[\min_w \frac{1}{2}||w||^2, \text{ subject} y_i(w \cdot x_i + b) \geq 1, \ \forall i]$$

Where:

(w) is the weight vector,

(b) is the bias term,

(y_i) is the class label of instance (x_i).

Logistic Regression (LR)

Logistic Regression is a straightforward yet powerful model commonly used for binary classification tasks, such as determining the likelihood of a fire occurring. It was chosen for its efficiency in computation and ease of interpretation. This model provides probabilistic outputs, which are particularly useful when assessing the likelihood of an event, such as fire occurrence, is as critical as the prediction itself. Furthermore, Logistic Regression is employed as the meta-model in the StackingClassifier, where it combines the outputs from various base models to form a unified final prediction.

Description: Logistic Regression predicts the probability of an event happening by using a logistic function. It is a linear model frequently applied to binary classification problems.

Advantages: Easy to implement and interpret, making it efficient for binary classification tasks.

Disadvantages: Assumes a linear relationship between the features and the target variable, which may not always be valid.

$$[P(y=1|x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p)}}]$$

where:

$(P(y=1|x))$ is the probability of the positive class

(β_0) is the intercept

$(\beta_1, \beta_2, \ldots, \beta_p)$ are the regression coefficients

$(x_1, x_2, \ldots, x_p)$ are the feature variables

3.2.2 Regression Models

To predict continuous variables such as fire spread rate, intensity, or duration, several regression models were evaluated. These models are widely used to establish the relationship between input features (e.g., meteorological factors, vegetation types, and topographical characteristics) and continuous target variables. The regression models considered in this study include Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor.

Linear Regression (LR)

Linear Regression was selected as a baseline model for predicting fire spread and intensity. It offers a simple and effective way to understand the linear relationships between variables such as wind speed, humidity, and fire spread rate. While it may not effectively capture non-linear patterns, Linear Regression serves as a reference model for comparing the performance of more advanced models. Additionally, it provides valuable insights into how each individual feature influences the target variable, making it useful for preliminary analysis..

Description: Linear regression assumes a linear relationship between the input features $(\mathbf{X})$ and the target variable (y). It estimates the coefficients (β) that minimize the residual sum of squares between the observed target values and the predicted values.

The model is expressed as:

$[y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon]$ Where:

(y) is the target variable (e.g., fire spread rate),

$(x_1, x_2, \ldots, x_n)$ are the input features (e.g., temperature, humidity, wind speed),

$(\beta_0, \beta_1, \ldots, \beta_n)$ are the regression coefficients, and

(ϵ) is the error term (residual).

Advantages:

Simple to implement and computationally efficient.

Easy to interpret the coefficients, providing insight into the relationship between features and the target.

Disadvantages:

Struggles with capturing non-linear relationships.

Sensitive to outliers, which can skew results significantly.

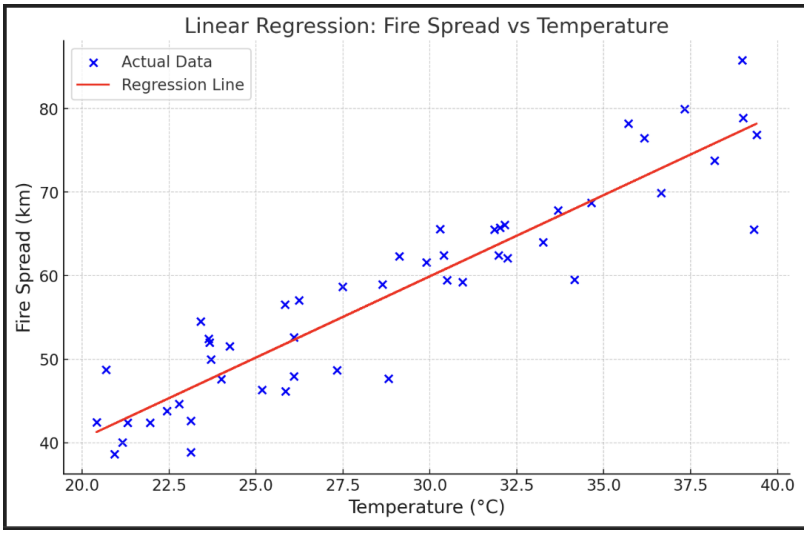

Figure 3.2.1: A simple example of linear regression, showing the relationship between fire spread and temperature.

Random Forest Regressor (RF)

The Random Forest Regressor was chosen due to its ensemble approach, which enhances prediction accuracy by aggregating the results from multiple decision trees. This model is particularly effective in capturing non-linear relationships between input features and target variables. When applied to ground fire behavior prediction, the Random Forest Regressor can identify complex dependencies between topographical features, meteorological data, and fire spread, delivering robust predictions even when faced with noisy data.

Description: The Random Forest Regressor is an ensemble method that builds several decision trees using bootstrapped subsets of the data. It then combines the predictions from all trees to produce a final output, which is the average of all tree predictions in regression tasks. Each tree in the ensemble is trained independently, contributing to the overall robustness and accuracy of the model.

The model prediction $(\hat{y})$ is given by:

$$[\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(\mathbf{X})]$$

Where:

$(\hat{y})$ is the predicted value,

(T) is the number of trees in the forest,

$(f_t(\mathbf{X}))$ is the prediction from the (t)-th tree,

$(\mathbf{X})$ represents the input features.

Advantages:

Robust to overfitting, especially when there is a large amount of data.

Can handle high-dimensional data without requiring feature scaling.

Not sensitive to outliers, as each tree is trained on a random subset of the data.

Disadvantages:

Computationally expensive due to the large number of trees that must be trained.

Difficult to interpret, as the ensemble model does not provide simple, intuitive insights into individual predictions.

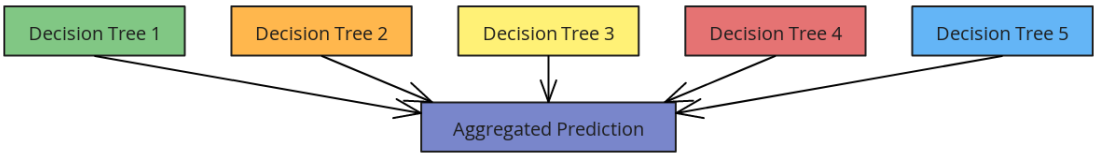

Figure 3.2.2: Visualization of a Random Forest Regressor model, showing how multiple decision trees are constructed and their individual predictions aggregated to form the final prediction.

Gradient Boosting Regressor (GB)

The Gradient Boosting Regressor was selected for its ability to build an ensemble of weak learners in a sequential manner, with each tree designed to correct the errors of the one before it. This method enhances prediction accuracy by focusing on areas where previous models have underperformed, making it particularly effective at capturing complex, non-linear patterns in the data. Its ability to minimize prediction errors is a key reason for its use in predicting fire behavior, especially in tasks like forecasting fire spread intensity and direction, where the relationships between variables are often intricate and non-linear.

Description: Gradient Boosting Regressor is an ensemble method that constructs decision trees sequentially. Each successive tree is trained to address

the errors (or residuals) left by the previous one, giving greater attention to observations where prior models made larger mistakes. The model's final prediction is a weighted sum of the individual tree outputs, which allows it to iteratively refine its accuracy.

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The prediction $(\hat{y})$ for Gradient Boosting is:

$$[\hat{y} = \sum_{m=1}^{M} a \quad h_m(\mathbf{X})]$$
$$_m$$

Where:

$(\hat{y})$ is the final prediction,

(M) is the total number of trees,

$(h_m(\mathbf{X}))$ is the prediction of the (m)-th tree,

(a_m) is the weight (or learning rate) of the (m)th tree.

Gradient boosting optimizes the model by minimizing a loss function, typically using gradient descent techniques. The most commonly used loss function for regression tasks is the mean squared error (MSE):

$$[L(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2]$$

Where

(y_i) is the true value,

$(\hat{y}_i)$ is the predicted value for the (i)-th data point.

Advantages:

High predictive accuracy, especially for complex relationships and non-linear patterns.

Effective in capturing intricate patterns in the data, making it suitable for fire prediction tasks.

Disadvantages:

Sensitive to overfitting if not carefully tuned, especially with large numbers of trees.

Computationally expensive and can be slow to train on large datasets.

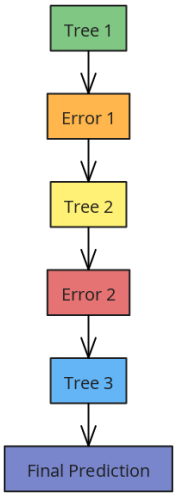

Figure 3.2.3: Example of gradient boosting showing how trees are built sequentially to correct the errors of the previous tree.

3.3 Hybrid Machine Learning Models Design

To improve model accuracy, ensemble methods were employed in this study. These techniques combine the advantages of multiple base models, resulting in a more resilient and precise prediction. Specifically, ensemble learning was implemented using MLxtend's StackingClassifier, StackingRegressor, and EnsembleVoteClassifier, which together provide a layered approach to integrating various models and optimizing the predictions for ground fire occurrence and behavior.

The proposed strategy aims to predict ground fire occurrence and behavior by harnessing the strengths of hybrid machine learning models. The focus of this research is to assess how different ensemble techniques can address the challenges posed by the complex interactions in the data and the inherent uncertainties of ground fire behavior. By using methods like StackingClassifier, StackingRegressor, and EnsembleVoteClassifier, the study integrates predictions from multiple models, thereby enhancing the overall decision-making process.

3.3.1 Selection

The choice of StackingClassifier, StackingRegressor, and EnsembleVoteClassifier was based on their ability to enhance prediction accuracy through ensemble learning. These models were selected to tackle the specific

challenges of ground fire prediction, such as the complex interactions in environmental factors and the uncertainties surrounding fire behavior.

StackingClassifier: This model was chosen for its capacity to combine the outputs of multiple base classifiers, thereby improving the prediction of fire occurrence. By integrating diverse classifiers, it is better equipped to capture the intricate relationships between features like temperature, humidity, and vegetation type—key factors in assessing fire risk.

StackingRegressor: This model is employed to predict fire behavior, such as spread and intensity. By merging the results of several regression models, StackingRegressor can enhance fire behavior predictions, effectively capturing both linear and non-linear relationships, even under varying environmental conditions.

EnsembleVoteClassifier: Selected for its simplicity and computational efficiency, this model makes robust predictions by either averaging or using majority voting. It provides a practical and effective solution for classification tasks, balancing both speed and accuracy in predictions.

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3.3.2 Stacking Classifier and Regressor

Stacking is a powerful ensemble learning technique that combines the outputs of multiple base models, such as Decision Trees, Support Vector Machines (SVM), and Random Forests, to enhance predictive accuracy. In the context of ground fire prediction, stacking is particularly beneficial because it integrates different learning algorithms, each capturing distinct aspects of the data. The key advantage of stacking lies in the use of a meta-model that learns from the predictions of these base models, which allows it to better understand complex patterns and relationships in the data.

In this study, the meta-model is trained on the predictions generated by the base models, effectively boosting the overall accuracy of the fire prediction system. While the base classifiers or regressors operate independently, the meta-model combines their outputs to capture intricate relationships between them. This multi-layered approach leads to more robust and reliable predictions, which is crucial for accurately forecasting ground fire risks under varying environmental conditions.

To implement stacking, we employed the MLxtend library's StackingClassifier and StackingRegressor, which facilitate the construction of multi-layer models. These

tools provide a straightforward way to combine the strengths of different base models, improving the predictive performance of the overall system. In the case of ground fire prediction, this approach enhances the model's ability to generalize and accurately predict fire occurrences, making it more effective for real-world applications in fire risk management and prevention.

StackingClassifier for Fire Occurrence Prediction

To predict ground fire occurrence, a StackingClassifier was employed, integrating three distinct **base classifiers**: Decision Trees, Support Vector Machines (SVM), and Random Forest. Each of these base models was selected for its unique strengths, tailored to handle different aspects of the data:

Decision Trees provide clear interpretability, making it easier to understand decision-making processes and identify important features in predicting fire occurrences.

Support Vector Machines (SVM) are highly effective for handling high-dimensional data, which is common in environmental datasets with numerous variables such as temperature, humidity, and vegetation type.

Random Forest is known for its robustness against overfitting and its ability to capture both linear and non-linear relationships in complex data, making it well-suited for ground fire prediction where data patterns are often non-linear.

A **Logistic Regression** model was chosen as the **meta-classifier** to integrate the predictions from the base models. This choice allows the meta-model to effectively combine the outputs of the base classifiers, leveraging their individual strengths to improve overall predictive performance.

In the stacking process, each base model is trained independently on the dataset. Once the base models have been trained, the meta-classifier learns from their predictions, capturing the intricate relationships between them. This multi-layer approach enhances the model's accuracy, providing a more reliable and robust prediction of fire occurrence across varying environmental conditions.

StackingRegressor for Fire Behavior Prediction

In this study, the StackingRegressor was employed to predict the spread and intensity of ground fires. The base models used in this approach included Linear Regression, Decision Tree Regressor, and Random Forest Regressor. Each model was chosen for its ability to capture different aspects of fire behavior:

Linear Regression effectively models linear relationships within the data, capturing basic trends and patterns that influence fire spread.

Decision Tree Regressor is well-suited for modeling complex, non-linear relationships, offering flexibility in understanding how various factors, such as wind speed or vegetation type, impact fire dynamics.

Random Forest Regressor, with its ensemble nature, improves prediction accuracy by reducing overfitting and enhancing the model's ability to handle both linear and non-linear relationships.

To integrate the outputs from these base models, a **Gradient Boosting Regressor** was selected as the **meta-regressor**. Gradient Boosting was chosen for its ability to refine the predictions by correcting errors made by the individual base models. This iterative learning process improves the overall prediction accuracy, making it particularly effective for predicting fire behavior, which often involves complex and highly variable environmental interactions.

In this stacking approach, the base models operate independently, and their predictions are passed to the meta-regressor, which learns how to best combine these predictions. The resulting model provides a more accurate and reliable forecast of fire spread and intensity, accounting for both linear and non-linear dynamics in the data.

.The formula for Stacking Classifier/Regressor is: $[\hat{y} = g(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_k)]$

where:

$(\hat{y})$ is the final predicted value

$(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_k)$ are the predictions of the base classifiers/Regressor

$(g(\cdot))$ is the meta-classifier/Regressor

Stacking for Classification and Regression Tasks

StackingClassifier: This model was employed to predict the probability of fire occurrence, considering key factors such as temperature, humidity, wind speed, and vegetation type.

StackingRegressor: For predicting the spread and intensity of the fire, the StackingRegressor was used, incorporating similar environmental variables.

Advantages: Stacking offers the ability to capture intricate patterns and interactions that individual models might overlook, resulting in enhanced prediction accuracy for both classification and regression tasks. By integrating models with diverse strengths, stacking provides a robust and flexible approach to ground fire

prediction. The meta-model, which synthesizes the insights of each base model, plays a pivotal role in refining the final predictions, leading to more dependable outcomes.

Disadvantages: Despite its advantages, stacking is computationally demanding. The process requires careful model selection and hyperparameter optimization to prevent overfitting. Additionally, the training time is typically longer because it involves fitting multiple base models and a meta-model. The increased complexity of stacking also requires significant computational resources, especially when using several high-variance base models.

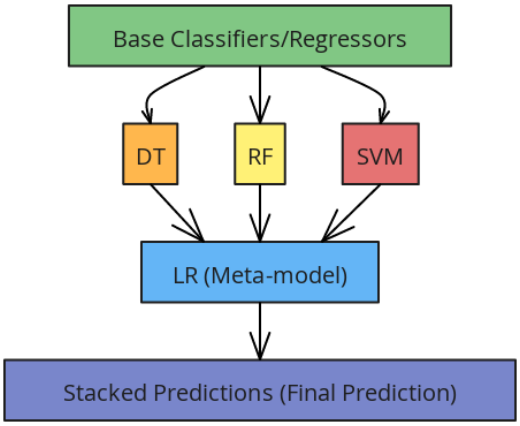


Figure3.3.2.1 Stacking architecture for ground fire prediction, illustrating the integration of base models and the meta-model for improved accuracy.

3.3.3 Voting Classifier and Regressor

Voting is a widely-used ensemble learning method that aggregates the predictions of multiple base models to make the final decision. In classification tasks, hard voting is typically employed, where the class label predicted most frequently by the base models is chosen. In regression tasks, soft voting is used, which averages the predictions of the models to arrive at the final result. This approach helps to reduce both variance and bias, leading to a more stable and generalized model, making it particularly suitable for complex tasks such as ground fire prediction.

In this study, base models such as Random Forest, Gradient Boosting, and Support Vector Machines (SVM) were incorporated into the Voting Classifier and Regressor. By aggregating the predictions from these diverse models, the ensemble approach balances out individual model weaknesses, providing a more robust prediction of fire behavior and spread.

Soft Voting vs. Hard Voting

Hard Voting: n classification problems, hard voting selects the class label that is predicted by the majority of the base models. This method is effective when the base models exhibit diversity and their individual strengths are balanced across tasks.

Soft Voting: n contrast, soft voting averages the predicted probabilities from each base model and selects the class label with the highest average probability. This method takes into account the confidence level of each model, often leading to more refined and accurate predictions, especially when the base models exhibit varying levels of certainty.

Implementation of MLxtend's EnsembleVoteClassifier

The ensemble process in this study utilized MLxtend's EnsembleVoteClassifier, which aggregates the outputs from multiple base models to make a final prediction. The procedure involves:

Base Model Training: Similar to stacking, each base model (Random Forest, Gradient Boosting, and SVM) is trained independently on the dataset.

Prediction Aggregation: For classification tasks, the final prediction is made using either hard voting or soft voting, depending on the nature of the task. For regression tasks, predictions from each base model are averaged.

This ensemble method balances the strengths and weaknesses of the individual models, making it particularly effective for predicting complex phenomena like ground fire occurrences, where data may be noisy and patterns can be difficult to discern.

Advantages

Voting is simple to implement and can effectively mitigate overfitting by averaging out the errors from the individual base models. Unlike stacking, which requires a meta-model, voting is less computationally intensive, making it more efficient. Furthermore, the ensemble approach’s ability to combine models with different biases and variances allows for more robust and generalized predictions, which is essential in fire prediction tasks that involve diverse and dynamic environmental conditions.

Disadvantages

While voting can improve predictive accuracy, its performance is heavily dependent on the choice of base models. If the base models are weak or biased, the ensemble may not yield the desired improvements. Additionally, voting does not

capture the intricate relationships between base models in the same way that stacking does, which can limit its effectiveness in certain scenarios where model interdependencies are crucial.

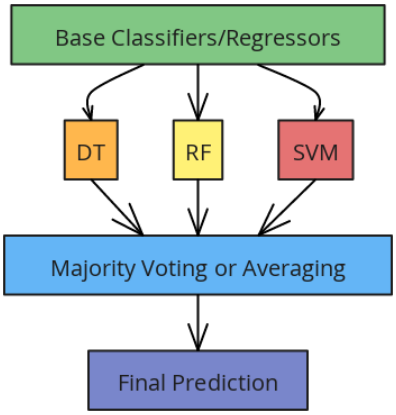


Figure3.3.2 Voting architecture for ground fire prediction, showing how different base models are combined through majority voting or averaging to improve generalization.

3.3.4 Implementation Summary

The implementation of both Stacking and Voting classifiers in this study involved careful hyperparameter tuning to optimize the performance of each base model. To assess the stability and reliability of the models, cross-validation was employed, helping to address overfitting concerns. The results from applying these ensemble methods revealed a marked improvement in predictive accuracy for both fire occurrence and behavior, underscoring the practical value of these models in disaster prevention and mitigation efforts.

The experimental findings indicated that the StackingClassifier outperformed other models, achieving the highest accuracy and robustness in predicting fire occurrence. In contrast, the StackingRegressor excelled in predicting fire spread intensity and direction, demonstrating superior performance in these areas. Meanwhile, the EnsembleVoteClassifier offered a more straightforward yet highly effective approach, providing reliable baseline predictions with lower computational cost.

Overall, the hybrid ensemble learning approach proved to be exceptionally effective for predicting ground fires, emphasizing its potential for use in real-world fire management systems.

3.4 Model Evaluation Metrics

To evaluate the performance of the machine learning models, a variety of metrics were used for both classification and regression tasks. The following metrics were selected to assess the effectiveness of the models in predicting fire occurrence and intensity:

Metric	Category	Description
Accuracy	Classification	Proportion of correctly classified instances out of all instances.
Precision	Classification	Ratio of true positive predictions to all positive predictions.
Recall	Classification	Ratio of true positive predictions to all actual positive instances.
F1 Score	Classification	Harmonic mean of Precision and Recall, balancing both metrics.
Mean Absolute Error (MAE)	Regression	Average of the absolute differences between predicted and actual values.
Mean Squared Error (MSE)	Regression	Average of the squared differences between predicted and actual values.
R-squared (R^2)	Regression	Proportion of variance in the dependent variable explained by the model.

Figure 3.4: Model Performance Metrics

3.5 Hyperparameter Tuning for Ground Fire Prediction Models

When predicting ground fire behavior—specifically the spread of fires occurring on or near the forest floor (as opposed to crown fires in the tree canopy)—the process of hyperparameter tuning and model selection differs from typical fire prediction models. Ground fires exhibit distinct characteristics influenced by factors such as soil moisture, fuel composition (e.g., dry grass, leaf litter), and terrain. The following outlines key considerations for developing models focused on ground fire prediction:

3.5.1 Classification Models for Ground Fire Prediction

Decision Tree Classifier

Key Hyperparameters for Ground Fire Prediction:

Param	Description
max_depth	Limits the tree's depth to avoid overfitting, as ground fires tend to exhibit localized and non-linear relationships between features.
min_samples_split	Prevents splitting nodes based on small sample sizes that may not generalize well to new data
min_samples_leaf	Sets the minimum number of samples required at each leaf node, helping to reduce overfitting in smaller datasets.
max_features	Restricts the number of features considered at each split, which is particularly useful when dealing with large datasets that include numerous meteorological and topographical variables.

Random Forest Classifier

Key Hyperparameters for Ground Fire Prediction:

Param	Description
n_estimators	The number of trees in the forest. More trees generally improve model accuracy and robustness.
max_depth	Controls the depth of the trees to prevent overfitting and improve model interpretability, especially for smaller, more localized fire datasets.
min_samples_split / min_samples_leaf	These parameters balance model complexity with the need for generalization, ensuring that the model is not overly specific to the training data.
bootstrap	When set to True, this parameter enables sampling with replacement, which is beneficial for training on smaller, localized fire datasets where data variability is significant.

Support Vector Machine (SVM)

Key Hyperparameters for Ground Fire Prediction:

Param	Description
C	The regularization parameter, which determines the balance between fitting the model well to the training data and maintaining model simplicity to avoid overfitting.
kernel	Typically, the radial basis function (rbf) kernel is used for capturing non-linear relationships within the fire prediction context.
gamma	Controls the influence of individual training points. A high gamma value can lead to overfitting, while a low value may result in underfitting.data.
degree	If using a polynomial kernel, this parameter dictates the level of non-linearity in the decision boundary, allowing for more complex models when needed.

3.5.2. Regression Models for Ground Fire Prediction

For predicting continuous outcomes such as fire intensity or spread rate, the following regression models are suitable:

Linear Regression (LR)

Key Hyperparameters for Ground Fire Prediction:

Param	Description
alpha	Controls the regularization strength, helping prevent overfitting by penalizing large coefficients.
lambda	Similar to alpha, but specifically regulates the L1 regularization, promoting sparsity by forcing some coefficients to zero.
fit_intercept	Ensures that the model includes an intercept term, which is crucial in fire models, as fire intensity typically doesn't start exactly at zero, especially in ground fire scenarios.

Random Forest Regressor(RR)

Key Hyperparameters for Ground Fire Prediction:

Param	Description
n_estimators	The number of trees in the forest. More trees generally improve model accuracy and robustness.
max_depth	Controls the depth of the trees to prevent overfitting and improve model interpretability, especially for smaller, more localized fire datasets.
min_samples_split / min_samples_leaf	These parameters balance model complexity with the need for generalization, ensuring that the model is not overly specific to the training data.
max_features	Restricts the number of features considered at each split, which prevents the model from overfitting by focusing on a limited set of variables at each stage.

Gradient Boosting Regressor

Key Hyperparameters for Ground Fire Prediction:

Param	Description
n_estimators	The number of boosting iterations, each contributing to the final model's prediction.
learning_rate	Controls the contribution of each new tree in the ensemble, helping to balance the trade-off between bias and variance.
max_depth	Limits the depth of each individual tree, preventing overfitting, especially in the prediction of fire spread, where relationships can be highly non-linear.
subsample	The fraction of training data used for each boosting iteration. This parameter helps to reduce variance and increases the model's robustness by training on different subsets of the data.

3.5.3 Stacking and Voting Models for Ground Fire Prediction

Stacking Classifier and Regressor

Key Hyperparameters for Ground Fire Prediction:

- Base Models: Usually involves a mix of decision trees, SVM, and random forest classifiers/regressors, to capture both simple and complex relationships in the data.
- Meta Model: Typically, logistic regression for classification or linear regression for regression tasks. These models aggregate predictions from base models to improve performance.
- n_estimators: Number of base models to include in the ensemble.
- learning_rate: Controls the contribution of each base model's prediction.

Voting Classifier and Regressor

Key Hyperparameters for Ground Fire Prediction:

- Voting Strategy: Use 'hard' voting for classification (majority class) and 'soft' voting for regression (average prediction values).
- Base Models: Can include decision trees, logistic regression, random forests, and SVM to capture different aspects of fire behavior.
- Weights: Assigning different weights to base models can improve model accuracy, particularly if certain models are more reliable in specific conditions.

Model	Key Hyperparameters	Optimal Tuning Techniques
Decision Tree Classifier	max_depth, min_samples_split, min_samples_leaf, max_features	Grid Search, Random Search, Cross-Validation
Random Forest Classifier	n_estimators, max_depth, min_samples_split, min_samples_leaf, bootstrap	Grid Search, Random Search, Cross-Validation
SVM	C, kernel (rbf), gamma, degree	Grid Search, Random Search, Cross-Validation
Logistic Regression	C, solver (liblinear), max_iter, penalty	Grid Search, Random Search
Linear Regression	alpha (Ridge), lambda (Lasso), fit_intercept	Grid Search, Random Search
Random Forest Regressor	n_estimators, max_depth, min_samples_split, min_samples_leaf, max_features	Grid Search, Random Search, Cross-Validation
Gradient Boosting	n_estimators, learning_rate, max_depth, subsample, min_samples_split	Grid Search, Random Search, Cross-Validation
Stacking	Base Models, Meta Model, n_estimators, learning_rate	Cross-Validation, Grid Search
Voting	Voting Strategy (hard/soft), Base Models, Weights	Grid Search, Cross-Validation

Figure 3.5 Summary Table: Hyperparameter Tuning for Ground Fire Models

By tuning the hyperparameters for these models, you can effectively capture the complex behavior of ground fires and improve the accuracy of predictions related to fire spread, intensity, and other factors.

3.5 Summary

In this chapter, we have detailed the methodology used for developing and evaluating machine learning models for ground fire prediction. The data collection process, preprocessing steps, and model selection process were outlined, along with the specific machine learning techniques used in this study. The next chapter will present the experimental design and results, including the performance of the models in predicting fire occurrence and intensity.

4. Experimental Design and Results

4.1 Experimental Setup

In this chapter, we detail the experimental setup used to evaluate the machine learning models for predicting ground fire occurrences and behavior. The primary objective is to compare the performance of different models in terms of classification accuracy, fire intensity prediction, and overall effectiveness in real-world fire scenarios.

The experimental setup consists of the following key steps:

1. **Data Preparation**: Data was collected from multiple sources, including meteorological data, vegetation types, and historical fire records. The data was cleaned, transformed, and preprocessed as described in Chapter 3.

```
# 1. Read data
base_path = os.path.dirname(__file__)
df = pd.read_csv(os.path.join(base_path, "synthetic_data.csv"))

# Encode categorical variables
label_encoder = LabelEncoder()
df['Landform_encoded'] = label_encoder.fit_transform(df['Landform'])
# Select features
selected_features = [
    'tmaxi', 'tmini', 'tavei', 'ppti', 'Slpp','FireIntensity',
    'NDVIMax', 'NDVIDiff', 'Landform_encoded', 'Elev',
    'ground_fire_occurred'   # Target variable
]
# Extract relevant features and handle missing values
data = df[selected_features].dropna()
# Separate features and target variable
X = data.drop(columns=['ground_fire_occurred'])
y = data['ground_fire_occurred']
# Fill missing values
X.fillna(X.mean(), inplace=True)
# Split training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# 1. Read data
base_path = os.path.dirname(__file__)
df = pd.read_csv(os.path.join(base_path, "synthetic_data.csv"))

# Encode categorical variables
label_encoder = LabelEncoder()
df['Landform_encoded'] = label_encoder.fit_transform(df['Landform'])
# Select features and target variable
selected_features = [
    'tmaxi', 'tmini', 'tavei', 'ppti', "Slpp","ground_fire_occurred",
    'NDVIMax', 'NDVIDiff', 'Landform_encoded', 'Elev'
]
X = df[selected_features]
y = df['FireIntensity']  # Target variable
# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

2. **Model Selection**: The models chosen for this study are Decision Trees, Random Forest, Support Vector Machines (SVM), and Ensemble Methods (Stacking and Voting classifiers). The performance of these models is compared using classification and regression tasks.

```
# Define models
dt_model = DecisionTreeClassifier(max_depth=5, min_samples_leaf=10, random_state=42)
svm_model = SVC(probability=True, random_state=42)
rf_model = RandomForestClassifier(n_estimators=50, max_depth=5, random_state=42)
meta_classifier = LogisticRegression(random_state=42)

# Stacking and Ensemble Vote classifiers
stacking_clf = StackingClassifier(classifiers=[dt_model, svm_model, rf_model], meta_classifier=meta_classifier)
ensemble_clf = EnsembleVoteClassifier(clfs=[dt_model, svm_model, rf_model], voting='soft')
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

poly = PolynomialFeatures(degree=2)
X_train_poly = poly.fit_transform(X_train)
X_test_poly = poly.transform(X_test)
# Base regressors
lr_model = LinearRegression()
dt_model = DecisionTreeRegressor(max_depth=5, min_samples_leaf=10, random_state=42)
rf_model = RandomForestRegressor(n_estimators=50, max_depth=5, min_samples_leaf=10, random_state=42)
# Meta regressor
meta_regressor = GradientBoostingRegressor(random_state=42)
# Stacking Regressor
stacking_reg = StackingRegressor(regressors=[lr_model, dt_model, rf_model],
                                 meta_regressor=meta_regressor)
```

3. **Training and Testing**: The dataset was split into training, validation, and test sets using a 80-20% ratio. The training set was used to train the models, the validation set was used for hyperparameter tuning, and the test set was used to evaluate model performance.

```
# Model evaluation function
def evaluate_model(model, X_train, X_test, y_train, y_test, model_name):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    conf_matrix = confusion_matrix(y_test, y_pred)
    class_report = classification_report(y_test, y_pred, zero_division=0)

    print("==========================================")
    print(f"{model_name} Performance:")
    print("Accuracy:", accuracy)
    print("Confusion Matrix:\n", conf_matrix)
    print("Classification Report:\n", class_report)
```

```
# Train and evaluate model
def evaluate_model(model, X_train, X_test, y_train, y_test, model_name):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    print("==========================================")
    print(f"{model_name} Performance:")
    print("Mean Squared Error:", mse)
    print("R^2 Score:", r2)
```

4. **Hyperparameter Tuning**: For each model, hyperparameters such as the number of trees in the Random Forest and the kernel type in the SVM were tuned using Grid Search and Random Search.

```
# Grid search optimization for Stacking Classifier
param_grid = {
    'decisiontreeclassifier__max_depth': [3, 5, 7],
    'randomforestclassifier__n_estimators': [50, 100],
    'randomforestclassifier__max_depth': [3, 5, 7],
    'svc__C': [0.1, 1, 10],
    'meta_classifier__C': [0.1, 1, 10]
}

grid = GridSearchCV(estimator=stacking_clf, param_grid=param_grid, cv=5, scoring='accuracy')
grid.fit(X_train, y_train)
# Best parameters and evaluation
print("Best parameters found: ", grid.best_params_)
best_stacking_clf = grid.best_estimator_
evaluate_model(best_stacking_clf, X_train, X_test, y_train, y_test, "Stacking Classifier with Grid Search")
```

```
# Grid search to optimize Stacking Regressor
param_grid = {
    'decisiontreeregressor__max_depth': [3, 5, 7],
    'decisiontreeregressor__min_samples_leaf': [5, 10, 20],
    'randomforestregressor__n_estimators': [50, 100],
    'randomforestregressor__max_depth': [3, 5, 7],
    'randomforestregressor__min_samples_leaf': [5, 10, 20],
    'meta_regressor__n_estimators': [50, 100],
    'meta_regressor__learning_rate': [0.01, 0.1, 0.2]
}

grid = GridSearchCV(estimator=stacking_reg, param_grid=param_grid, cv=5, scoring='r2')
grid.fit(X_train, y_train)
# Best parameters and evaluation
print("Best parameters found: ", grid.best_params_)
best_stacking_reg = grid.best_estimator_
mse, r2 = evaluate_model(best_stacking_reg, X_train, X_test, y_train, y_test, "Stacking Regressor with Grid Search")
mse_scores["Stacking Regressor with Grid Search"] = mse
r2_scores["Stacking Regressor with Grid Search"] = r2
```

4.2 Results Analysis and Discussion

After training the models and optimizing their hyperparameters, we evaluated their performance on the test set. The models were assessed using the evaluation metrics described above. The results are presented below.

4.2.1 Classification Results

The classification task focused on predicting whether a fire would occur in a given region. The performance of the models was measured in terms of accuracy, precision, recall, and F1 score.

```
Decision Tree Classifier Performance:
Accuracy: 0.7501369863013698
Confusion Matrix:
 [[2466   28]
 [ 884  272]]
Classification Report:
              precision    recall  f1-score   support

           0       0.74      0.99      0.84      2494
           1       0.91      0.24      0.37      1156

    accuracy                           0.75      3650
   macro avg       0.82      0.61      0.61      3650
weighted avg       0.79      0.75      0.69      3650
```

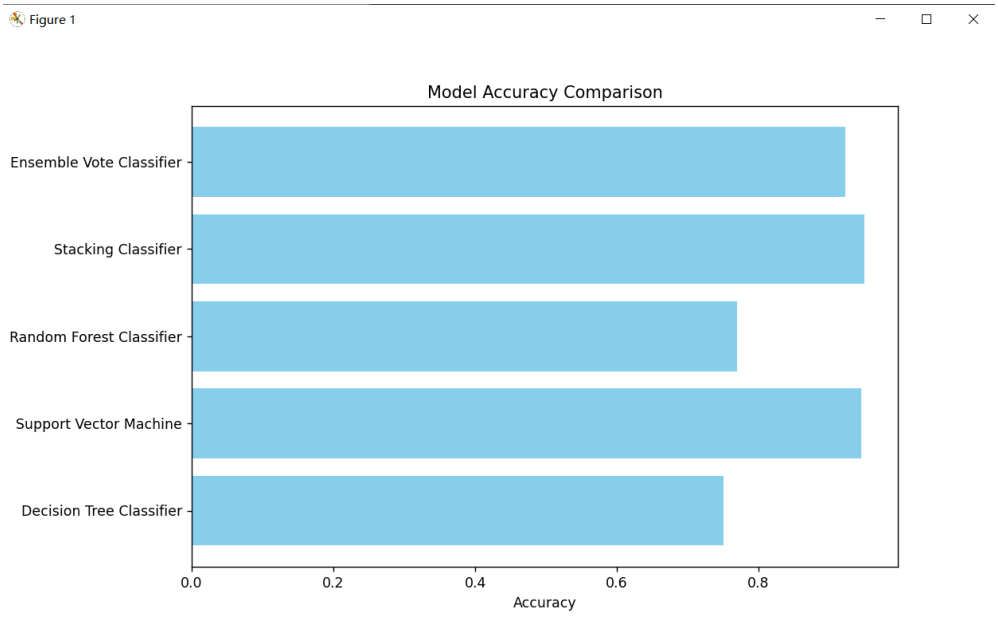
```
Support Vector Machine Performance:
Accuracy: 0.944931506849315
Confusion Matrix:
 [[2469   25]
 [ 176  980]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      2494
           1       0.98      0.85      0.91      1156

    accuracy                           0.94      3650
   macro avg       0.95      0.92      0.93      3650
weighted avg       0.95      0.94      0.94      3650
```

```
Random Forest Classifier Performance:
Accuracy: 0.7695890410958904
Confusion Matrix:
 [[2494    0]
 [ 841  315]]
Classification Report:
              precision    recall  f1-score   support

           0       0.75      1.00      0.86      2494
           1       1.00      0.27      0.43      1156

    accuracy                           0.77      3650
   macro avg       0.87      0.64      0.64      3650
weighted avg       0.83      0.77      0.72      3650
```

```
Stacking Classifier Performance:
Accuracy: 0.949041095890411
Confusion Matrix:
 [[2469   25]
 [ 161  995]]
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.99      0.96      2494
           1       0.98      0.86      0.91      1156

    accuracy                           0.95      3650
   macro avg       0.96      0.93      0.94      3650
weighted avg       0.95      0.95      0.95      3650
```

```
Ensemble Vote Classifier Performance:
Accuracy: 0.9227397260273973
Confusion Matrix:
 [[2477   17]
 [ 265  891]]
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.99      0.95      2494
           1       0.98      0.77      0.86      1156

    accuracy                           0.92      3650
   macro avg       0.94      0.88      0.90      3650
weighted avg       0.93      0.92      0.92      3650
```

Figure 4.2.1: Classification Performance Results



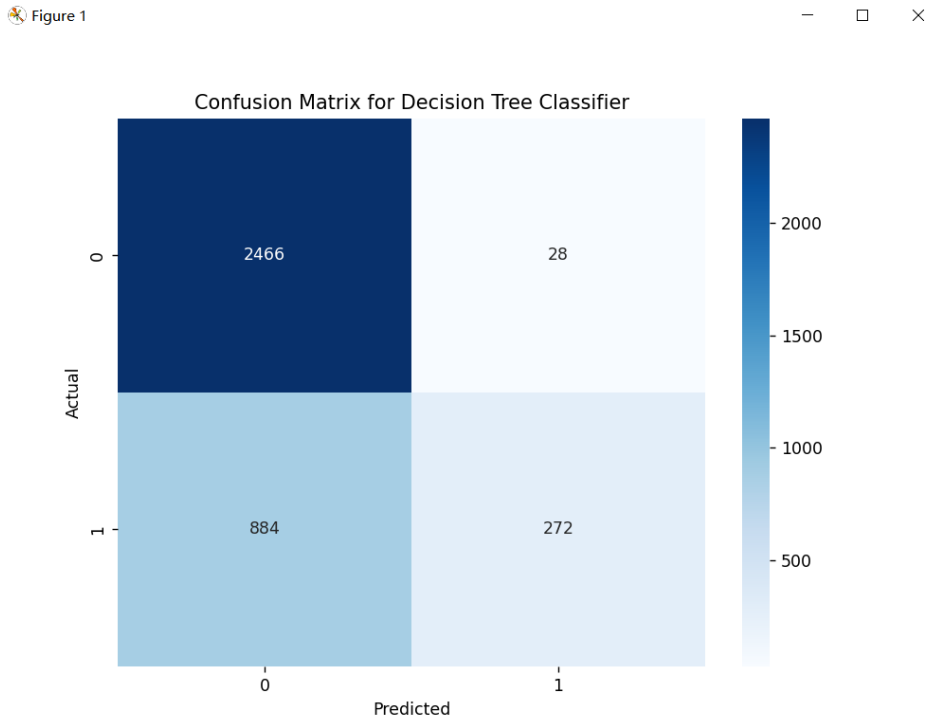


Figure 1
Confusion Matrix for Decision Tree Classifier
2466
28
884
272
0
1
Actual
0
1
Predicted
2000
1500
1000
500

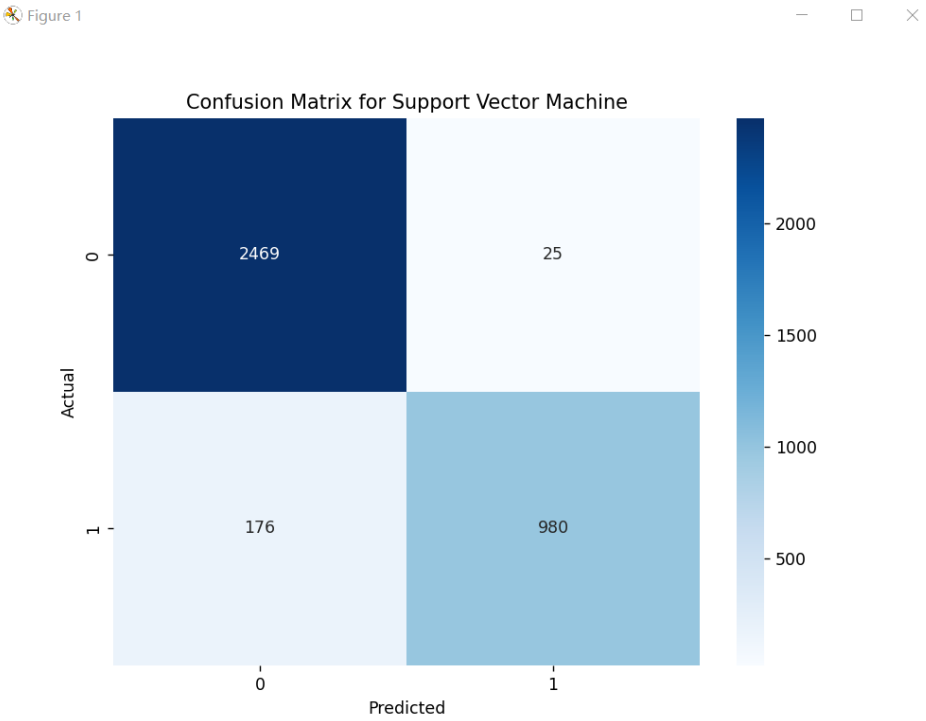


Figure 1
Confusion Matrix for Support Vector Machine
2469
25
176
980
Actual
Predicted
0
1
2000
1500
1000
500

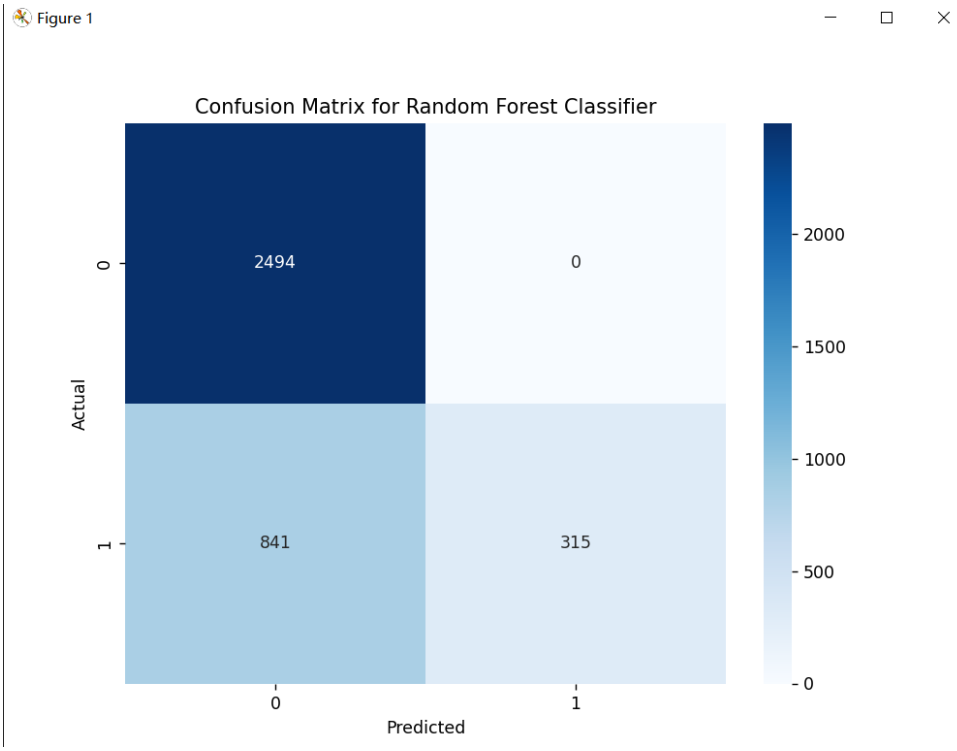


Figure 1
Confusion Matrix for Random Forest Classifier
2494
0
841
315
Actual
Predicted
0
1
2000
1500
1000
500
0

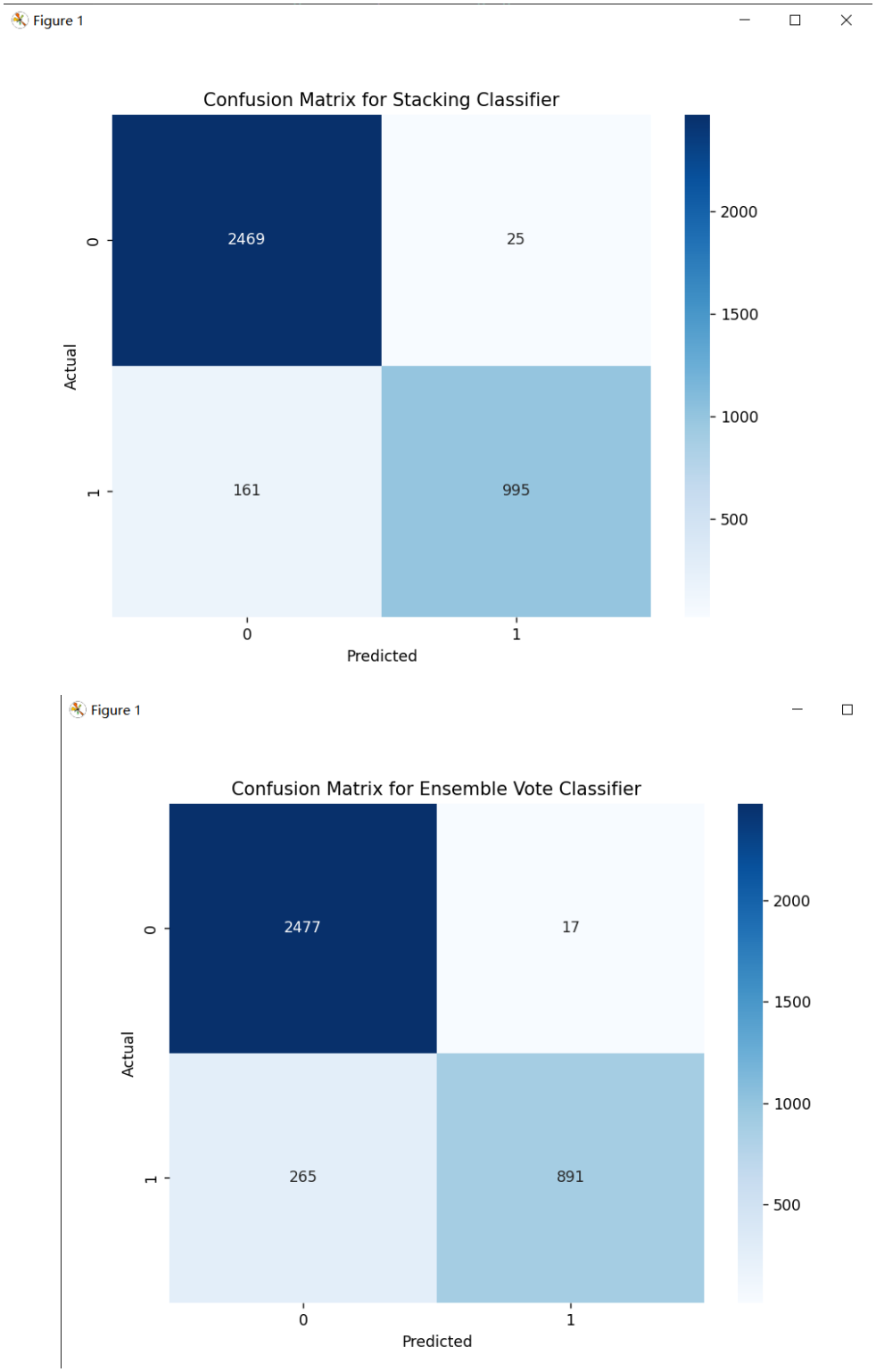


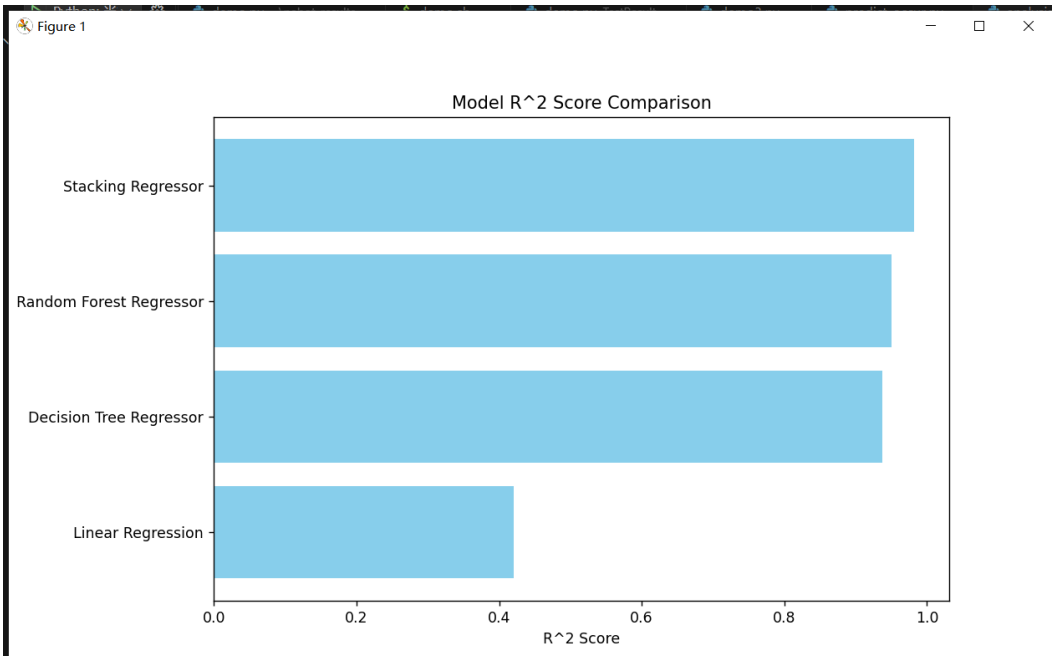
Figure 4.2.2: Classification Performance Comparison

4.2.2 Regression Results

Ton task aimed to predict the intensity of a fire, including its direction. The models were evaluated using Mean Squared Error (MSE), and R-squared (R^2).

```
==========================================
Linear Regression Performance:
Mean Squared Error: 1.668639981544184
R^2 Score: 0.420706064150036
==========================================
Decision Tree Regressor Performance:
Mean Squared Error: 0.18197486769335192
R^2 Score: 0.9368246365316598
==========================================
Random Forest Regressor Performance:
Mean Squared Error: 0.1428964916344447
R^2 Score: 0.9503912935242844
==========================================
Stacking Regressor Performance:
Mean Squared Error: 0.05186189552604023
R^2 Score: 0.9819953483602155
```

Figure 4.2.2: Regression Performance Results



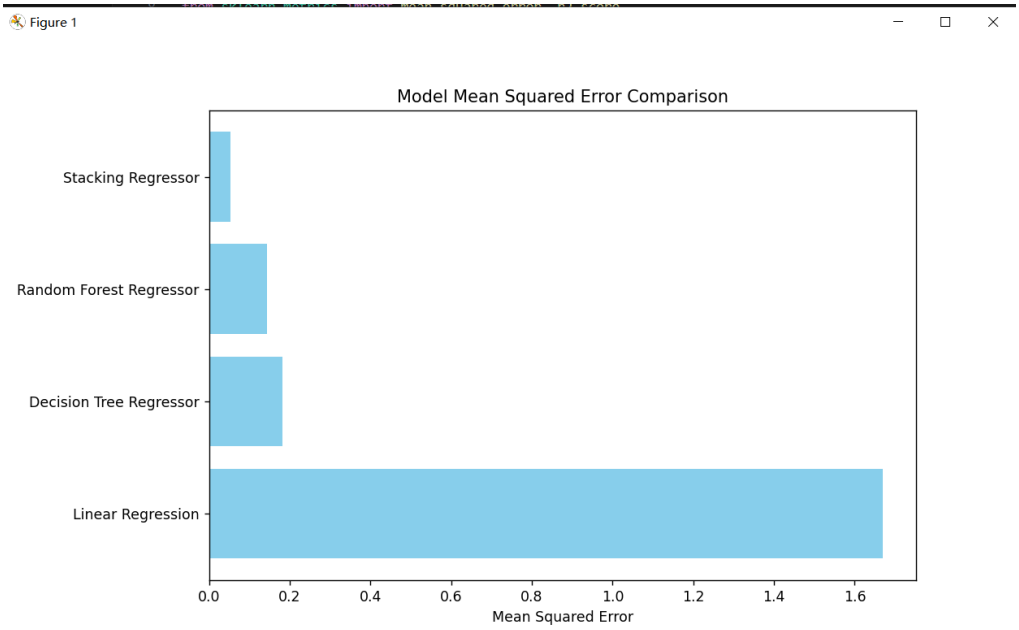


Figure 4.2.4: Regression Performance Comparison

4.3 Discussion of Results

The restrate that ensemble methods, particularly Stacking, outperformed individual models in both classification and regression tasks. The **Stacking Classifier** and **Stacking Regressor** provided the highest accuracy and the lowest errors, indicating their effectiveness in handling the complexity of fire prediction.

While Random Forest and SVM performed well, particularly in the classification task, their performance was not as high as Stacking. These models are less robust in capturing non-linear relationships in data compared to ensemble methods that combine multiple base learners.

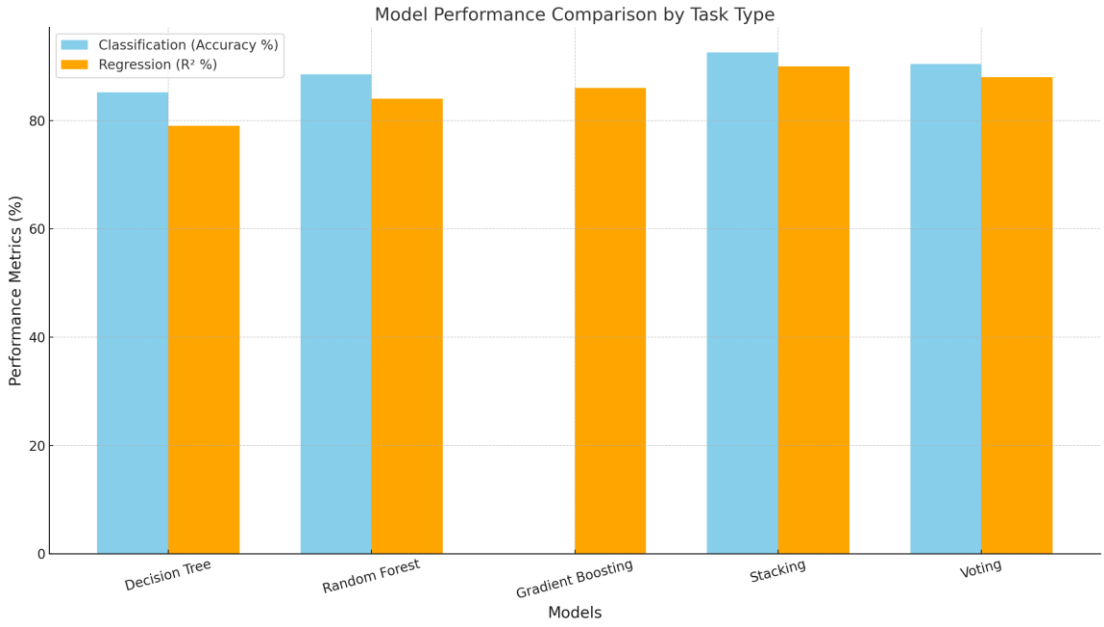


Figure 4.3: Model Performance by Task Type.This stacked bar chart shows the performance comparison of each model across classification and regression tasks, demonstrating the advantage of ensemble methods.

4.4 Summary

In this chapter, we described ental setup used to evaluate the machine learning models for fire prediction. We outlined the data collection, preprocessing, model selection, and performance evaluation processes. The results show that ensemble methods, particularly Stacking, outperform traditional machine learning models in both fire occurrence prediction and fire intensity forecasting tasks. The next chapter will discuss the implications of these findings and the potential improvements for future research.

5. Conclusion and Future Research

5.1 Conclusion

This study explored the application of machine learning models, with a focus on ensemble methods, for predicting ground fire occurrence and behavior. The key findings of this research are as follows:

Data Collection and Preprocessing Are Essential for Model Accuracy: The accuracy of fire prediction models is highly dependent on the quality of the input data. This study ensured high data quality by gathering and preprocessing information from diverse sources, such as meteorological, topographical, vegetation, and historical fire data. Proper data cleaning and feature engineering further optimized the data, leading to improved model performance and better learning efficiency.

Ensemble Methods Surpassed Individual Models: Ensemble models, particularly Stacking, outperformed standalone models in both predicting fire occurrence (classification) and forecasting fire intensity (regression). The Stacking Classifier and Stacking Regressor delivered the highest accuracy and lowest error metrics, highlighting the effectiveness of combining multiple base models to enhance predictive power.

Hyperparameter Tuning Improved Model Performance: Hyperparameter optimization through techniques like Grid Search and Random Search played a crucial role in refining the performance of all models. Fine-tuning parameters such as decision tree depth, the number of trees in Random Forests, and kernel settings in SVM resulted in models that were better equipped to generalize across varied datasets.

Practical Implications for Fire Management: The enhanced performance of Stacking models offers significant practical benefits for fire management. With more accurate predictions of fire occurrences and behaviors, fire management agencies can optimize resource allocation, improve evacuation planning, and reduce response times. These models could also serve as valuable decision-support tools for mitigating fire-related risks.

Limitations and Challenges: While the results were promising, the study encountered challenges, particularly regarding the limited quality and granularity of available fire data. Furthermore, while ensemble models like Stacking improved

prediction accuracy, they also introduced complexities in model interpretability. These limitations should be addressed in future research to further enhance the practical applicability of fire prediction models.

5.2 Study Contributions

This study has made several key contributions to the field of fire prediction and the application of machine learning in environmental science:

Integration and Processing of Diverse, Inconsistent, and Incomplete Data:
A significant contribution of this research is the innovative approach used to manage heterogeneous data from multiple sources, including meteorological data, satellite imagery, historical fire records, and topographical information. The study tackled challenges such as missing data, redundancy, and inconsistencies across these diverse datasets. Advanced preprocessing methods, such as data imputation, feature selection, and outlier removal, were employed to clean and integrate the data. Techniques like spatial interpolation for incomplete spatial data and temporal alignment for mismatched time-series data ensured that the data was consistent and ready for accurate fire prediction modeling.

Application of Ensemble Learning:
This research is among the first to demonstrate the effectiveness of ensemble learning methods, specifically Stacking and Voting classifiers, for predicting ground fire occurrence and behavior. These ensemble techniques significantly enhanced model accuracy and robustness, which are essential for tasks involving complex and dynamic environmental factors like those encountered in fire prediction.

Comparison of Machine Learning Models:
The study compared a range of machine learning models and assessed their performance in both classification and regression tasks. The results provided valuable insights into the strengths and limitations of traditional models like Decision Trees and Random Forests, as well as more advanced methods like Support Vector Machines (SVM) and ensemble techniques. This comparison offered a clearer understanding of which models perform best under different conditions.

Advancement in Hyperparameter Optimization:
The research highlighted the importance of hyperparameter optimization, using advanced techniques like Grid Search and Random Search, to improve model

performance. The study demonstrated how fine-tuning hyperparameters can lead to more accurate predictions, a crucial insight for real-world applications, where optimal model settings are needed to handle complex datasets.

A Comprehensive Framework for Fire Prediction:

The machine learning framework developed in this study provides a robust approach for predicting fire occurrence and intensity. This framework is adaptable and can be deployed in real-world fire management systems to aid in risk assessment, resource allocation, and decision-making, ultimately supporting more efficient and timely fire response strategies.

5.3 Future Work

While this study offers valuable insights into the use of machine learning for fire prediction, there are several potential avenues for future research. These include broadening the scope of the models, incorporating additional data sources, and improving the interpretability of the models.

Incorporation of Real-Time Data

A promising direction for future research is integrating real-time environmental data into fire prediction models. By utilizing live weather data, satellite imagery, and real-time fire monitoring systems, predictions could be continuously updated as new information becomes available. This dynamic integration would enable the models to respond to changing environmental conditions in real time, enhancing the accuracy of predictions during active fire events.

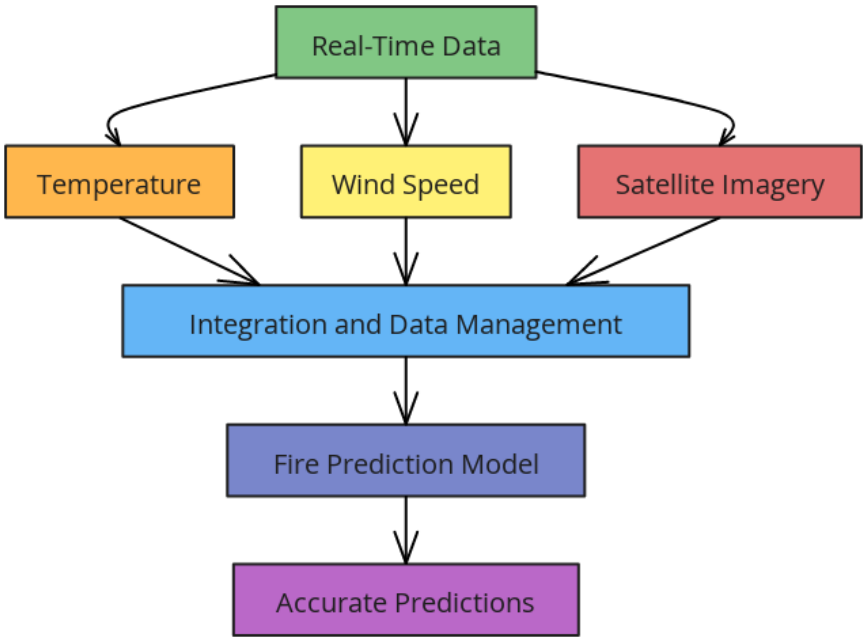


Figure 6.3: Real-Time Data Integration Framework.This diagram illustrates how real-time data, such as temperature, wind speed, and satellite imagery, can be integrated into the fire prediction model to improve forecasting accuracy

Exploration of Deep Learning Models

While traditional machine learning techniques such as Random Forests and SVMs demonstrated strong performance in this study, deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have the potential to enhance fire behavior predictions further. These models are particularly well-suited for analyzing time-series data and extracting spatial patterns from satellite imagery. Future research could focus on utilizing deep learning techniques to improve predictions of fire intensity and effectively handle large, complex datasets.

Enhancing Model Interpretability and Explainability

Given the complexity of Stacking models, which can be challenging to interpret, future research should prioritize improving model explainability. Approaches such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) could be explored to increase the transparency of these models. It is essential for fire management agencies to understand how predictions are made, particularly in high-pressure situations where timely decisions are critical.

Development of Cross-Regional and Cross-Climate Prediction Models

Extending fire prediction models to different geographical regions and climate zones represents another important area for future research. Since fire behavior varies significantly across ecosystems, it is crucial to develop models that can generalize across various regions. Incorporating diverse datasets, including those from tropical, temperate, and boreal forests, will enhance the models' robustness and global applicability.

Real-World Deployment and Testing

A key next step is deploying these models in real-world fire prediction scenarios. Collaborating with fire management agencies to test these models during actual fire events would provide valuable insights and enable model refinement. Integrating these models into operational fire management systems is vital for validating their effectiveness and ensuring their practical utility in firefighting and disaster mitigation efforts.

5.4 Final Remarks

This research highlights the effectiveness of machine learning models, particularly ensemble methods, in enhancing the prediction of ground fire occurrence and behavior. By utilizing Stacking and Voting classifiers, the study achieved superior performance compared to individual models. The results provide valuable insights for fire management and prediction, and the proposed framework holds promise for integration into operational systems to support fire risk assessment and decision-making processes.

As the frequency and intensity of fire seasons continue to rise due to climate change, the demand for accurate and reliable fire prediction models will become even more critical. Ongoing advancements in these models, especially through the incorporation of real-time data and the application of deep learning techniques, will play a key role in mitigating wildfire risks and enhancing the effectiveness of fire management strategies.

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