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***Research paper***

# Development of A Novel Machine Learning Model for Accurate Classification of Forest Fire Scenarios

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**Abstract**

Forest fires pose significant environmental and economic threats, necessitating accurate classification for timely intervention. Traditional classification methods often lack precision due to complex fire dynamics and environmental variability. This research aims to develop a novel Machine Learning (ML) model that enhances the classification accuracy of forest fire scenarios by addressing data imbalance and improving feature selection. The proposed model involves Modified Mayfly Optimizer Tuning Gradient Boosting Decision Trees (MMO-GBoostDT). The MMO is employed to optimize hyper parameters for GBoostDT model. By fine-tuning the hyper parameters, the proposed MMO-GBoostDT model improves the model's ability to generalize and prevent over fitting. The dataset consists of aerial and terrestrial images. Noise reduction employing median filtering is utilized to remove unwanted noise in aerial images. Independent spectral features were extracted to enhance fire classification using independent component analysis (ICA), and Mutual Information (MI). Experimental results indicate that the proposed MMO-GBoostDT method outperforms existing methods by achieving a higher precision (97.8%), recall (98.5%), accuracy (98.65%) and F1-score (98.2%). The model effectively reduces the false positive and enhances classification robustness. The model demonstrates superior classification accuracy and resilience against data imbalance.

***Keywords***: *: Forest Fires; Modified Mayfly Optimizer Tuning Gradient Boosting Decision Trees (MMO-GBoostDT); Environmental Variability; Classification.*

## 1. Introduction

The forest has an important and dynamic function in the recreational, global, environmental, and ecological systems. It has a significant impact on the quantity of Green House Gases (GHGs), atmospheric carbon absorption, and soil erosion reduction [2]. In general, Forest Fires (FF) is grouped into three primary types: ground fires, surface fires, and crown fires [1]. The forest is a huge region covered with trees, dried leaves, and forests. When the fire begins, these components help it to spread. Fires can start for a variety of causes, including high temperatures in the summer, smoking, or gatherings with fireworks. Once a fire begins, it will continue until it is fully distinguished [19].

FF is a reason for concern as it inflicts significant harm to the environment, property, and human lives. This can help to save the region's flora and wildlife, as well as its resources. FF represents a significant concern as it remains undetected for a long time before causing damage to the city. The major causes of FF are natural and man-made. Man-made sources such as an electric spark, bare flame, or cigarette can also ignite fires [3]. Natural causes include dry weather, lightning, wind, coal-seam fires, volcanoes, meteorites, smoking and heating, whereas human-caused fires include cooking, accidents, or deliberate acts of neglect. Both natural and human-caused fires have a profound impact on animal and human life [20].

FF can negatively influence the forest dynamics by disrupting the carbon cycle in the affected region. One of the primary causes of global warming is the reduction in the forest acreage worldwide. The origin and spread of fire are caused by a mix of ignition sources (both natural and man-made), vegetation, meteorological conditions, and human factors [5]. Unfortunately, Forest Fire scenarios (FFS) occur often as

an outcome of unrestrained human activity and irregular environmental conditions. These fires are by far the most devastating to both environmental assets and human ecology. FFS have become more common as an outcome of global warming, mortality, and other factors. Identifying and monitoring such FFS has become a global issue for groups focused on FFS management. Traditional classification approaches frequently lack accuracy due to complicated fire dynamics and environmental unpredictability. The research aims to create a new ML model that improves the classification accuracy of FFS by resolving data imbalance and enhancing feature selection. The proposed model uses Modified Mayfly Optimizer Tuning Gradient Boosting Decision Trees (MMO-GBoostDT) [4].
The organization of the research contains the following structure: Section 2 illustrates the related works and Section 3 depicts the methods utilized for the research. Section 4 contains the result of the research. Section 5 discusses the merits of the proposed method and the demerits of the existing methods. Section 6 concludes the research [6].

## 2. Related works

To improve FF detection, the research [7] addressed issues with different fire appearances and decreased false positives. For fire detection, the technique combined Yolov5 and EfficientDet, while EfficientNet gathered global data. To increase accuracy, decisions were taken collectively. The results demonstrated a 51.3% decrease in false positives without additional delay and a 2.5%–10.9% performance gain. One drawback was the possible reliance on dataset variety for generalization. To improve next-day wildfire prediction, the research [21] created an ML algorithm that uses topography, weather, Earth observation data, and past fire incidence to reliably identify high-risk locations. To balance sensitivity (>90%) and specificity (>65%), state-of-the-art classifiers were optimized using two validation approaches. Although the results demonstrate successful large-scale predictions, problems with managing data imbalance and improving spatial granularity for increased accuracy and generalization yet exist [8].
Particle Swarm Optimization (PSO) was used [9] to optimize the Random Forest (RF) model, improving the prediction of fire risk. It mapped the fire risk using the PSO-RF model, and obtained the greatest AUC (0.908). Although accuracy has increased, there are indeed issues with region-specific applicability and possible over fitting. Ensemble learning techniques were used [22] to improve FF prediction. It used high gradient boosting to classify large-scale fires and modified RF to forecast burnt areas. Predictive accuracy was high, according to the results. Nevertheless, there were drawbacks such as possible biases in the data and difficulties applying models to various forest environments [10].
MaxENT and RF categorization techniques were used [11] to evaluate the danger of wildfires. Bioclimatic factors, vector data, and satellite images were examined. The findings demonstrated a significant human effect on fire danger, with MaxENT performing well at the micro scale and RF performing well at the macro scale. The requirement for sophisticated distant sensing techniques was a drawback. Using an ensemble approach and five ML models, such as Boosted Regression Trees (BRT), Classification and Regression Trees (CART), RF, Support Vector Machine (SVM) and Multivariate Adaptive Regression Splines (MARS), the research [23] determined the areas that were susceptible to FF. The greatest AUC (0.87) was obtained by RF using spatially adjusted Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (SNPP-VIIRS) fire data and 32 predictor variables. The ensemble map helps with management by highlighting high-risk locations. Potential data errors and regional model transferability were among the limitations [12].
Using MARS, SVM, and BRT models, the investigation [13] forecasted the likelihood of FF. Model appropriateness was evaluated using resampling approaches and 14 fire predictors. The best-performing BRT had an AUC of 0.91. Resampling increased accuracy, but there were drawbacks, such as possible biases in the data and the generalizability of the model. Results support methods for managing fires in areas that were at risk. Using Deep Learning (DL)-based sensitivity analysis, ML algorithms (MLAs), and geospatial tools, the research [14] evaluated and mapped the susceptibility of FF. The ensemble model has the greatest accuracy (AUC = 0.977) out of the five MLAs that were verified using ROC. Evapotranspiration was determined by sensitivity analysis to be the most significant element. The investigation was constrained by the availability of data and the possibility of regional model generalization.
To facilitate fire control, the research [15] forecasted the behavior and expansion of wildfires. To train many ML models, a dataset comprising topography, anthropogenic, satellite, and climatic characteristics was used. With the highest accuracy of 91%, AdaBoost outperformed SVM (81%), Artificial Neural Network (ANN) by 86% and RF (88%). The model's application was restricted by regional data availability and geographic variances that impact forecast generalizability, notwithstanding its performance. A wireless sensor network and a ML regression model were used [16] to create an early FF detection system with increased accuracy. The technique used solar energy and rechargeable batteries to power sensor nodes that were strategically positioned in challenging forest conditions. Trials conducted in actual tropical forests have revealed lower latency warnings compared to current systems. Limitations, however, include the possibility of animals and severe weather damaging the sensors.

## 3. Methodology

This section outlines the following procedure: Firstly, the data is gathered that consists of aerial and terrestrial images. Secondly, the gathered data was preprocessed to remove unwanted noise in aerial images by using Median Filtering (MF). Thirdly, the preprocessed data was extracted by using the Independent Component Analysis (ICA), and selected the most relevant metrological data using the Mutual Information (MI). Finally, the selected data was used for accurate classification of forest fire scenarios using Modified Mayfly Optimizer Tuning Gradient Boosting Decision Trees (MMO-GBoostDT). Fig. 1 depicts the overview of the methodology.

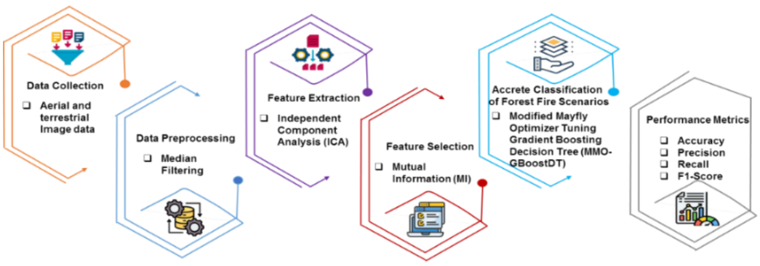


**Fig. 1:** Overview of the Methodology.

### 3.1. Data collection

The data was gathered from the open source Kaggle link:https://www.kaggle.com/datasets/mhd01ali/forest-fire-classifier-dataset. The collection contains 4,506 images that depict fire, smoke, and non-fire conditions, including aerial and terrestrial images. It includes a wide range of climatic variables both during the day and at night, allowing a thorough depiction of FFS for effective model training and assessment.

### 3.2. Data preprocessing using median filtering

Median Filtering (MF) is a noise reduction method that successfully removes undesired noise from aerial images by replacing the value of each pixel with the median value of its neighbors. It is used to enhance the quality of the input data, resulting in more accurate FF classification. By minimizing noise, the model could extract more significant features and enhance the model's performance in classifying fire situations. The median is computed using the original value of the pixel. The formula for MF is given by Equation (1).

$$\hat{f}(y,z) = \underset{(s,t)\in S_{yz}}{\text{median}}\{h(s,t)\} \tag{1}$$

### 3.3. Feature extraction using independent component analysis (ICA)

The preprocessed data was then used to extract the independent spectral features to enhance fire classification using ICA. It is a computing approach for separating mixed signals into statistically independent components. It is frequently used in feature extraction and noise reduction. It is used to determine a linear representation of non-Gaussian data, ensuring that retrieved spectral characteristics from aerial and terrestrial images are as statistically independent as feasible. Various spectral bands $y_1, y_2, \ldots, y_L$can be considered as linear mixes of independent components $s_1, s_2, \ldots, s_L$, which comprise both fire-related properties and redundant information such as noise, as described by Equation (2).

$$y_j = a_{k1}s_1 + a_{k1}s_1 + \cdots + a_{kL}s_L, \text{for all k} \tag{2}$$

Equation (2) is rewritten as Equation (3) in matrix notation.

$$y = As \tag{3}$$

Equation (3) can be referred to as the ICA model. By denoting the columns of Aas $a_k$, the ICA model could be rewritten as Equation (4).

$$y = \sum_{j=1}^{n} a_j s_j \tag{4}$$

### 3.4. Feature selection using mutual information (MI)

The extracted data was then selected as the most relevant metrological by using the MI. It is a statistical metric that calculates the amount of information one variable offers about another to quantify the reliance between variables. By identifying the information that meteorological and spectral variables overlap, MI is used to assess the significance of these features in the context of classifying FF. It is described as Equation (5).

$$I(Y;Z) = H(Y) + H(Z) - H(Y,Z) \tag{5}$$

As seen in Equation (6), the KL divergence of the product $P(Y)P(Z)$ of the two marginal probability distributions from the joint probability distribution $P(Y,Z)$, where $p(y,z) = P(Y = y, Z = z)$, is also the measure of I.

$$I(Y;Z) = D_{KL}(P(Y,Z)||P(Y) \cdot P(Z) = \sum_y \sum_z \left[p(y,z) \log\left(\frac{p(y,z)}{p(y).p(z)}\right)\right] \tag{6}$$

### 3.5. Accurate classification of forest fire scenarios using modified mayfly optimizer tuning gradient boosting decision trees (MMO-GBoostDT)

To enhance the classification accuracy of FFS by addressing data imbalance and improving feature selection, the research uses the proposed MMO-GBoostDT model. The MMO increases exploration and convergence, resulting in strong classification even with unbalanced data. GBoostDT decreases false positives and improves reliability by efficiently identifying complex patterns in spectral and meteorological data. MMO-GBoostDT improves prediction accuracy by adjusting hyper parameters to improve generalization and prevent over fitting.

#### 3.5.1. Gradient boosting decision trees (GBoostDT)

GBoostDT is an ensemble learning technique that builds Decision Trees (DT), with each tree addressing the preceding one's flaws using gradient-based optimization. It improves prediction accuracy by correctly handling complex patterns in meteorological and spectral data, reducing false positives, and enhancing model robustness. The fire scenario data can be represented as $\{y_j, z_j\}_{j=1}^{n}$, where $y_j = (y_{1j}, y_{2j}, \ldots, y_{pj})$,$y_j$ is the anticipated fire scenario label, and p is the number of predicted variables. The steps for implementing GBDT in FF classification are as follows.

- Initialization: The model minimizes the loss function $L(z_j, \beta)$ by starting with the initial constant value $F_0(y)$ as shown in Equation (7).

$$F_0(y) = \arg\min_{\beta} \sum_{j=1}^{n} L(z_j, \beta) \tag{7}$$

- Gradient Calculation: The gradient of the residuals is calculated for each iteration $m = 1: M$to modify model predictions as represented in Equation (8).

$$z_j^* = \left[\frac{-\partial L(z_j, F(y_j))}{\partial F(y_j)}\right]_{F(y)-F_{m-1(y)}}, j = \{1,2,\dots,N\} \tag{8}$$

- Fitting the Model: The gradient residuals are used to train a weak decision tree $h(y_j; a)$ to suit the fire scenario data. The squared error is minimized to determine the ideal parameter $a_m$ as depicted in Equation (9).

$$a_m = \arg\min_{\beta} \sum_{j=1}^{n} [z_j^* - \beta h(y_j; a)]^2 \tag{9}$$

- Step Size Calculation: By minimizing the loss function, the optimal step size $\beta_m$, is given by Equation (10).

$$\beta_m = \arg\min_{\alpha,\beta} \sum_{j=1}^{n} L(z_j, F_{m-1(y)} + \beta h(y_j; a)) \tag{10}$$

- Model Update: To enhance classification performance, the model is updated repeatedly by using Equation (11).

$$F_m(y) = F_{m-1(y)} + \beta_m\, h(y_j; a) \tag{11}$$

### 3.5.2. Modified mayfly optimization (MMO)

MMO is an upgraded swarm intelligence technique that improves exploration and exploitation to achieve greater global convergence in optimization challenges. It is used to adjust the hyper parameters of a ML model, boosting its generalizability and reducing over fitting. This section offers an MMO that incorporates three strategies: exponent decreasing inertia weight, an upgraded crossover operator and an adaptive Cauchy mutation technique.

- Exponent Reducing Inertia Weight Approach

There are several reducing inertia weight strategies, including linear, adaptive, logarithmic, and others. The early period's higher inertia weight facilitates particle exploration, allowing particles to investigate a greater region. The lower inertia weight in the latter phase facilitates particle utilization. This approach incorporates the exponent decreasing inertia weight into MMO. The formula is as follows in Equation (12).

$$h = h_{min} + \exp\left(1 - \frac{iter_{max}}{iter_{max} - iter + 1}\right) * (h_{max} - h_{min}) \tag{12}$$

Where $h_{max}$and $h_{min}$ are the minimum and maximum weights, respectively. Iterand $iter_{max}$represent the present and total number of iterations, respectively.

- Adaptive Cauchy Mutation (CM) Approach

The location of each male mayfly should be modified using a Cauchy-based mutation. Equation (13) describes the probability density function for the standard Cauchy distribution and Equation (14) expresses the relevant distribution function for $-\infty < y < \infty$.

$$f(x) = \frac{1}{\pi} \times \frac{1}{1+y^2} \tag{13}$$

$$F(y) = \frac{1}{\pi}\arctan(y) + \frac{1}{2} \tag{14}$$

The following Equation (15) shows random numbers generated using the conventional Cauchy distribution.

$$CM = \tan\left(\pi \times \left(\varepsilon - \frac{1}{2}\right)\right) \tag{15}$$

Where CM signifies a random value created by the inverse function of the standard Cauchy distribution function, meaning a uniform distribution-generated random value in the range of 0to 1. The location of each male mayfly should be readjusted using Equation (15), which combines the CM approach with an adaptive mutation as given in Equation (16).

$$Y_j^{t+1} = y_j^{t+1} + y_j^{t+1} \times CM \times \exp((1-t) \times \alpha) \tag{16}$$

Where $y_j^{t+1}$ is the $j^{th}$ computed individual, and $Y_j^{t+1}$ is the modified individual. $\alpha$ is a contraction-expansion coefficient that determines the rate of convergence and is specified as 0.15.

- Enhanced Crossover Operator

Although mayfly crossover and reproduction procedures give the MMO with exploration ability while also increasing the MMO's convergence speed, the MMO has limited exploration ability. To enhance it, apply the horizontal crossover search. Equation (17) describes the MMO's improved Crossover Operator (CO), which uses horizontal crossover search.

$$\begin{cases} \gamma_1 = L \times male + (1 - L)female + c_1(male - female) \\ \gamma_2 = L \times female + (1 - L)\, male + c_2\,(female - male) \end{cases} \tag{17}$$

Where $c_1$and $c_2$, the expansion coefficients, are both random numbers generated by a uniform distribution between -1 and 1. Equation (18) is the formula for the crossover operator of the MMO enhanced by reducing the search space.

$$\begin{cases}\gamma_1 = d_1 \times (L \times male + (1 - L)female) \\ \gamma_2 = d_3 \times (L \times female + (1 - L)\, male)\end{cases} \tag{18}$$

Where the contraction coefficients, $d_1$and $d_3$, are both random values generated by a uniform distribution and range from 0.7 to 1. Equation (19) is the formula for the CO of the MMO enhanced by enlarging the search space.

$$\begin{cases}\gamma_1 = d_2 \times (L \times male + (1 - L)female) \\ \gamma_2 = d_4 \times (L \times female + (1 - L)\, male)\end{cases} \tag{19}$$

Where the expansion coefficients, $d_2$and$d_4$, are both random values generated by a uniform distribution between 1 and 1.3. Therefore, Equation (20) (21) could be used to characterize the improved CO formula of MMO, where rand 1, rand 2, and rand 3 are the random input numbers between [0, 1].

$$\gamma_1 = \begin{cases} L \times male + (1 - L)female, rand_1 < p_{one} \\ L \times male + (1 - L)female) + c_1(male - female), rand_1 > p_{one}, rand_2 < p_{two} \\ d_1 \times (L \times male + (1 - L)female), rand_1 > p_{one}, rand_2 < p_{two}, rand_3 < p_{three} \\ d_3 \times (L \times male + (1 - L)female) rand_1 > p_{one}, rand_2 < p_{two}, rand_3 > p_{three} \end{cases} \tag{20}$$

$$\gamma_2 = \begin{cases} L \times male + (1 - L)female, rand_1 < p_{one} \\ L \times male + (1 - L)female) + c_1(male - female), rand_1 > p_{one}, rand_2 < p_{two} \\ d_1 \times (L \times male + (1 - L)female), rand_1 > p_{one}, rand_2 < p_{two}, rand_3 < p_{three} \\ d_3 \times (L \times male + (1 - L)female) rand_1 > p_{one}, rand_2 < p_{two}, rand_3 > p_{three} \end{cases} \tag{21}$$

MMO-GBoostDT enhances classification accuracy through hyper parameter optimization that reduces over fitting and increases generalization. It minimizes false positive results with its efficient detailed analysis of complex patterns exhibited in spectral with their corresponding meteorological data and, hence, enhances reliability. The model very effectively treats imbalanced datasets to ensure good performance across different fire scenarios. Moreover, it results in speed and accuracy of fire detection, helping in disaster prevention and timely action. It has an excellently expressive model that handles imbalanced data to assure proper performance across various fire scenarios.

## 4. Result

This section executes the result of the research. The research uses performance metrics such as recall, F1-score, accuracy, and precision for accurate classification of FFS.

- Accuracy

Accuracy calculates the overall accuracy of the classification model by measuring the proportion of properly predicted fire scenarios to all predictions. A high accuracy of the MMO-GBoostDT model offers precise identification of fire scenarios, reducing the risk of misclassification. This enhances early detection capacity, leading to quicker action and reduced environmental impact. Table 1 and Fig. 2 depict the outcomes of the accuracy.

**Table 1:** Outcomes of the Accuracy

| Methods | Accuracy (%) |
|---|---|
| FFHDM [17] | 98 |
| CNN [18] | 97.63 |
| MMO-GBoostDT [Proposed] | 98.65 |

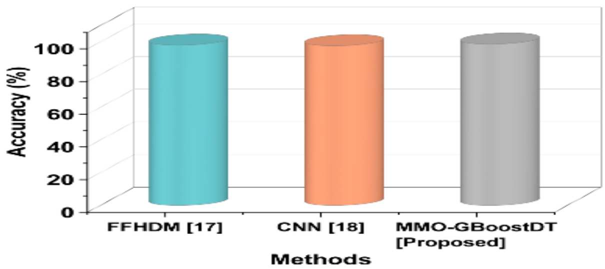


**Fig. 2:** Graphical Representation of the Accuracy.

Training accuracy refers to the percentage of correctly predicted instances during the training phase. Accuracy loss is the reduction in a model's classification performance caused by issues such as data imbalance, noise, or over fitting. In research, decreasing accuracy loss allows reliable identification of fire situations, lowering false alarms and missing detections for successful fire control. A high training accuracy (0.98) often indicates that the model has learned patterns from the training data. The outcomes of the accuracy loss are depicted in the Fig. 3 where the value of accuracy loss is 0.35%.

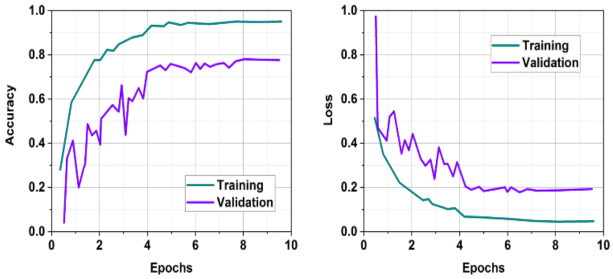

**Fig. 3:** Graphical Representation of the Accuracy and Accuracy Loss.

Table 1 show that the MMO-GBoostDT model has a maximum accuracy of 98.65%, exceeding both FFHDM (98%) and CNN (97.63%). This improvement demonstrates that the proposed method effectively reduces categorization errors. Higher accuracy indicates more dependability in real-world FF detection applications.

- Precision

Precision is the fraction of accurately predicted fire situations among all the positive predictions, demonstrating the model's ability to reduce false alarms. The great precision of MMO-GBoostDT guarantees that only actual fire incidences are detected, avoiding needless alarms. This increases the reliability of fire detection systems and optimizes resource allocation. Table 2 and Fig. 4 depict the outcomes of the precision.

**Table 2:** Precision

| Methods | Precision (%) |
| --- | --- |
| FFHDM [17] | 97 |
| CNN [18] | 97 |
| MMO-GBoostDT [Proposed] | 97.8 |

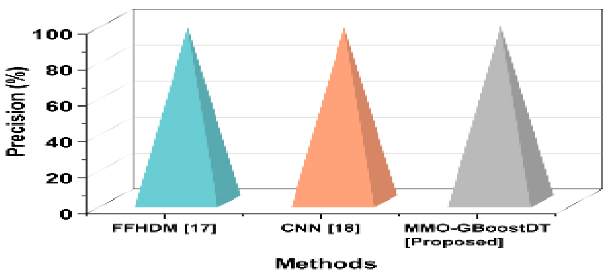

**Fig. 4:** Graphical Representation of the Precision.

Table 2 demonstrates that the MMO-GBoostDT obtains 97.8%, outperforming FFHDM (97%) and CNN (97%), demonstrating its better capacity to reduce false positives. A higher precision score indicates that the proposed model successfully lowers unnecessary fire alarms.

- Recall

Recall assesses the model's capability to accurately identify actual fire scenarios by calculating the percentage of correctly identified fire incidents among all actual fires. A high recall in MMO-GBoostDT implies fewer missed fire detections, resulting in improved responsiveness. This is critical for minimizing undiscovered fire hazards and avoiding widespread tragedies. Table 3 and Fig. 5 depict the outcomes of the recall.

**Table 3:** Recall

| Methods | Recall (%) |
| --- | --- |
| FFHDM [17] | 95 |
| CNN [18] | 98 |
| MMO-GBoostDT [Proposed] | 98.5 |

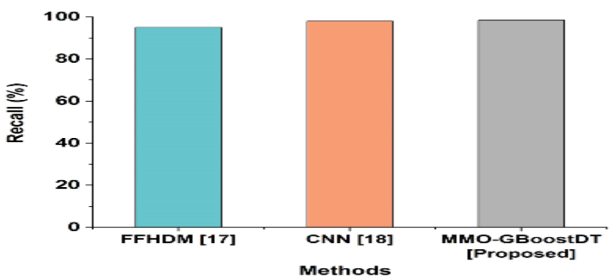

**Fig. 5:** Graphical Representation of the Recall.

Table 3 shows that MMO-GBoostDT has the highest recall at 98.5%, comparable to CNN (98%) and FFHDM (95%). A greater recall value increases the number of real fire instances discovered, lowering the danger of missing crucial accidents. This is especially crucial in early fire detection, as missing a fire can have devastating effects.

- F1-Score

The F1-score is calculated as the harmonic mean of recall and precision, wherein it balances false negatives and false positives to assess the classification performance. For MMO-GBoostDT, an excellent F1-score demonstrates the best trade-off between detecting real flames and making errors in categorization. Thus, it promotes resilience in classifying different fire scenarios while the environment keeps changing. Table 4 and Fig. 6 present the F1-score results.

**Table 4:** F1-Score

| Methods | F1-score (%) |
|---|---|
| FFHDM [17] | 96 |
| CNN [18] | 98 |
| MMO-GBoostDT [Proposed] | 98.2 |

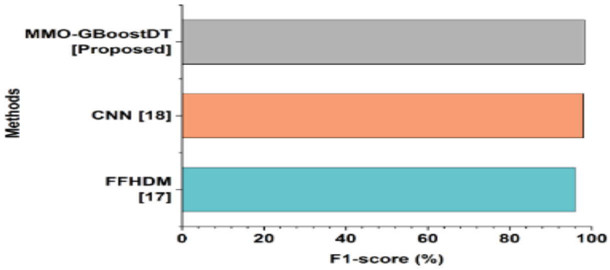

**Fig. 6:** Graphical Representation of the F1-Score.

Table 4 demonstrates that the MMO-GBoostDT model obtains 98.2%, surpassing FFHDM (96%), and CNN (98%), indicating a well-optimized trade-off. A higher F1-score shows that the model retains strong detection capacity and precision while reducing false positives and false negatives.

## 5. Discussion

The existing FF classification methods, such as FFHDM and CNN, have a certain shortcoming. While FFHDM achieves high accuracy and low recall, it misses out on certain genuine fire incidences. The CNN approach is able to enhance its recall but not its precision, which leads to false positives. These problems are primarily caused by weak feature selection and data imbalance. The MMO-GBoostDT model improves classification reliability, lowers false positives, and increases the accuracy of fire detection by minimizing accuracy loss. The MMO- proposed GBoostDT approach is capable of solving some of these problems by optimizing the hyper parameters using the MMO for better generalization and less over fitting. In terms of more suitable feature selection and data management, MMO-GBoostDT delivers better accuracy scores, and a higher recall and precision, leading to a few false positives and negatives and more genuine fire detections.

## 6. Conclusion

The MMO-GBoostDT model improved FF classification by optimizing hyperparameters and resolving data imbalance. The MMO-GBoostDT model had the greatest precision (97.8%), recall (98.5%), accuracy (98.65%), and F1-score (98.2%), resulting in enhanced classification performance with fewer false positives and better fire detection. These findings demonstrate that MMO-GBoostDT outperforms prior approaches by eliminating false alarms and providing reliable and robust classification of fire situations under complicated environmental settings, making it ideal for real-world applications. The model's effectiveness could be affected by significant environmental fluctuations and a scarcity of high-quality labeled information. Future research includes incorporating real-time satellite data, boosting model responsiveness to dynamic fire conditions, and increasing computing efficiency for large-scale deployment.

## References

[1] Alkhatib, A. A., Abdelal, Q., & Kanan, T. (2021). Wireless Sensor Network for Forest Fire Detection and behavior Analysis. *International Journal of Advances in Soft Computing & Its Applications*, *13*(1), 82-104.

[2] Sudhir, M. (2022). Untangling Pancard by Designing Optical Character Reader Tool Box By Correlating Alpha Numeric Character. *International Journal of communication and computer Technologies*, *10*, 7-10. https://doi.org/10.31838/ijccts/10.01.03.

[3] Pragati, S. S., & Umbrajkar, P. (2020). Forest fire detection using machine learning. *International Journal of Advance Scientific Research and Engineering Trends*, *4*(12), 6-12.

[4] Cadé, D., & Blanchet, B. (2013). From Computationally-Proved Protocol Specifications to Implementations and Application to SSH. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 4*(1), 4-31.

[5] Sevinc, V., Kucuk, O., & Goltas, M. (2020). A Bayesian network model for prediction and analysis of possible forest fire causes. *Forest Ecology and Management*, *457*, 117723. https://doi.org/10.1016/j.foreco.2019.117723.

[6] Park, H. B., Kim, Y., Jeon, J., Moon, H. S., & Woo, S. (2019). Practical Methodology for In-Vehicle CAN Security Evaluation. *Journal of Internet Services and Information Security, 9*(2), 42-56.

[7] Xu, R., Lin, H., Lu, K., Cao, L., & Liu, Y. (2021). A forest fire detection system based on ensemble learning. *Forests*, *12*(2), 217. https://doi.org/10.3390/f12020217.

[8] Ananthi, J., Sengottaiyan, N., Anbukaruppusamy, S., Upreti, K., & Dubey, A. K. (2022). Forest fire prediction using IoT and deep learning. *International Journal of Advanced Technology and Engineering Exploration*, *9*(87), 246-256. https://doi.org/10.19101/IJATEE.2021.87464.

[9] Shi, C., & Zhang, F. (2023). A forest fire susceptibility modeling approach based on integration machine learning algorithm. *Forests*, *14*(7), 1506. https://doi.org/10.3390/f14071506.

[10] Itasanmi, S. A., & Okanlawon, O. (2019). Information Needs and Information Seeking Pattern of Adult Learners. Indian Journal of Information Sources and Services, 9(2), 110–115. https://doi.org/10.51983/ijiss.2019.9.2.612.

[11] Janiec, P., & Gadal, S. (2020). A comparison of two machine learning classification methods for remote sensing predictive modeling of the forest fire in the North-Eastern Siberia. *Remote Sensing, 12*(24), 4157. https://doi.org/10.3390/rs12244157.

[12] Arnita, V., Zainal, S. R. M., & Jalaludin, D. (2018). To Be or Not to Be? The Influencing Factors towards Pursuing as Professional Accountant Among Indonesian S1 Accounting Students. *International Academic Journal of Science and Engineering, 5*(2), 1–10. https://doi.org/10.9756/IAJSE/V5I1/1810022.

[13] Kalantar, B., Ueda, N., Idrees, M.O., Janizadeh, S., Ahmadi, K., & Shabani, F., 2020. Forest fire susceptibility prediction based on machine learning models with resampling algorithms on remote sensing data. Remote Sensing, 12(22), p.3682. https://doi.org/10.3390/rs12223682.

[14] Rihan, M., Bindajam, A.A., Talukdar, S., Naikoo, M.W., Mallick, J. and Rahman, A. (2023). Forest fire susceptibility mapping with sensitivity and uncertainty analysis using machine learning and deep learning algorithms. *Advances in Space Research, 72*(2), 426-443. https://doi.org/10.1016/j.asr.2023.03.026.
[15] Raktur, H., & Jea, T. (2024). Design of compact wideband wearable antenna for health care and internet of things system. National Journal of Antennas and Propagation, 6(1), 40–48. https://doi.org/10.31838/NJAP/06.01.06.
[16] Hoa, N. T., & Voznak, M. (2025). Critical review on understanding cyber security threats. Innovative Reviews in Engineering and Science, 2(2), 17-24.
[17] Lakshmanaswamy, P., Sundaram, A., & Sudanthiran, T. (2024). Prioritizing the right to environment: Enhancing Forest fire detection and prevention through satellite data and machine learning algorithms for early warning systems. *Remote Sensing in Earth Systems Sciences, 7*(4), 472-485. https://doi.org/10.1007/s41976-024-00140-0.
[18] Rahman, A.K.Z.R., Sakif, S., Sikder, N., Masud, M., Aljuaid, H., & Bairagi, A.K. (2023). Unmanned aerial vehicle assisted forest fire detection using deep convolutional neural network. *Intelligent Automation & Soft Computing, 35*(3), 3259-3277. https://doi.org/10.32604/iasc.2023.030142.
[19] Singh, S., Jha, M., Talati, B., & Jaiswal, A. (2024). Forest fire detection using CNN.
[20] Abdusalomov, A.B., Islam, B.M.S., Nasimov, R., Mukhiddinov, M., & Whangbo, T.K., 2023. An improved forest fire detection method based on the detectron2 model and a deep learning approach. *Sensors, 23*(3), 1512. https://doi.org/10.3390/s23031512.
[21] Apostolakis, A., Girtsou, S., Giannopoulos, G., Bartsotas, N.S., & Kontoes, C. (2022). Estimating next day's forest fire risk via a complete machine learning methodology. *Remote Sensing, 14*(5), 1222. https://doi.org/10.3390/rs14051222.
[22] Xie, Y., & Peng, M. (2019). Forest fire forecasting using ensemble learning approaches. *Neural Computing and Applications, 31*(9), 4541-4550. https://doi.org/10.1007/s00521-018-3515-0.
[23] Sarkar, M.S., Majhi, B.K., Pathak, B., Biswas, T., Mahapatra, S., Kumar, D., Bhatt, I.D., Kuniyal, J.C., & Nautiyal, S., (2024). Ensembling machine learning models to identify forest fire-susceptible zones in Northeast India. *Ecological Informatics, 81*, 102598. https://doi.org/10.1016/j.ecoinf.2024.102598.
[24] Parizi, L., Dobrigkeit, J., & Wirth, K. (2025). Trends in software development for embedded systems in cyber-physical systems. SCCTS Journal of Embedded Systems Design and Applications, 2(1), 57–66.
[25] Sadulla, S. (2024). Optimization of data aggregation techniques in IoT-based wireless sensor networks. Journal of Wireless Sensor Networks and IoT, 1(1), 31-36. https://doi.org/10.31838/WSNIOT/01.01.05.
[26] Veerappan, S. (2025). Digital Twin Modeling for Predictive Maintenance in Large-Scale Power Transformers. National Journal of Electrical Machines & Power Conversion, 39-44.
[27] Nabadova, G. (2024). Controlling the movement of hexacopter along the intended route. Results in Nonlinear Analysis, 7(4), 26-34.
[28] Subermaniam, L., Kuppusamy, M., Isakulova, N., Ghate, A. D., Subrahmanyam, S., & John, B. (2025). A Systematic Review of Sustainability Management in Small and Medium Enterprises to Improve Sustainable Development Goals. Acta Innovations, 38-48.
[29] Sriwardany, S., Fadhilah, D. D., & Sunny, R. (2025). risk management in rice farming using hybrid fmea-ahp: a case study from hamparan perak, indonesia. Acta Innovations, 24-37.