Forest Fire Detection Using Convolutional Neural Networks (CNN) and Shapley Additive exPlanations (SHAP)

Xin Yi Wong1, a), Shih Yin Ooi1, 2, b), Yee Jian Chew1, 2, c), Ying Han Pang1, 2, d), Sheriza Mohd Razali3, e)

*1Faculty of Information Science and Technology (FIST), Multimedia University, Jalan Ayer Keroh Lama, Melaka, 75450, Malaysia*

*2Centre for Advanced Analytics (CAA), COE for Artificial Intelligence, Multimedia University, Jalan Ayer Keroh Lama, Melaka, 75450, Malaysia*

*3University of Putra Malaysia, Jalan Universiti 1, 43400 Serdang, Selangor, Malaysia*

*b) Corresponding author: syooi@mmu.edu.my*

*a) wong.xy.z0613@gmail.com*

*c) chewyeejian@mmu.edu.my*

*d) yhpang@mmu.edu.my*

*e) sheriza@upm.edu.my*

**Abstract.** Forest fires are uncontrollable and spread quickly until they become a threat. Early detection of forest fires is crucial to preventing forest damage and identifying fires before they spread. In this paper, a forest fire detection system is proposed by using Convolutional Neural Networks (CNN) to develop a powerful forest fire detection system. To precisely identify the fire in the images, the CNN model can extract characteristics from the provided image data and analyze the intricate patterns. Furthermore, Explainable Artificial Intelligence (XAI) techniques are integrated to improve the model’s interpretability. Shapley Additive exPlanations (SHAP) are used in this paper to help people understand the characteristics that lead the model to make this choice.

# INTRODUCTION

Forest fires are one of the natural hazards that cause major area damage and are difficult to fight against. It will damage the habitats of plants and animals, leading to an unbalanced ecosystem. In Malaysia, the case of forest fires is considered a high-confidence alert in 2024. There are still many cases of forest fires that have not been detected on time, resulting in large areas of forest being burned. [1] explained that this problem harms the ecosystem permanently, reduces biodiversity, and raises carbon emissions. In remote and dense areas, the fires cannot be discovered quickly. This is due to limited accessibility and a lack of surveillance equipment. Those areas make it difficult to detect any fire breakouts and permit them to spread unchecked. In its early stages, a forest fire cannot be accurately identified by human or manual observation. When they know there has been a fire and that there is a high probability that more plants will be affected, this issue causes them to delay responding.

[2] describes that for fires to be detected earlier, a project proposing a forest fire detection system that includes machine learning needs to be implemented. K-Nearest Neighbour (KNN), Random Forest, Support Vector Machine (SVM), YOLOv5, MobileNet, Convolutional Neural Network (CNN), and others are machine learning models that have been proposed and used by others to detect and predict forest fires. Each machine learning method has its benefits and limitations. In this project, the Convolutional Neural Network (CNN) has been chosen to analyze and detect forest fires. CNN is a part of deep learning that can recognize features in images through training and learning. [3] has described the architecture of CNN, which consists of many layers, allowing it to process complicated image data and extract features, making the CNN highly appropriate for detecting fires from image feeds. Furthermore, the Explainable Artificial Intelligence (XAI) technique will be integrated into the decision-making process of CNN to ensure that the decisions made can be traced back to comprehensible and transparent justifications. Shapley Additive exPlanations (SHAP) will be integrated with CNN to foster trust and a deeper understanding among stakeholders about the model’s interpretations.

This machine learning-based forest fire detection is developed to achieve the objectives listed below:

* Detect forest fires using machine learning to enhance detection accuracy.
* Alert the forest fire quickly and inform the fire station promptly to reduce response times.
* Establish a community-based system for detecting forest fires in Melaka state.

## RELATED WORK

The deployment of machine learning enables real-time detection, allowing for a rapid response when identifying a fire. The most popular methods proposed by researchers for forest fire detection are KNN, Random Forest, SVM, CNN, YOLOv5, and MobileNet. According to [4], KNN uses a value of K to find the class that is nearest to an object. [4] tested the algorithm by using a dataset derived from fire simulations that start from leaves, wood, grass, paper, and plastic to model combustion outcomes in both wet and dry conditions. [5] proposed a forest fire smoke detection based on random forest, which is a flexible algorithm that has good anti-noise performance and a great fitting ability. [6] describe the SVM works by finding the best hyperplane to divide the input data into two classes with the largest margin between them. A variety of datasets in video and image formats are used to train the SVM to detect fires in video frames. [7] The YOLO model is used to convert target detection from a classification problem to a regression problem, which has significantly increased detection efficiency. YOLOv5 can identify and recognize the flame picture in the flame dataset more rapidly and accurately with less computation and fewer resource consumption requirements. According to [8], Mobile Net is made to function on PCs with poor or non-existent graphics processing units (GPUs), embedded systems, and mobile devices. Mobile Net is integrated with Random Forest and SVM to identify fires.

[9] Use a CNN with a Sigmoid Activation Function that enables the model to make binary predictions, specifically, whether there is a fire or not. The sigmoid activation assigns a probability to each class.[10] proposed an early detection of forest fires by a trained CNN model. They used multiple convolutional layers and increased the filter count to record more complex features from the input data. [11] proposed an MDCNN that has a higher detection efficiency for forest fires since it is lighter and more capable of recognizing images of forest fires. This model provides a high accuracy in recognizing forest fires and performs well in flame detection.

## Different Machine Learning Models Proposed By Others

Table 1 presents the accuracy of various machine learning models in detecting, predicting, and classifying forest fires.

## Explainable Artificial Intelligence (XAI)

It is essential to understand how AI works and how it makes decisions. [12] explained that XAI is the key to realizing AI’s potential while ensuring its safe and ethical application lies in a sector focused on creating AI models that provide humans with understandable justifications for their choices and outputs. [13] explained that transparency, interpretability, and explainability are the three concepts that are crucial when the XAI algorithm is created. Transparency AI can observe the cycles that result in dynamics within models. It resolves this problem by effectively utilizing interpretable models. Interpretability is the ability to accurately predict a model’s result without being aware of the underlying causes. The interpretability of XAI enables humans to understand the procedures and results easily. Explainability is crucial for overcoming false positives and enabling analysts to immediately and easily understand system outputs. It helps to clarify computations, expectations, and information.

Shapley Additive exPlanations (SHAP) and Gradient-Weighted Class Activation Mapping (Grad-CAM) are XAI techniques that have been used to explain CNN models. [14] employs both techniques to explain the CNN model that detects plant nutrient deficiency. [15] integrates both SHAP and Grad-cam into lightweight multi-scale (LW-MS) CNN models to identify lung and colon cancer. In this paper, SHAP and Grad-CAM are considered for use in explaining the proposed model.

# METHODOLOGY

In this paper, a Convolutional Neural Network (CNN) is used to detect forest fires. The use of CNN can reduce response time and prevent large areas of forest from being burned. The goal is to establish a community-based system for Melaka state’s forest fire detection, alerting the fire quickly and informing the fire station. A key feature is the integration of XAI, which improves transparency, interpretability, and explainability. The existence of XAI enables developers to clearly understand the architecture of CNN, which can improve the system’s performance and increase user trust in CNN’s results.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **TABLE 1.** Performance comparisons of different machine learning methods | | | | |
| **Author** | **Method** | **Application** | **Accuracy** | **Limitation** |
| [4] | K-Nearest Neighbour (KNN) | Prediction | 93.88% | There is no capture of complex spatial patterns in the fire. |
| [5] | Random forest | Detection | 83.52% and 84.68% | The quality of satellite images may be affected by other factors. |
| [6] | Support Vector Machine (SVM) | Classification | 93.33% | Different lighting conditions and backgrounds affect the system’s generalizability. |
| [7] | YOLOv5 | Detection | 83.9% | The dataset and metrics used to validate the model’s performance are not specified. |
| [9] | Convolutional Neural Network (CNN) with Sigmoid | Prediction | 95.79% | Complex and computational overhead in training and tuning |
| [10] | Convolutional Neural Network (CNN) | Detection | 98% | Specific information and architecture are not provided in detail. |
| [11] | Modified Deep Convolutional Neural Network (MDCNN) | Recognition | 95.8% | Lack of explainability of the model. |
| [8] | Mobile Net with random forest | Prediction | 90.85% | Further optimization is needed for the complex tasks in fire detection. |
| [8] | Mobile Net with SVM | Prediction | 94.85% | Further optimization is needed for the complex tasks in fire detection. |

## Convolutional Neural Network (CNN)

Among the various machine learning methods used to detect forest fires, the CNN method is the focus of this research. Compared to other methods, CNN can provide higher accuracy in predicting forest fires. [16] CNN can automatically learn to recognize features in images, which means it can perform well in image-based fire detection. CNN’s architecture consists of multiple layers, each of which performs a different function during image classification. The different layers with varying functionality within the CNN architecture make it more powerful in image processing compared to other image classification methods. [3]describes that in the input layer, preprocessing tasks like normalization and de-averaging are carried out on the input data. Next, the data’s features are extracted by the convolutional layer. At this layer, mathematical operations are performed, and by adjusting the number of parameters, the specific procedure utilizes filters to extract various levels of features from the input data. By using filters, the input data, which is the image, will be convolved to a particular size. Then, the output of the convolutional layer is mapped nonlinearly by the activation function layer. To a certain extent, the pooling layer can mitigate the overfitting condition and compress the network’s parameters. The data is sent to the fully connected layer, which is the last layer of the CNN, following the convolutional and pooling processes. The neurons in this layer are used to determine the category’s probability and have connections with every neuron in the previous layer. Figure 1 below, adapted from Gayathri [17], illustrates an example of a Convolutional Neural Network Architecture.

## Metrics for Convolutional Neural Network (CNN)

The mathematical operation occurs within the CNN model to extract features from the input data. The key metrics that are used to indicate the high ability to identify fire or no fire are accuracy, precision, recall, and F1-Score.

1. As shown by [2], accuracy is defined as the percentage of correct predictions among the total number of predictions.

(

A diagram of a computer network

AI-generated content may be incorrect.

**Figure 1.** An overall diagram of the proposed methodology

1. As shown by [2], precision is the ratio of true positive predictions out of all the positive predictions.

(

1. As shown by [2], recall is the ratio of true positives out of the sum of true positives and false negatives.

(

1. As shown by [2], the F1 score calculates the harmonic meaning of precision and recall.

(

TP represents true positive, TN represents true negative, FP represents false positive, FN represents false negative, P is precision, and R is recall. [18]explained that TP means out of all the true positive occurrences in the dataset, the model correctly predicts the positive class or event. TN means out of all the true negative occurrences in the dataset, the model correctly predicts the negative class. FP symbolizes the error made by the model when it forecasts the existence of a particular condition or event that does not occur. If not appropriately handled, this kind of error —also known as a Type I error — can result in poor decisions. FN means that, out of all the real positive occurrences in the data, the model incorrectly predicts that there won’t be an event. It evaluated the model’s capacity to create type II errors or overlook positive cases.

## Shapley Additive exPlanations (SHAP)

SHAP is considered to be used to explain the proposed CNN model. [14] explained that SHAP employs an explanation strategy that features are relevant. It uses Shapley values to interpret and explain the ML model. The Shapley values are the only way to assess a feature’s relevance while maintaining two essential qualities: local accuracy and consistency. SHAP can highlight the pixels that contribute positively or negatively to the detection, which is more useful than Grad-CAM, as it uses a gradient to highlight the parts that influenced the detection in the image and provide detailed attribution.

# experiments result

Google Colab is used in this project for implementing the CNN model for forest fire detection. In this project, TensorFlow is used to train a dataset of forest fire images. The dataset contains 950 fire images and 950 no-fire images. The Forest Fire dataset is split into three categories, comprising 70% of the training set, 15% of the validation set, and 15% of the testing set.

## Convolutional Neural Network (CNN) Layers and Result

Figure 2 shows that the created model has 4 convolutional layers, followed by a max pooling layer after each convolutional layer. The convolutional layers are created with 5x5 sizes for 32 filters and 3x3 sizes for 64 filters, and the first 128 filters are created with 5x5 sizes. The last 128 filters are created with 5x5 sizes. The Rectified Linear Unit (ReLU) is used to correct the output from the convolutional layer. The filters are increased in the second and third layers, which are set to 64 and 128, allowing the CNN model to extract more complex features. In the max pooling layer, 2x2 sizes are used to decrease the spatial dimension of the feature maps while retaining more texture information. The first dense layer has 512 neurons to learn the complex relationships between the extracted features, while the second dense layer, with a single neuron and a sigmoid activation function, classifies whether the image is a fire or not.

The trained CNN model has 99.61% accuracy on the training set and 97.89% on the validation set. This model can accurately detect images with or without fire on the test dataset. The precision of the proposed model is 95.86%, the recall score is 97.2%, and the F1-score is 96.53%. The false positive and false negative rates are less than 5%. The performance of the proposed model demonstrates its ability to detect the positive class or event in the test dataset with high accuracy. Figure 2 shows the overall performance of the proposed CNN model.

Compared to other CNN methods proposed by others, this model achieves a higher accuracy and F1-score than the others. [9] shows that the CNN with the Sigmoid model has 95.79% accuracy and a 95.86% F1 score. The MDCNN model, proposed by [11], has an accuracy of 95.8% and an F1-score of 92.5%. This means the proposed CNN model works well in detecting forest fires and has fewer errors or inaccuracies made by the model. Figure 3 shows that the trained machine can correctly detect fire and non-fire images.

A graph of a performance metrics

AI-generated content may be incorrect.

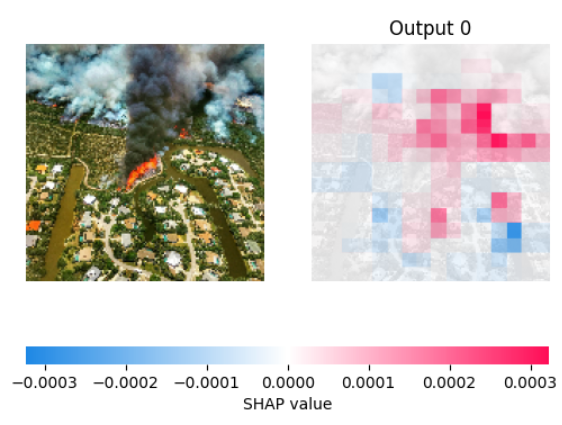
**Figure 2.** Overall performance of the proposed CNN model

## Shapley Additive Explanations (SHAP)

In Figure 4, the SHAP value is shown on the right side. The red areas indicate a positive contribution, while the blue areas indicate a negative contribution. The blue areas indicate that the model predicts no fire conditions, while the red areas indicate fire conditions. The SHAP provides numerical scores that are meaningful for the color pixels with different depths in color. In Figure 4, the part where smoke appears has more color pixels than other areas. This means the SHAP does not highlight the texture, but it focuses on more relevant features of the fire, such as smoke and flame.

|  |  |
| --- | --- |
| A screenshot of a computer screen  Description automatically generated | A graph of mountains with text  AI-generated content may be incorrect. |
| (a) | (b) |

**Figure 3.** Sample images showing the detection of (a) “Fire” and (b) “No fire”



**Figure 4.** SHAP representations of an image

# CONCLUSION

Convolutional Neural Network [19] is a machine learning that can provide high performance and analysis on image classification. As all machine learning models act as black box models [20], no one knows how they arrive at their results and whether they are trustworthy or not. Therefore, Explainable Artificial Intelligence is used in this project to make all the decisions made by CNN transparent and understandable to people. The implemented CNN models have 99.61% training accuracy and 97.89% validation accuracy in detecting forest fires. The SHAP algorithm of XAI is used to explain the decisions made by CNN. In the experimental results, the training accuracy is higher than the validation accuracy, which means the CNN model only reads the image and does not attempt to learn the features. This problem may be that the created CNN model is too complex, with too many layers or neurons. This problem can lead to some wrong predictions of the images.

# References

1. F. de A. à P. do E. de S. Paulo, “Fire in the Amazon Associated with Agricultural Burning and Deforestation,” Lab Manager, (n.d.).
2. Y.J. Chew, S.Y. Ooi, Y.H. Pang, and K.-S. Wong, “A Review of Forest Fire Combating Efforts, Challenges and Future Directions in Peninsular Malaysia, Sabah, and Sarawak,” Forests **13**(9), 1405 (2022).
3. Y. Li, “Research on Application of Convolutional Neural Network in Intrusion Detection,” in *2020 7th International Forum on Electrical Engineering and Automation (IFEEA)*, (IEEE, Hefei, China, 2020), pp. 720–723.
4. T.Y. Datubakka, Istikmal, and A.I. Irawan, “Comparison Analysis Of K-Nearest Neighbor (K-Nn) Algorithm With Naive Bayes For Fire Source Detection Mitigation,” in *2022 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS)*, (IEEE, BALI, Indonesia, 2022), pp. 370–375.
5. X. Li, G. Zhang, S. Tan, Z. Yang, and X. Wu, “Forest Fire Smoke Detection Research Based on the Random Forest Algorithm and Sub-Pixel Mapping Method,” Forests **14**(3), 485 (2023).
6. Md.A. Rahman, S.T. Hasan, and M.A. Kader, “Computer Vision Based Industrial and Forest Fire Detection Using Support Vector Machine (SVM),” in *2022 International Conference on Innovations in Science, Engineering and Technology (ICISET)*, (IEEE, Chittagong, Bangladesh, 2022), pp. 233–238.
7. W. Wang, Q. Huang, H. Liu, Y. Jia, and Q. Chen, “Forest Fire Detection Method Based on Deep Learning,” in *2022 International Conference on Cyber-Physical Social Intelligence (ICCSI)*, (IEEE, Nanjing, China, 2022), pp. 23–28.
8. D. Sungeetha, S. PushpaLatha, N. Legapriyadharshini, A. Akilandeswari, N. Yamsani, and S. Padmakala, “Forecasting Fire Using MobileNet Architecture,” in *2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, (IEEE, Coimbatore, India, 2023), pp. 1161–1164.
9. S. Gaur, J.S. Kumar, and S. Shukla, “A Comparative Assessment of CNN-Sigmoid and CNN-SVM model for Forest Fire Detection,” in *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)*, (IEEE, Pune, India, 2024), pp. 1–6.
10. J. Singh, M.S. Aarthi, and A.S. Idikkula, “Convolutional Neural Networks for Early Detection of Forest Fires,” in *2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS)*, (IEEE, Pudukkottai, India, 2023), pp. 777–780.
11. S. Zheng, X. Zou, P. Gao, Q. Zhang, F. Hu, Y. Zhou, Z. Wu, W. Wang, and S. Chen, “A Forest Fire Recognition Method Based on Modified Deep CNN Model,” Forests **15**(1), 111 (2024).
12. O. Petrosian, and Y. Zhang, “Solar Power Generation Forecasting in Smart Cities and Explanation Based on Explainable AI,” Smart Cities **7**(6), 3388–3411 (2024).
13. S.U. Hamida, M.J.M. Chowdhury, N.R. Chakraborty, K. Biswas, and S.K. Sami, “Exploring the Landscape of Explainable Artificial Intelligence (XAI): A Systematic Review of Techniques and Applications,” BDCC **8**(11), 149 (2024).
14. J. Mkhatshwa, T. Kavu, and O. Daramola, “Analysing the Performance and Interpretability of CNN-Based Architectures for Plant Nutrient Deficiency Identification,” Computation **12**(6), 113 (2024).
15. M.A. Hasan, F. Haque, Saifur Rahman Sabuj, H. Sarker, F. Goni, F. Rahman, and M.M. Rashid, “An End-to-End Lightweight Multi-Scale CNN for the Classification of Lung and Colon Cancer with XAI Integration,” Technologies **12**(4), 56–56 (2024).
16. S. Sah, S. Prakash, and S. Meena, “Forest Fire Detection using Convolutional Neural Network Model,” in *2023 IEEE 8th International Conference for Convergence in Technology (I2CT)*, (IEEE, Lonavla, India, 2023), pp. 1–5.
17. K. Gayathri, J.V.D. Prasad, T.D. Kiran, and V. Mythili, “Forest Fire Detection Using Convolution Neural Networks,” in *2022 IEEE 2nd International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, (IEEE, Tumkur, Karnataka, India, 2022), pp. 1–5.
18. M. Krichen, “Convolutional Neural Networks: A Survey,” Computers **12**(8), 151 (2023).
19. C.C. Chai, W.H. Khoh, Y.H. Pang, and H.Y. Yap, “A Lung Cancer Detection with Pre-Trained CNN Models,” Journal of Informatics and Web Engineering **3**(1), 41–54 (2024).
20. S.Y. Ooi, S.C. Tan, and W.P. Cheah, “Temporal sampling forest (TS - F): an ensemble temporal learner,” Soft Computing **21**(23), 7039–7052 (2017).