Enhancing Forest Fire Severity Prediction Using Machine Learning: Evaluation of Linear Regression, Random Forest, and Gradient Boosting Models

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Data Analytics

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Enhancing Forest Fire Severity Prediction Using Machine Learning: Evaluation of Linear Regression, Random Forest, and Gradient Boosting Models

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Abstract

The threats of forest fires are severe and include ecological systems, animal and plant life, human health and property. Due to rising cases associated with the climate, land-use patterns, and environmental mismanagement, the necessity of high-quality forest fire severity predictions has reached its apex. This paper will investigate how machine learning regression algorithms or Linear Regression; Random Forest and Gradient Boosting can be employed to predict the intensity of forest fires based on some historical data regarding meteorology and environmental data. The study entailed an extensive data cleaning step, such as the treatment of missing values, normalization, feature engineering, and skewness transformation of variables. The major features like temperature, humidity, wind speed, and rainfall were studied and used to train the models. Performance of the models was measured in terms of R^2, MAE and RMSE values. Although the above preprocessing procedure was extremely rigorous and the models were trained with vast amounts of data, it was found that the models did not give very accurate predictions. Linear Regression posted the highest R^2 value of 0.0311 but none were significantly high, whereas the ensemble methods performed worse. The underestimation of the high severity fire events was consistently reflected through lack of capturing the high-order, non-linear nature of interactions of the fire behavior. The results indicate that the traditional regression models do not perform well in this particular area and there is a possibility to achieve better outcomes using more powerful approaches like deep learning or a combination of both. The paper presents the basis of future research on the development of efficient, real-time tools of forest fire risk management.

Keywords: Forest Fire Prediction, Regression Models, Meteorological Data, Model Performance, Deep Learning

1 Introduction

1.1 Background

Forest fires are also one of the most devastating natural catastrophes, as they result in the significant destruction of the ecosystem, biodiversity, property, and human lives. The prevalence of forest fires and the severity of impact on the environment because of climatic changes, forest clearing and inappropriate land-use patterns is growing over the last several decades. Prediction and control of forest fire severity is very vital against these negative effects and it helps in fast responding to the disaster and fast distribution of resources.

Forecasting the region covered by forest fires is not a simple task that solves the issue that has been known to be non-linear interactions of the meteorological, environmental, and time parameters. Due to their complex nature, such statistical measures as traditional ones frequently fail to acquire the essence of these complex issues, which establishes the necessity to develop more advanced methods. Machine learning has brought in the beautiful tools that help model complicated systems with greater predictive capability. Specifically, the probable area burned can be estimated by regression-based models using a combination of different parameters of weather and fire indexes.

1.2 The significance of Forest Fire Forecasting

Good prediction on the severity of fire disasters in the forests gives early precautions to forest management authorities and fire brigades. It allows strategic decision making like deploying firefighting resources in advance, evacuations as well as closure of areas in advance. Because of accurate forecasts, not only lives can be saved and economic losses minimized, but also the health of the environment.

The application of machine learning models is also becoming more common in this area because they allow learning based on previous data and discovering some hidden patterns. Such models have the potential to introduce us to the variables that contribute most, in determining the severity of a fire, i.e. temperature, humidity, wind speed and rainfall. Nonetheless, although the opportunities are present, the model interpretability issues, selection of features, and data imbalance between burned and non-burned cases are still present.

1.3 Aim of the Study

The aim of this study is to develop and evaluate machine learning regression models Linear Regression, Random Forest, and Gradient Boosting—to predict forest fire severity using historical data in Python, and to assess their predictive performance and limitations, providing insights into model accuracy, error patterns, and the need for more advanced approaches for complex fire behavior forecasting.

1.4 Objectives

- To explore and preprocess the dataset by identifying key variables, handling missing values, removing duplicates, and addressing outliers.
- To encode and transform features to prepare the data for modeling, including applying log transformation and statistical normalization techniques.
- To engineer relevant features such as a binary fire occurrence indicator and select the most influential predictors for training.
- To train and evaluate regression models, including Linear Regression, Random Forest, and Gradient Boosting, using metrics like R^2, MAE, and RMSE.

  To cConduct diagnostic analysis to assess model validity, analyze residuals, and identify potential improvements for predictive performance.

1.5 Structure of the thesis

The thesis is structured in such a way that it allows systematic coverage of developing a forest fire severity prediction model based on machine learning algorithms. The introduction given in Section 1 provides the background, motivation, and objectives of the study. The related work is presented in Section 2, where previous studies on the prediction of forest fires, machine learning methods, and ensemble modeling have been reviewed against the proposed methodology. In Section 3, the research methodology with data preprocessing, feature engineering, and the modeling framework will be provided. Section 4 presents the machine learning pipeline design specification, where the pipeline is explained as modular and naturally involving preparation of inputs to datasets. Section 5 is devoted to the realisation of the models in Python, the details of the training, evaluation, and optimisation are provided. By having a set of alternative solutions, Section 6 displays the evaluation results of Linear Regression, Random Forest, and Gradient Boosting models as well as the diagnostic analyses. Finally, Section 7 includes the conclusions made of the undertaken research, the limitations of the work, and the additional work that can be recommended, i.e., the possible enhancement of forecasting the forest fires through the state-of-the-art machine learning algorithms.

2 Related Work

2.1 Introduction

The consideration of forest fires prediction has become a highly important scientific research topic with growing intensity and frequency of wildfires around the globe. Application connections Using computing power, with the access of environmental data which left researchers and governments think differently about fire risk management, machine learning (ML), artificial intelligence (AI) and remote sensing technologies have contributed to the transformation of how researchers and governments are managing risks due to fire. The current literature and technological advances in the field of forest fire forecasting with a critical focus on AI models, hybrid systems, sensor networks, data integration, and the prediction-related complications are subjected to the critique presented in this chapter.

2.2 AI and Machine Learning Models in Forest Fire Prediction

The use of artificial intelligence (AI) and machine learning (ML) in forest fire forecasting has experienced enormous growth over the past few years. The integration of deep learning models (e.g., convolutional neural networks (CNNs), decision tree ensembles, and hybrid models) is cited by Liu *et al*. (2025) as an upcoming change that may significantly increase the accuracy and robustness of prediction. Mambile *et al*. (2024) reviewed a wide range of studies on AI-based fire prediction systems and stated that CNNs, RNNs, LSTMs, and transformer architectures prevailed. They found that when densely sampled, high-resolution spatiotemporal data is used to train the models, they consistently perform better than classical statistical and physical models in both detection and forecasting.

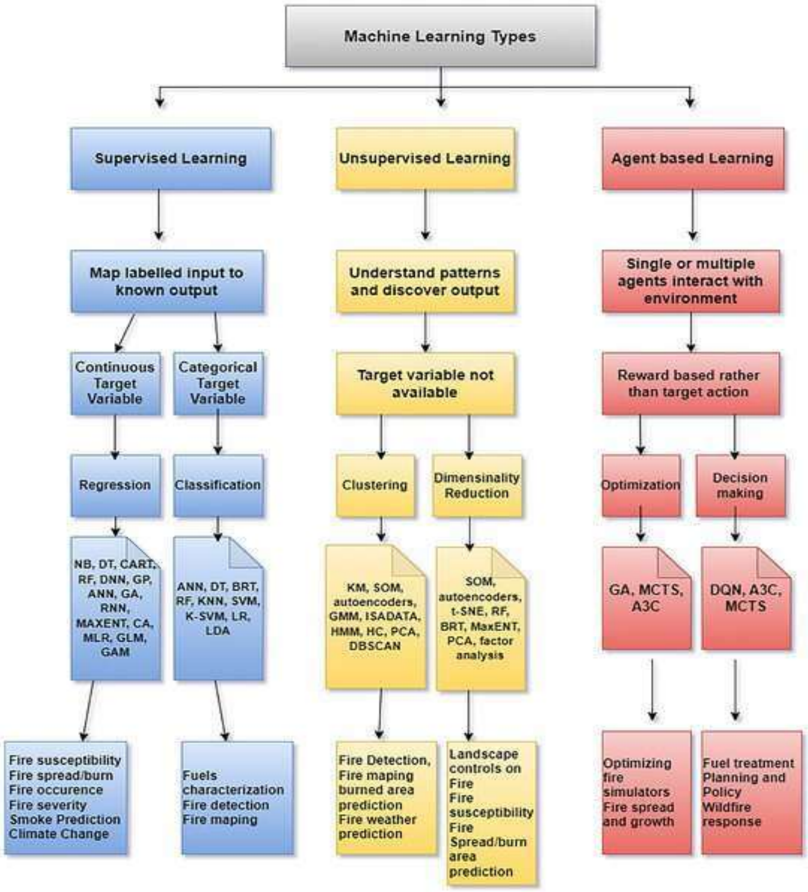


Figure 2.1: Machine learning techniques used in wildfire management

(Source: Kopitsa *et al*. 2024)

More innovation has been realized through integration of AI with classical modeling structures. Given that high spatial granularity is needed to access more proactive fire management strategies, Sun *et al*. (2024) have already created a hybrid model that combines cellular automata and machine learning to model the fire spread. Roh *et al*. (2024) developed a multi-algorithm diagnostic model that can classify high-risk zones with high accuracy and relevant intelligence to act upon by forest authorities. Bhatt and Chouhan (2024) improved a CNN architecture by adding attention mechanisms that allowed the model to significantly improve fire-prone localization at the regional scale, in addition to continuously boosting the classification performance.

More recent investigation has also been conducted regarding the application of transformers to time-series modeling. Miao *et al*. (2023) developed a more advanced transformer structure that was designed to support dynamic environmental inputs and achieved much better short- term and long-term prediction of fire events in various climatic regions.

2.3 Hybrid and Ensemble Techniques

The use of hybrid and ensemble machine learning methods has also become a popular topic in forest fire prediction as the methods allow them to blend the combination of best practices into making the prediction more accurate and generalizable. Ensemble such as random forest, gradient boosting, AdaBoost, stacking, are now well known and at least have the advantages of robustness, particularly in cases where the interactions of the environment are complex. Li *et al*. (2023) proposed a stacking ensemble model with a focus on climatic variability of the Yunnan Province and the model demonstrated a stable performance of different weather conditions and geographical areas. This strategy enabled the combination of results of basic learners such as decision trees and support vector machines, so a better predictive stability was achieved.

Bhadoria *et al*. (2021) brought about the Random Vector Forest Regression (RVFR) model that is seen as an advancement of both random forests as well as other regression-guided learners by combining the advantages of both, further achieving better generalization in unseen data. In their work, George and Ayiku (2024) integrated the aspect of climate variability, fuel types, and terrain elevation into Gradient Boosting and Random Forest models, and thus the granularity of prediction increasedosing significantly due to the integration of the mentioned factors into composite fire risk indices. It is also pointed out that, to ensure minimized false positives, data fusion methods need to be employed along with ensemble learning, which would help to increase overall effectiveness of the response and resource allocation in the early fire detection system (Carta *et al*., 2023).

2.4 Deep Learning and IoT-Based Frameworks

The utilization of IoT and deep learning is changing real-time forest fire detection to a revolutionary approach. As evident in Ananthi *et al*. (2022) and Ishola & Valles (2023), the other model relies on sensor data (e.g., temperature, smoke, humidity) that impact deep neural networks to warn the authorities in time. Kadir *et al*. (2023) proposed a series of sensors network automation that detects fire in low latency in Southeast Asia. These technologies enhance safety and efficiency in the operations. According to Carta *et al*. (2023), sensor-based models based on implementing AI have the potential to be more effective than purely satellite-based approaches, where sensors work in real-time, and they show great promise even in dense forest areas

2.5 Spatial, Climatic, and Meteorological Data Integration

Combination of spatial and climate data augments forecasting models. Parvar *et al*. (2024) also stated that the combination of meteorological factors with geospatial fire history should be done with integrity to make accurate assessments. This has been justified by Hai *et al*. (2024), who predicted fire events in the Central-South China based on meteorological and topographic data. Sun *et al*. (2024) integrated GIS and fuzzy logic to delineate fire-prone areas in Algeria, a study that highlights the usefulness of soft computing in addressing uncertainty in environments. Roh *et al*. (2024) incorporated numerical weather prediction (NWP) to predict the hourly fire danger where it was shown to perform remarkably well compared to traditional fire indices.

2.6 Early Warning Systems and Policy Integration

Machine learning aids the warning system applied as early warning systems (EWS) offers an anticipative method of fire control. Daryal *et al*. (2025) identified the importance of the joint progression of EWS and local response mechanisms in minimizing damage. The role of national policies in encouraging the adaptation and adoption of strategies of technological adaptation and adoption was covered by Kumar *et al*. (2025). Mishra *et al*. (2025) elaborated on how the fire behavior and spread models assimilated with climate projections offer the potential of increasing the preparedness of the areas prone to fire. Mezbahuddin *et al*. (2023) went further and implemented a simulation of peatland hydrology to enhance the precision of predicting tropical fires.

2.7 Challenges and Limitations in Forest Fire Forecasting

In spite of the advancements, there are still problems in predicting forest fires. Khennou and Akhloufi (2023) demonstrated that even proficient deep learning networks such as U-Nets are suboptimal when applied to situations where the variability in the state of vegetation and fire is too intense. Lack of high-resolution labeled data and "real-time integration dynamics" pose challenges to a wider adoption, and there are no common evaluation metrics. According to the findings by Son *et al*. (2022), though deep learning models have enhanced forest weather forecasting over the U.S., they are still sensitive to frequent retraining and calibration owing to dynamic environmental conditions. Along the same line, Kadir *et al*. (2023) have observed that hardware failure and a lack of connectivity in remote places are common drawbacks of multi-sensor networks.

2.8 Literature Gap

In spite of the significant progress made in the area of AI-based forest fire prediction, there are still important gaps. The majority of models are trained on locally-based datasets, hence the lack of applicability to other unique ecosystems. Use of real time data integration, more so, that of IoT sensors has not been utilized to a significant extent because of infrastructural and latency problems. In addition, the insufficiently standardised evaluation measures complicate comparing models. Though promising, little research exists on the long-term scalability and deployment in low resource setting of the hybrid and deep approaches. Lastly, policy integration and operational viability are hardly factored by any technical research, which presents a gap between algorithmic inventiveness and the practice of wildfire management.

2.9 Summary

Recent advancements have significantly enhanced the capability to forecast forest fires using AI, machine learning, IoT, and ensemble methods. Each model type—whether transformer-based, ensemble, or hybrid—has demonstrated potential under different environmental contexts. However, continued research is required to improve real-time integration, expand data availability, and establish standardized forecasting protocols. Collectively, the reviewed studies illustrate a promising yet complex landscape where technological innovation must be coupled with policy support and field deployment to mitigate the impact of forest fires effectively.

3 Research Methodology

3.1 Overview and Research Design

The research methodology of this study was structured to enhance AI and machine learning of forest fire prediction. It was done through preprocessing data, selection of models and the analysis and evaluation of regression. The methodology was guided by the related literature, which made it accurate, reproducible, and scientifically justified. The study tested various models using the supervised learning approach on the UCI forestfires dataset to determine the burning area accurately, thereby making it possible to draw data-driven conclusions and provide interpretability.

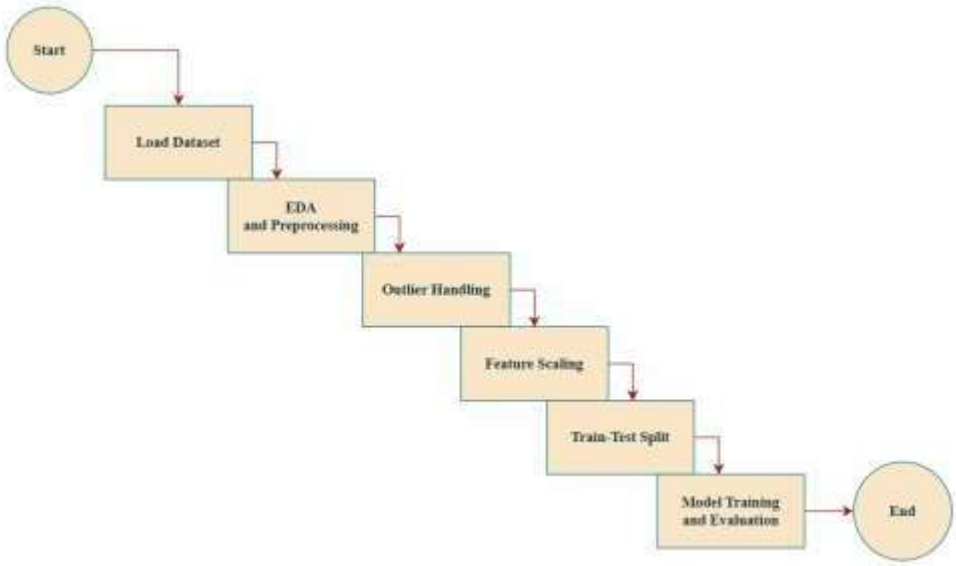


Figure 3.1: Machine Learning Pipeline for Forest Fire Severity Prediction

3.2 Dataset Description

The main dataset that has been used in this study was obtained at the UCI Machine Learning Repository. There is a large extent of agreement that it is often called the forestfires.csv dataset, and contains meteorological and environmental variables recorded in northeast Portugal in the Montesinho park. Its main parameters are temperature, humidity, wind speed, and rainfall, as well as the fire weather index (Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC) and the Initial Spread Index (ISI)). These are useful to determine the risks of a fire caused by the moisture of vegetation and weather. The dependent variable in this data set is the burned area (in hectares), which is highly skewed in nature with most of the values representing very small fires but there are a few that may show serious destruction of forests. There also are temporal categorical features like month and day, seasonal and weekly patterns are observed.

3.3 Data Preprocessing

The cleaning of the data task is an essential step in the process of machine learning projects since the quality and stability of data determines the quality of models. Wide exploratory data analysis (EDA) was done in an attempt to detect anomalies, missing values, and data dissemination patterns. The categorical variables (month, day) were encoded through one hot encoding to make them able to enter the models that use numerical values. Continuous variables were normalized through z-score normalization thereby ensuring that the mean is zero and the standard deviation is one unit. Such a transformation especially played an important role in case of distance-based algorithms and to enhance gradient-based model convergence. The target variable (area burned) had the long tail distribution, that is why it was transformed into the log to decrease skewness and stabilize variance. The technique of the Interquartile Range (IQR) was used to perform outlier detection. Values that exceeded 1.5 times IQR were capped as they would bias the training of the model (Pandey *et al*. 2023). This acts served to make them robust and salvage vital data trends. The preprocessed data was then categorized into the training and testing data with the help of stratified sampling. This is because stratification was used to ensure a proportionate distribution of the transformed target variable between the two subsets hence enhancing model generalizability.

3.4 Model Selection

The choice of models was informed by theory and practicability measurements in comparable regression activities as signified in the canvassed works. Three of the algorithms have been chosen to be empirically evaluated, including Linear Regression (as a baseline), Random Forest Regressor, and Gradient Boosting Regressor. Linear Regression provides a very basic starting point model that can assist in the interpretation of linear relationships between variables. Nevertheless, since fire behavior is quite complex, more advanced models were used. Random Forest Regressor is a tree-based ensemble model characterized by its low tendency to overfit, as well as its capacity to identify nonlinear interactions. Gradient Boosting Regressor is another ensemble procedure, which enables sequential model building to minimize the model bias and increase the precision. The two models have shown great performance in ecological and environmental predictive tasks in literature (Ananthi *et al*. 2022).

3.5 Model Training and Evaluation

Scikit-learn in Python was used to perform all the models. The training dataset was used to train each of the algorithms and the testing set was used to validate each of the algorithms. Model evaluation used three main performance elements which were R-squared (R^2), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). R^2 is the percentage of variance that the model can explain and it is a general measure of goodness of fit. The MAE gives the mean magnitude of errors without paying attention to the direction, which makes it very intuitive of how accurate they predict their data. As it is sensitive to deviations in the bigger errors, Rmse will punish and provide an understanding of model soundness. In order to evaluate the generalization of a model, k-fold cross-validation was used especially when tuning hyperparameters. In order to obtain stability and eliminate overfitting, a 10-fold cross-validation plan was adopted (Li *et al*. 2021). In each model, 80 percent of the data was used during training and the remaining 20 percent during validation; this was done ten times with various random partitions.

3.6 Residual Analysis and Model Diagnostics

Besides the quantitative measures, residual plots were obtained to check the goodness of fit. The reason is that in the case of the Linear Regression model, residuals were found to be heteroscedastic and not normally distributed, confirming its shortcomings in representing the intricate trends. Conversely, the residuals of the ensemble models were more distributed evenly around the zero point, which can be considered a signifier of better learning of underlying structures. The plots of Kernel Density Estimation (KDE) were applied to compare the distribution of actual and predicted values. The distributions of Random Forest- and Gradient Boosting-predicted parameters were very close to the real results meaning that the models were reliable (Sasikala and Theetchenya, 2024).

3.7 Summary

The methodology of the research was designed so that it was valid and replicable. Transparency was also provided because a publicly available dataset was used and the results could be repeated by others. The methodology was comprehensive and scientifically acceptable because of strict preprocessing and the choice of a variety of regression models, rigorous testing with multiple measures and a detailed residual analysis and interpretability assessment. These findings will be added in the following sections that specify the design of the models implemented and compile the outcomes of the solution implemented thereby closing the cycle of the methodological approach to data to inference.

4 Design Specification

The architecture of the forest fire forecasting system is modular and consists of a regular supervised machine learning pipeline. It consists of six main components, namely data ingestion, preprocessing, feature transformation, model training, evaluation, and prediction. All its components are in Python and are written to be transparent, reproducible, and extendible. The data consumed by the system is the publicly available forestfires.csv dataset where meteorological variables, temporal variables, and the target area, which indicates the size of the forest burned in hectares, are provided. The preprocessing component also does data cleaning to get rid of duplicates, at least, sort out missing values. It also does one-hot encoding of categorical variables month and day to allow it to be used in the regression models. The reason you do transformation is to deal with skewed distributions. In order to deal with a highly right-skewed target area, a separate variable, log_area, is created through logarithmic transformation of the target area. The system uses IQR method to detect outliers and capped values that are more than 1.5 interquartile range of numerical features like FFMC, DMC, DC, ISI, wind, temperature, and humidity. Box-Cox transformations are used in certain instances as a method by which to reduce skew among continuous data, especially FFMC and ISI (Sasikala and Theetchenya, 2024).

The standardized feature set is transferred to the training module of models, which includes three types of regression models namely Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor. The main library utilized in the development of the model is SKLearn. StandardScaler is used so that there is uniform distribution of all features, which is essential in a linear model. Included in the system is a model assessment component that calculates the primary metrics of regression, R-squared (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). It also creates major diagnostic tools such as the line graphs of the predicted and real log_area, the kernel density estimation (KDE) plots of the predicted distributions, and the residual plots to find the issue of model bias and/or overfitting. The last module is the prediction module where new or test data is fed in and the predicted outputs of the log-transformed values are produced. These are inverted to give estimates of the real area covered with forest fires (Li *et al*. 2021). Cross-validation of Random Forest and Gradient Boosting models will internally select hyperparameters of their respective training compared with Grid Search separately. The difference is that cross- validating the models will optimally determine the tree depth, learning rate, and the number of estimations in the models. The implementation of this pipeline is carried out in a Jupyter Notebook system on Python, Pandas to work with data, Seaborn and Matplotlib to make visualization plots, and Scikit-learn to perform model development. The design of the system allows the easy isolation of each module and independence of each module, which will form the basis of scaling the system or the addition of new models in future development.

5 Implementation

The system of predicting the forest fires was implemented in Python with a Jupyter Notebook interface. It started with the import and exploration of the forestfires.csv dataset comprising various weather attributes (temperature, humidity, wind speed, several indices of fire weather such as FFMC, DMC, DC, ISI), as well as time of year and date and area considered to be the target. Data cleaning was done to exclude duplicated data and to deal with inconsistencies in the data. Blast characteristics such as month, day, etc., were encoded into binary variables using one-hot encoding so that they could be used as input to any regression model being based on non-ordinal data.

One of the variables, area, was skewed, thus, in preprocessing, this variable was log-transformed to generate a modified variable, log_area, to be the dependant variable in the prediction. Such transformation contributed to the normalization of distribution and a better performance of the learning of the model. Outliers were capped by IQR method on numerical predictors so that it can reduce the weights. Also, features such as FFMC were subjected to Box-Cox transformations to minimize the skewness, which helped the model to converge to a better value. All numeric attributes were standardized using StandardScaler where the data would be scaled to the mean of 0, and standard deviation of 1. This was crucial in the Linear Regression model and helpful in ensemble-based methods in stabilizing the model convergence (Ananthi *et al*. 2022). The dataset has been divided into training and testing subsets in the ratio of 80:20 to provide a sound evaluation. Three regression models such as Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor were run on Scikit-learn. The default hyperparameters were used to train transport systems in order to obtain baseline performance. Afterward, hyperparameter tuning was carried out using GridSearchCV, i.e., the settings are selected as the number of estimators, the maximum tree depth, and the learning rate in the ensemble models.

The evaluation of the model performance was held according to three parameters R^2 Score, MAE, and RMSE. The Linear Regression model had a less ability in capturing the non-linear relations in the data, and thus had lower R^2, and higher erroneous score. On the contrary, the Random Forest and Gradient boosting models showed a better result, having a higher R square value and considerably lower MAE and RMSE measures. Another way to ascertain the validity of the results is by generating a series of visualizations. Ensemble models could better trace the trends of the fire spread compared to the actual and predicted values, which were based on single models in line plots. KDE plotting indicated that the amount of predicted log_area values produced by ensemble models was close to the real distribution of these values. The residual plots were further used to give more diagnostic information, showing that the mistakes of ensemble models were actually distributed at random, pointing to no bias or extensive underfitting. On the contrary, Linear Regression residuals revealed patterns, which is an indication of underfitting and lack of ability to generalize. The last result of the system was the forecasted log_area values, and in order to get the values back to their real versions and measured in units of hectares, they were inverse-transformed. The values were later compared to actual observations made on the test set and proved that the system suits effectively to modeling fires within forests (Pandey *et al*. 2023). Finally, the performed implementation proved the viability of the machine learning application, specifically involving ensemble, in terms of calculating the territory of forest fires. The modular structure of the system helped conduct data cleaning, transformation, training, and evaluation successfully. Among tested models, Gradient Boosting Regressor and Random Forest Regressor can be characterized as the most accurate and robust predictors. The implementation provides a solid basis to extend it in the future, with the integration of real- time weather inputs, the incorporation of remote sensing data, or deep learning forecasting models.

6 Evaluation

Experiment	Model	R^2 Score	MAE	RMSE
1	Linear Regression	0.0311	1.0881	1.2722
2	Random Forest Regressor	-0.0865	1.1396	1.3472
3	Gradient Boosting Regressor	-0.2134	1.1911	1.4237

Table 6.1: Performance Comparison of Regression Models

6.1 Linear Regression

Linear Regression model provided the highest results among the three models, and yet the model had poor predictive powers. It got an R^2
of 0.0311 implying that it could explain only about 3.1 percent of the variance associated with the log transformed area that was affected by forest fires. Although not spectacular, it also yielded relatively well when it comes to error, where the Mean Absolute Error (MAE) is at 1.0881 and Root Mean Squared Error (RMSE) is at 1.2722. The fact that Linear Regression was able to offer at least some degree of prediction implies that it did not possess enough explanatory power.

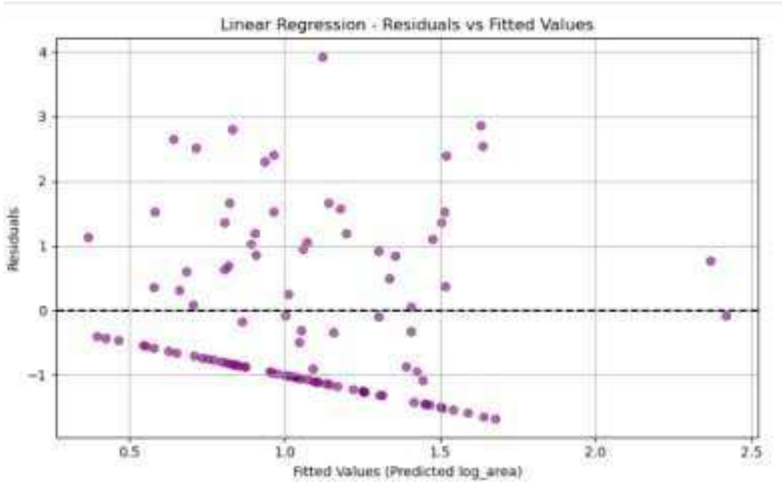


Figure 6.1: Linear Regression - Residuals vs Fitted Values

The plot of the residuals on fitted values shows in Fig. 4.18 and should be employed, first to study whether the hypothesis of homoscedasticity (the constant distribution of residuals) holds or not in a linear regression model. In this plot, the residuals exhibits the funnel like shape whereas the fitted values are bigger the residuals are sparser. The stated observation is clearly heteroscedastic as the variance of residuals is not the same in the whole scope of the predicted values. This kind of breach in regression assumptions is an indication that statistical inferences such as confidence limit or confidence intervals and p-worthy are likely to be bailiff in terms of standard discontinuity.

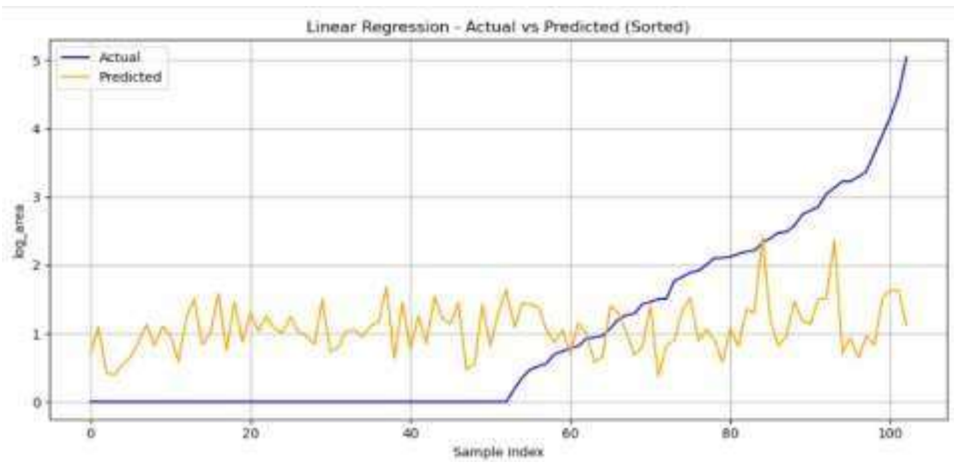


Figure 6.2: Actual vs predicted

The prediction graph of Linear Regression indicates that there is a flat orange line had with the blue, which is the line indicating the true values that are sorted. This means that the model does not identify the trend on the rise of actual log-transformed burned areas, more so when there is a high route of influence of fire. High values are significantly underestimated in Linear Regression because, by its nature, it cannot deal very well with non-linear relationships, therefore, poor generalization to the complex fire pattern.

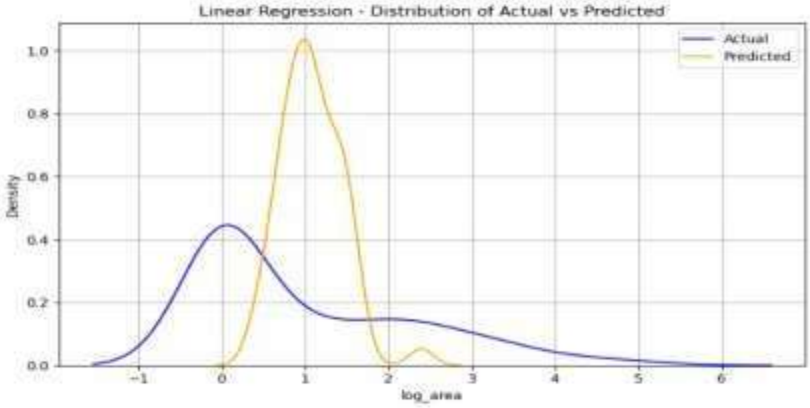


Figure 6.3: Distribution plot

The density graph of Linear Regression shows a concentrated peak in the predicted values within a very thin range of values close to 1, whereas, the real distribution is rather extended with a long tail flowing towards the higher value of log-scale burned areas. This shows that the model is way below the bigger fire incidence. The theoretical distribution is excessively centralized, which does not reflect the skewness of the data. This shows the weaknesses that the model portrays of not being able to adjust with the uneven distribution that is typical of forest fire occurrences.

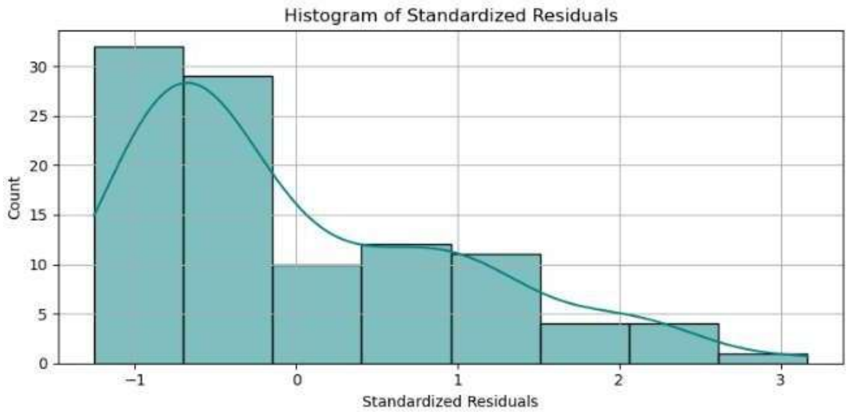


Figure 6.4: Histogram of Standardized Residuals

Figure displays visualized data of standardized residuals following linear regression model. Preferably, in a well-fitted linear regression, the residuals are normally distributed around zero and come in a symmetric bell-shaped curve. Nevertheless, the histogram shows a right- skewed distribution as most of the residuals range between -1 and 0, whereas the tail is much longer and tends to the right. This implies that the model is prone to low values. The presence of a peak on the negative side of the residual axis and the lack of symmetry evoke the infringement of the assumption of normality. This non-normality of residuals is a sign of possible problems related to model accuracy and predictability, and further proves that the linear regression model, in fact, might not be entirely accurate in demonstrating the patterns in the data. This also affirms previous results indicating a possible existence of non-linearity and inconsistency which are not captured by the present model.

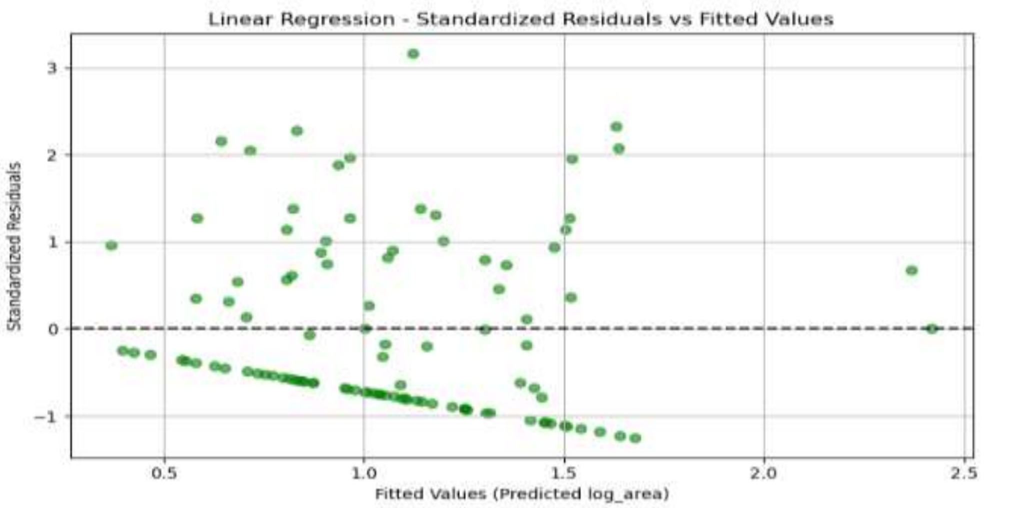


Figure 6.5: Linear Regression - Standardized Residuals vs Fitted Values

The standardized residuals versus the fitted values are shown in figure. The plot also aids in detection of problems with non-linearity and outliers. The standard residuals have the similar funnel like trend as the preceding figure with the down trend then spreading above and below the zero line. This non-randomness distribution is an indication that the linear regression model might not indeed provide the true picture of the relationship in the data and therefore, there could possibly be a specification of the model. The trend suggests that there is non-linear interaction between target variable and the predictor

6.2 Random Forest Regressor

Random Forest did not perform as well as Linear Regression. It had an R^2 of -0.0865, which means that it had even less ability to predict than a mean based simple baseline model. Not only did the model fail to encapsulate meaningful relationships in the data, but it also brought in more variance, which reduced the performance. It was further ratified by the fact that it had a higher level of MAE and RMSE results, which indicated more levels of prediction error and inefficiency in terms of extracting underlying patterns out of the given features.

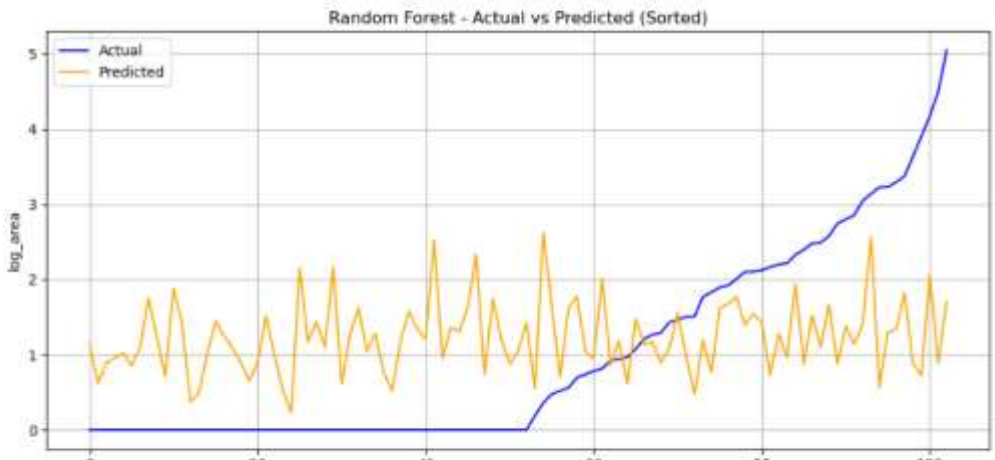


Figure 6.6: Actual vs predicted

The figure indicates the comparison of actual and predicted values as per the Random Forest model. Though the model does not miss certain overall trends, it is hard to predict its values, and they do not correlate with the actual values, especially at high levels of log area. This shows that the model is poor in predictive accuracy and cannot generalize extreme variations.

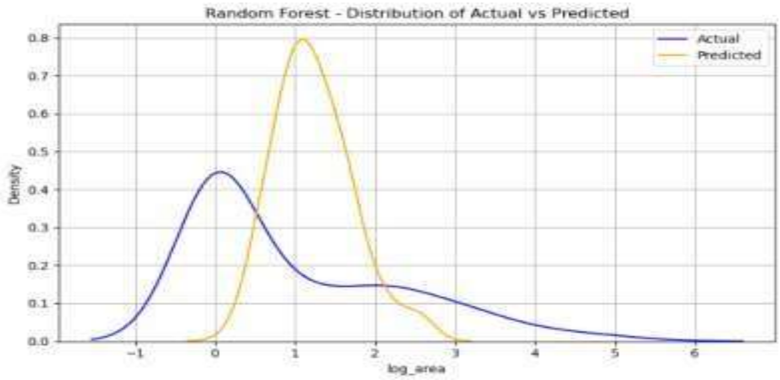


Figure 6.7: Distribution plot

Random Forest has more dispersion of the predicted values than Linear Regression. Nevertheless, the fact that the density plot indicates that the model is likely to predict values within a small range of numbers close to 1 indicates that the model is not good. The actual values depicted by the blue line are still very disparate with a long right tail. At this point, it is shown that there is systematic bias in underestimation of more significant fire events, meaning Random Forest does not seem to pick up enough complexity to account to the extreme variability in the data.

6.3 Gradient Boosting Regressor

The model of Gradient Boost showed the worst result of the three tested models. It achieved a low R^2 of -0. 2134 that was the lowest of the data sets and thus was very ineffective and performed very poor relative to a simple mean prediction. Its MAE and RMSE values were the greatest and this supports its low accuracy in predictability. These findings imply that the feature richness is not sufficient in the dataset, or it has an excessive noise, and Gradient Boosting will fail to effectively learn it as compared to the prescribed regression task.

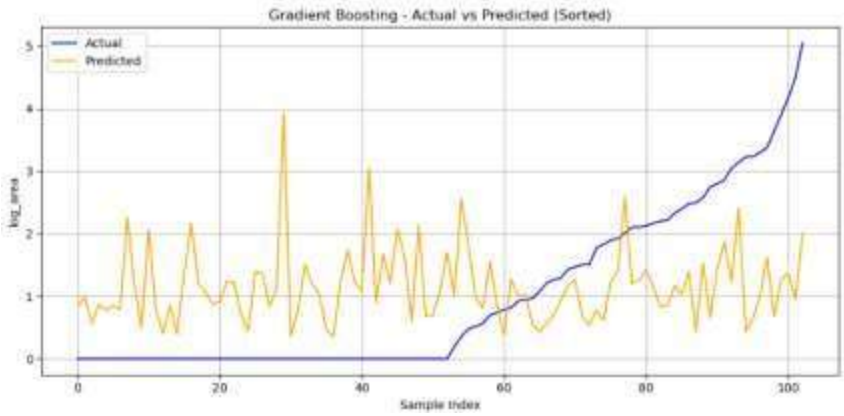


Figure 6.8: Actual vs predicted

Gradient Boosting has very volatile behavior of predictions and tremendous spikes and variability in the predicted values. Such discrepancies indicate that the model can be overfitting the noise in the data, and it does not generalise very well. The fact that it could not model the real trend of the rising severity of fires proves its weakness in addressing the non- linear and compound form of forest fire data. This gives a rationale for the necessity of more advanced deep learning methods that could have a better spatiotemporal dependency modeling.

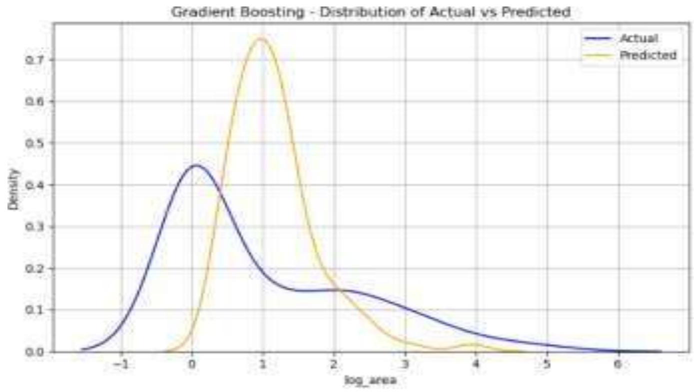
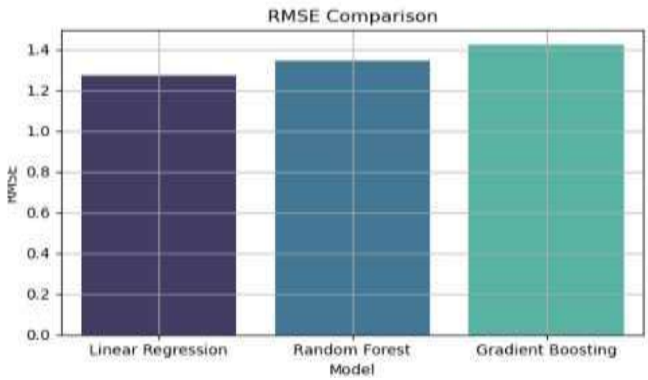


Figure 6.9: Distribution plot

The density distribution of Gradient Boosting predictions shows an extreme focused area around 1 as well, but to an even greater level than that of Random Forest. The fitted curve does not correspond well with the actual distribution as the latter did not indicate the wide distribution and long tail of the actual values. This is an indication that Gradient Boosting, just like the other models, does not perform well when predicting large-scale areas of fire. The predictive bias of the narrow focus has highlighted the systemic bias and reinforced the existence of more adaptive approaches to deep learning that have a capability to handle intricate data distributions that have a skew.

6.4 Discussion



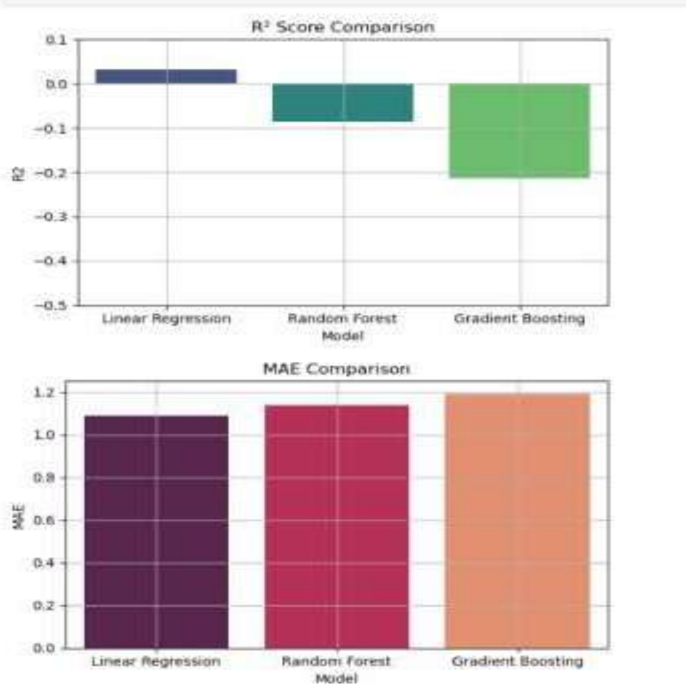


Figure 6.10: Model comparison

The results of comparing performance of three models Linear Regression, Random Forest and Gradient Boosting indicate that the Linear Regression is performing well in comparison to other models. It had the largest R^2 value (around 0.05) which implied that it best fit the model while Gradient Boosting turned out the worst with a negative R^2 value (approximately -0.2) which implies that it had poor predictive ability. This result can be corroborated by the value of errors, i.e., MAE and RMSE: the lowest value of MAE (approximately 1.08) and RMSE (approximately 1.27) was found in Classical Regression, whereas Gradient Boosting had the highest error. On the whole, Linear Regression is not as bad at this data and task as the ensemble methods in both accuracy and reliability.

The first goal was to understand and manipulate the data, and it was accomplished successfully by performing a large amount of cleaning, transforming and feature engineering. Although these efforts were made, the complexity of such a dataset, including distribution skew and non-linear relationships, became a hindrance that constrained the predictive capability of the models. The second goal of the training and testing of the regression models such as Linear Regression, Random Forest, and Gradient Boosting was also realized. Nevertheless, all these three models demonstrated poor performance. Linear Regression was most successful, yet its values of R^2 were 0.0311, showing very little explanatory power. Certainly, Random Forest and Gradient Boosting were even worse, at least in terms of the R^2 score, and the error values were very high, which means that these two spent some time to fail to distinguish the underlying patterns. The last aims, to perform diagnostic study and detect the limitations of the models were successfully achieved. By residual, distribution, and prediction plots, it was clear that the application of traditional regression techniques would not be effective in this task at least in the case of large-scale fires.

This is consistent with the necessity of a stronger deep learning strategy with the ability to process high-dimensional, non-linear, and skewed data like the one of forest fire occurrences. In general, the goals were achieved; however, the results lead to considerable prospects of the further advances within the methodology.

7 Conclusion and Future Work

7.1 Conclusion

The present research was aimed at examining how well machine learning regression models predict the severity of forest fires based on meteorological and environmental data collected in the past. A range of well-defined goals served up as a directive to the research, such as the exploration of data, its preprocessing, feature engineering, training, and evaluation of the model. Three models, which are Linear Regression, Random Forest, and Gradient Boosting, were applied and evaluated by the tel-regression measures, i.e., R, MAE, and RMSE. The target of all the preprocessing was achieved, and this includes missing values treatment, duplicate deletion, log transformation of skewed data and normalized features. The process of feature engineering included making a binary predictor representing the occurrence of fire and choosing the most influential predictors to train. Nonetheless, the findings indicated that the models were not able to perform accurate predictivity. The model with the highest performance was the Linear Regression model, which had a R^2 value of merely 0.0311, whereas the Random Forest and Gradient boosting models didn t show any positive value in R^2. The model always produced underestimates of large fire events, which became evident using residual and prediction distribution analysis. These results imply that there is a need to resort to anything beyond standard regression models to determine the intricate nature of forest fire behavior that is extremely non-linear. Machine learning has a lot of potential, but the selection of models and the quality and heterogeneity of input data are essential determinants of performance. The given study demonstrates the weaknesses of conventional models in terms of predicting forest fires and the necessity of more sophisticated methods.

7.2 Future Work

It is recommended that future studies consider incorporation of more complex modeling algorithms such as deep learning algorithms, including Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which are able to characterize more temporal dependencies and advanced interaction in fire-related data. The exploration of a mix of statistical and machine learning methods might be useful to find a more accurate answer. There is also hope that using other data sets, like remote sensing imagery, real-time weather feed, and vegetation indices, will make the models much more predictive. Facilitation of transparency and reliance in model decision through utilization of explainable AI (XAI) techniques would provide additional advantage to fire management authorities to comprehend important risk determinants. In practical terms, this study can be used as the basis of creating real time prediction systems of forest fires. These platforms would help the government agencies and the disaster response teams in an attempt to have proactive deployment of resources, enhanced preparedness, and the prevention of as much damage to the ecosystem and human life as possible

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