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Article

Advancing Forest-Fire Management: Exploring Sensor Networks, Data Mining Techniques, and SVM Algorithm for Prediction

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Abstract: Forest-fire is a pressing global problem that has far-reaching effects on human life and the environment, with climate change exacerbating their frequency and intensity. There is an urgent need for advanced predictive systems to mitigate these impacts. To address this issue, this study introduces a forest-fire prediction framework integrating wireless sensor networks (WSNs), data analysis, and machine learning. Sensor nodes deployed in a forest area collected real-time meteorological data, which was transmitted using LoRaWAN technology. Data mining techniques prepared the data for analysis using the SVM algorithm, revealing relationships between meteorological parameters and wildfire risk. The SVM model demonstrated an accuracy of 86% in classifying forest-fire risk levels based on temperature, humidity, wind speed, and rainfall data. The integrated framework of WSNs and the SVM algorithm provides a high-accuracy model for forest-fire risk prediction. The model is compared to the Canadian Forest Fire Hazard Rating System to validate its accuracy, demonstrating strong agreement with historical records and reports. The model's practical implications include efficient management, early detection, and prevention strategies. However, the model's limitations suggest avenues for future research, we should consider broader geographic applications and using advanced machine-learning methods to enhance the model's predictive capabilities.

Keywords: forest-fire prediction; wireless sensor networks; data analysis; machine learning; meteorological parameters

1. Introduction

Forest-fire poses a significant threat to natural ecosystems and human settlements worldwide, resulting in loss of life, destruction of property, and severe environmental impacts [1,2]. The increased frequency and intensity of forest-fire in many regions due to climate change and other factors has increased the need for advanced predictive systems to mitigate their effects [3,4]. Forest-fire has wide-ranging consequences, affecting the environment, economy, and society [5]. They lead to economic losses through the destruction of property, cause public health problems due to air pollution, and result in ecological damage that often leads to soil erosion and biodiversity loss [6].

Significant progress has been made in forest-fire prediction and risk assessment by integrating state-of-the-art technologies and rigorous scientific methodologies [7,8]. This section provides an overview of crucial academic contributions that revolve around the intersection of wireless sensor networks (WSNs), data mining, and machine learning algorithms [9,10], highlighting their pivotal roles in advancing forest-fire prediction and forest-fire research [11,12].

WSNs are vital in numerous domains, including environmental monitoring, traffic control, intelligent battlefield systems, and home automation. When it comes to forest-fire prediction and management, the combination of WSNs with technologies like the Internet of Things (IoT) [13], drones [14], artificial intelligence [15], and cloud computing [16] has resulted in intelligent forest-fire prediction systems. This integration empowers forest management authorities and firefighters with data-driven insights, ultimately leading to more effective strategies for preventing and mitigating forest-fire. Innovative energy-efficient hybrid routing protocols have been proposed to address energy constraints in forest areas, optimizing energy usage and extending network lifespan.

Data mining techniques are instrumental in advancing predictive models across various domains, particularly in forest-fire forecasting [17,18]. They are essential for mitigating forest-fire risks, especially given the increasing challenges of forest-fire. Recent research emphasizes the fusion of technology and environmental awareness. Machine learning and data mining techniques take center stage, enhancing forest-fire risk assessment and providing insights into the impacts of these disasters. These studies estimate population exposure to delicate particulate matter during forest-fire seasons, predict forest-fire incidents, and optimize algorithms for assessing the extent of forest-fire. These studies comprehensively understand how forest-fire affect human communities and natural landscapes by integrating data from various sources, including remote sensing, meteorological data, and ecological information. They also investigate associations between climate data and forest-fire, aiding in better early prediction and strategic planning.

Machine learning has been extensively applied to forest-fire modeling and risk assessment [19,20]. Researchers have used these techniques to model forest-fire and their potential outcomes, integrating geospatial information systems (GIS) [21]. Machine learning algorithms are also used to simulate the spread of fire smoke, utilizing data fusion methods such as multi-linear regression, generalized boosting, and random forest. Dynamic elements have notably been introduced into once-static models, enhancing predictive accuracy. These applications have resulted in development prediction maps and risk assessment models that contribute to effective forest ecosystem management and disaster preparedness.

Numerous studies have deepened our understanding of the intricate connections between climate change, forest-fire, and ecosystems [22,23]. These research endeavors have illuminated the repercussions of human-induced forest-fire, climate change's influence on biomass, and the dynamics of fuel flammability. They emphasize the importance of considering climate-induced fuel alterations when predicting carbon emissions from boreal forest-fire. They also explore the interplay among climate, disturbances, and vegetation, transforming spatial landscape patterns and ecosystem dynamics. By modeling landscapes, identifying thresholds, and investigating the effects of forest-fire on habitat components, these studies enhance our comprehension of how climate change, forest-fire, and ecological factors interact to shape ecosystems.

In these critical domains, a range of scholarly works has advanced our understanding and capabilities, forming the foundation for further research and innovation in addressing the multifaceted challenges posed by forest-fire. Nonetheless, although the examined studies provide important insights and contributions to their respective fields, there are several widespread limitations in the current literature on forest-fire prediction.

(1) Interdisciplinary Integration: Most existing studies focus on a specific aspect of forest-fire prediction, such as WSNs, data mining, or machine learning. There is a need for more comprehensive, interdisciplinary approaches that integrate these technologies to provide a holistic understanding of forest-fire risk.

(2) Dynamic Modeling: Forest-fire prediction models often lack the dynamic nature required to adapt to changing environmental conditions and real-time data. Dynamic modeling is crucial as forest-fire responds to shifting parameters like weather and fuel availability.

(3) Climate Interactions: Climate change is a significant driver of forest-fire and understanding its interactions with forest-fire dynamics is essential. Many studies have yet to explore these connections fully, which is critical for accurate risk assessment.

(4) Data Fusion and Advanced Techniques: While some studies use advanced techniques in data mining and machine learning, the potential for improving prediction accuracy remains untapped through data fusion, ensemble models, and emerging approaches in artificial intelligence.

This study aims to address the critical need for effective forest fire prediction by examining the efficacy of an integrated framework that utilizes wireless sensor networks (WSNs), data mining techniques, and machine learning algorithms, specifically the Support Vector Machine (SVM) algorithm, in predicting and assessing forest fire risks. We aim to contribute to understanding forest-fire prediction and provide valuable insights for policymakers and forest management authorities. By employing advanced technologies and analytical methods, we strive to enhance the early detection and management of forest-fire risks, ultimately contributing to protecting ecosystems and human settlements in vulnerable regions.

This paper presents a comprehensive framework that leverages these technologies and methods to predict and assess forest-fire risks. We have deployed a wireless sensor network in a forest area to collect real-time meteorological data. Data mining techniques are applied to clean and prepare the data for analysis. A Support Vector Machine (SVM) algorithm is used to assess forest-fire risk based on temperature, humidity, wind speed, and rainfall data. The model's accuracy is validated using the Canadian Forest-fire Danger Rating System (CFFDRS) [24].

The severity of the forest-fire problem necessitates a comprehensive understanding of its causes and challenges [25,26]. Climate change, land use changes, and human activities contribute to forest-fire frequency forest-fire. The complex dynamics of forest-fire, influenced by weather conditions, fuel availability, and topography, pose significant challenges to their prediction and prevention [27–29]. To address these challenges, modern technologies and data-driven approaches are essential. Wireless sensor network technology [30,31], data mining [32], and machine learning [33] algorithms offer advanced tools for predicting and assessing forest-fire risks. By integrating these modern technologies and analytical methods, this study seeks to enhance the early detection and management of forest fire risks, ultimately contributing to protecting ecosystems and human settlements in vulnerable regions such as Jiangsu Province. The findings are expected to provide valuable insights for policymakers and forest management authorities, aiding in developing more informed and effective forest fire management strategies.

This paper is structured to provide a comprehensive framework for forest fire risk prediction and assessment. It begins with this introduction, followed by a method section that outlines the deployment of the WSN and the analytical techniques used, a result section that presents the findings of the SVM model's performance, a discussion of the implications of the results, and finally, conclusions and recommendations for future research.

2. Methods

2.1. System Architecture

This section presents a clear and comprehensive overview of the system architecture for our forest-fire prediction framework. The framework comprises three main components: wireless sensor networks, data mining, and machine learning. The functions of each element and their respective roles within the overall architecture are explored. The entire architecture of the system is illustrated in Figure 1, providing a systematic and well-structured approach to using wireless sensor networks and machine learning techniques to forecast forest-fire. This approach aims to mitigate the risk of fires in remote forest regions proactively.

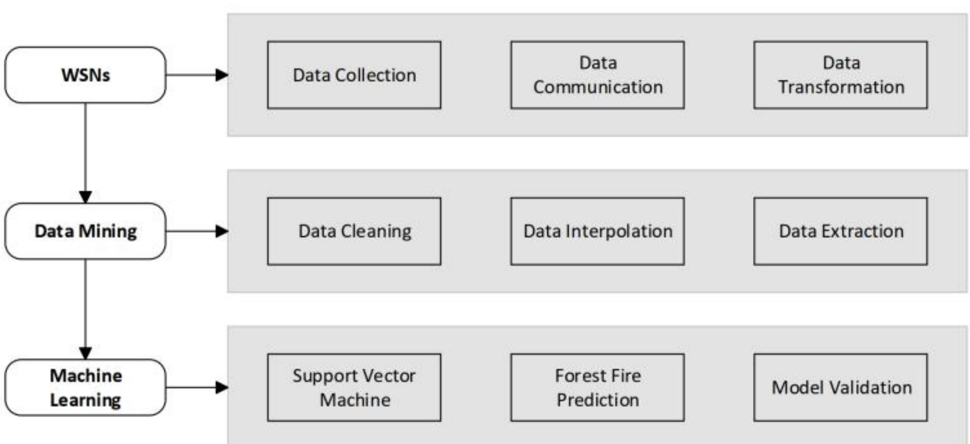

Figure 1. A framework system for forest-fire prediction.

As shown in Figure 1, our forest-fire prediction system is built upon a three-tiered architecture comprising Wireless Sensor Networks, Data Mining, and Machine Learning. This well-structured architecture empowers us to predict and mitigate forest-fire in remote regions proactively.

By deconstructing our framework into these distinct components and components, we aim to offer a clear and organized understanding of how each element contributes to our forest-fire prediction system. This approach enhances our predictions' accuracy and empowers timely fire risk mitigation in remote forest regions.

In developing our forest-fire prediction model, we consciously decided to focus on meteorological parameters due to their direct influence on fire risk conditions. However, we acknowledge that forest-fire dynamics are multifaceted and involve various factors, including topography, vegetation type, and human activity. While not included in our current model, these factors are recognized as significant contributors to fire risk. The exclusion of topographical, vegetational, and anthropogenic factors was a strategic choice driven by several considerations:

(1) Data Availability: Access to comprehensive and high-quality data for these variables across different forest regions can be limited.

(2) Model Complexity: Incorporating these factors would significantly increase the model's complexity, potentially affecting its interpretability and computational efficiency.

(3) Research Focus: Our primary aim was to demonstrate the efficacy of using meteorological data from WSNs for fire risk prediction, which could be a foundational layer for future models.

The deployment of sensor nodes and monitoring systems on Zijin Mountain enables us to gather critical weather data in a region that encapsulates the ecological diversity and climatic variations of Jiangsu Province. This data is the foundation for our forest-fire prediction system in this dynamic and environmentally significant area.

2.2. Study Area

Our forest-fire prediction system was applied in Jiangsu Province, China, an area known for its unique ecological and geographical characteristics. Jiangsu Province is in eastern China characterized by a high population density and a notable vulnerability to forest-fire. The geographical features of Jiangsu Province do not include very high mountains, and its width from east to west is relatively limited. However, the climate varies considerably along a north-south gradient, resulting in distinct zonal trends in vegetation distribution.

For our research, we deployed an extensive network of sensor nodes and monitoring systems on Zijin Mountain, located in Nanjing, China. Zijin Mountain is situated within Jiangsu Province and is an excellent representative location for our study. These sensor nodes collect a wide range of weather observation data, including temperature, humidity, wind speed, and more, as shown in Figure 2.

Figure 2. Experiment site.

2.3. Wireless Sensor Networks

2.3.1. Data Collection

The advantages of utilizing wireless sensor networks for data collection are that, firstly, we can deploy massive wireless sensors in remote forest areas due to their low cost. We strategically deploy a variety of sensors across the forest, with an average spacing that varies based on risk assessment. High-risk areas are equipped with sensors every 100 m, while lower-risk zones have a sensor every 500 m, ensuring comprehensive coverage with a cost-effective approach. To enhance reliability, we implement data redundancy for critical parameters, providing a safeguard against sensor failures and offering multiple data points for cross-verification —a critical practice in scientific research. As a result, the meteorological parameters, such as rainfall, temperature, humidity, and wind speed acquired by sensor nodes, are timelier and more dependable than those obtained by traditional weather stations. Secondly, forest areas are inaccessible or remote, and setting up a well-equipped weather station is impractical. Fortunately, the sensors can take advantage of environmental energy, such as solar and wind power. Hence, we can use this technology to prolong the sensors' service life when nodes are deployed to detect forest-fire everywhere. In our research, as seen in Figure 3, wireless sensors will be commonly used in forest-fire prediction.

Figure 3. Wireless sensors are deployed in forest areas.

Our decision to use wireless sensor networks in our research is based on critical factors that highlight their appropriateness and efficiency:

(1) Sensor Diversity for Holistic Data Collection:

Our network amalgamates diverse sensor types, each meticulously chosen to capture meteorological parameters. For instance, we use rain gauges for exact rainfall measurements, specialized temperature and humidity data sensors, and anemometers for top-quality wind speed assessment. This methodical selection and deployment of sensors ensure a comprehensive and all-encompassing approach to data collection, allowing us to address various meteorological variables concurrently.

(2) Calibration and Precision Maintenance:

Our unwavering pursuit of data accuracy is at the core of our data collection methodology. We adhere to stringent calibration and maintenance protocols, aligning our sensors meticulously with industry-standard instruments. This meticulous calibration process guarantees the precision and reliability of the measurements, adhering to widely recognized scientific standards and practices and reinforcing the accuracy of the data obtained.

(3) Data Redundancy and Cross-Verification:

To bolster data reliability, we introduce the concept of data redundancy, particularly for critical parameters. This redundancy serves as a safety net, protecting against potential sensor failures. Simultaneously, it offers the advantage of multiple data points for cross-verification, which is a well-established practice in scientific data collection and analysis.

(4) Real-Time Monitoring for Data Completeness:

Ensuring the completeness of data is crucial, and we achieve this through continuous monitoring of sensor functionality in real-time. Our system seamlessly incorporates automated checks to promptly identify and correct any gaps, anomalies, or discrepancies within the data stream. This proactive approach adheres to established scientific data integrity principles, guaranteeing the completeness of our dataset.

2.3.2. Data Communication and Data Transformation

In forest-fire detection, most contemporary data collection systems rely on sensors for data acquisition and employ ZigBee technology for short-range wireless communication. However, ZigBee's transmission distance is inherently limited, spanning a mere 100 m, rendering it inadequate for more extensive forest areas. To address this constraint and optimize energy consumption, our forest-fire prediction system harnesses the potential of LoRaWAN (Long Range) technology for wireless data transfer. The architectural framework for this data transmission is elucidated in Figure 4.

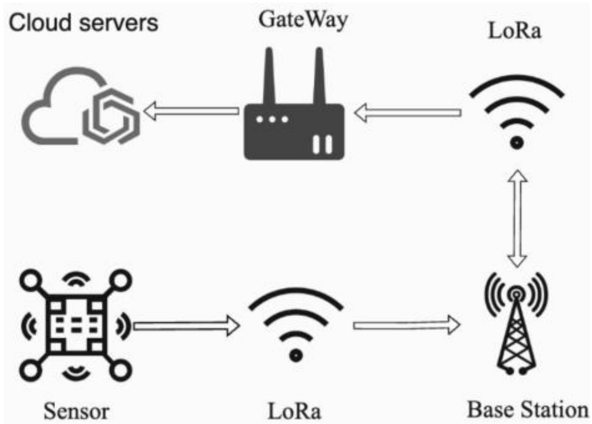

Figure 4. Data communication architecture.

In this study, we use LoRaWAN technology for data transmission. LoRaWAN is a low-power, wide-area networking (LPWAN) technology that is highly suitable for long-distance communication applications. LoRaWAN technology can achieve communication ranges from several kilometers to tens of kilometers without the need for additional relay equipment, significantly reducing the cost of network cabling. The selection of LoRaWAN technology for our system brings forth several distinct advantages:

(1) Long Range:

In urban environments, the communication range of LoRaWAN typically reaches 2–5 km, while in rural environments, this range can extend up to 15 km. This far-reaching capability is especially critical for forest areas characterized by their remoteness and limited access.

(2) Energy Optimization:

Implementing adaptive data rate technology in LoRaWAN enhances data transmission efficiency and contributes to substantial energy savings. The system operates at low power, drawing less than 20 mA in sleep mode and only 10 mA during data reception, significantly extending the operational life of sensor nodes.

(3) End-to-end Security:

Security in data communication is paramount. LoRaWAN ensures secure communication through end-to-end encryption, safeguarding the integrity of the transmitted data.

However, the communication range of LoRaWAN can be influenced by various factors, including receiver sensitivity, transmission power, antenna gain, atmospheric loss, carrier frequency, obstacles, antenna height, electromagnetic interference, weather conditions, and the mobility of the devices. Therefore, the actual communication range between LoRaWAN sensors will depend on the specific application environment and the factors mentioned above. Under ideal conditions, LoRaWAN technology can achieve very long communication distances, but in practical applications, these distances may be reduced due to environmental factors.

To overcome these challenges, network planning and optimization tailored to the unique topography of forest areas are essential. The Adaptive Data Rate (ADR) strategy is one of the key technologies for enhancing the propagation performance of LoRaWAN signals in forested regions. With the ADR mechanism, the network can dynamically adjust the data transmission rate and signal bandwidth based on the actual received signal quality at each end-node. For nodes located at a distance or in complex terrain, such as behind mountains, the ADR mechanism may automatically select a higher Spreading Factor (SF) to improve the link budget and signal strength. Conversely, nodes that are closer to the gateway or have a clear line-of-sight can use a lower SF to achieve faster transmission speeds. This dynamic adjustment mechanism effectively balances signal coverage and transmission rate, ensuring reliable communication in diverse environments. Additionally, its low-power operation enables the use of battery-powered sensor nodes with solar recharging capabilities. This method ensures virtually maintenance-free operation, particularly in remote forest regions where accessibility may be limited.

Within our system, numerous sensor nodes, each equipped with LoRaWAN capability, are strategically deployed throughout the forest to gather essential data. This data travels across multiple hops, surmounting the challenges posed by dense forest foliage, to reach LoRaWAN gateway stations equipped with high-gain antennas and robust power supplies. These gateways are seamlessly interconnected through backhaul links, eventually converging into a central cloud platform. This platform is the nexus for data aggregation and processing, facilitating efficient and timely sensor data analysis.

In summary, integrating LoRaWAN technology and deploying solar-powered sensor nodes is a pivotal step in revolutionizing wireless sensor networks for forest-fire detection. It furnishes an efficient, low-maintenance architecture that combines extensive connectivity with sustainable, renewable power sources. The combination of these factors significantly enhances the reliability and sustainability of the system, ensuring early and efficient detection of forest-fire.

2.4. Data Mining

2.4.1. Data Cleaning

Data cleaning is a fundamental step in refining the raw data collected by wireless sensor networks. In the context of forest-fire prediction, this step plays a critical role in ensuring the accuracy and reliability of the dataset. Imperfections in weather data can arise from various sources, including physical equipment failures, technical glitches in sensors, communication systems, or even software issues on servers. The challenges associated with weather data cleaning are manifold, primarily revolving around two main topics:

(1) Data Exception:

Geographical weather parameters should naturally fall within a reasonable range. For example, in Nanjing, China, the temperature typically varies between −20 °C and 40 °C, and humidity ranges from 0 to 100. When weather parameters deviate from these expected ranges, it is termed a "data exception". Addressing these exceptions is vital to maintaining data accuracy.

(2) Missing Data:

The wireless sensor network technology facilitates the collection of weather parameters at least once a day. Unfortunately, data parameters can be lost due to sensor malfunctions or technical interruptions, resulting in "missing data".

When either of these issues occurs, it introduces the potential for inaccuracies in the weather information. To mitigate this, several data-cleaning techniques come into play. Specifically, when data is missing, the 'NAN' identifier fills the void the absent data leaves.

In the following section, we will delve into the methods for handling these 'NAN' markers, elucidating how they are instrumental in rectifying missing data. This critical data-cleaning process ensures that the dataset used for analysis is robust and reliable, setting the stage for accurate forest-fire prediction.

2.4.2. Data Interpolation

Data interpolation is a crucial step in the data processing pipeline, designed to enhance the quality and completeness of our dataset. This step follows the handling of erroneous or missing data and is essential for ensuring that our analysis is robust and reliable. Our approach to data interpolation is outlined below.

The primary goal of data interpolation is to fill in missing or 'NAN' values in our dataset using a method that is both statistically sound and reflective of the underlying patterns in our data. We achieve this by leveraging the K-Nearest Neighbor (KNN) algorithm, which is chosen for its effectiveness in estimating missing values based on the data from neighboring points in the feature space.

(1) Construction of the Correlation Coefficient Matrix:

To Understand the relationships between different weather parameters and to identify which parameters are most closely related to each other. This helps in selecting the most relevant neighbors for the KNN algorithm.

Step 1: Begin by inputting the training data set, which includes weather parameters like rainfall, wind speed, temperature, and humidity.

Step 2: Initialize the data matrix, creating a complete data matrix ($X_{m\times n}$), where m represents the data records' rows, and n signifies the number of data dimensions.

Step 3: Before we proceed to calculate the covariance, it is essential to normalize the data to ensure that each variable has a mean of 0 and a standard deviation of 1. This step is crucial for placing data of different scales into the same matrix, thereby avoiding bias due to scale differences. The normalization process is achieved by applying in Equation (1):

$$Z(X) = \frac{x - \bar{x}}{s(x)} = \frac{x - \bar{x}}{\sqrt{\frac{(x - \bar{x})^2}{n}}} \tag{1}$$

Equation (1) represents the normalization procedure, where $Z(X)$ is the normalized value, x is the original data point, $\bar{x}$ is the mean of the dataset, $s(x)$ is the standard deviation, and n is the number of data points. This equation ensures that all variables contribute equally to the analysis regardless of their initial scale.

Step 4: We proceed to calculate the covariance of the standardized data matrix, which is a crucial statistic for measuring the relationship between two random variables. The formula used for this calculation is as follows in Equation (2):

$$cov(x, y) = \frac{\sum_{r=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{n - 1} \tag{2}$$

Equation (2) represents the covariance between two variables X and Y, where X_i and Y_i are individual sample points, $\bar{X}$ and $\bar{Y}$ are the means of the X and Y samples respectively, and n is the total number of data points.

For an n-dimensional data matrix, the covariance can be derived from the two-by-two data, resulting in an $n \times n$ covariance matrix.

(2) Calculation of the KNN Algorithm Estimate:

To estimate the missing values by considering the influence of the K nearest neighbors, weighted by their distance from the point with missing data.

Step 1: Calculate the Euclidean distance for the entire data set. The Euclidean distance matrix of the X matrix is determined, considering only the non-missing data for the distance calculation. The distance between two pairs is calculated using the Euclidean distance formula.

Step 2: Since distance is a crucial parameter in most KNN algorithms, the value of the distance plays a significant role in determining the efficiency and precision of collecting the K nearest neighbors. The K nearest neighbors' weighted value is determined as the weighted mean, where Equation (3) gives the final substituted value:

$$x_0 = \frac{\sum_{a=1}^{K} \left(\frac{d_a}{\sum_{i=1}^{K} d_i} \times X_{pj} \right)}{\sum_{a=1}^{K} \left(\frac{d_a}{\sum_{i=1}^{K} d_i} \right)} \tag{3}$$

where X_{pj} is the value of the nearest neighbor's corresponding position; p is the number of columns corresponding to the distance matrix's number of rows in the original data matrix.

(3) Calculation of Dimensional Correlation Values to the Final Fill Value:

To refine the initial KNN estimate by considering the dimensional correlations, which account for the impact of each attribute on the missing data dimension.

Step 1: Determine the deviation by subtracting the mean of the statistics for each attribute from each value. This deviation indicates how much a value deviates from the center and is calculated in Equation (4):

$$a = x_{ij} - \frac{\sum_{i=1}^{m_0} x_{ij}}{m_0} \tag{4}$$

where: m_0 is the number of non-missing attributes in this property; x_{ij} is the corresponding statistic.

Step 2: Calculate the difference and the corresponding covariance matrix, reflecting the impact of the attribute on the dimension of the missing data.

Step 3: Add the resulting estimates and the dimensional correlations to obtain the final estimate of the missing values, as shown in Equation (5).

$$x = x_0 + x^{'} \tag{5}$$

The correlation coefficient matrix provides insights into the relationships between different weather parameters, which is crucial for selecting the most relevant neighbors for the KNN algorithm. The KNN algorithm then uses these relationships to estimate missing values. The dimensional correlation values further refine this estimate by considering the specific impact of each attribute on the missing data dimension, leading to a more accurate and context-aware interpolation.

By following these steps, it is ensured that the interpolated data is not only complete but also reflects the true underlying patterns in the dataset. This methodical approach to data interpolation is vital for the reliability of the subsequent analysis in this paper and predictions in the field of forest-fire prediction.

2.4.3. Data Extraction

After completing the data cleaning and interpolation processes, the final step of the approach is data extraction. In this phase, we extract and refine the essential parameters from the datasets. The purpose is to create a more focused dataset with only the necessary information for our analysis. For instance, in forest-fire prediction, we primarily focus on the impact of rainfall, wind speed, temperature, and humidity on the occurrence and behavior of forest-fire.

Following the completion of data cleaning and interpolation, the final step in the data processing approach is data extraction. This phase is pivotal for refining the dataset to include only the essential parameters necessary for our analysis. In the context of forest-fire prediction, we concentrate on parameters that significantly influence the occurrence and spread of forest fires, such as rainfall, wind speed, temperature, and humidity.

Our data processing and analysis are conducted using Python, a versatile programming language widely recognized for its efficiency in handling complex data tasks. We use the Pandas library, a powerful tool within the Python ecosystem, to manage and analyze our datasets.

(1) Data Loading:

We initiate the data extraction process by specifying the data path and loading the datasets. These datasets encompass the meteorological parameters collected by the wireless sensor network.

(2) Data Reading:

Leveraging Python and Pandas, the loaded data is read and organized into a structured format. This step is crucial as it transforms the raw data into a form that is amenable to analysis and modeling.

(3) Value Extraction:

The core of data extraction lies in isolating and extracting the values of specific parameters that are critical for the forest-fire prediction model of the study. Values for rainfall, wind speed, temperature, and humidity are meticulously extracted.

Data extraction is a fundamental step in the methodology of this study, as it prepares the dataset for subsequent data mining and machine learning processes. By focusing on the relevant meteorological parameters, a refined dataset is created, which serves as the cornerstone for developing and validating our forest-fire prediction models.

Employing systematic steps in data extraction ensures that the analysis is grounded in precise, relevant, and comprehensive data. This rigorous approach is essential for the accuracy of forest-fire prediction and early detection, ultimately contributing to more effective prevention and response strategies.

2.5. SVM

The relationship between forest-fire and climate variables can be effectively modeled as a machine-learning problem. Support Vector Machine (SVM), a powerful supervised learning model, is particularly well-suited for this task due to its ability to handle high-dimensional data and non-linear relationships.

In the context of SVM, "optimal hyperplanes" refer to the decision boundaries that best separate different classes of data in a feature space. These hyperplanes are considered optimal because they maximize the margin between the nearest data points of different classes, which leads to better generalization and robustness of the model.

Python is used for the implementation of the SVM model, leveraging the efficiency and flexibility of the language in data processing and machine learning. Specifically, the scikit-learn library, a widely used Python package is employed, which provides a comprehensive suite of tools for machine learning, including SVM. SVM is adapted in our model to classify forest-fire risks based on meteorological parameters such as temperature, humidity, wind speed, and rainfall. The steps involved in our SVM approach are as follows.

The dataset we work with, denoted as X, consists of weather parameters collected through Wireless Sensor Networks (WSNs) deployed in forest areas. These weather parameters include temperature, humidity, wind speed, and rainfall, represented as x_i. The forest-fire risk is categorized into y levels, ranging from 1 to 5. For instance, if $y = 5$, it signifies a high forest-fire risk. The problem at hand is to determine which forest-fire risk level corresponds to each set of weather parameters, x_i. We use the function $F(x, y)$ to represent the relationship between x_i and y.

Our training dataset, denoted as T, is structured as a set of pairs, (x_i, y_i), where x_i is a vector consisting of weather parameters: $(x_{i1}, x_{i2}, x_{i3}, x_{i4})$, representing rainfall, temperature, humidity, and wind speed, respectively. The variable y_i is the class label, taking values in the range from 1 to 5, corresponding to the forest-fire risk levels. Here, i ranges from 1 to m, where m represents the number of samples.

SVM is fundamentally concerned with finding a hyperplane that can effectively separate data points belonging to different classes. A linear equation $w \cdot x + b = 0$ represents the hyperplane, and its associated classification decision function is $f(x) = sign(w \cdot x + b)$, where w is the average vector determining the hyperplane's direction, and b is the displacement term. To ensure that the hyperplane is well-positioned, we aim to maximize the functional interval of the hyperplane concerning the sample points in the training dataset. This can be framed as an optimization problem, where we maximize the interval while ensuring that all sample points meet specific constraints, is given by Equation (6):

$$
\begin{gathered}
max_{w,b}\, r \\
s.t. \\
y_i(w \cdot x_i + b) \geq 1, i \in [1, m].
\end{gathered}
\tag{6}
$$

where r represents the minimum functional interval of all sample points in the training dataset. The problem of finding a partition hyperplane can be transformed into a constrained optimization problem. By introducing a relaxation variable ξ_i ($\xi_i \geq 0$) for each sample point, the optimization problem becomes Equation (7):

$$
\begin{gathered}
min_{w,b,\xi} \frac{1}{2}|w|^2 + \sum_{i=1}^{m} \xi_i \\
s.t. \\
y_i(w \cdot x_i + b) \geq 1 - \xi_i, i \in [1, m], \xi_i \geq 0
\end{gathered}
\tag{7}
$$

where C ($C > 0$) is called the penalty parameter, and its value influences the trade-off between maximizing the interval and minimizing misclassification errors.

To solve the SVM optimization problem, we introduce Lagrange multipliers α_i and μ_i ($\alpha_i \geq 0$, $\mu_i \geq 0$) to construct the Lagrange function. By taking partial derivatives of the Lagrange with respect to w, b, and x_i (slack variables), and setting them equal to zero, we convert the original primal optimization problem into a dual optimization problem. The dual problem, which is often easier to solve, is given by Equation (8):

$$\min_{\alpha} -\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\alpha_i\,\alpha_j y_i y_j x_i \cdot x_j + \sum_{i=1}^{m}\alpha_i$$

$$s.t. \tag{8}$$

$$\sum_{i=1}^{m}\alpha_i y_i = 0,\ \ 0 \le \alpha_i \le C, i \in [1, m]$$

The optimization problem results in a set of optimal Lagrange multipliers $\alpha^* = (\alpha_1^*, \alpha_2^*, \ldots, \alpha_m^*)^T$. Using these Lagrange multipliers, we can calculate the values of w^* and b^* as Equation (9):

$$\begin{aligned} w^* &= \sum_{i=1}^{m}\alpha_i^* y_i x_i \\ b^* &= y_j - \sum_{i=1}^{m}\alpha_i^* y_i\,(x_i \cdot x_j) \end{aligned} \tag{9}$$

The binary classification decision function is then transformed to Equation (10):

$$f(x) = sign(\sum_{i=1}^{m}\alpha_i^* y_i\,(x \cdot x_i) + b^*) \tag{10}$$

This final decision function is the outcome of the SVM process, and it enables us to classify forest-fire risk levels based on the collected weather parameters. SVM is crucial in identifying patterns and relationships between weather data and forest-fire risk levels, contributing to more accurate forest-fire prediction.

By employing SVM through the scikit-learn library in Python, we benefit from a robust and efficient implementation that allows us to accurately classify forest-fire risks using the collected meteorological data. This approach is crucial for identifying patterns and relationships between weather data and forest-fire risk levels, thereby enhancing the precision of our forest-fire predictions.

3. Experiment

3.1. Analysis

This analysis uses the SVM algorithm to predict forest-fire risk in Jiangsu Province, China, based on two key weather parameters: temperature and humidity. Forest-fire risk prediction is classified into five levels: extremely high, relatively high, high, moderate, and low. We focus on understanding how temperature and humidity interact to influence these risk levels.

As depicted in Figure 5, a significant relationship emerges. High temperatures coupled with low humidity levels serve as a clear indicator of a high risk of forest-fire. On the other hand, when high humidity levels are observed along with lower temperatures, it suggests a more moderate risk of forest-fire. The rationale behind this relationship is as follows: high temperatures contribute to vegetation drying, making it more susceptible to ignition. At the same time, low humidity levels limit the availability of moisture to inhibit the spread of fires. These factors combine to elevate the risk of forest-fire in high temperature and low humidity conditions.

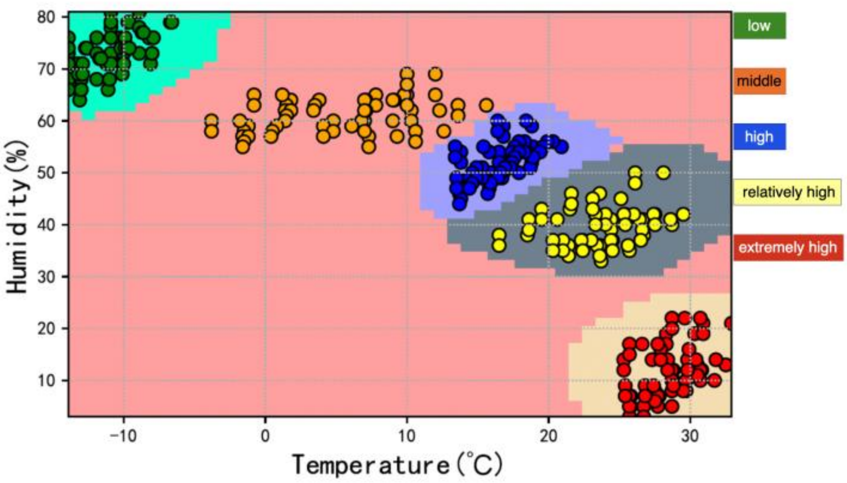

Figure 5. The SVM algorithm for forest-fire risk prediction based on temperature and humidity.

A similar pattern in the analysis, based on temperature and rainfall data, is illustrated in Figure 6. Once again, the forest-fire risk index is categorized into five levels: low, moderate, high, relatively high, and extremely high. High temperatures coupled with low rainfall are associated with a high risk of forest-fire, while high rainfall or lower temperatures are linked to a more moderate forest-fire risk.

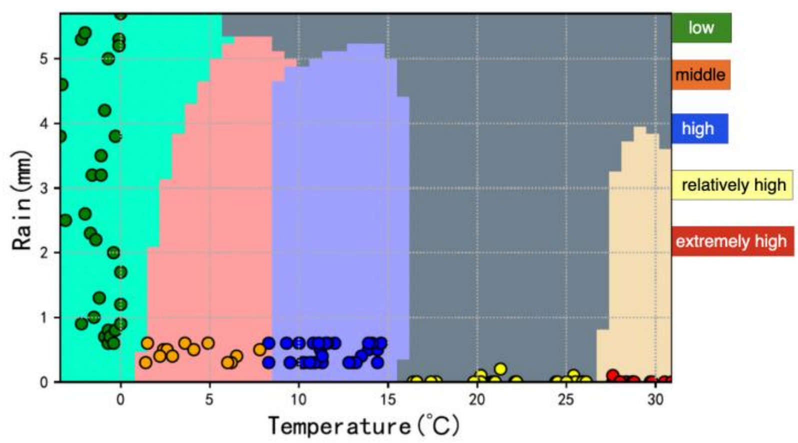

Figure 6. The SVM algorithm for forest-fire risk prediction based on temperature and rainfall.

These findings emphasize the significance of considering temperature, humidity, and rainfall as pivotal factors in predicting forest-fire. The visual representation of these relationships in Figures 5 and 6 enhances our understanding of the complex interactions that influence forest-fire risk.

3.2. Principal Component Analysis

The previous section explores the relationship between forest-fire risk levels and two key weather parameters: temperature and humidity. However, it is acknowledged that wind speed and rainfall also play pivotal roles in influencing the occurrence of forest-fire. Therefore, it is essential to consider all four weather parameters when predicting forest-fire. In this section, Principal Component Analysis (PCA) is used to identify and analyze the most significant features among these weather parameters. The insights gained from PCA are instrumental in enhancing the performance of the SVM algorithm for forest-fire prediction.

PCA is a powerful technique that allows to reduce the dimensionality of data while preserving as much information as possible. Our system works with four weather parameters, making the data inherently four-dimensional. PCA enables us to transform this complex data into a more manageable two-dimensional form. This transformation is designed to retain critical information while simplifying the data. It's akin to projecting our data onto a new axis set that maximizes the data's variance.

The initial step in this analysis involves examining the correlation coefficients between the four weather parameters using meteorological data for Nanjing, as presented in Table 1. These correlation coefficients provide insights into the relationships between the parameters. Notably, a relatively weak correlation among these meteorological parameters is observed, suggesting that they are relatively independent of one another and not significantly influenced by other parameters.

Table 1. The correlation coefficients for weather parameters.

Items	Rain	Wind	Temperature	Humidity
Rain	1.00	0.11	0.10	0.38
Wind	0.11	1.00	0.04	0.14
Temperature	0.10	0.04	1.00	0.14
Humidity	0.38	0.14	0.14	1.00

To make PCA effective, it's crucial to identify the most significant features among the parameters. Applying the PCA algorithm to the data, we discovered that approximately 99.9% of the variance can be explained using only two dimensions. This high variance retention indicates that these two dimensions represent the original four-dimensional data. Practically, we can express the four weather parameters (temperature, humidity, wind speed, and rainfall) using only temperature and humidity. This insight is depicted in Figure 7, which showcases the utilization of the SVM algorithm for forest-fire prediction based on all parameters using PCA.

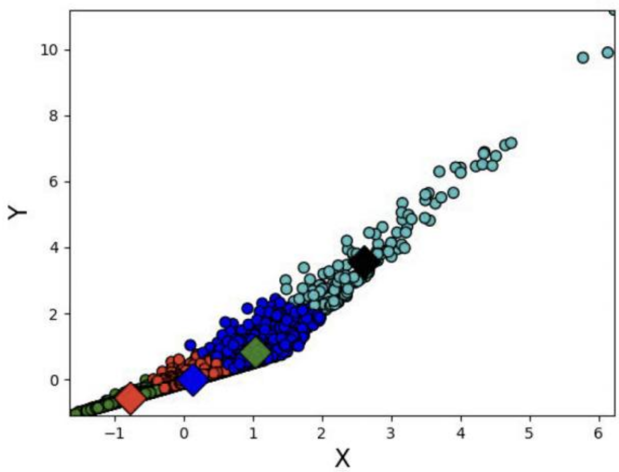

Figure 7. The SVM algorithm for forest-fire prediction based on all parameters using PCA.

After simplifying the data from four to two dimensions, we can delve deeper into understanding the individual contributions of each parameter to the PCA process. A cumulative variance contribution analysis reveals the effectiveness of this comprehensive evaluation and serves as a practical dimension reduction method. The contributions of each weather parameter when reducing the data from four dimensions to two dimensions using PCA are outlined in Table 2. Notably, it is found that temperature and humidity have primary roles in one dimension, while wind speed and rainfall contribute more significantly to the two dimensions. The cumulative variance contribution of these first two principal components accounts for approximately 52.46% of the total variance.

Table 2. The contribution of weather parameters when four-dimension is reduced to two-dimension.

Items	One-Dimension	Two-Dimension
Rainfall	0.53	0.14
Wind	0.02	−0.01
Temperature	0.11	0.44
Humidity	−0.14	0.23

With the knowledge gained from PCA, we can employ temperature, humidity, wind speed, and rainfall to construct a map of forest-fire risk levels. This empowers us to analyze the distribution of fire risk levels over the years. Utilizing the PCA model, we categorize forest-fire risk levels into five classes. From 2019 to 2023, the data indicates 835 days with low risk, 402 days with moderate risk, 419 days with high risk, 133 days with relatively high risk, and 37 days with extremely high risk. To visualize this classification, we present a bar chart (Figure 8). The results show that approximately 45.7% of the days fall under the low-risk category, 22.0% in the moderate-risk category, 22.9% in the high-risk category, 7.3% in the relatively high-risk category, and 2.1% in the extremely high-risk category.

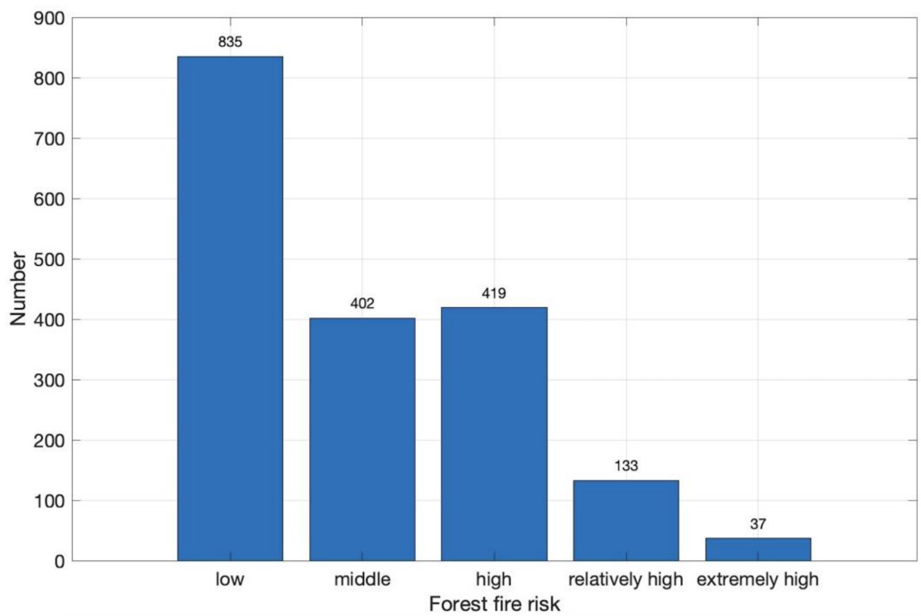

Figure 8. The forest-fire risk index scales divided into five levels.

In conclusion, this section demonstrates how the power of data analysis is leveraged, specifically PCA, to enhance the accuracy of our forest-fire risk predictions. Considering all four key weather parameters, this research aims to provide a more comprehensive and accurate assessment of the risk levels, thereby contributing to improving forest-fire management and prevention.

3.3. Model Validation

The SVM model developed for predicting forest-fire risk underwent a meticulous validation process to ensure its precision and dependability. The objective of this study was to assess how well the SVM model performs compared to established benchmarks, such as the Canadian Forest Fire Weather Index (FWI) system when applied to a different geographical location.

Both the SVM model and the FWI system used meteorological data collected by WSNs deployed in forest areas. This data included temperature, humidity, wind speed, and rainfall, which are critical parameters for assessing forest-fire risk. To assess the accuracy of the models, a dataset spanning five years was employed, from 2019 to 2023, encompassing 1826 data points. This dataset included temperature and humidity data for Nanjing during the specified period, as visualized in Figure 9.

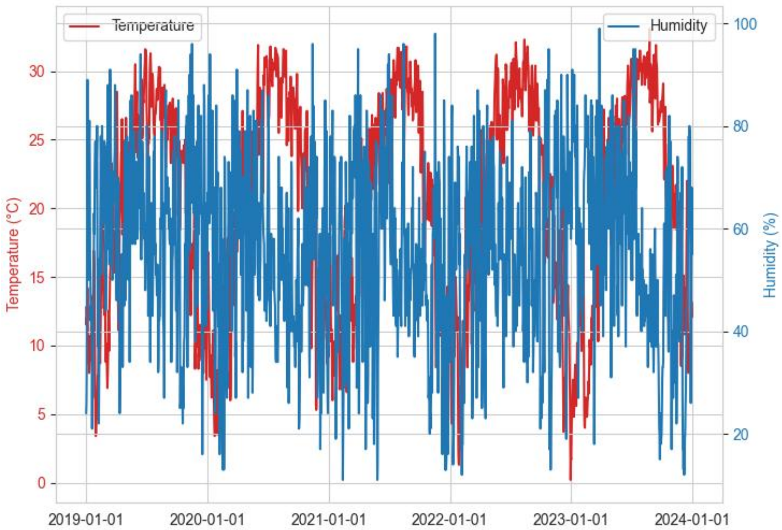

Figure 9. The temperature and humidity from 1 January 2019 to 31 December 2023 in Nanjing, China.

Our approach involved the application of data mining and machine learning techniques, specifically the SVM algorithm, to compute forest-fire risk ratings for each day from 2019 to 2023. These risk ratings, divided into five levels, were based on an assessment of weather data. The trend revealed higher forest-fire risk during spring (March–May), primarily attributed to rising temperatures and decreasing humidity. These conditions lead to the drying of foliage, rendering it more susceptible to forest-fire. Figure 10 visually illustrates the distribution of forest-fire risk levels based on the results of the SVM model.

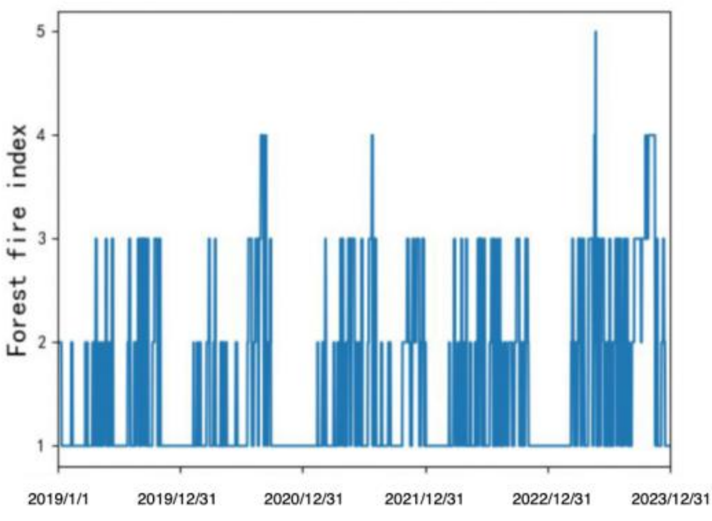

Figure 10. The forest-fire danger based on SVM.

Regarding the accuracy of this SVM model, a thorough evaluation was conducted. The SVM model's performance was measured using standard metrics such as accuracy, precision, recall, and F1-score. The results are presented in Table 3, which details the classification performance of the SVM model for each forest-fire risk level.

Table 3. SVM model performance metrics.

Metric	Value
Accuracy	86.17%
Precision	85.97%
Recall	86.07%
F1-Score	86.02%

The table above demonstrates that this SVM model achieved an accuracy of 86% in classifying the forest-fire risk categories, indicating its effectiveness in predicting forest-fire risks based on the collected weather parameters.

To provide a clear and quantitative comparison between this SVM model and the FWI system, we calculated the percentage of days where the predicted forest-fire risk levels matched between the two models. The comparison, as illustrated in Figure 11, shows that this SVM model and the FWI system agreed on the risk level for about 78% of the days within the study period. This percentage indicates the degree of concordance between the two models and offers a tangible measure of this SVM model's accuracy in the context of Nanjing.

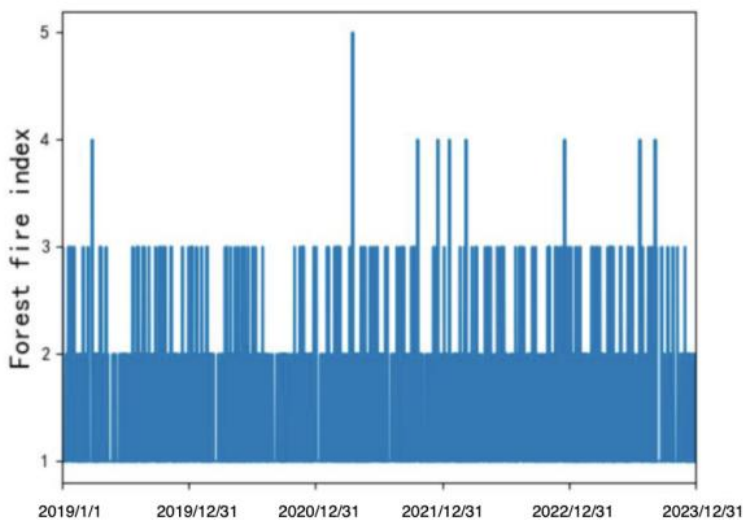

Figure 11. The forest-fire risk prediction based on FWI.

By conducting this comparative analysis with the CFFDRS-based FWI system, the SVM model's accuracy and ability to predict forest-fire risk can be evaluated. The results provide valuable insights into the SVM model's effectiveness in risk assessment and its potential for aiding in proactive forest-fire prevention efforts.

4. Conclusions

It is paramount to accurately predict the risk of forest-fire in areas vulnerable to such disasters. To enhance the accuracy of forest-fire risk prediction, a study prioritized deploying WSNs to collect real-time weather data. The study's significance lies in its contribution to forest-fire prevention and management efforts. With the integration of WSNs and SVM, a model was developed to assess forest-fire risk with high accuracy. The model thus provides timely response strategies for allocating resources, public awareness, and firefighting preparedness.

The deployment of WSNs played a crucial role in this study. These networks made it possible to collect critical meteorological data in real-time, providing a solid foundation for this prediction model and improving its accuracy and reliability. In addition, the data integration of the sensor networks distributed throughout the region made a detailed and comprehensive analysis of the local meteorological conditions possible. The advantage of WSNs is the ability to continuously update the data, ensuring that the models can adapt to changing weather patterns.

The SVM algorithm is a central tool for predicting forest-fire risk. Utilizing the model's weather parameters makes it possible to identify potential fire hazards, with particular attention to temperature, humidity, wind speed, and rainfall. The experimental results indicate that the SVM model of this study performed exceptionally well in classifying forest fire risk levels, achieving an accuracy rate of 86%, which attests to its potential and effectiveness in practical applications. The results emphasize the relationship between these weather parameters and forest-fire risk. High temperatures and low humidity indicate high forest-fire risk, while the opposite conditions imply moderate risk. These insights are critical for early detection and risk mitigation.

Although this study provides a research framework for forest-fire prediction, some limitations must be recognized. One limitation is the inherent complexity of forest-fire dynamics. This model did not include factors such as topography, vegetation type, and human activity, which may significantly influence fire risk. Future research could extend the model to account for these variables, thereby improving its predictive power. In addition, the accuracy of the model predictions depends on the quality and extent of meteorological data coverage. To improve the data quality and expand the model's applicability to different environmental conditions, it is recommended that the WSNs be expanded, and additional environmental sensors integrated. Future research could also consider integrating historical fire data for a more data-driven and accurate risk assessment. In addition, utilizing advanced machine learning techniques and integrating remote sensing data can further improve the predictive capability of this model.

In conclusion, this study provides an effective way to predict forest-fire risk. By deploying a wireless sensor network and implementing the SVM algorithm, a model capable of assessing forest-fire risk with high accuracy was created. Although this model provides valuable insights for forest-fire prevention and management, there is still room for further development, especially in integrating more variables and expanding the sensor network. And this study provides a knowledge contribution to forest-fire prediction and emphasizes the potential of advanced technologies to mitigate the effects of these natural disasters.

Author Contributions

Conceptualization, S.Z. and M.Y.; methodology, S.Z. and M.Y.; software, S.Z.; formal analysis, S.Z. and M.Y.; investigation, S.Z. and M.Y.; writing—original draft preparation, M.Y.; writing—review and editing, M.Y. and S.Z.

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Institutional Review Board Statement

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Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

Data will be made available upon kind request.

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Conflicts of Interest

The authors declare no conflict of interest.

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