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Prediction of Forest Fires using Machine Learning Algorithm

Selamet Riadi[1], M.Zulpahmi [2]

Abstract

Forest fires pose a serious threat to ecosystems, biodiversity, and surrounding communities, making early prediction important for supporting mitigation and management efforts. This study applies the Random Forest algorithm to predict forest-fire likelihood using climate variables, including rainfall, solar radiation, humidity, and temperature. The study utilizes climate and hotspot data collected from BRIN and BMKG for the period from January to December 2023. The integrated dataset is evaluated using three training and testing split ratios, namely 70:30, 80:20, and 90:10. The experimental results show that the Random Forest model achieves accuracies of 85.8%, 85.9%, and 86.4%, respectively. The 90:10 split produces the highest accuracy. The confusion matrix for the 70:30 split records 1,082 correctly classified No Fire samples and 38 correctly classified Fire samples, while 21 No Fire samples and 163 Fire samples are misclassified. Feature importance analysis identifies solar radiation as the most influential variable with an importance value of approximately 0.48, followed by temperature at 0.26, humidity at 0.20, and rainfall at 0.06. These findings demonstrate that Random Forest can provide consistent forest-fire classification performance using climate-based variables. The results also indicate the need to improve the identification of actual fire occurrences, particularly for samples that the model classifies as No Fire.

Keywords:
Forest Fires, Prediction, Random Forest, Machine Learning

1. Introduction

Indonesia Forest fires pose a serious threat to ecosystems, biodiversity, human communities, and economic resources. Their occurrence can spread rapidly and create substantial environmental damage. Climate-related changes and dry weather conditions further increase the need for early prediction and detection. Traditional monitoring methods often depend on field observation or manual surveillance. These approaches face limitations in coverage, response time, and scalability. Machine learning provides an alternative because it can learn patterns from meteorological, environmental, satellite, and sensor data. Recent research therefore increasingly applies machine learning to predict fire occurrence and support early disaster management [10], [16].

Recent studies show that meteorological and environmental variables provide useful information for forest fire prediction. Rastogi et al. develop a dual-task system that predicts forest fire occurrence and estimates fire intensity through the Fire Weather Index. Their approach uses the Algerian Forest Fire dataset and processes environmental and meteorological variables before applying several machine learning models. The study also develops a Streamlit application to provide prediction results through an interactive interface. This approach connects prediction with practical decision support. However, the study focuses on the Algerian dataset and does not establish whether the developed

Corresponding Author: Selamet Riadi, Universitas Teknologi Mataram, Indonesia (selametriadi.1897@gmail.com)
1. Selamet Riadi, Universitas Teknologi Mataram, Indonesia
2. M.Zulpahmi, Universitas Teknologi Mataram, Indonesia

models maintain similar performance across different geographic and environmental conditions. Regional variation remains an important issue for forest fire prediction [1].

Khan et al. address the need for rapid and reliable fire detection through an intelligent wireless sensor network. Their Universal Trust Model combines sensor reliability assessment with machine learning and uses variables such as temperature, humidity, and CO_2 concentration. The researchers evaluate the system using 7,200 real-world samples and report reduced processing time and detection delay. The trust mechanism also helps assess communication, energy, and data reliability among sensor nodes. This approach demonstrates the value of integrating machine learning with real-time sensing. However, sensor-based systems depend on adequate sensor placement, communication, and data quality. These requirements can become challenging when the monitoring area expands or environmental conditions change [2].

Satellite imagery provides another important source for forest fire monitoring because it can cover large geographic areas. Singh et al. apply Landsat-8 imagery and Support Vector Machine to detect active wildfires and classify burned areas in the Wolgan Valley, Australia. The study combines spectral information from Shortwave Infrared and Near-Infrared bands and introduces the Normalized Difference Fire Index to improve fire identification. This approach expands monitoring beyond the limitations of ground-based observation. However, the researchers also identify data availability and model interpretability as continuing challenges. Satellite-based prediction therefore requires appropriate feature selection and reliable models that can handle changing fire conditions [3].

Ong et al. demonstrate the practical use of machine learning for forest fire prediction through the FIREfly project in Northern Thailand. The study uses satellite fire data and weather information to train RF and SVM models. Both models achieve approximately 60% accuracy in predicting forest fire occurrences. The researchers then integrate the prediction results into an online dashboard that displays fire probabilities under current weather conditions. This system improves situational awareness and supports proactive responses. Nevertheless, the reported accuracy remains moderate. The result indicates that weather and satellite variables alone may not fully capture the complex relationships associated with forest fire occurrence. This issue creates a need to investigate additional features and more effective learning approaches [4].

Environmental variables also support conventional machine learning approaches for fire-risk classification. Ramya et al. evaluate Random Forest, Support Vector Machine, and Logistic Regression using temperature, humidity, wind speed, and rainfall. Their study shows that machine learning can classify fire-prone conditions and identify important factors affecting fire risk. The researchers also propose integration with IoT sensors and satellite data for real-time monitoring. This approach offers a relatively simple framework for practical deployment. However, the study mainly focuses on identifying fire-prone conditions rather than modeling the broader spatial and environmental relationships that influence fire occurrence. The selection and combination of environmental features remain important issues for improving prediction reliability [5].

Several studies extend forest fire prediction by integrating spatial, topographical, vegetation, and human-related factors. Jiang and Peng combine meteorological conditions, terrain characteristics, anthropogenic factors, and vegetation information using Logistic Regression, Random Forest, XGBoost, and Support Vector Machine. Their RF model achieves 89.53% accuracy, 92.31% recall, 90.28% F1-score, and 0.9555 AUC. The study also uses SHAP to examine feature contributions and identifies minimum relative humidity as an influential variable. This multi-source strategy captures more factors than models based only on weather variables. However, combining many heterogeneous variables also increases the complexity of feature processing and model interpretation. The model must therefore maintain predictive performance while handling different types of environmental information [13].

Spatial susceptibility mapping provides another perspective for predicting areas that are vulnerable to forest fires. Muhammad et al. combine MODIS fire products with topographic, climatic, vegetation, and human activity variables. They evaluate Logistic Regression, RF, SVM, and XGBoost for fire susceptibility prediction. RF achieves 86.2% accuracy and an AUC of 95.4, while XGBoost achieves 87.2% accuracy and an AUC of 95.2. NDVI, skin temperature, and population density emerge as important predictors. Similarly, Uthappa et al. combine remote sensing, GIS variables, AHP, and machine learning to classify forest fire susceptibility in the Western Ghats. These studies show the importance of spatial and environmental features. However, susceptibility mapping identifies areas with higher risk rather than directly predicting the occurrence of a fire at a specific future time [11], [12].

The existing studies indicate that machine learning has considerable potential for forest fire prediction, but several issues remain. Current approaches use different data sources, including weather observations, satellite imagery, wireless sensors, vegetation indices, topography, and human activity. Researchers also apply different algorithms, such as Random Forest, SVM, Logistic Regression, XGBoost, and neural networks. These differences make model performance strongly dependent on the dataset, geographical area, feature composition, and prediction objective. Reviews also identify data imbalance, generalization, computational constraints, and regional adaptability as persistent challenges. Therefore, this paper focuses on developing a machine learning approach for forest fire prediction that can learn relationships among relevant environmental variables and provide reliable classification results. The proposed approach aims to support earlier identification of fire-prone conditions and improve the basis for forest fire prevention and management [8], [16].

2. Related Works

Rastogi et al. developed a machine learning framework for forest fire prediction using the Algerian Forest Fire dataset [1]. Their study addressed two related tasks. The first task classified the occurrence of forest fires, while the second estimated fire intensity using the Fire Weather Index. The researchers used meteorological and environmental variables as model inputs. They also developed a Streamlit-based application to provide prediction results through an interactive interface. This approach showed the practical value of combining machine learning with decision-support applications. However, the study focused on the Algerian dataset. The authors did not establish how well the models generalized to other geographic regions. The use of multiple prediction tasks also increased the complexity of the system. These limitations indicated the need for a focused prediction model that could maintain reliable performance with relevant environmental variables [1].

Khan et al. proposed a trust-driven machine learning system for early forest fire detection using an intelligent wireless sensor network [2]. Their system combined environmental measurements with sensor reliability information. The researchers used temperature, humidity, and CO_2 concentration to support fire detection. They also introduced trust ratings based on communication, energy, and data reliability. Experiments with 7,200 samples showed that the system reduced detection delay and improved data processing. The integration of sensor networks and machine learning provided an important strength because the system supported real-time monitoring. However, the approach depended strongly on sensor deployment and communication quality. Large monitoring areas could require many sensor nodes. Environmental changes could also affect sensor reliability. Therefore, the study demonstrated the value of real-time machine learning while also showing the challenges of maintaining reliable prediction infrastructure [2].

Singh et al. investigated active wildfire detection through satellite imagery and machine learning in the Wolgan Valley, Australia [3]. They applied Support Vector Machine to

Landsat-8 imagery and used spectral information to identify active fires and burned areas. The researchers emphasized the contribution of Shortwave Infrared and Near-Infrared bands. They also introduced the Normalized Difference Fire Index to improve fire identification. This study showed that satellite imagery could provide broader spatial coverage than conventional ground observation. It also demonstrated the importance of selecting informative spectral features. However, the researchers identified data availability and model interpretability as continuing limitations. The study mainly addressed active fire detection and burned-area classification rather than direct prediction of future fire occurrence. This distinction limited its direct application to predictive forest fire systems [3].

Ong et al. developed the FIREfly project for forest fire monitoring and prediction in Northern Thailand [4]. The researchers used publicly available satellite fire data and weather information as model inputs. They evaluated RF and SVM for predicting forest fire occurrences. Both models achieved approximately 60% accuracy in the initial experiments. The researchers then integrated the predictions into an online dashboard. The dashboard displayed fire probabilities based on current weather conditions and supported situational awareness for emergency response. This work demonstrated the practical value of combining machine learning with real-time visualization. However, the moderate accuracy showed that the selected data and models did not fully capture the complexity of forest fire occurrence. The study also focused on a specific geographic region. These limitations suggested the need for further feature selection and model improvement [4].

Ramya et al. examined forest fire detection and risk prediction using environmental variables [5]. Their study considered temperature, humidity, wind speed, and rainfall as important predictors. The researchers compared Random Forest, Support Vector Machine, and Logistic Regression for classifying fire-prone conditions. They also analyzed feature importance to identify factors associated with fire risk. The study demonstrated that conventional machine learning algorithms could provide practical and scalable fire prediction systems. The researchers further proposed integration with IoT sensors and satellite data for real-time monitoring. However, the study concentrated mainly on environmental measurements and fire-prone conditions. It did not extensively examine spatial relationships or complex interactions among different environmental sources. The limitation indicated the importance of incorporating broader data characteristics when developing a forest fire prediction model [5].

Reddy et al. developed a Forest Fire Spread Behavior Prediction model that combined cellular automata with machine learning [6]. Their framework contained a Forest Fire Spread Process Prediction component and a Forest Fire Spread Results Prediction component. The first component predicted fire direction and spread speed, while the second estimated the burned area. The researchers evaluated the approach using a forest fire case in China and a real fire dataset from Montesinho National Forest Park in Portugal. The spread process model predicted a burned area of 286.81 hectares with a relative error of 28.94%. The study provided a strong contribution because it addressed both fire propagation and burned-area estimation. However, its main objective concerned fire spread rather than the initial prediction of fire occurrence. The combination of cellular automata and machine learning also introduced additional modeling complexity. Thus, the study showed the importance of modeling fire dynamics while leaving room for simpler occurrence prediction approaches [6].

Jiang and Peng developed a machine learning framework that integrated meteorological, terrain, anthropogenic, and vegetation information for forest fire prediction [13]. They compared LR, RF, XGBoost, and SVM. RF achieved the strongest reported performance, with 89.53% accuracy, 92.31% recall, 90.28% F1-score, and 0.9555 AUC. The researchers also applied SHAP to interpret the contribution of individual variables. Minimum relative humidity emerged as an influential factor in fire prediction. The integration of multiple data sources represented a major strength because forest fire occurrence depends on several interacting conditions. However, the large number of heterogeneous variables increased the complexity of the prediction process. The study also required appropriate feature processing and interpretation to avoid misleading relationships. These issues remained important when applying machine learning to forest fire prediction [13].

Choi et al. compared RF, XGBoost, and ANN for forest fire risk prediction in South Korea [14]. The researchers used 2,289 fire events and 4,578 non-fire events from 2020 to 2023. They derived twelve environmental variables from Google Earth Engine and included climate, vegetation, topographic, and socio-environmental information. XGBoost produced the highest F1-score of 0.511 and an AUC of 0.76, while RF and ANN achieved lower scores. DEM, NDVI, and population density consistently contributed to the predictions. This study showed the value of cloud-based remote sensing for large-scale fire risk analysis. It also demonstrated that a more complex neural network did not automatically produce better results than tree-based models. However, the relatively modest F1-score indicated remaining classification challenges. The authors also suggested incorporating seasonal, real-time meteorological, and human activity data to improve future prediction performance [14].

3. Proposed Method

RF is an ensemble-based classification algorithm that combines multiple decision trees to determine the final class of an input sample. Each decision tree independently generates a class prediction, while the RF determines the final class based on the majority vote of all decision trees. This approach reduces the influence of individual trees and improves the robustness of the classification process.

During the tree-building process, Gini Index (GI) is used to determine the best attribute for splitting each node. A lower Gini Index indicates a purer node and therefore a better split. The Gini Index is formulated as:

$$GI = 1 - \sum_{i=1}^{C} P_i^2 \tag{1}$$

where P_i represents the probability of a sample being classified into class i, and C represents the total number of classes.

After all decision trees generate their predictions, RF determines the final class using majority voting. The final prediction can be formulated as:

$$\hat{y} = \underset{c \in C}{\operatorname{argmax}} \sum_{n=1}^{N} I(h_n(x) = c) \tag{2}$$

where $\hat{y}$ represents the final predicted class, N represents the number of decision trees, $h_n(x)$ represents the prediction generated by the n-th decision tree for input x, and $I(h_n(x) = c)$ is an indicator function that takes a value of 1 when the prediction of the n-th tree belongs to class c, and 0 otherwise.

We evaluated RF model using a confusion matrix to summarize the relationship between the actual and predicted classes. The results from the confusion matrix are then used to calculate accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correctly classified samples, while precision measures the correctness of positive predictions. Recall measures the ability of the model to correctly identify samples belonging to a particular class, and the F1-score represents the harmonic mean between precision and recall.

4. Experimental Setup

The research used two datasets collected from the BRIN and BMKG websites, namely climate data and hotspot data. The climate dataset contained rainfall, solar radiation, humidity, and temperature variables, while the hotspot dataset contained the hotspot identification number, date, time, latitude, longitude, satellite confidence level, probability radius, administrative location, and hotspot type. The datasets covered observations from January to December 2023. The climate variables were treated as independent variables, while the hotspot occurrence was used as the dependent variable. The two datasets were integrated based on the observation date to construct the dataset used for RF classification. The hotspot attributes were used to identify the occurrence and characteristics of hotspots, while the climate attributes represented the environmental conditions associated with hotspot occurrence.

After data integration and pre-processing, the resulting dataset was divided into training and testing subsets to evaluate the RF model. The training dataset was used to build the classification model, while the testing dataset was used to evaluate its performance on unseen data. An 80:20 data split was applied, as shown in Table 4. The training and testing data maintained the same feature structure, including rainfall, solar radiation, humidity, temperature, and the hotspot class. The model performance was subsequently evaluated using a confusion matrix and classification metrics, including accuracy, precision, recall, and F1-score.

Table 1: Training and Testing Dataset Split

Dataset	**Proportion**	**Variables**
Training	80%	Rainfall, solar radiation, humidity, temperature, hotspot class
Testing	20%	Rainfall, solar radiation, humidity, temperature, hotspot class
Total	100%	Rainfall, solar radiation, humidity, temperature, hotspot class

Table 2: Dataset Variables Used for Modeling

Code	**Attribute Name**	**Role**	**Description**
Y0	Date	Reference	Date of climate observation
Y1	Rainfall	Feature	Rainfall intensity
Y2	Solar Radiation	Feature	Duration/intensity of solar radiation
Y3	Humidity	Feature	Air humidity level
Y4	Temperature	Feature	Air temperature
X11	Hotspot Type	Target	Hotspot occurrence/class

5. Result and Analysis

In this study, we evaluated the model using three data split ratios, namely 70:30, 80:20, and 90:10, to examine its classification performance in predicting forest-fire likelihood from climate data. The 70:30 and 80:20 configurations produced stable accuracy values of 85.8% and 85.9%, respectively, while the 90:10 configuration achieved the highest accuracy of 86.4%. Fig. 1 show that the RF model maintained consistent performance across the evaluated split configurations, with the 90:10 ratio producing the highest classification accuracy.

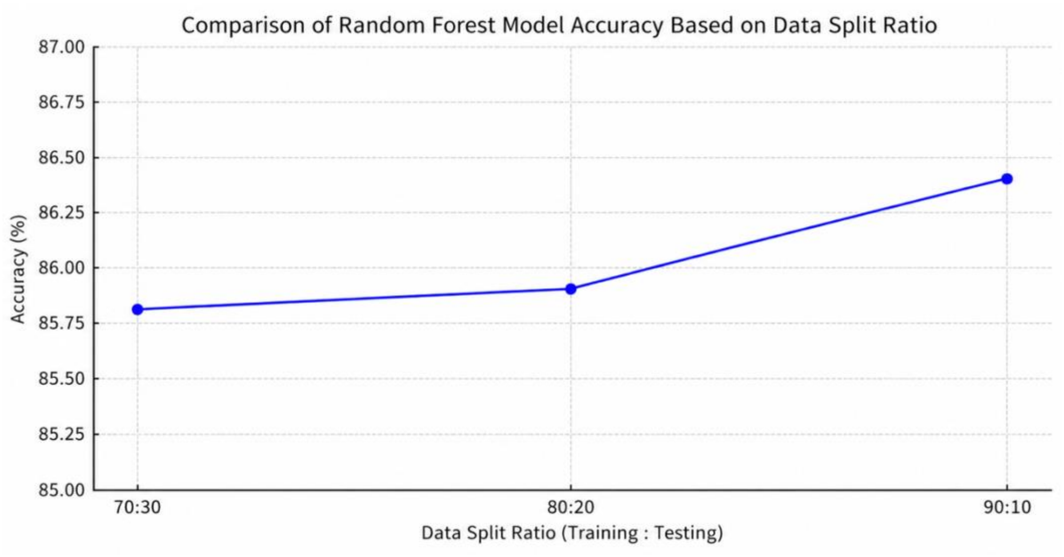

Fig. 1 Comparison of RF model across split configurations,

Fig. 2 depicts the confusion matrix for the 70:30 data split shows that the RF model correctly classified 1,082 samples as No Fire and 38 samples as Fire. The model incorrectly classified 21 No Fire samples as Fire, while 163 actual Fire samples were classified as No Fire. These results indicate that the model identified non-fire conditions more effectively than fire occurrences, with a total of 1,120 correct predictions out of 1,304 test samples, corresponding to an accuracy of approximately 85.9%.

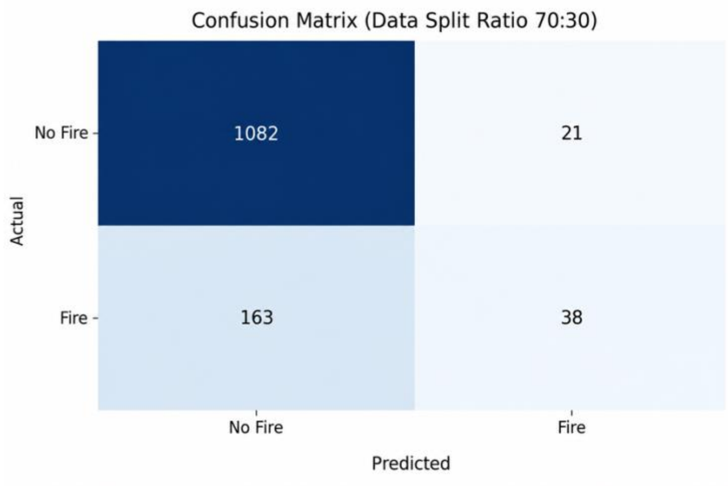

Fig. 2 Confusion Matrix

Fig. 3 shows that solar radiation was the most influential variable in the RF model, with an importance value of approximately 0.48. Temperature ranked second with an importance value of approximately 0.26, followed by humidity at approximately 0.20. Rainfall contributed the least to the model, with an importance value of approximately 0.06. These results indicate that solar radiation, temperature, and humidity contributed more strongly to the model's forest-fire prediction than rainfall.

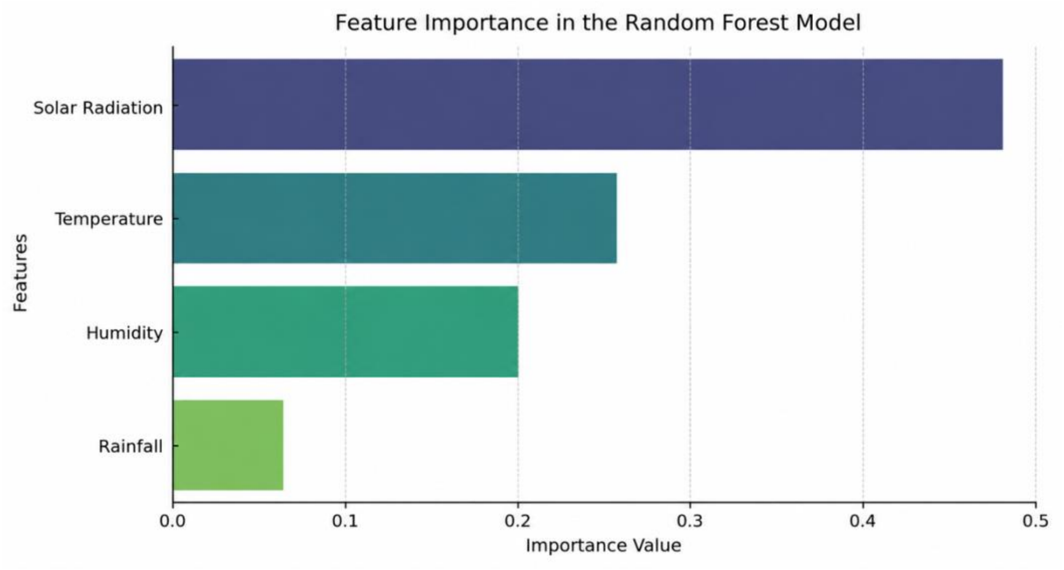

Fig. 3 Feature Importance in RF Model

6. Conclusion

This paper utilizes the RF algorithm to predict forest-fire likelihood from climate data using rainfall, solar radiation, humidity, and temperature as input variables. We evaluate the model using three data split ratios: 70:30, 80:20, and 90:10. The results show consistent classification performance across the three configurations. The 70:30 split achieves 85.8% accuracy, while the 80:20 split reaches 85.9%. The 90:10 split produces the highest accuracy at 86.4%. These results indicate that the RF model can classify forest-fire conditions with stable accuracy across different training and testing configurations.

We further analyze the 70:30 configuration using a confusion matrix to examine the model predictions in more detail. The model correctly classifies 1,082 No Fire samples and 38 Fire samples. However, the model misclassifies 21 No Fire samples as Fire and 163 Fire samples as No Fire. The model therefore produces 1,120 correct predictions from 1,304 testing samples, corresponding to an accuracy of approximately 85.9%. These findings show that the model recognizes No Fire conditions more effectively than Fire conditions. The relatively high number of Fire samples classified as No Fire also indicates that the model still needs improvement in identifying actual fire occurrences.

This paper also utilizes feature importance analysis to identify the climate variables that contribute most to the RF predictions. Solar radiation provides the highest importance value at approximately 0.48, followed by temperature at 0.26 and humidity at 0.20. Rainfall contributes the lowest importance value at approximately 0.06. These findings show that solar radiation, temperature, and humidity provide stronger contributions to forest-fire prediction than rainfall within the utilized dataset. We apply RF with climate-based features as a predictive approach and demonstrate its potential for forest-fire classification, while the results also highlight the need for further improvement in detecting Fire conditions.

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