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ForestSenseNet: A Feature-Aware Machine Learning Model for Forest Fire Prediction

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ABSTRACT

The fires continue to represent life-threatening dangers to both the public's safety, property and environmental health. As a result of the growing uncertainty of weather and the rapid growth of urbanization, demand for an efficient and effective fire alert system rises. This research specific work is concentrated on developing a good classification module which can predict fires using machine learning (ML), but not limited as it possesses ability to guide the predictive performance by exploiting hybrid equation and feature selection techniques. Designing a multi-phase methodology that uses data pre-processing first, followed by a variety of conventional classifiers including Random Forest (RF), Naïve Bayes, Support Vector Machine (SVM), and Decision Tree, is the primary objective. Additionally, hybrid models combining SVM with other classifiers were used to capitalize on their complementing characteristics. Recursive Feature Elimination (RFE) was used to minimize the volume of data and make interpreting feature selection methods like RF rank easier. Additionally, we provide FireSenseNet, a network that analyzes various heterogeneous features in parallel, including weather indices Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), meteorological variables (temperature, relative humidity (RH), wind, and rain), as well as geographical ones (X, Y) and temporal ones (month, day). Features concurrently increase fire prediction and generalization across a large number of situations. Important performance indices that were incorporated in the cross-validation procedure were the confusion matrix, accuracy F1-score, and receiver-operating characteristic curve (ROC) analysis. Compared to individual classifiers, FireSenseNet, the hybrid strategy and the hybrid method with feature selection and fine-tuning works better on the experimental level. In addition to this, the model could be used in classification of certain associated variables like RH into a few types of risk thus offered a combined perspective on fire situation. The current key work offers a systematic, comparative, forecasting how to predict fires through parallelism, ensemble techniques and optimization methods. It has practical implications on early warning and can be the basis of future developments based on real-time sources of information.

1. INTRODUCTION

Fires are incessantly damaging to ecological systems, property and public safety. The rate at which the number and intensity of fire incidences have been increasing in recent years is quite alarming, and this has been mostly blamed on climate change and increased human activity. Due to the ever-growing space of cities and a rise in unpredictability of weather conditions, the possibility of a large-scale fire that can lead to massive losses is very high. Increase in the number of fire incidences [1, 2] has highlighted the necessity of efficient and precise mechanisms of fire detecting that will help forecast the future occurrence before it leads to severe losses.

Fires have serious both direct and indirect effects on human society, infrastructure and ecosystems. In addition to such a dreadful loss in human lives, they lead to a massive economic destruction and extensive, chronic environmental pollution. Fires also cause an imbalance in the ecological system, which causes the loss of biodiversity and the poor quality of the air as a result of harmful pollutants release. Here, the formation of new fire prediction models (high accuracy within a limit of time) is very vital [3].

Among the main limitations of fire occurrence prediction, there is the nature of the complexity and interdependence of the parameters that contribute to it. Fire behavior is very erratic since it is affected by many factors such as change of temperatures, RH, speed of the wind, availability of fuel, and the activities of the human beings. Due to the multidimensional and dynamic characteristics of real-world fire data, the traditional fire prediction systems usually cannot effectively model these complex interactions leading to performance levels that are not adequate to satisfy practical and operational needs. To top it all, such systems are not necessarily suitable in real-time processing since they are computationally expensive and inflexible in such matters as region-specific aspects [4, 5]. Figure 1 illustrates the design of the forest fire prediction system.

Recently, the use of machine learning (ML) to predict wildfires has gained significant attention as one of the possible solutions to these issues [4].

ML is highly applicable when dealing with large-scale data and to the learning of intricate patterns in data, hence allowing a more specific and granular evaluation of fire peril [6]. However, by themselves the ML models are still encouraging; one can even obtain even better results when it comes to hybrid whereby themselves different algorithms and methods of feature selection are incorporated. These hybrid models are more accurate and robust and are of more use in terms of real-world fire alert systems [7].

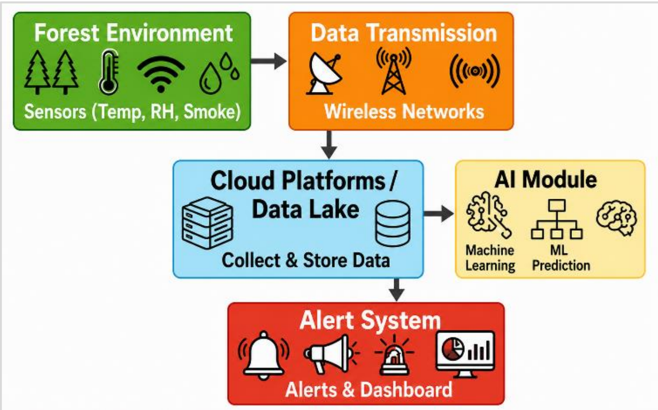

Figure 1. Overview of forest fire prediction system

1.1 Problem statement

Though there are a number of useful predictive models suggested in the literature [8], there is a major issue that is reliability and accuracy of their predictions. Algorithms based on conventional alarms are still frequently used; they are however, frequently not able to reflect the natural dynamics of fires. The models, therefore, face serious difficulties in terms of data preprocessing, generalization ability and scalability as indicated in analysis of experiment. Furthermore, classical procedures are often less accurate in a range of geographical locations or a high-dimensional data set.

One of the inherent weaknesses of classical fire prediction methods is the inappropriateness of modelling the dynamic covariates. An example is that the difference in humidity, temperature, and unexpected changes in wind direction are usually underrepresented in the classical prediction models. Moreover, most of the available models are based on the one-size-fits-all approach, which fails to recognize the risks factors of the region and the local geographical features. This has made the prediction of fire outcomes to often be erratic, resulting in more false alarms or false detection [9, 10].

As it has been observed, hybrid ML models that use the strength of different algorithms can significantly enhance the level of accuracy in prediction. Moreover, operation of feature selection methods is successful to find the most effective variables and also sparse model without loss in performance. Motivation Despite these possible advantages, there has been limited work on the use of hybrid fire prediction models with a lack of consideration for practical implementation.

The present study overcomes the lack of generalization, inability to deal with multi-source data, and hybrid approaches in existing fire prediction methods. Existing approaches typically use single classifiers and are unable to comprehensively account for the interactions between meteorological, spatial and temporal features, resulting in poor accuracy and false alarms. The current study addresses this by proposing a hybrid ensemble framework and feature selection for enhanced prediction. Further, the FireSenseNet model allows for parallel processing of multi-source data, increasing scalability and resilience. The proposed work (i) integrates hybrid ML models, (ii) uses feature selection, and (iii) introduces a multi-branch deep learning (DL) model to enhance fire prediction.

1.2 Objective and scope of the study

The primary objective of this project is to develop an effective and reliable model for fire type identification via ML techniques. The aim of the research is to improve the performance in comparison to traditional classifiers through hybrid models and feature selection process. The following are the proposed objectives of the proposed work:

i. Hybrid models combining Support Vector Machine (SVM) with Decision Tree, Naïve Bayes, and Random Forest (RF) are developed to improve prediction performance.
ii. Feature selection is applied using Recursive Feature Elimination (RFE) and RF-based importance ranking to retain the most relevant variables.
iii. FireSenseNet is introduced as a multi-stream DL architecture that processes spatial, temporal, weather indices, and meteorological features in parallel for improved prediction accuracy and stability.
iv. The influence of RH on fire size variation is analyzed to understand its role in environmental fire dynamics.
v. Model performance is evaluated using cross-validation based on accuracy, F1-score, and receiver-operating characteristic curve (ROC) analysis.

We consider the whole process of preprocessing data, modeling building, feature selection, and model interpretation. The dataset is processed to clean and normalize the inputs in order to allow the model to perform efficiently. Models will be trained and validated and their effectiveness will be assessed after that. This undertaking will provide a fresh direction on how the fire alert system can be designed because of the emphasis on the hybrid models and the effectiveness of feature selection.

1.3 Significance of the study

There are also a number of unanswered critical questions especially on the scholarly input of the internet facilitated fire prevention models. Timely and dependable fire alerts might be critical to saving lives and property. Such systems are necessary to facilitate rapid response to minimize human casualties, damages to infrastructure and environmental impacts. Also, the incorporation of ML in fire alarm systems will enable the continuous learning and adjustment to the changing conditions, increasing the robustness of the system and its effectiveness in the long term.

Our model has applications in safety engineering through early warning and risk assessment for fire management. It can be used with sensor monitoring systems for real-time warnings based on environmental factors. The model's predictions can help decision-makers and response teams to identify at-risk areas and develop fire mitigation plans. It can also be integrated with IoT-based monitoring systems for real-time monitoring in forest-urban interface areas. This is an important aspect in improving fire safety and mitigation of risks.

2. LITERATURE REVIEW

Research on forest fire prediction has made important advances with the application of ML and DL methods for early warning and risk forecasting. The current literature has investigated various techniques, such as conventional classifiers, real-time fire detection, and hybrid models combining multiple data streams. These approaches show enhanced prediction performance, but vary in accuracy, computational efficiency and capacity to adapt to different environments. There have also been recent studies exploring the integration of multimodal data and IoT-based systems for improving real-time detection. But there are issues with the integration of multimodal data, regional variabilities and performance stability. The main contributions in these fields and their limitations to the proposed solution are discussed in this section.

2.1 Machine learning and deep learning-based fire detection approaches

The last few years have witnessed a high level of interest in ML and DL methods of fire detection. These novel methods as a part of innovative alternatives to the traditional early fire detection systems exhibit high abilities in handling the bulk of data and drawing valuable patterns. CNNs have become one of the most popular approaches to real-time fire detection, due to their ability to process visual information and increase the accuracy and strength of fire detection systems [11]. Also, the recent works have utilized the capabilities of the YOLOv8 framework to detect fire events in the smart city setting, namely the real-time object detection capabilities encompassed by the framework so that fire events can be detected rapidly and reliably [12].

Deep neural networks can also be developed to create effective automatic fire detection systems that have enhanced capability of detecting fire occurrences in different conditions. These types of models can streamline the calculation of data in real-time and are especially valuable in the work that requires the rapid generation of alert [13]. Also, the principle of constant learning, or learning without forgetting, has been integrated into the fire detection models to allow detecting the fire and the smoke at the same time, and maintains the high predictive accuracy. This is especially useful in the long-term fire monitoring systems [14]. Besides this, it is also found that the merger of on-device ML models and low-power IoT gadgets will amplify the effectiveness of fire detecting, particularly in remote or resource-constrained settings where there is the scarcity of computational and power resources [15].

With these improvements, ML-based and DL-based fire detection systems are still associated with the issues of computational complexity and the necessity to update models at a regular rate to ensure the accuracy of prediction. Furthermore, a great number of the models that exist are specific to particular datasets and have a low ability to be generalized. It is therefore desirable that more robust and adaptive models are developed which are able to work reliably in various regions prone to fire.

However, while these methods have improved, the ML and DL techniques are still limited by high computational cost, data dependency, and lack of generalization with varying environmental conditions This hampers their potential use in large and dynamic fire-prone environments.

2.2 Real-time fire detection and situational assessment

The real-time fire detection is essential in the timely emergency response and effective firefighting tactics. Developed advanced algorithms that are able to integrate real-time data processing with predictive analytics have been established to increase situational awareness. The strategies include the use of real-time flame detecting algorithms that are specifically created to be used in firefighting robots, which can help speedily detect fire outbreaks and assess the situation [16]. The other notable contribution is the creation of better YOLOv4-based systems, which offer automated fire detection and notification, which could be useful to people with visual impairments [17]. These systems are inclusive and efficient in operation.

More developments include developing fire warning systems that are friendlier to the visually impaired, incorporation of improved notification systems that guarantee quick warnings are received by users [18]. The implementation of edge computing in automated image-based fire detection is essential for minimizing latency, which is crucial for real-time applications [19]. In addition, the techniques that make use of the UV signal based fire detection have demonstrated to be effective in detecting the early fire indicators, thereby creating reliability to the real-time systems [20].

Even though the applications of real-time fire detection systems have been successful, the system is limited in terms of data accuracy and latency control. To make our real-time predictions more accurate, we should take better advantage of the multiple sources of data.

But these systems can be difficult to manage in terms of latency and data quality, especially under changing environmental circumstances. Ineffective integration of multiple data sources also hampers their prediction accuracy.

2.3 Integrated and multimodal approaches for fire prediction

The ability to make predictions of fire in complicated situations usually presupposes the work with sensorial information and various analytical instruments. ML models that combine ensemble hybrid models with multi-modal sensors data has been capable of detecting fire in smart building with satisfactory outcomes. In order to enhance the accuracy boloeffectiveness and consistency, such models take advantage of feature of individual classifiers [21]. Hybrid machine learning-deep learning (ML-DL) methods have also been suggested to evaluate the susceptibility of forest fires in hilly areas, such as the Himalayan region [22].

Not the least, the combination of big data analytics and AI has been used in the development of the early risk warning systems in the cities of smart cities. These solutions are capable of processing vast amount of data so as to avert future potential fire hazards [23]. Moreover, IoT-based approaches to detect fire early have been used in agricultural settings to dynamically determine the threat of fire by integrating sensor data with prediction algorithms [24]. Moreover, the satellite-based wildfire warning also possess the potential of offering continuous surveillance of large areas that will go a long way in offering early warning at an early stage [25].

Nevertheless, even these combined approaches have been found to be problematic in processing speed and data heterogeneity especially when it comes to multimodal inputs.

In the scientific community, the connection of the accurate fire risk assessment with the real-time data processing is still a challenge.

However, such methods continue to struggle with efficient integration of diverse data sources, and real-time prediction accuracy. Data integration from multiple sources is still computationally intensive and may not be scalable.

2.4 Comparison of current methods

Conventional ML models are simple but lack the ability to model complex interactions between features, resulting in reduced accuracy. DL enhances feature learning but is computationally expensive and data-intensive. Hybrid and multimodal approaches offer improved accuracy but encounter difficulties in integrating data, scalability and adapting in real-time. These challenges suggest the need for an organized hybrid approach integrating feature selection and parallel processing of diverse data sources.

2.5 Research gap

Despite recent progress in fire detection and prediction models, there are problems when integrating multiple data sources, optimizing computational efficiency, keeping high accuracy across diverse environments. There is no practical hybrid model available that accurately integrates long-term fire risk assessments and real-time data. Existing approaches will be improved by developing adaptive models that can respond adequately to multimodal input and changes in the environment. This gap is bridged by proposing two complementary approaches for improved wildfire prediction in this paper. The first method introduces a mixed ML model which enhances the accuracy and efficiency of fire prediction applying ensemble techniques and feature selection methodologies. The second approach is to propose FireSenseNet, a DL model that simultaneously processes weather, meteorological, spatial and temporal information for accurate wildfire predictions.

3. METHODOLOGY

3.1 System architecture

In order to generate a precise fire forecast, phases are linked within the system through the analysis of environmental data. Figure 2 illustrates the proposed system architecture for the forest fire prediction system. The initial step is to import the fire dataset. It includes all relevant meteorological data such as location, temperature, humidity, wind speed, and precipitation. These inputs form the basis of the generation of the model. Once the data is obtained, it is taken into consideration to arrive at an analysis. Here, you will want to clean up the data by trying to eliminate redundant information, break down categories into numbers with the help of label encoding, and standardize the scales of each feature. Once the data preprocessing is completed, two processes are done at once. The first is that feature selection is used to eliminate redundant predictors that are not relevant which enhances modeling efficiency and limits the number of computations performed. Second, rules of classification are specified in the context of fire occurrence prediction as well as RH categorization. For instance, RH levels may be classified into low, medium, or high categories, while fire occurrence is treated as a binary outcome.

Once the data has been refined, it is put through hyper-parameter optimization to be sure that every classifier runs at its optimal level. After that, several ML and hybrid models are built such as SVM, RF, NB, DT along with SVM + RF, SVM + DT or RF + DT combinations. Further enhancements to prediction accuracy and overall performance are achieved by utilizing the proposed FireSenseNet model.

Trained models are tested with a reserved set of 20% of the data. The evaluation is carried out separately for each task: fire and RH classification (label). Lastly, the accuracy and F1-score are measured for each model, making it easy to compare them and find the best approach for classifying the data.

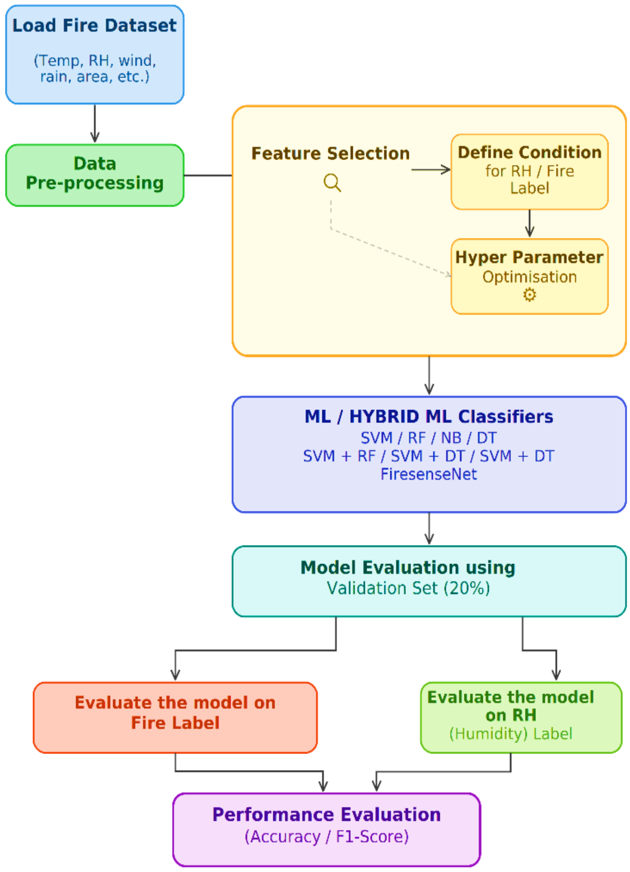

Figure 2. Proposed system architecture diagram

3.2 Dataset preparation

The collection includes weather, meteorological, geographical, and temporal data about forest fires. The spatial characteristics (X, Y) are the geographic coordinates of each of the observations. Seasonal patterns are observed through the temporal qualities (month, day) which indicate the time when that takes place. Weather indices (Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI)) are used to determine the fuel moisture and fire hazard levels and the meteorological factors (temperature, RH, wind and rain) are used to describe the ambient conditions which affect the fire behavior. The dataset comes from the UCI Repository [26]. Figure 3 presents a sampling of the dataset.

3.2.1 Fire as a class label

All features are utilized for the Hybrid Ensemble Model, while the dataset is segmented into various attributes for the

FiresenesNet Model, encompassing temporal parameters (day and month) and spatial features (X, Y coordinates) that denote the location of fire incidents. Additionally, seasonal and temporal variations, fuel moisture conditions, fire risk levels, and other meteorological factors are assessed using weather indices (FFMC, DMC, DC, ISI). Meteorological variables that characterize environmental influences on fire behavior including temperature, RH, wind, and precipitation.

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
27	7	4	sep	mon	90.9	126.5	686.5	7.0	19.4	48	1.3	0.0	0.00
380	5	4	jul	wed	93.7	101.3	458.8	11.9	19.3	39	7.2	0.0	7.73
24	7	4	aug	sat	93.5	139.4	594.2	20.3	23.7	32	5.8	0.0	0.00
351	4	4	sep	fri	92.1	99.0	745.3	9.6	15.4	53	6.3	0.0	7.31

Figure 3. Dataset sample of forest fire [26]

3.2.2 Relative humidity as class label

The first step is to clean and transform the dataset which is exactly the same as the fire-class task. Categorical variables are turned into encoded labels. All the features are adjusted to a standard scale using a common approach. RH is divided into certain categories by using fixed thresholds [27]. RH values are grouped into discrete categories using defined thresholds, Figure 4 shows the categorizing RH values:

$$RH < 40\% : \text{Low}$$
$$40\% \leq RH < 70\%: \text{Medium}$$
$$RH \geq 70\%: \text{High}$$

This transform the continuous RH feature into 3-class classification task. Let:

$$RH_{category} = \begin{cases} 1 & \text{if } RH < 40\% \\ 2 & \text{if } 40\% \leq RH < 70\% \\ 3 & \text{if } H \geq 70\% \end{cases}$$

```
# Define the conditions for categorizing RH values
conditions = [
    (df['RH'] > 70),  # High RH
    (df['RH'] <= 70) & (df['RH'] >= 40),  # Medium RH
    (df['RH'] < 40)  # Low RH
]
```

Figure 4. Categorizing relative humidity (RH) values

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	RH_Category
0	7	5	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	Medium RH
1	7	4	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	Low RH
2	7	4	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	Low RH
3	8	6	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	High RH
4	8	6	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	High RH

Figure 5. Updated dataset with relative humidity (RH) category

The data set used in this research comes from the UCI repository, offering a benchmark for performance evaluation. Yet, in the fire prediction use case, data are often more dynamic, noisy, and large-scale, such as from sensors, satellites or IoT devices. The proposed model is flexible to various input formats, and can accommodate such dynamic data streams. With suitable integration of real-time data, the model can be used in early warning and monitoring systems. This suggests that the proposed model can be successful in real-world fire risk assessment scenarios. Figure 5 shows the Updated dataset with RH Category.

3.3 Data preprocessing

The process starts by removing any columns in the dataset that are not helpful. The next step is to exclude the data that is missing. Label encoding is used to change categorical data into a format that machines can interpret. To normalized the data, "StandardScaler" is used to make the data values fit within a similar range. Let the feature set be $X = \{x_1, x_2, x_3 \dots x_n\}$. Normalization is performed using:

$$x_i' = \frac{x_i - \mu}{\sigma} \tag{1}$$

where μ and σ are the "mean and standard deviation of the feature x_i".

3.4 Feature selection

3.4.1 Feature selection for hybrid ensemble machine learning model

RFE ("Recursive Feature Elimination") and RF importance are used for decreasing the number of features. RFE remove the feature with the smallest weight in the classifier's vector at every step.

$$RFE(f) = \arg\min_{S \subset F}[loss(M, S)] \tag{2}$$

where, F is the "feature set", S is "subset of selected features" and M is the "learning model".

3.4.2 Feature selection for fire sense net model

The selected features are systematically grouped based on their inherent characteristics to enhance model interpretability and learning efficiency. Static features, such as the spatial coordinates (X, Y), represent fixed geographical information related to fire occurrences. Seasonal fluctuations and time-dependent patterns impacting fire behavior are captured by categorical or temporal parameters, such as the day and month. Fire severity and spread are affected by climatic circumstances that alter and build over time; this is shown by sequential factors such the weather indices (FFMC, DMC, DC, and ISI). Finally, meteorological factors such as temperature, RH, wind, and precipitation exemplify environmental aspects that elucidate the atmospheric conditions facilitating the onset and propagation of fire in real time.

3.5 Model implementation

The dataset is partitioned using 80:20 train-test split. Four primary classifiers are used to trained on the processed date namely- "SVM, Naïve Bayes, Decision Tree and RF".

SVM seeks a hyperplane $w^T x + b = 0$ such that it maximizes the margin between classes:

$$\min \|w\|^2 \; subject\ to\ y_i(w^T x + b) \geq 1 \tag{3}$$

RF combines predictions from multiple Decision Trees

$T_1, T_2 \dots . T_k$ with the final predictions being a majority cote:

$$\hat{y} = mode(T_1(x), T_2(x) \dots T_k(x)) \tag{4}$$

3.5.1 Designing with a hybrid model

To make predictions more accurate, hybrid ensemble models are used; SVM + RF, SVM + NB or SVM + DT, where each model's output serves as a feature for the next one. By using this approach, various features are captured and each model's weaknesses are reduced.

3.5.2 Parallel deep learning architecture (FireSenseNet)

Model Overview: The proposed FireSenseNet architecture employs a multi-branch neural network design that processes heterogeneous input features in parallel. Each stream is customized to the distinct characteristics of the data, facilitating specialized feature extraction and enhancing wildfire prediction efficacy. Figure 6 shows multi-branch input to the model. The Following stream are used for multi-branch neural network input:

- Spatial Stream (Dense Layer)
  Input: X, Y
  Processed using one or more Dense layers
  Captures location-based variation in fire risk
- Temporal Stream (LSTM Layer)
  Input: Encoded month/day
  Modeled data as sequences over time (e.g., time-series records): LSTM
- Weather Index Stream (Conv1D Layer)
  Input: FFMC, DMC, DC, ISI
  Treated as a short sequence and processed using Conv1D to capture local patterns and transitions
  Conv1D is effective for modelling fire-prone conditions based on preceding indices
- Meteorological Stream (Dense Layer / LSTM)
  Input: Temperature, RH, Wind, Rain
  Modelled using LSTM as sequences over time are available

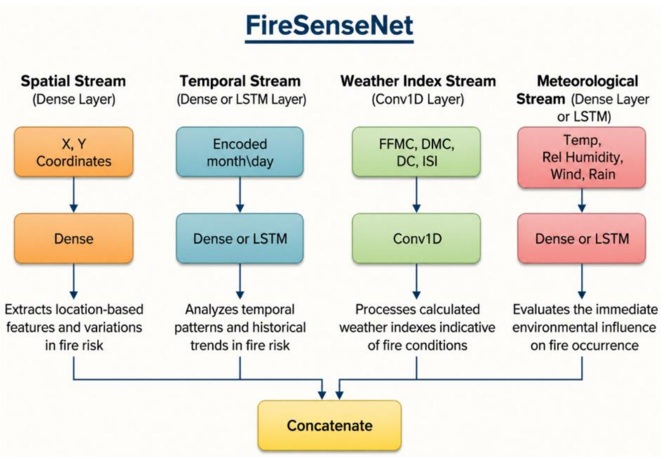

Figure 6. Multi-branch input to the model

Feature Fusion and Classification: After each feature stream is processed independently, their outputs are merged to form a unified representation. The integration allows the model to represent interactions between weather indices, meteorological variables, time and geographical characteristics in a complex manner. The concatenated feature is subsequently input into one or more fully linked layers to facilitate the cooperative learning of features. The final output layer employs a sigmoid activation function for binary fire occurrence classification and softmax activation function for multi-class fire severity prediction. The proposed FireSenseNet model architecture is illustrated in Figure 7, while the subsequent section details the algorithmic procedures underlying the FireSenseNet model.

 # Pre-processing Phase
FOR each row in dataset DO
IF TEMP < 40 THEN
TEMP_Binary ← 1
ELSE
TEMP_Binary ← 0
END IF
END FOR
#Train-Test Split
X ← all features EXCEPT 'TEMP_Binary', 'TEMP_Category'
y ← TEMP _Binary
Split X, y into training and testing sets: (X_train, X_test, y_train, y_test)
#Features Grouping
X_train_spatial ← columns ['X', 'Y'] from X_train
X_test_spatial ← columns ['X', 'Y'] from X_test
X_train_temporal ← columns ['month', 'day'] from X_train
X_test_temporal ← columns ['month', 'day'] from X_test
X_train_weather ← columns ['FFMC', 'DMC', 'DC', 'ISI'] from X_train
X_test_weather ← columns ['FFMC', 'DMC', 'DC', 'ISI'] from X_test
X_train_meteo ← columns ['temp', 'RH', 'wind', 'rain'] from X_train
X_test_meteo ← columns ['temp', 'RH', 'wind', 'rain'] from X_test
#FireSenseNet Model Definition
#Input Features
Input1 ← shape (2) #Spatial
  x1 ← Dense(32, ReLU) → Input1
  x1 ← Dense(16, ReLU) → x1
Input2 ← shape (2) #Temporal
  x2 ← Reshape((2,1)) → Input2
  x2 ← LSTM(16) → x2
Input3 ← shape (4,1) #Weather
  x3 ← Conv1D(16, kernel=2, ReLU) → Input3
  x3 ← Flatten() → x3
Input4 ← shape (4,1) #Meteorological
  x4 ← LSTM(16) → Input4
#Merge Features and Process
Merged ← Concatenate([x1, x2, x3, x4])
Dense1 ← Dense(64, ReLU) → Merged
Drop1 ← Dropout(0.3) → Dense1
Dense2 ← Dense(32, ReLU) → Drop1
Output ← Dense(1, Sigmoid) → Dense2
#Training and Validation Phase
Train Model using:
Inputs: [X_train_spatial, X_train_temporal, X_train_weather, X_train_meteo]
Target: y_train
Validation: ([X_test_spatial, X_test_temporal, X_test_weather, X_test_meteo], y_test)
Model ← Define with inputs [Input1, Input2, Input3, Input4], output
Output ←Compile Model with Adam optimizer, BinaryCrossentropy loss, Accuracy metrics

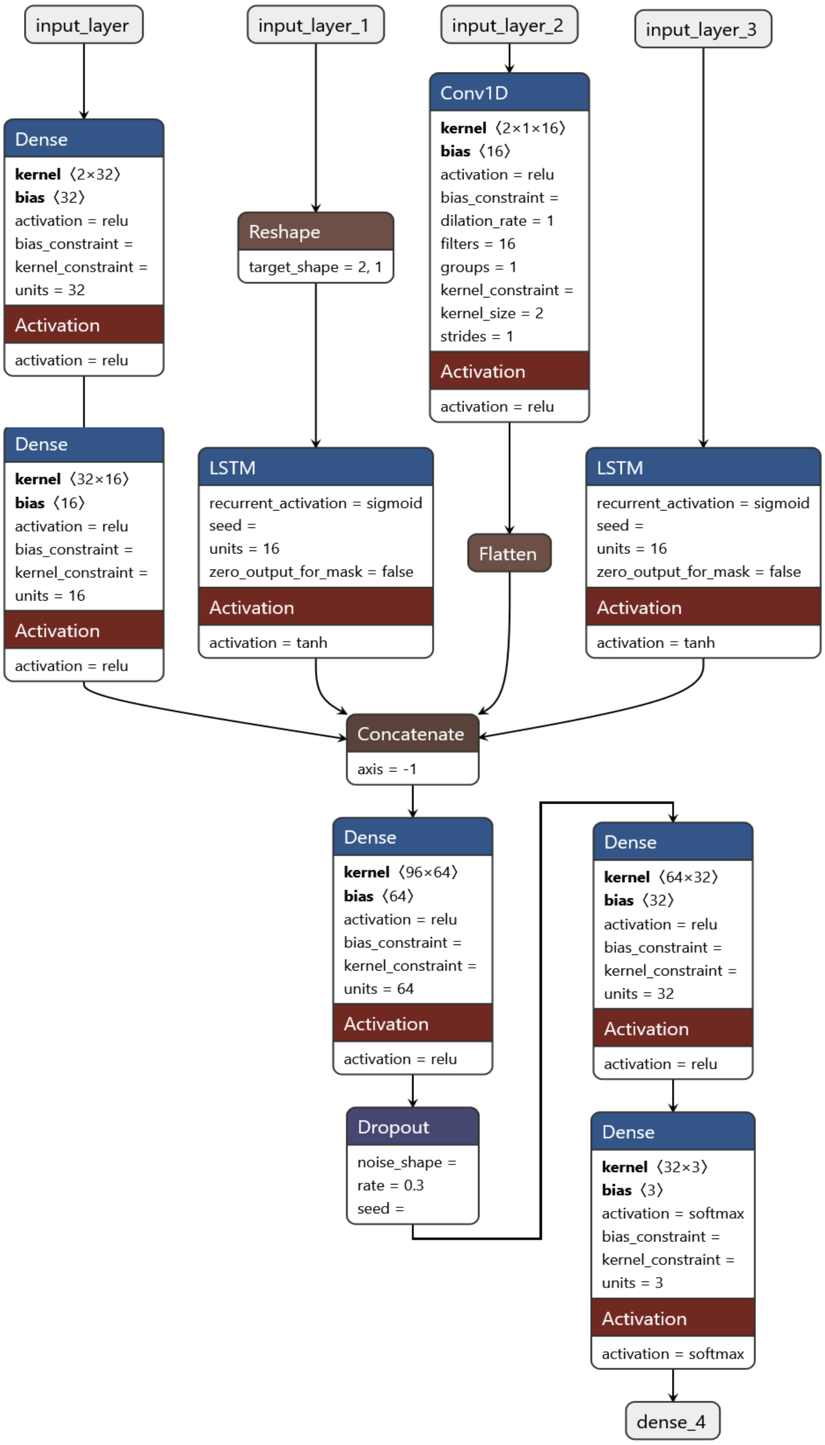

Figure 7. FireSenseNet model architecture

Table 1. Overview of the FireSenseNet architecture

Component	Input Features	Layer / Operation	Key Setting	Output
Spatial Stream	X, Y	Dense → Dense	32 neurons, ReLU → 16 neurons, ReLU	Spatial feature vector
Temporal Stream	Month, Day	Reshape → LSTM	Shape: (2,1), 16 LSTM units	Temporal feature vector
Weather Index Stream	FFMC, DMC, DC, ISI	Conv1D → Flatten	16 filters, kernel size 2, ReLU	Weather feature vector
Meteorological Stream	Temp, RH, Wind, Rain	LSTM	Shape: (4,1), 16 LSTM units	Meteorological feature vector
Feature Fusion	All stream outputs	Concatenation	Combined multi-source features	Fused vector
Dense Block	Fused vector	Dense → Dropout → Dense	64 ReLU → 0.3 dropout → 32 ReLU	Learned feature vector
Output Layer	Dense block output	Dense	1 neuron, Sigmoid	Fire/No-Fire prediction
Training	Model output	Adam + Binary Crossentropy	80:20 split, accuracy metric	Final classification result

Note: Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI)

FiresenseNet Architecture Overview: Table 1 presents a comprehensive overview of the FireSenseNet architecture, including the different input streams, types of layers, and a selection of important parameters. It offers insight into the processing and fusion of heterogeneous features. This enhances transparency and reproducibility of the proposed method.

3.6 Model tuning and validation

The classes are equally represented in each section of the split when employing stratified K-fold cross validation. By employing grid search to modify hyper-parameters such the estimators in RF, the maximum depth in trees, and the kernel in SVM, the model is enhanced.

3.6.1 Training and model selection

Eighty percent of the RH-labeled data is applied for training, while twenty percent is used for testing. SVM, NB, DT, and RF are used to group the data. Since this task involves categorizing multiple genres of music, you must employ criteria beyond accuracy. A confusion matrix and the macro F1-score are used to evaluate performance. Using Bayes' theorem, Naïve Bayes makes the assumption that each feature is independent. The Byes theorem is applied by Naïve Bayes under the feature independence assumption:

$$P(y|x_1, \dots .x_n) = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1 \dots .x_n)} \tag{5}$$

where, y: Target class (e.g., fire / no fire or RH category), $x_1, \dots, x_n$: Input features (temperature, humidity, wind, etc.), $P(y \mid x_1, \dots, x_n)$: Posterior probability of class y given features, $P(y)$: Prior probability of class y , $P(x_i \mid y)$: Likelihood of feature x_i given class y, $P(x_1, \dots, x_n)$: Evidence (normalization term), n: Total number of features.

GridsearchCV is employed for hyper-parameter tuning. In the case of RF, it tunes: - No. of estimators, Max depth of each tree, Minimum samples per leaf.

3.6.2 Ensemble optimization

The fine-tuned models are put through an evaluation process. The best model achieves 99% accuracy and a 97% F1-score and is named FT + RF. Ensemble optimization combines the predictions of several classifiers by voting on the results:

$$\hat{y} = argmax_y \sum_{i=1}^{k} I\left(h_i(x) = y\right) \tag{6}$$

where, k : number of classifiers in the ensemble, $h_i(x)$: prediction of the i^{th} classifier for input sample x, $I(\cdot)$: indicator function (1 if condition true, else 0), arg max : selects class with highest votes.

The evaluation of the experiments is performed by running several iterations, and the results are reported as the average. The same random seed is set for data splitting and training to enhance reproducibility. We check the data for class imbalance and use techniques such as class weighting in training to prevent the model from being biased towards the majority class. This ensures that the results are consistent, reliable and not affected by randomness.

3.6.3 Performance parameters

- Confusion Matrix (Figure 8): The confusion matrix is designed to visualize classification performance. Each cell C_{ij} represents the no. of observations called to be in group i and predicted to be i a group j.

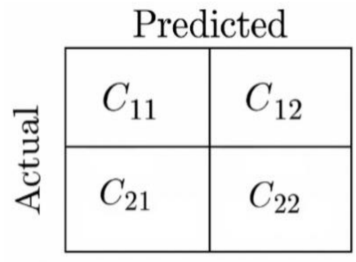

Figure 8. Confusion matrix

- Accuracy: The accuracy for a binary classification issue with n classes, represented by a confusion matrix C of size n × n, is calculated as:

$$Accuracy = \frac{\sum_{i=1}^{n} C_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij}} \tag{7}$$

C_{ii}: Correct predictions (diagonal elements of confusion matrix), C_{ij}: Instances of actual class i predicted as class, n: Number of classes.

The use of RH and Fire as class label provides contextual insights for fire-prone conditions and support proactive systems.

- F1-Score: The F1-score is a performance metric that combines recall and precision into a single value by calculating their harmonic mean. When there is a significant disparity in the distribution of classes, it becomes very advantageous. For class I specifically, the following are the definitions of recall and precision:

$$Precision_i = \frac{C_{ii}}{\sum_{j=1}^{n} C_{ji}} \tag{8}$$

$$Recall_i = \frac{C_{ii}}{\sum_{j=1}^{n} C_{ij}} \tag{9}$$

$$F1_i = 2 \times \frac{Precision_i \times Recall_i}{Precision_i + Recall_i} \tag{10}$$

where,

$\sum_{j=1}^{n} C_{ji}$ is total samples predicted as class i

$\sum_{j=1}^{n} C_{ij}$ is total actual samples belonging to class i

The F1-score is crucial for evaluating classification performance when false negatives and false positives have significant consequences—as is the case in fire detection systems.

4. RESULTS AND OUTPUTS

Table 2 and Figure 9 presents that the proposed FireSenseNet and FS + RF + Fine-tune model excels over any other model, with an achieved accuracy of 94%, 90% and an F1-score of 93%, and 89% respectively. In the case of traditional models, RF is more successful than both SVM, NB, and DT, namely: 47% of accuracy and 40% of F1-score. The hybrid combinations of SVM and RF also displayed better results as compared to the results in single classifiers, SVM + RF: 51% accuracy. Also show improvements models that combine feature selection (FS) with traditional classifiers, which also means that the feature optimization is important.

Table 2. Performance comparison of models (fire label)

Models	Accuracy	F1-Score
SVM	49	22
NB	21	12
DT	44	42
RF	47	40
SVM + RF	51	42
NB + RF	49	22
SVM + DT	49	22
SVM + NB	49	22
DT + RF	46	42
SVM + DT + RF	45	48
SVM + RF + DT	49	48
FireSenseNet (Ours)	90	89
Fine-tuned FireSenseNet	94	93

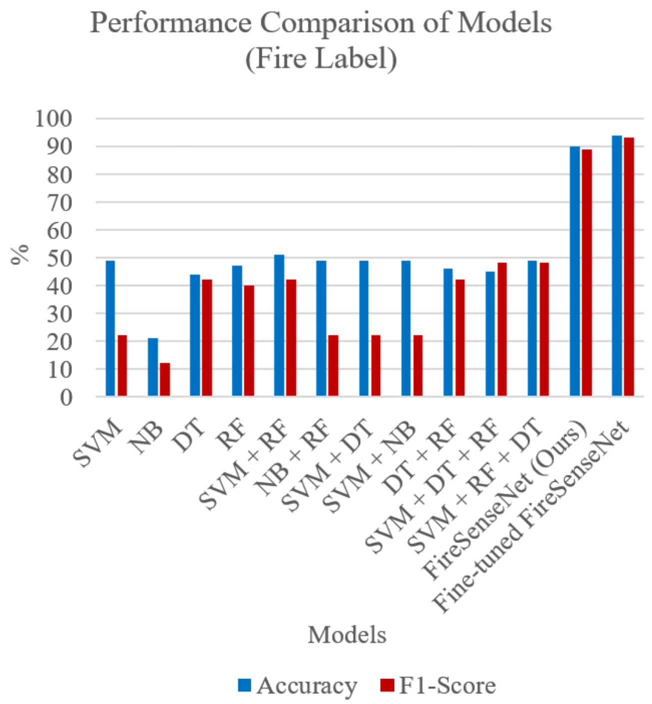

Figure 9. Comparative analysis of forest fire prediction models (fire label)

Figure 10 provides comparison of FireSenseNet Model and Hybrid models when RH is taken as class label. FireSenseNet Model has 99% accuracy and 99% of F1-score followed by FT + RF model having accuracy of 99% with 97% F1 scores which means that these combinations are most effective for RH classification. Compared to the FT + NB model, the latter shows poorer accuracy (side by side 76%) and F1-score (side by side 74%), which is pointed out at the weakness of Naïve Bayes in processing RH data. The FT+ SVM model also shows performance, with accuracy and F1 score of 94% and 92% respectively, justifying its application of RH-based classification.

The combination of feature selection and ensemble methods significantly increases the level of accuracy of predictions, particularly when the RH label is taken into consideration. The derived fine-tuned RF model constantly produces better performances in both fire prediction and RH scenario.

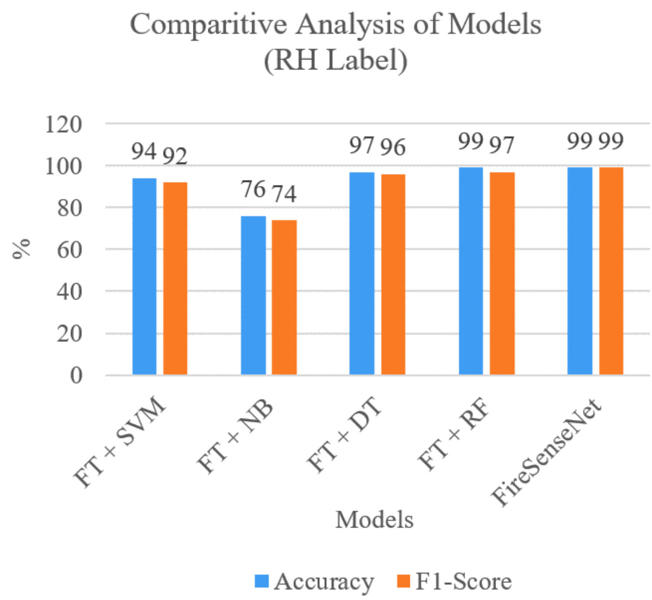

Figure 10. Comparative analysis of models (RF label)

Figure 11(a) presents the classification report highlighting the performance of the FireSenseNet model for fire prediction. The model attains an accuracy of 94%, indicating robust reliability in differentiating between fire and non-fire events. The precision and recall numbers are comparable, indicating the model's balanced performance across all classes. The model attains a remarkably low incidence of false positives and false negatives, as evidenced by the resulting F1-score of 93%. This score is a symmetric mean of recall and accuracy. The success of the model may be explained by the combined effect of feature selection the fine-tuning that reduces model dimensionality and increases prediction accuracy. Figure 11(b) represents the confusion matrix of the FireSenseNet model when predicting RH categories. From the matrix, it is apparent that there are 89 cases which the model identifies as "No Fire" and 5 cases that are classified as "Fire". However, 6 cases are misclassified in which actual fire cases are predicted as "No Fire". The lack of false positives (predicting fire when no such exists) reflects the model's precision. However, the false negative rate shows that some fire cases were not captured. The model's effectiveness in estimating RH-based fire risks is indicated by the overall accuracy of 94%. The fine-tuning when combined with the RF increases the predictive powers of the RF, however, further improvements may expunge the false negatives to improve safety measures. Figure 12 shows the ROC Curve of FireSenseNet (Fire Label) model.

The proposed model outperforms existing methods [28] by achieving higher predictive accuracy and improved generalization through effective integration of feature selection and hybrid learning techniques. The enhancement in performance of hybrid models can be explained by the capacity to merge the strengths of individual classifiers and thus capture a range of patterns in the data. Feature selection is also crucial as it removes extraneous and irrelevant features, leading to simpler and more effective models. Consequently, hybrid models with feature selection exhibit improved performance and stability over single classifiers. Moreover, the improved performance of FireSenseNet is achieved by parallel data processing of spatial, temporal and meteorological features, allowing them to capture more information about fire events.

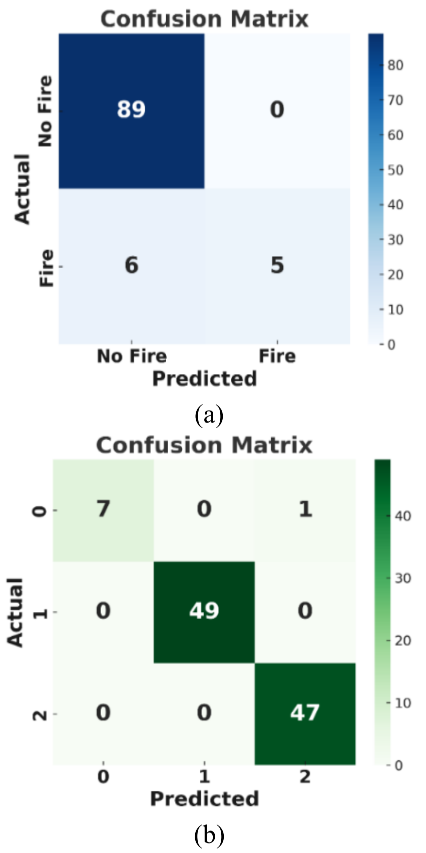

Figure 11. Confusion matrix of FireSenseNet model. (a) fire label and (b) RH label

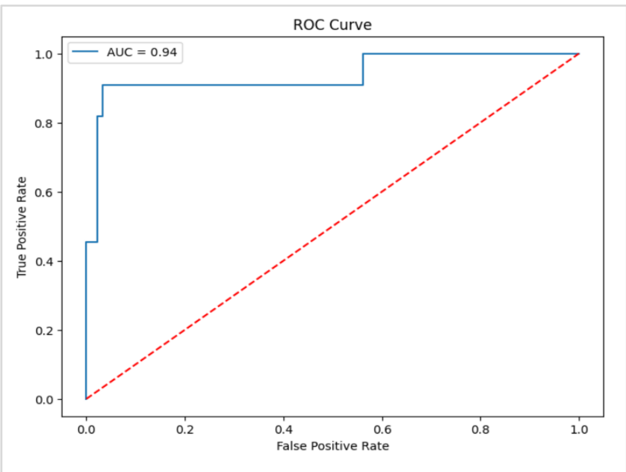

Figure 12. ROC curve of proposed FireSenseNet model

5. CONCLUSION AND FUTURE SCOPE

Accurate prediction of fires is important to reduce fire risks and losses the traditional fire alert systems cannot frequently provide the prediction of the occurrence of fires very well, and it is difficult for them to give an accurate detection result when they face complex data representation with high dimensions. This study mitigated the previously described drawbacks by presenting the FireSenseNet model and a hybrid ML framework that amalgamates various classifiers with feature selection methodologies. Experimental findings indicate that the proposed FireSenseNet and ensemble-based hybrid models substantially exceed traditional methods regarding accuracy, F1-score, and overall predictive reliability for both binary fire occurrence prediction and multiclass classification based on RH levels. The proposed FireSenseNet model was a powerful and effective DL architecture for wildfire prediction. Through simultaneous modeling of spatial, temporal, weather and meteorological features, FireSenseNet was able to effectively capture complex dependences among different types of data. It was more generalizable and converged quicker than other models due to its structure.

Despite the positive results, it has certain problems, primarily those related to incorporating multimodal sources of data, as well as real-time data processing. These issues will be addressed to enhance the strength and adaptability of the proposed framework to different fire-prone regions. In bringing out the importance of hybrid and feature selection-based models in predicting fire, the work contributes significantly towards developing reliable fire alerts.

To enhance predictive capabilities of fires in dynamic scenarios, the next study can examine how hybrid models can be combined with real-time IoT data. DL can enhance accuracy through the application of recurrent and convolutional neural networks. Another potential way to increase the resilience and responsiveness of the fire prediction system towards changing environmental conditions is the development of adaptive models that can learn on the basis of the constantly updated information.

DATASET AVAILABILITY

The data supporting this study are publicly available from the UCI Machine Learning Repository (Forest Fires Dataset) at https://archive.ics.uci.edu/dataset/162/forest+fires. The dataset was originally published by Cortez and Morais (2007) [26] in "A Data Mining Approach to Predict Forest Fires Using Meteorological Data."

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