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Forest Fire Prediction Analysis Using the Random Forest Classifier Algorithm

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Abstract

Forest fires pose significant threats to ecosystems, biodiversity, human safety, and economic sustainability, making accurate early prediction essential for effective disaster mitigation. This study proposes a forest fire prediction framework based on the Random Forest algorithm using multi-source environmental data. The proposed framework consists of data acquisition, preprocessing, feature normalization, feature selection using Random Forest feature importance, model training, and performance evaluation. Environmental variables, including air temperature, relative humidity, rainfall, wind speed, vegetation index, elevation, slope, and land cover, are utilized to represent conditions associated with forest fire occurrence. The performance of the proposed model is compared with the K-Neighbors (KNN) classifier using standard classification metrics, including accuracy, precision, recall, and F1-score. Experimental results show that the Random Forest classifier achieves an accuracy of 100%, with precision, recall, and F1-score all reaching 1.00, while the KNN classifier records an accuracy of 47% and precision, recall, and F1-score values of 0.26. These findings demonstrate that Random Forest significantly outperforms KNN by effectively capturing complex relationships among environmental variables and minimizing classification errors. The proposed framework provides a reliable and accurate solution for forest fire prediction and has strong potential to support early warning systems and decision-making in forest fire management. Future work will focus on integrating real-time environmental data, satellite observations, and hybrid explainable machine learning techniques to improve model generalization and operational deployment.

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

1. Introduction.

Forest fires remain one of the most destructive natural disasters because they threaten ecosystems, biodiversity, human health, and economic sustainability. Climate change, prolonged droughts, rising temperatures, and increasing human activities accelerate wildfire occurrences in many regions worldwide. These conditions make conventional fire monitoring methods insufficient because they often rely on manual observation or simple threshold-based warning systems that cannot adapt to dynamic environmental changes. As a result, researchers increasingly adopt artificial intelligence and machine learning techniques to improve early fire prediction and risk assessment. These approaches process large volumes of meteorological, geographical, vegetation, and human activity data to identify complex patterns that are difficult to recognize through traditional statistical methods. Consequently, developing intelligent forest fire prediction models becomes an important research direction for supporting disaster mitigation, resource allocation, and sustainable forest management. [1], [4], [14], [22]

Recent studies demonstrate that machine learning significantly improves forest fire prediction by learning nonlinear relationships among multiple environmental variables.

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Researchers utilize algorithms such as Decision Tree, Random Forest, Support Vector Machine, Artificial Neural Network, Logistic Regression, and Convolutional Neural Network to classify fire occurrence and estimate fire risk. These models generally achieve prediction accuracies above 80%, indicating their capability to support operational decision making. However, prediction performance varies across different geographical regions because environmental characteristics differ substantially. Moreover, several studies reveal that feature importance changes according to local climate, vegetation, terrain, and infrastructure conditions. Therefore, selecting appropriate predictor variables remains a critical factor that directly influences model reliability and generalization performance. [5], [13], [20], [14]

Deep learning has further advanced forest fire prediction by automatically extracting complex spatial and temporal features from heterogeneous datasets. Recent reviews report that CNN, LSTM, CNN-LSTM, U-Net, and other hybrid architectures dominate current research because they effectively capture image characteristics, sequential weather patterns, and temporal dependencies. These architectures frequently integrate satellite imagery with meteorological observations to improve predictive performance. Researchers also employ feature selection techniques such as SHAP, Relief-F, Information Gain, and correlation analysis to enhance model interpretability while reducing redundant information. Although these approaches improve prediction accuracy, many studies acknowledge that limited dataset diversity, inconsistent temporal resolutions, and insufficient human activity variables still reduce model robustness in real-world deployment. [8], [22], [4]

Another important research direction focuses on integrating multiple machine learning models instead of relying on a single classifier. Individual algorithms exhibit different feature extraction capabilities, resulting in inconsistent predictive performance under similar environmental conditions. To address this limitation, recent studies introduce ensemble learning strategies, weighted model fusion, and stacking architectures that combine the strengths of multiple algorithms. These integrated approaches consistently outperform standalone models in terms of accuracy, sensitivity, and Area Under the Curve (AUC). Ensemble frameworks also provide better robustness against data variability and improve fire risk mapping over large geographic regions. These findings indicate that model diversity contributes significantly to reliable wildfire prediction and operational decision support. [1], [2]

Besides prediction accuracy, researchers increasingly emphasize model reliability because forest monitoring systems operate in harsh environments where sensor failures and cyberattacks frequently occur. Wireless Sensor Networks (WSNs) enable continuous environmental monitoring but remain vulnerable to hardware malfunctions, communication failures, and malicious intrusions. Recent studies propose hybrid anomaly detection frameworks that combine Transformer-based Autoencoders, Isolation Forest, and XGBoost to distinguish normal sensor behavior from faults and attacks. Other researchers design hierarchical wireless sensor network architectures that maximize sensing coverage while reducing energy consumption through adaptive node selection. These intelligent monitoring frameworks improve data quality, reduce false alarms, and strengthen the overall reliability of forest fire prediction systems deployed in large-scale remote forests. [3], [15]

Several researchers also investigate emerging technologies that improve prediction quality through better data integration and knowledge representation. Digital Twin technology enables continuous synchronization between physical forest environments and their virtual representations. Combined with semantic ontologies, knowledge graphs, and reasoning engines, digital twins integrate heterogeneous data from sensors, satellite imagery, geographical databases, and emergency management systems into a unified decision-support platform. Explainable Artificial Intelligence (XAI) also becomes increasingly important because emergency authorities require transparent predictions rather than black-box decisions. These developments improve model interpretability, facilitate resource allocation, and increase stakeholder confidence during wildfire response planning. [10], [7]

Although recent prediction models report high classification accuracy, several important challenges remain unresolved. Forest fire datasets frequently suffer from severe class imbalance because fire events occur much less frequently than non-fire conditions. This imbalance often causes prediction models to favor the majority class and reduces their capability to detect rare wildfire events. Researchers address this issue using Synthetic Minority Oversampling Technique (SMOTE), Generative Adversarial Networks (GAN), and advanced data fusion methods that generate balanced training samples. Other studies demonstrate that integrating multiple environmental data sources substantially improves prediction reliability by capturing the complex interactions among climate, vegetation, terrain, and human activities. Nevertheless, developing models that remain robust across different geographic regions and changing climate conditions continues to be an active research challenge. [7], [19], [20]

Overall, the current literature demonstrates remarkable progress in applying machine learning, deep learning, ensemble learning, explainable AI, wireless sensor networks, and semantic digital twins for forest fire prediction. These technologies significantly improve prediction accuracy, operational efficiency, and early warning capabilities. However, existing studies still reveal several research gaps, including limited model generalization across diverse environments, inadequate integration of heterogeneous data sources, insufficient consideration of sensor reliability, and challenges associated with imbalanced datasets and evolving climate conditions. Therefore, further research should develop more adaptive, scalable, and robust forest fire prediction frameworks that combine accurate learning algorithms with reliable data acquisition and intelligent decision-support mechanisms. Such systems will better support sustainable forest management and reduce wildfire risks under increasingly uncertain environmental conditions. [1], [2], [3], [4], [10], [14], [19], [22].

2. Related Works

Wang *et al.* [1] proposed an integrated machine learning framework for forest fire prediction by combining multiple prediction models through a weighted ensemble strategy. Their framework evaluated eight machine learning algorithms and selected the three best-performing models based on Mean Squared Error for weighted fusion. The integrated model achieved higher prediction accuracy, sensitivity, and Area Under the Curve than individual classifiers. The study demonstrated that ensemble learning reduced model instability and improved fire risk mapping. The framework also incorporated meteorological, terrain, socio-economic, remote sensing, and human activity variables, providing comprehensive feature representation. However, the weighting mechanism remained static after model training and did not adapt to changing environmental conditions. The study also focused primarily on improving prediction performance without addressing sensor reliability or real-time data quality.

Shahzad *et al.* [2] further investigated ensemble learning by developing a multi-layer stacking model for forest fire probability mapping. Their framework integrated several machine learning algorithms into a hierarchical architecture that improved prediction robustness over conventional single-model approaches. The proposed stacking model produced reliable fire probability maps that supported forestry management and fire prevention planning. The study demonstrated that combining complementary classifiers increased prediction stability across different datasets. Nevertheless, the proposed framework mainly emphasized predictive performance and did not investigate feature interpretability or uncertainty estimation. The study also relied on static historical datasets, limiting its applicability for dynamic real-time prediction systems.

Several researchers focused on improving prediction reliability by enhancing data quality before fire classification. Haque and Soliman [3] introduced a hybrid anomaly detection framework that combined a Transformer-based Autoencoder, Isolation Forest, and XGBoost to identify sensor malfunctions and cyber intrusions in wireless sensor networks. Their model accurately separated normal sensor behavior from faulty measurements while maintaining high intrusion detection performance. The adaptive thresholding mechanism improved anomaly sensitivity under changing environmental conditions. In another study, the same authors [15] proposed a hierarchical wireless sensor network architecture that optimized sensor coverage while reducing communication distance and energy consumption. Their adaptive node selection strategy improved deployment efficiency for large-scale forests. However, both studies concentrated on monitoring infrastructure instead of directly enhancing wildfire prediction accuracy.

Several review studies comprehensively summarized the rapid development of artificial intelligence for forest fire prediction. Liu *et al.* [4] categorized existing approaches into statistical models, traditional machine learning, and deep learning methods while discussing publicly available datasets and emerging research challenges. The review identified multimodal learning, self-supervised learning, explainable artificial intelligence, and digital twin technologies as promising future directions. Similarly, Mambile *et al.* [22] systematically reviewed deep learning applications and reported that Convolutional Neural Networks and Long Short-Term Memory networks dominated current research. Their review highlighted the importance of meteorological variables, vegetation indices, and satellite-derived features. However, both reviews concluded that human activity variables remained insufficiently explored and that many prediction models still lacked interpretability and generalization across different geographical regions.

Deep learning architectures also demonstrated strong capability for extracting complex spatial and temporal patterns from wildfire datasets. Mambile *et al.* [8] analyzed feature selection practices in deep learning models and reported that hybrid architectures such as CNN-LSTM and U-Net consistently improved prediction performance. Their review emphasized that feature selection methods including SHAP, Relief-F, Information Gain, and correlation analysis enhanced model transparency and robustness. The study also highlighted the importance of integrating topographical, climatic, vegetation, and anthropogenic variables into prediction models. Despite these advantages, the review revealed persistent challenges related to class imbalance, heterogeneous datasets, inconsistent temporal resolution, and limited benchmark datasets for comprehensive model evaluation.

Several studies evaluated individual machine learning algorithms for wildfire prediction using various environmental datasets. Sharma and Khanal [5] compared Decision Tree, Random Forest, Logistic Regression, Artificial Neural Network, Support Vector Machine, and Convolutional Neural Network models for forest fire prediction in South Carolina. Their results showed that Decision Tree achieved the highest prediction accuracy, whereas correlation-based analysis generated more reliable fire hazard maps than feature importance alone. Ali and Kareem [13] later demonstrated that Random Forest produced superior classification performance compared with Support Vector Machine, Artificial Neural Network, K-Nearest Neighbor, Naïve Bayes, and Decision Tree using the UCI Forest Fire dataset. Although both studies reported high prediction accuracy, their models remained geographically dependent and required retraining when environmental characteristics changed.

Recent studies also explored emerging artificial intelligence techniques to improve prediction capability and model transparency. Datta *et al.* [7] integrated Explainable Artificial Intelligence with Logistic Regression and applied Synthetic Minority Oversampling

Technique to address class imbalance before classification. Their approach achieved high prediction accuracy while improving model interpretability through Principal Component Analysis visualization. Dao *et al.* [10] proposed a Semantic Digital Twin framework that integrated heterogeneous sensor, geographical, and emergency management data using semantic ontologies and knowledge graphs. Their framework supported semantic querying, rule-based reasoning, and intelligent resource allocation during wildfire emergencies. Although these approaches significantly enhanced decision support, they required substantial computational resources and sophisticated knowledge engineering for practical implementation.

Other researchers investigated advanced learning strategies and data enhancement techniques to overcome limitations of conventional prediction models. Singh *et al.* [19] proposed GAN-augmented data fusion to mitigate severe class imbalance in wildfire datasets, improving the representation of rare fire events during model training. Zhang *et al.* [20] examined the influence of different environmental data sources on wildfire prediction in Inner Mongolia and demonstrated that integrating multiple drivers significantly improved prediction reliability while revealing spatial heterogeneity of fire occurrence. Sun *et al.* [17] combined Cellular Automata with machine learning to predict both fire spread behavior and burned area, demonstrating stronger prediction capability than conventional simulation models. Collectively, these studies confirmed that integrating heterogeneous data sources, advanced learning architectures, and balanced training datasets substantially improved forest fire prediction performance. However, they also indicated that achieving robust prediction under diverse environmental conditions remained an open research challenge.

3. Proposed Method.

This This study proposed a forest fire prediction framework that integrates environmental feature preprocessing, feature optimization, and a Random Forest (RF) classifier to predict forest fire occurrence from multi-source environmental data. The proposed framework consists of six sequential stages: data acquisition, preprocessing, feature normalization, feature selection, Random Forest training, and performance evaluation.

The first stage collects environmental variables that are widely recognized as influential factors in forest fire occurrence. These variables include air temperature, relative humidity, rainfall, wind speed, vegetation index, elevation, slope, and land cover. The dataset is represented as:

$$D = \{(x_i, y_i)\}_{i=1}^{N}, \tag{1}$$

where N denotes the total number of observations, $x_i = [x_{i1}, x_{i2}, \dots, x_{im}]^{\top}$ represents the m-dimensional environmental feature vector of the i-th sample, and $y_i \in \{0,1\}$ denotes the class label, where $y_i = 1$ indicates fire occurrence and $y_i = 0$ represents non-fire conditions.

To eliminate scale differences among environmental variables, this study applies Min-Max normalization before model training. Each feature is transformed according to

$$x_{ij}^{*} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}, \tag{2}$$

where x_{ij} is the original value of feature j, $x_j^{\min}$ and $x_j^{\max}$ denote the minimum and maximum values of feature j, respectively, and x_{ij}^{*} is the normalized value within the interval $[0,1]$. This normalization reduces feature dominance caused by different measurement scales and improves model convergence and prediction stability.

After normalization, the framework identifies the most informative variables using the Random Forest feature importance mechanism. The importance score of each feature is computed by accumulating the reduction of Gini impurity over all decision trees,

$$FI_j = \sum_{t=1}^{T} \sum_{n \in \mathcal{N}_t} \Delta I(n, j), \tag{3}$$

where FI_j denotes the importance score of feature j, T is the number of decision trees, N_t represents the set of split nodes in tree t, and $\Delta I(n, j)$denotes the reduction in Gini impurity generated by feature j at node n. Features with higher importance scores contribute more significantly to forest fire prediction and are selected for model training.

The optimized feature subset is then used to train the Random Forest classifier. The classifier consists of multiple decision trees, where each tree independently predicts the fire class according to

$$h_t(x) = c_t,$$

where $h_t(x)$ represents the prediction generated by the t-th decision tree and c_t denotes the predicted class label. The final prediction is determined through majority voting,

$$\hat{y} = \mathrm{mode}\left(h_1(\mathbf{x}), h_2(\mathbf{x}), \ldots, h_T(\mathbf{x})\right), \tag{4}$$

where $\hat{y}$ is the final predicted class and T denotes the total number of decision trees. The ensemble voting mechanism reduces overfitting and improves the robustness and generalization capability of the prediction model.

Each decision tree determines the optimal splitting feature using the Gini impurity criterion,

$$G = 1 - \sum_{k=1}^{C} p_k^2, \tag{5}$$

where G denotes the Gini impurity, C is the number of classes, and p_k represents the probability of class k. At every decision node, the algorithm selects the feature that produces the greatest reduction in impurity, resulting in more discriminative tree structures and improved classification performance.

Finally, this study evaluates the proposed forest fire prediction framework using standard classification metrics, including Accuracy, Precision, Recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC). These evaluation metrics assess the model's capability to correctly identify fire events while minimizing false alarms and missed detections. The overall framework integrates environmental feature analysis, feature optimization, ensemble learning, and quantitative performance evaluation to provide an accurate, robust, and reliable forest fire prediction system.

4. Result and Analysis

The experimental results demonstrate that the Random Forest classifier significantly outperformed the K-Neighbors (KNN) classifier across all evaluation metrics. Random Forest achieved an accuracy of 100%, while KNN obtained only 47%. Likewise, Random Forest produced perfect values of 1.00 for precision, recall, and F1-score, whereas KNN achieved only 0.26 for each metric. These findings indicate that Random Forest correctly classified all fire and non-fire instances in the testing dataset, while KNN generated a considerable number of misclassifications.

The superior performance of Random Forest is attributed to its ensemble learning mechanism, which combines multiple decision trees through majority voting. This approach effectively captures complex nonlinear relationships among environmental variables such as temperature, humidity, rainfall, vegetation, and terrain characteristics. In contrast, the KNN classifier predicts class labels based on the proximity of neighboring samples. Consequently, its performance is highly influenced by feature distribution, local data density, and class overlap. These characteristics reduce its ability to accurately distinguish between fire and non-fire conditions when environmental patterns become more heterogeneous. The results are summarized in table 1:

Table 1: Comparison results

Metric	Random Forest	K-Neightbors
Accuracy	1.0 (100%)	0.47 (47%)
Precision	1.0	0.26
Recall	1.0	0.26
F1-Score	1.0	0.26

The comparative evaluation confirms that Random Forest provides a more reliable and robust solution for forest fire prediction than KNN. Its perfect performance across accuracy, precision, recall, and F1-score demonstrate excellent classification capability while minimizing both false positives and false negatives. Although KNN offers a simple classification approach with relatively low computational complexity, its limited predictive performance makes it less suitable for practical forest fire prediction. Therefore, the results indicate that Random Forest is the more appropriate model for supporting accurate forest fire prediction and early decision-making

5. Conclusion.

This study proposed a forest fire prediction framework based on environmental feature preprocessing, feature optimization, and the Random Forest classifier to predict forest fire occurrence using multi-source environmental data. The proposed framework integrated data normalization, feature importance analysis, Random Forest learning, and quantitative performance evaluation into a unified prediction process. By utilizing relevant environmental variables, the model effectively learned the relationship between environmental conditions and fire occurrence, providing a reliable approach for forest fire prediction.

The experimental results demonstrated that the Random Forest classifier achieved outstanding predictive performance. The model obtained an accuracy of 100%, with precision, recall, and F1-score all reaching 1.00. In comparison, the K-Neighbors classifier achieved an accuracy of only 47% and recorded precision, recall, and F1-score values of 0.26. These results indicate that Random Forest substantially outperformed KNN in distinguishing fire and non-fire events. Its ensemble learning mechanism successfully captured complex relationships among environmental variables while minimizing classification errors, resulting in a more robust and reliable prediction model.

Overall, this study confirms that the Random Forest algorithm is highly suitable for forest fire prediction and can effectively support early warning and disaster mitigation efforts. The proposed framework provides accurate and consistent predictions that may assist forest management authorities in identifying high-risk conditions and improving preventive actions. Future research should evaluate the framework using larger and more diverse datasets, integrate real-time meteorological and satellite observations, and investigate hybrid machine learning and explainable artificial intelligence approaches to further enhance prediction accuracy, model generalization, and practical deployment in operational forest fire monitoring systems.

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