TRANSPARENT WILDFIRE DETECTION SYSTEMS: THE ROLE OF FIREDETXPLAINER IN EXPLAINABLE AI MODELS

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ABSTRACT

Advanced detection systems are required to improve the efficacy of response efforts in the face of the growing threat posed by wildfires to ecosystems and communities. Wildfires' dynamic nature frequently renders conventional detection methods inadequate. This paper introduces FireDetXplainer, a novel framework that is intended to enhance wildfire detection by incorporating transparent and explainable AI techniques. FireDetXplainer guarantees interpretability and clarity in decision-making processes by employing state-of-the-art machine learning models. Our strategy is designed to improve the accuracy of detection and foster stakeholder trust by offering actionable insights into AI predictions. The model's overall accuracy is significantly enhanced by the integration of convolutional blocks and advanced image pre-processing techniques. FireDetXplainer implements Explainable AI (XAI) tools to guarantee comprehensive result interpretation by utilizing a variety of datasets from Kaggle and Mendeley. The FireDetXplainer outperforms current top models and achieves remarkable accuracy, as evidenced by the extensive experimental results. This renders it a highly efficient method for image classification in wildfire management.

Keywords: *Wildfire Detection, Explainable AI, LIME, Meteorological Data, Deep Learning*

1. INTRODUCTION

Wildfires pose a significant threat to ecosystems, communities, and economies worldwide. The increasing frequency and intensity of these fires, exacerbated by climate change and human activities, underscore the urgent need for advanced detection and response systems. Traditional methods of wildfire detection, which rely on manual observation and static sensors, are often inadequate in addressing the dynamic and unpredictable nature of wildfires. Recent advancements in artificial intelligence (AI) and machine learning have offered promising solutions for improving wildfire detection through automated and real-time analysis of large datasets. However, these AI systems often function as "black boxes," providing predictions without clear explanations of their decision-making processes. This opacity can hinder trust in the system and impede the effective deployment of its outputs in critical situations. In response, the domain of artificial intelligence, especially deep learning, has experienced notable progress, providing encouraging solutions for the detection and analysis of wildfires. The advancement of effective convolutional neural networks (CNNs), particularly designs have transformed image classification tasks, which play a crucial role in identifying and tracking wildfires. According to world economic forum, FireCNN is trained on satellite imagery and weather data to identify areas of high fire risk. It also stated that interventions that would cut the number of fires by 50 to 76 per cent [1]. Various forest fire detection techniques, aiming to highlight advancements and identify areas for improvement in fire monitoring systems. detection methods are categorized traditional and modern approaches. Traditional approaches involve in visual Observation and thermal imaging, while, modern approaches involve in remote sensing, sensor networks [2]. A combination of neural network committee machines and LiDAR (Light Detection and Ranging) technology is presented for automatic forest fire detection [3]. Optical remote sensing techniques like Satellite Imagery and Aerial and Drone Imaging can enhance the early detection of forest fires by leveraging various imaging techniques and sensor technologies [4]. Machine Learning applications designed to enhance various aspects of wildfire management, including prediction, detection, and response [5]. In [6] a novel forest fire detection system that integrates wireless sensor networks (WSNs) with machine learning (ML) techniques to enhance the early detection of forest fires is presented. A novel approach to wildfire detection using deep learning techniques is applied to imagery from the Himawari-8 satellite platform, which provides high-frequency and high-resolution imagery of the Earth's surface, including thermal and optical bands relevant for detecting wildfires. This model, utilizing both spatial and temporal data, significantly enhanced detection times, reaching an average initial recognition time of only 12 minutes. The convolutional neural network (CNN) method surpassed conventional random forest (RF) approaches, demonstrating its ability to recognize spatial patterns effectively. The results showed an overall accuracy of 0.98 and an F1-score of 0.74, respectively [7]. forest fire spatial modeling through the application of Ordered Weighted Averaging (OWA) multi-criteria evaluation (MCE) for enhancing the spatial analysis of forest fire risk by integrating multiple factors and criteria to produce more accurate and reliable fire risk maps [8]. Big data and EfficientNets, a family of deep learning models, is utilized to improve the accuracy and efficiency of automatic wildfire detection. EfficientNets outperformed InceptionV3 and MobileNetV2 on the same dataset, attaining a true detection rate of 89.2% and a remarkably low false positive rate of just 0.306% [9]. In [10], integration of Internet of Things (IoT) and Artificial Intelligence (AI) technologies in the domains of forest fire prevention, detection, and restoration is discussed. High resolution satellite imagery utilization and AI-Embedded detection system is proposed for wildfire detection systems [11], [12]. Genetic algorithms (GAs) are applied to calibrate models for predicting wildfire spread. Calibration involves adjusting model parameters to improve accuracy and reliability in predicting how wildfires will spread [13]. In [14], a novel model architecture is proposed that combines convolutional neural networks (CNNs) for classification with advanced segmentation techniques. This unified model processes input data (such as satellite or aerial imagery) to simultaneously perform classification and segmentation.

The results following the training indicate that CNN surpasses AlexNet, achieving an accuracy of 88.19% in classification. In terms of segmentation, UNet demonstrated superior performance compared to SegNet, attaining a dice score of 0.6869. Investigation is carried out to obtain the relationship between fire weather conditions and wildfire occurrence in Puerto Rico. A fire season in a location can be defined only by climatic factors, where current relative conditions contribute to a higher probability of fire occurrence and current absolute conditions contribute to a higher probable of bigger size [15]. Four designs of Multilayer Perceptrons (MLPs) and Convolutional Neural Networks (CNNs) are developed: the pixel-based CNN-1D and MLP-1D models, and the grid-based CNN-2D and MLP-2D models. The contextual-based CNN-2D model effectively utilizes neighborhood information and achieves the maximum accuracy. By comparison, the MLPs model is better suited for pixel-based categorization

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[16]. Aerial fire detection using deep learning approaches is achieved by analyzing images captured by a camera integrated into a specifically engineered four-rotor Unmanned Aerial Vehicle (UAV). Evaluation of the effectiveness of YOLOv5 and YOLOv8 models in object detection, in comparison to the CNN-RCNN model for classification [17].

To bridge this gap, our research introduces FireDetXplainer, a novel framework designed to enhance wildfire detection by integrating transparency and explainability into AI-driven models. FireDetXplainer aims to not only improve the accuracy of wildfire detection but also to offer clear insights into how and why these predictions are made. By making AI systems more interpretable, FireDetXplainer addresses key challenges associated with the deployment of AI in high-stakes environments where understanding the rationale behind decisions is crucial.

In this paper, we explore the following objectives: To develop a robust AI model for wildfire detection that leverages advanced machine learning techniques while ensuring transparency in its operations. To implement explainability mechanisms that provide users with actionable insights into the model's decision-making process, thereby increasing trust and usability. To evaluate the effectiveness of FireDetXplainer through comprehensive testing and validation against real-world wildfire data, demonstrating its potential to enhance early detection and response strategies.

By providing both advanced detection capabilities and interpretability, FireDetXplainer represents a significant step forward in integrating AI into wildfire management systems. Our approach not only aims to improve detection performance but also to foster greater confidence among stakeholders by clarifying the operational workings of the AI technologies employed.

2. METHODOLGY

FireDetXplainer (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 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 FireDetXplainer (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 FireDetXplainer (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 FireDetXplainer (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.

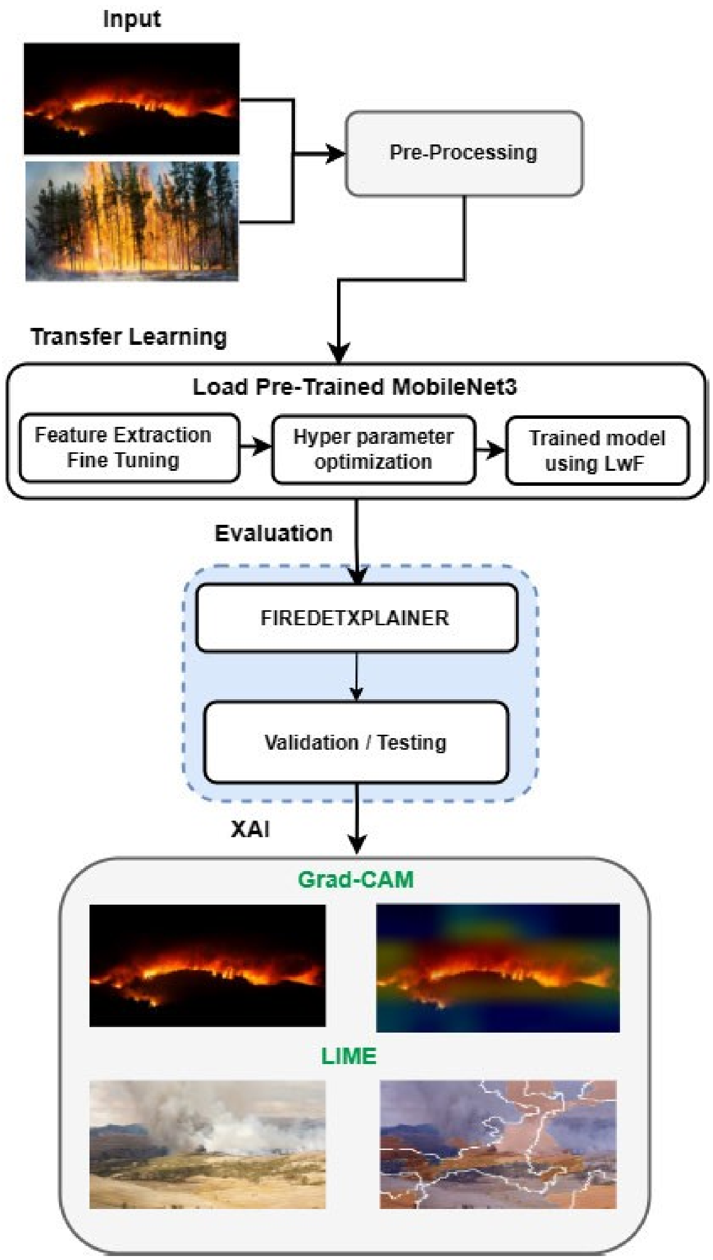

Figure. 1. Design of FireDetXplainer

The Learning without Forgetting (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 [21]. 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.

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 FireDetXplainer (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 FireDetXplainer 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 FireDetXplainer 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 [22]	N.A	94.4	96.5	98.7
2	Shuffle-NetV2-OnFire [23]	0.15M	94	94	95
3	LW-Fire [24]	1.1M	N.A	N.A	97.2
4	FireXplainer [25]	5.3M	99.1	99.3	99
5	Proposed Model	6.5M	99.89	99.93	99.92

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The performance metrics of the FireDetXplainer 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 FireDetXplainer 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 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.

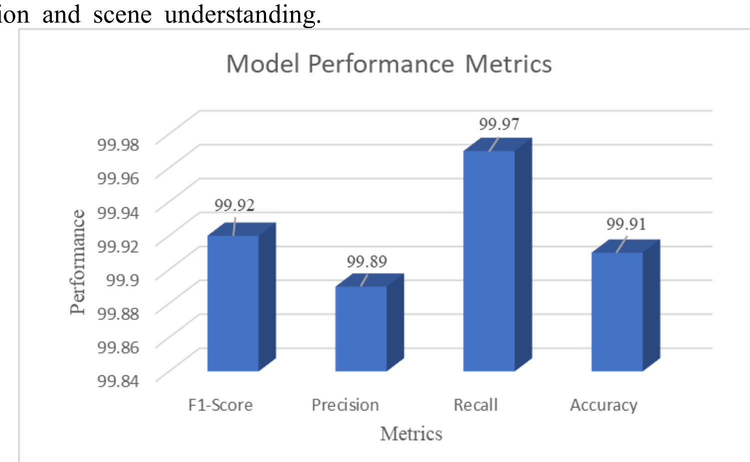

Figure 2. Performance Metrics of the Proposed Model

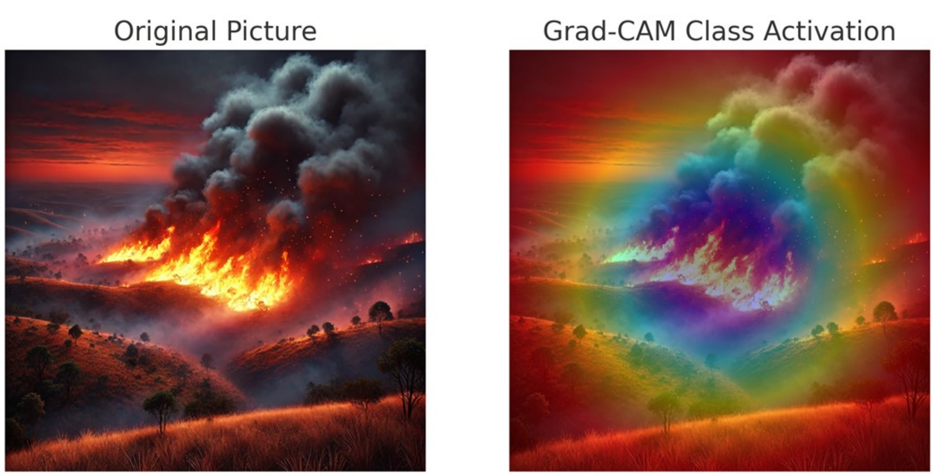

Figure 3. Visualization of (a) Original wildfire image and (b) Grad-CAM processed image.

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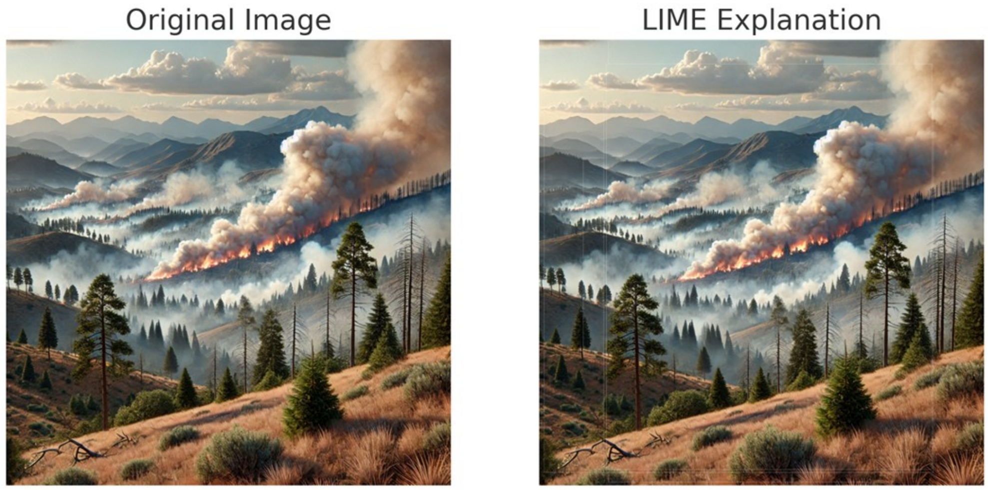

Figure 4. Visualization of (a) Original wildfire image and (b) LIME processed image.

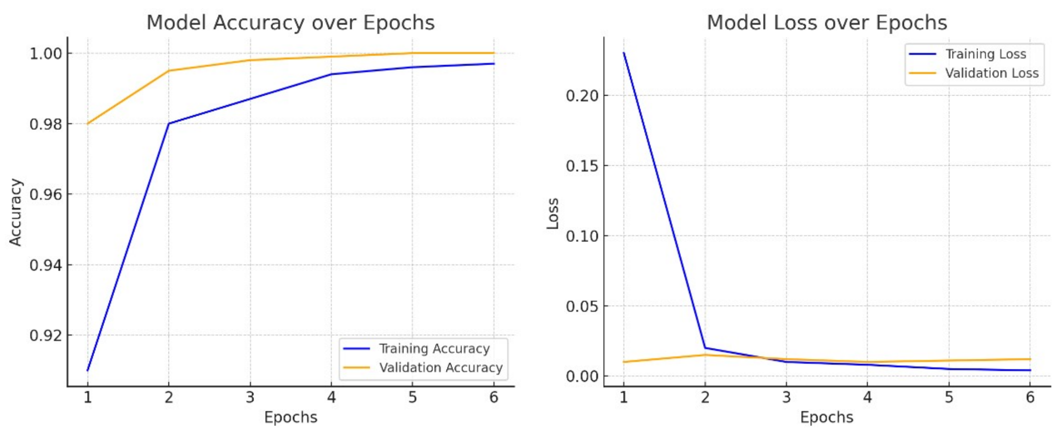

Figure 5. (a) FireDetXplainer model training accuracy and (b) loss convergence visualization over epochs

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 FireDetXplainer 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. TheFigure 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.

4. CONCLUSION

The study emphasizes the difficulty in effectively identifying wildfires, a challenge exacerbated by the visual resemblances between fire, smoke, and various natural components. This study utilizes transfer learning as its main methodology. The MobileNetV3 model has been carefully optimized and refined to improve precision in recognizing different categories of images. The results, backed by an impressive accuracy rate of 99.91%, underscore the model's effectiveness, further enhanced by Explainable AI techniques like Grad-CAM and LIME, which clarify the model's decision-making process. XAI tools provide clarity and highlight opportunities for enhancement. The analysis emphasizes various significant advantages of FireDetXplainer's methodology, such as enhanced model accountability, increased user involvement, and more efficient communication of risks and responses. Nonetheless, opportunities for further investigation persist to tackle limitations like the adaptability of models to diverse environmental conditions and their integration with current wildfire management systems. By maintaining our emphasis on improving the clarity and practical application of AI models, we can foster more efficient and transparent solutions to address the increasing risk of wildfires, ultimately aiding in the protection of ecosystems and communities.

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