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FireDetXplainer: an explainable artificial intelligence framework for wildfire detection

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ABSTRACT

Wildfires pose significant environmental, ecological, and socioeconomic threats, necessitating rapid and reliable detection systems for timely emergency response and disaster mitigation. Recent advances in deep learning have substantially improved wildfire detection accuracy; however, most existing models operate as black-box systems, limiting transparency and reducing user trust in safety-critical applications. This study proposes FireDetXplainer (FDX), an explainable artificial intelligence (XAI) framework designed to enhance the interpretability of deep learning-based wildfire detection while maintaining high predictive performance. The proposed framework integrates convolutional neural network (CNN)-based image classification with explainability techniques to identify the visual regions that contribute most to wildfire detection decisions. By generating intuitive visual explanations, FDX enables users to understand, validate, and trust the model's predictions, thereby supporting transparent and accountable decision-making. Experimental evaluation demonstrates that the proposed framework effectively distinguishes wildfire images from non-fire scenes while providing meaningful visual interpretations that improve model transparency without compromising detection performance. The findings highlight the potential of explainable AI to strengthen the reliability, usability, and practical deployment of intelligent wildfire monitoring systems for environmental surveillance, disaster management, and early warning applications.

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1. INTRODUCTION

Wildfires have become one of the most destructive natural hazards worldwide, causing extensive environmental degradation, biodiversity loss, economic disruption, and threats to human life. In recent years, the frequency, intensity, and geographical distribution of wildfires have increased considerably due to climate change, prolonged droughts, rising temperatures, and expanding human activities near forested regions. These events not only destroy natural ecosystems but also contribute significantly to greenhouse gas emissions, deteriorate air quality, and disrupt critical infrastructures. Consequently, the development of reliable and intelligent wildfire monitoring systems has become a global research priority for supporting early warning, rapid emergency response, and effective disaster management [1].

Conventional wildfire detection techniques primarily rely on human observation, watchtowers, thermal cameras, and static sensor networks. Although these methods have been widely adopted, they often suffer from limited spatial coverage, delayed response times, high operational costs, and susceptibility to environmental conditions such as smoke, fog, and changing illumination. As wildfire behavior is highly dynamic and unpredictable, traditional monitoring approaches are frequently unable to provide timely and accurate detection over large geographical areas. To address these limitations, recent advances in remote sensing, internet of things (IoT), wireless sensor networks (WSNs), unmanned aerial vehicles (UAVs), and artificial intelligence (AI) have enabled the development of automated wildfire detection systems capable of continuously analyzing large volumes of heterogeneous environmental data [2], [3].

Among these technologies, AI has emerged as a transformative solution for intelligent wildfire monitoring. Machine learning algorithms can automatically identify complex patterns associated with wildfire occurrence by analyzing satellite imagery, aerial photographs, meteorological variables, and sensor measurements. Compared with conventional rule-based approaches, AI-driven systems provide greater adaptability, scalability, and predictive capability, enabling earlier wildfire detection and reducing false alarm rates. Recent developments have demonstrated that AI models can significantly improve decision-making processes for wildfire prevention, risk assessment, and emergency response, thereby supporting more resilient environmental monitoring systems [4], [5].

The rapid advancement of deep learning has further accelerated the evolution of intelligent wildfire detection. Deep neural networks, particularly convolutional neural networks (CNNs), have demonstrated remarkable capabilities in extracting hierarchical spatial features from visual data without requiring handcrafted feature engineering. CNN-based architectures have become the dominant approach for wildfire image classification because of their ability to recognize complex fire patterns, smoke characteristics, and contextual scene information across diverse environmental conditions. According to the World Economic Forum, FireCNN combines satellite imagery with weather information to identify regions with elevated wildfire risk and has the potential to reduce wildfire occurrences by approximately 50–76%, highlighting the significant contribution of deep learning to proactive wildfire management [1].

In addition to CNN-based image classification, modern computer vision techniques have expanded wildfire detection capabilities through multisource data integration. Remote sensing platforms equipped with optical, infrared, and thermal sensors continuously monitor extensive forested regions, while LiDAR technology provides three-dimensional structural information that improves vegetation analysis and fire localization. Similarly, UAV-based imaging systems enable flexible, high-resolution observations in areas that are difficult to access using conventional monitoring methods. The integration of these sensing technologies with deep learning algorithms has substantially improved detection accuracy, robustness, and operational efficiency, supporting intelligent environmental surveillance across multiple spatial and temporal scales [3], [4].

Recent studies have proposed numerous AI-based wildfire detection approaches. Machine learning techniques have been successfully applied to wildfire prediction, detection, and emergency response by exploiting heterogeneous environmental datasets [5]. WSNs integrated with machine learning algorithms have demonstrated improved early fire detection through distributed sensing and intelligent data processing, enabling rapid identification of abnormal environmental conditions [6]. Furthermore, deep learning models utilizing imagery from the Himawari-8 satellite have achieved remarkable performance by simultaneously exploiting spatial and temporal information. The proposed CNN-based framework substantially reduced wildfire recognition time to approximately 12 minutes while outperforming conventional Random Forest classifiers, achieving an overall detection accuracy of 0.98 and an F1-score of 0.74 [7].

Beyond image classification, wildfire risk assessment has also benefited from advanced spatial analysis techniques. Ordered weighted averaging (OWA) integrated with multi-criteria evaluation (MCE) has been employed to generate more reliable wildfire susceptibility maps by combining multiple environmental risk factors into a unified spatial decision-making framework [8]. Meanwhile, recent progress in deep learning architecture design has introduced EfficientNet models for automatic wildfire detection using large-scale datasets. Compared with conventional architectures such as InceptionV3 and MobileNetV2, EfficientNet demonstrated superior detection capability, achieving a true detection rate of 89.2% while maintaining a remarkably low false positive rate of only 0.306%, illustrating the effectiveness of optimized deep neural networks for large-scale wildfire monitoring applications [9]. Furthermore, the integration of IoT technologies with AI has enabled the development of distributed wildfire monitoring systems capable of continuous environmental sensing, intelligent data transmission, and real-time decision support, thereby enhancing the overall reliability and responsiveness of wildfire management infrastructures [10].

The rapid development of intelligent sensing technologies has further expanded the capabilities of AI-driven wildfire detection systems. High-resolution satellite imagery, hyperspectral sensors, UAVs, and IoT devices continuously generate massive volumes of heterogeneous data that can be processed using advanced computer vision algorithms. The integration of AI with these sensing platforms enables continuous environmental monitoring, automatic fire localization, and rapid decision support, significantly improving the effectiveness of wildfire surveillance. Recent studies have proposed AI-embedded detection systems that combine high-resolution satellite imagery with intelligent image analysis to improve wildfire monitoring accuracy and minimize detection delays [11], [12]. These intelligent monitoring systems provide timely situational awareness for emergency responders and support proactive disaster management through automated analysis of large-scale environmental data.

Beyond wildfire detection, predictive modeling has become an important research direction for understanding wildfire behavior and supporting emergency planning. Genetic algorithms (GAs), for example, have been employed to optimize wildfire spread prediction models by automatically calibrating model parameters based on historical fire observations and environmental variables. Such optimization techniques improve the accuracy and reliability of wildfire propagation models, enabling more effective evacuation planning and resource allocation during emergency response operations [13]. Meanwhile, recent developments in deep learning have extended beyond image classification to include integrated classification and segmentation frameworks. Hybrid CNN architectures capable of simultaneously identifying wildfire occurrences and delineating affected regions have demonstrated superior performance compared with conventional models. Experimental results show that CNN-based classification achieved an accuracy of 88.19%, while UNet outperformed SegNet in wildfire segmentation with a Dice coefficient of 0.6869, illustrating the effectiveness of deep neural networks for comprehensive wildfire scene understanding [14].

Recent research has also highlighted the importance of incorporating contextual environmental information into wildfire prediction. Climatic variables such as temperature, humidity, wind speed, and precipitation strongly influence wildfire ignition and propagation. Investigations conducted in Puerto Rico demonstrated that wildfire occurrence is closely associated with seasonal weather patterns, where relative climatic conditions increase the likelihood of fire ignition and absolute environmental conditions determine wildfire severity and spatial extent [15]. Furthermore, contextual information extracted from neighboring pixels or surrounding geographical regions has been shown to improve classification accuracy. Comparative studies involving multilayer perceptrons (MLPs) and CNNs revealed that contextual CNN-based models consistently outperform pixel-based approaches by effectively exploiting spatial relationships within remote sensing imagery, thereby enhancing wildfire detection reliability [16]. Similarly, UAV-based wildfire monitoring has benefited from state-of-the-art object detection algorithms such as YOLOv5 and YOLOv8, which provide accurate real-time fire detection while maintaining high computational efficiency for aerial surveillance applications [17].

Despite these remarkable advances, most existing deep learning-based wildfire detection systems remain fundamentally black-box models. Although they often achieve high classification accuracy, they provide limited insight into the reasoning behind their predictions. In safety-critical applications such as wildfire monitoring, emergency response, and environmental risk management, prediction accuracy alone is insufficient. Decision-makers, emergency responders, environmental agencies, and policymakers must also understand why an AI model identifies a particular region as containing wildfire. The absence of transparent decision-making reduces user confidence, complicates model validation, and limits the practical deployment of AI systems in operational disaster management. Consequently, improving the interpretability and transparency of deep learning models has become an important research challenge in intelligent environmental monitoring.

Explainable artificial intelligence (XAI) has recently emerged as an effective approach for addressing this challenge by making AI models more transparent, interpretable, and trustworthy. Rather than producing predictions without justification, XAI techniques generate visual or feature-based explanations that reveal the evidence supporting model decisions. In computer vision applications, explainability methods such as saliency visualization, class activation mapping, and attention-based interpretation enable users to identify the image regions that contribute most significantly to the classification process. These capabilities not only facilitate model verification and debugging but also strengthen user trust, improve accountability, and support responsible deployment of AI technologies in safety-critical domains.

Motivated by these challenges, this research proposes FireDetXplainer (FDX), an XAI framework for transparent wildfire detection. Unlike conventional deep learning models that provide only classification outputs, FDX combines high-performance computer vision with explainability mechanisms to produce both accurate wildfire detection and intuitive visual explanations of the model's decision-making process. The proposed framework enables users to understand which image features and spatial regions influence wildfire predictions, thereby improving model interpretability while maintaining reliable detection performance. By integrating explainability into deep learning-based wildfire detection, FDXaddresses the growing demand for trustworthy AI systems capable of supporting real-world environmental monitoring and emergency response.

The primary objectives of this study are threefold. First, it develops a robust deep learning framework for automated wildfire detection using advanced computer vision techniques. Second, it incorporates explainable AI mechanisms that provide transparent and interpretable visual explanations, enabling users to validate and understand the model's predictions. Third, it comprehensively evaluates the proposed FDX framework using wildfire image datasets to assess both predictive performance and interpretability. The contributions of this research extend beyond improving wildfire detection accuracy by demonstrating how XAI can enhance transparency, reliability, and user trust in intelligent wildfire monitoring systems. Consequently, FDX represents a significant step toward the development of trustworthy AI-enabled environmental surveillance systems that effectively support disaster management, early warning, and sustainable ecosystem protection.

2. METHOD

FDX uses a revolutionary combination of the learning without forgetting (LwF) architecture, transfer learning, and fine-tuning to overcome catastrophic forgetting and improve the model's ability to retain and acquire new information. FDX accurately classifies wildfire imagery using the pretrained MobileNetV3 model, known for image classification. This advances the use of pre-trained models for environmental challenges. Convolutional blocks and extensive picture preprocessing are used to improve the model's capacity to identify complex wildfire imagery patterns. As a pioneering wildfire detection model, FDX uses Explainable AI technologies like Grad-CAM and local interpretable model-agnostic explanations (LIME) to provide clear and accessible explanations for its forecasts, boosting user confidence and model interpretability. Images are used by FDX to model wildfire detection. The 2,974 fire classification photos are divided into two groups. The first set shows active forest fires, whereas the second shows fire-free forests [18]. Fire forest categorization uses 80% training and 20% validation data. The collection has 1275 non-fire and 1672 fire photos. The FDX model, a unique wildfire detection method, advances machine learning for environmental protection. FDX is precisely designed to blend advanced neural network features with the pressing need for accurate wildfire identification and categorization. The FDX model uses MobileNetV3 for transfer learning and prioritizes performance and computational efficiency for real-time applications. This section discusses FDX's architecture and how it solves the complex wildfire detection problem. Figure 1 shows the FDX architecture and operations in detail.

The pre-trained MobileNetV3 model is adjusted for features and fine-tuning utilizing wildfire data. The model is trained and evaluated using Explainable AI approaches as Grad-CAM and LIME to give insightful visualizations and improve interpretability, resulting in performance indicators and trained models. Fine-tuning targets MobileNetV3 model top levels in the FDX architecture. This step is necessary to adjust the model to identify and categorize new data, especially wildfire photographs. This fine-tuning aims to balance wide and targeted learning. This method emphasizes on the model's highest layers, which can accommodate new data types well. Enhancing these layers helps FDX grasp wildfire image nuances. This strategy ensures that the model can handle various image kinds and improves its wildfire detection capacity. The main goal is to maintain the model's picture recognition ability while boosting its wildfire feature recognition. Hyper-parameter optimization is crucial to model effectiveness. The model's learning rate, batch size, and training epochs are accurately controlled [19], [20]. These parameters strongly impact model learning and precision. This optimization seeks the optimum equilibrium that avoids overfitting the model to the training data or undercapturing key data patterns.

The LwF approach plays a vital role in maintaining the model's original abilities while it acquires new skills. In the context of FDX, this involves preserving the model's overall image processing capabilities while tailoring it to meet the unique demands of wildfire detection. This approach is crucial for safeguarding the fundamental strengths of the model. This approach enables FDX to maintain its foundational learned behaviors, guaranteeing that a robust base of knowledge remains available, even as the model adapts to the intricate challenge of detecting wildfires. Data preparation is crucial for ensuring effective model training. This encompasses the use of diverse image manipulation methods, including rotations, flips, and color adjustments. By artificially expanding the dataset, FDX can gain deeper insights and improve its ability to apply knowledge from the training data to actual wildfire situations, thereby boosting its detection capabilities. These processes play a crucial role in ensuring uniformity in image quality and format. By standardizing the input data, FDX can enhance its ability to learn and identify patterns, which is essential for precise wildfire detection. This step guarantees that fluctuations in image brightness, contrast, or color do not impede the model’s learning and performance. The training process is crafted to be organized, allowing the model to progressively absorb knowledge from the enhanced dataset. This method integrates the established insights from MobileNetV3 with unique characteristics pertinent to wildfire imagery, fostering a strong learning framework. The primary goal of this training phase is to guarantee that the model is acquiring knowledge in a manner that is both impactful and resourceful. This involves enhancing the efficiency of computational resources while guaranteeing that the model attains a high level of precision in identifying wildfires. The approach is meticulously adjusted to achieve an equilibrium between swift acquisition of knowledge and comprehensive insight, enabling the model to excel in identifying various fire situations.

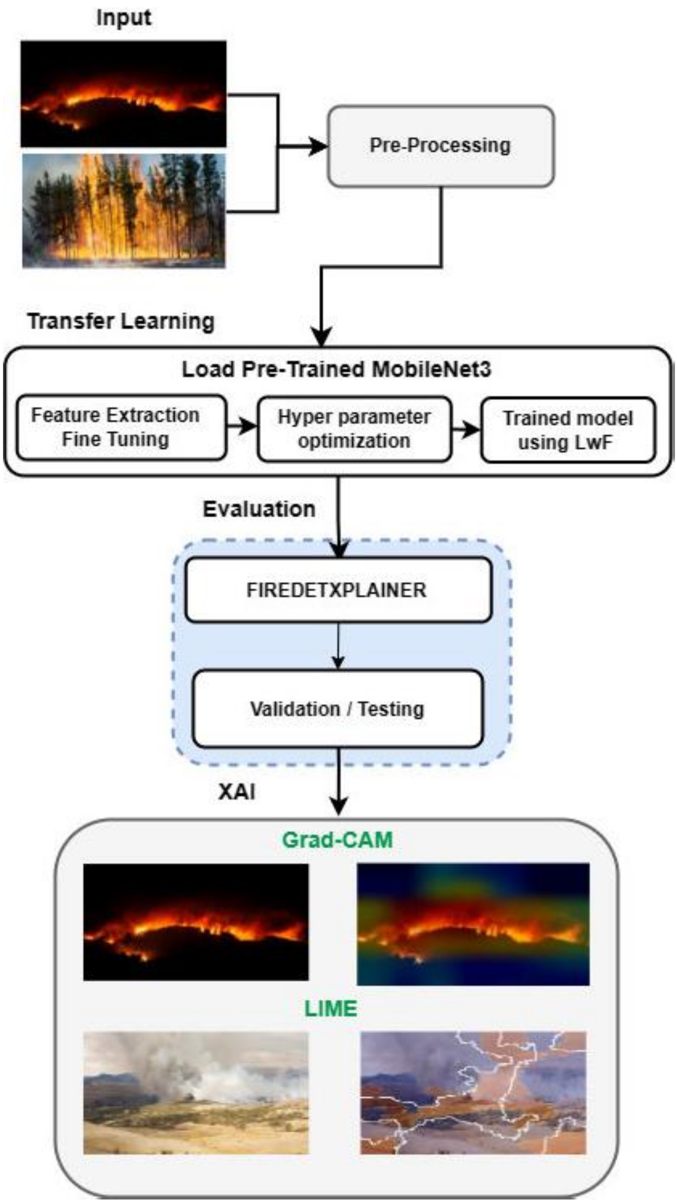


Figure. 1. Design of FDX

The dataset is first divided into separate subsets for training, validation, and testing, adhering to an 80:10:10 ratio. This approach is widely adopted to guarantee that the model encounters a diverse range of data while also allowing for precise validation and testing of its predictions. The division of data in this manner allows for a model to be evaluated not just on the data it has previously encountered, but also on new, unfamiliar data that it has not been exposed to before. Hyper-parameter tuning plays a crucial role in the training of deep learning models, vital for attaining peak performance. In this study, essential parameters such as the learning rate, batch size, and number of epochs were carefully optimized. The learning rate was intentionally set to a low value of 0.0001, selected to facilitate gradual and accurate modifications to the model's weights during training, thereby reducing the likelihood of overshooting. The batch size, which influences the model's convergence and generalization capabilities, was fine-tuned to 32, achieving a harmonious balance between computational efficiency and effective learning. Additionally, the model was trained for 100 epochs, a choice made to ensure that the network had enough iterations to learn from the complete dataset while avoiding the risk of over-fitting. The training process utilizes the powerful GPUs of Google Colab, which excel at executing the matrix and vector operations fundamental to deep learning. Utilizing this hardware speeds up the training process, enabling broader experimentation with hyper-parameters and accommodating larger datasets.

3. RESULTS AND DISCUSSION

The FDX model demonstrates remarkable capabilities that distinguish it in the field of wildfire detection. The accuracy of 99.91% and a recall rate of 99.93% demonstrate an outstanding capability to accurately distinguish between fire and non-fire situations with very few mistakes. The F1-score of 99.92% reinforces its accuracy, demonstrating a well-maintained balance between precision and recall. This holds great importance as it guarantees dependable fire detection while reducing false alarms, which is essential in emergency response situations. The table presents a comparison of the FDX outcomes with those of a leading model, utilizing various evaluation metrics. The model demonstrates an impressive accuracy rate of 99.91%, highlighting its strength and effectiveness in practical applications. The impressive accuracy rate reflects the model’s thorough understanding of the training data and its capacity to apply this understanding to new, previously unencountered data. The precision demonstrated in wildfire detection models is seldom reached, underscoring the sophisticated features of FDX. Table 1 presents a comparison of FDX alongside leading models, focusing on evaluation metrics including precision, recall, F1-score, and accuracy score.

Table 1. Comparison of the proposed model with existing models

S.No	Model	No of parameters	Precision	Recall	F1-Score
1	LwF and CNN [21]	N.A	94.4	96.5	98.7
2	Shuffle-NetV2- OnFire [22]	0.15M	94	94	95
3	LW-Fire [23]	1.1M	N.A	N.A	97.2
4	FireXplainer [24]	5.3M	99.1	99.3	99
5	Proposed model	6.5M	99.89	99.93	99.92

The performance metrics of the FDX model including precision, recall, F1-score, and accuracy - along with its effective learning as shown by its loss metrics, unmistakably highlight its advantages over current models. The interplay between numerous parameters and computational efficiency, coupled with remarkable accuracy, establishes the FDX model as a noteworthy progression in wildfire detection and management. Figure 2 demonstrates that the FDX model exhibited outstanding performance across all essential evaluation metrics, including precision, recall, F1-score, and accuracy score. The findings highlight the model's strength and dependability in tasks related to fire detection and explanation.

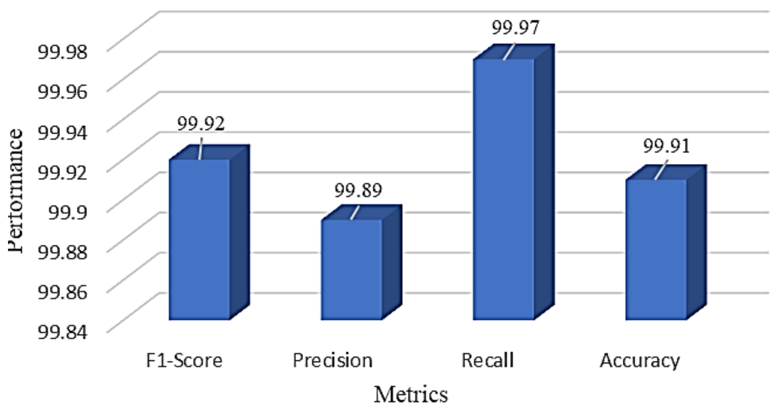


Figure 2. Performance metrics of the proposed model

Figure 3 presents an image processed using Grad-CAM, which emphasizes the regions contributing to the model's prediction of fire. The Figure 3(a) represents a wildfire on a hillside at night, with bright flames and thick smoke. This image serves as input for deep learning models in tasks like fire detection and scene understanding. The Figure 3(b) Grad-CAM Class Activation visualization overlays a heatmap, highlighting the regions the model focuses on to classify the image. In this case, the model correctly identifies the fire and smoke as key features. Grad-CAM enhances AI interpretability, helping researchers and developers understand model decisions in applications like disaster detection and medical imaging. In Figure 4, LIME identifies areas of smoke and specific color or texture regions that the model correlates with fire. The Figure 4(a) shows a wildfire in a mountainous landscape with thick smoke and flames spreading through dry vegetation. This image serves as input for an AI model analyzing fire-related scenes. The LIME Explanation highlights specific regions contributing to the model's classification decision shows in Figure 4(b). LIME segments the image into meaningful patches, showing which parts were most influential. This helps make deep learning models more interpretable by illustrating which areas led to predictions.


(a)


(b)

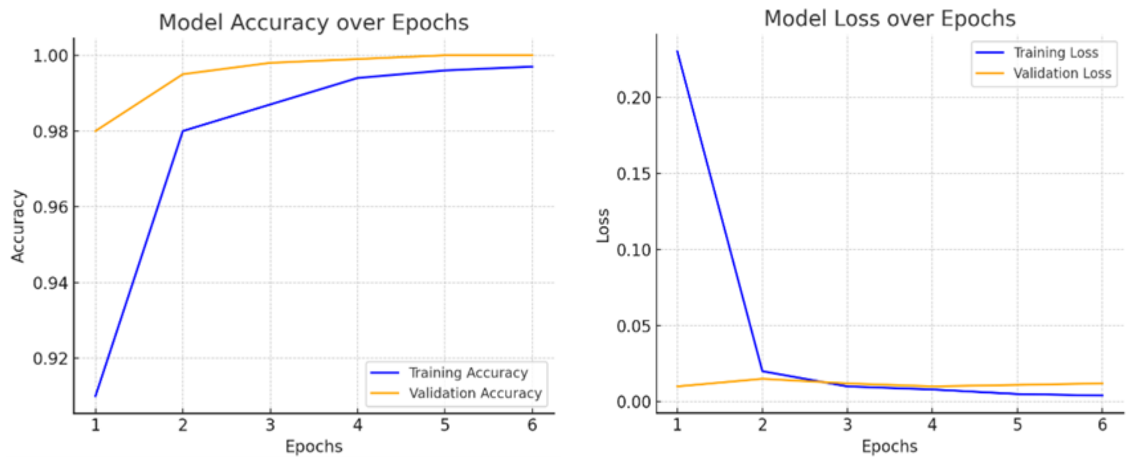
Figure 3. Visualization of (a) original wildfire image and (b) grad-CAM processed image


(a)


(b)

Figure 4. Visualization of (a) original wildfire image and (b) LIME processed image

Figure 5 presents a graph that illustrates these points, with the accuracy curve reaching a plateau at elevated levels, thereby confirming the model's reliable performance. The Figure 5(a) illustrates the training performance of the FDX model over six epochs. The left plot shows accuracy, where the training accuracy increases rapidly from 91% to nearly 99.7%, while validation accuracy remains consistently high, nearing 100%. This suggests strong generalization with minimal overfitting. The Figure 5(b) presents the loss, where training loss decreases sharply toward zero, and validation loss remains low with slight fluctuations. The declining loss and rising accuracy indicate effective model learning. The close alignment of training and validation metrics confirms that the model is well-optimized and performs reliably on unseen data.



(a) (b)

Figure 5. The accuracy curve reaches a stable point at a high level (a) FDX model training accuracy and (b) loss convergence visualization over epochs

4. CONCLUSION

This study proposed FDX, an XAI framework for transparent and reliable wildfire detection using deep learning. The framework addresses the inherent challenges of distinguishing wildfire scenes from visually similar environmental conditions, such as smoke, clouds, and complex natural backgrounds, by integrating transfer learning with explainability techniques. A fine-tuned MobileNetV3 model was employed as the backbone classifier, achieving an outstanding detection accuracy of 99.91%, demonstrating its capability for accurate and robust wildfire recognition. To enhance model transparency and trustworthiness, Grad-CAM and LIME were incorporated to generate intuitive visual explanations of the model's predictions. These explainability techniques enable users to identify the image regions that contribute most significantly to wildfire classification, thereby improving model interpretability, supporting validation, and increasing user confidence in AI-assisted decision-making. The experimental results demonstrate that FDX successfully combines high predictive performance with transparent decision support, making it suitable for safety-critical applications such as environmental monitoring, disaster management, and early wildfire warning systems. Although the proposed framework demonstrates excellent performance, several challenges remain. Future research should investigate its robustness under diverse environmental conditions, including varying weather, illumination, seasonal vegetation, and smoke density. In addition, integrating FDX with multimodal sensing platforms, such as satellite imagery, UAVs, IoT sensor networks, and edge AI devices, could enable real-time and large-scale wildfire monitoring. These advancements would further improve the scalability, reliability, and practical deployment of explainable AI systems for intelligent wildfire management.

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