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RESEARCH ARTICLE

FireDetXplainer: Decoding Wildfire Detection With Transparency and Explainable AI Insights

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ABSTRACT Recent analyses by leading national wildfire and emergency monitoring agencies have highlighted an alarming trend: the impact of wildfire devastation has escalated to nearly three times that of a decade ago. To address this challenge, we propose FireDetXplainer (FDX), a robust deep-learning model that enhances the interpretability often lacking in current solutions. FDX employs an innovative approach, combining transfer learning and fine-tuning methodologies with the Learning without Forgetting (LwF) framework. A key aspect of our methodology is the utilization of the pre-trained MobileNetV3 model, renowned for its efficiency in image classification tasks. Through strategic adaptation and augmentation, we have achieved an exceptional classification accuracy of 99.91%. The model is further refined with convolutional blocks and advanced image pre-processing techniques, contributing to this high level of precision. Leveraging diverse datasets from Kaggle and Mendeley, FireDetXplainer incorporates Explainable AI (XAI) tools such as Gradient Weighted Class Activation Map (Grad-CAM) and Local Interpretable Model-Agnostic Explanations (LIME) for comprehensive result interpretation. Our extensive experimental results demonstrate that FireDetXplainer not only outperforms existing state-of-the-art models but does so with remarkable accuracy, making it a highly effective solution for interpretable image classification in wildfire management.

INDEX TERMS Deep learning, explainable AI (XAI), transfer learning, wildfire detection.

I. INTRODUCTION

The escalating severity and frequency of wildfires globally necessitate advanced detection and management strategies. Recent studies highlight the role of climate change and human activities in exacerbating these events, making timely and accurate detection more crucial than ever [1], [2]. In response, the field of artificial intelligence, particularly deep learning, has seen significant advancements, offering promising solutions for wildfire detection and analysis. The development of efficient convolutional neural networks (CNNs), especially architectures like MobileNetV3, has revolutionized image classification tasks, which are integral to detecting and monitoring wildfires [3], [4].

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However, the adoption of these advanced AI models in critical areas like wildfire management is often impeded by their complexity and lack of interpretability. This challenge is addressed by integrating Explainable AI (XAI) methods such as SHAP, LIME, and CAM, which aim to provide clearer insights into the decision-making processes of AI models, thereby enhancing their reliability and trustworthiness [5], [6].

Another essential aspect in the evolution of AI models for environmental applications is the ability to continually learn and adapt to new data without forgetting previously acquired knowledge. Techniques like transfer learning and the Learning without Forgetting (LwF) framework have become crucial in this regard, facilitating efficient and comprehensive learning processes [7].

The increasing incidence and impact of wildfires, particularly in Mediterranean countries, underscore the urgency for effective detection and response mechanisms. Studies have emphasized the role of explainable artificial intelligence (XAI) in enhancing wildfire prediction models, advocating for models that are not only accurate but also interpretable [8]. Similarly, research by [9] highlights the importance of early fire detection using AI and deep learning techniques, stressing the need for models that maintain their effectiveness on new datasets without compromising on initial training.

Reference [10] explores the development of lightweight models for wildfire image classification and illustrates the need for efficient and scalable solutions in this domain. Furthermore, the advancement in model-agnostic explainable AI for object detection, as discussed in recent studies, aligns with the growing demand for transparent AI systems in various applications, including wildfire detection [11].

In a world increasingly reliant on artificial intelligence (AI), the field of explainable AI (XAI) has emerged as a beacon of clarity, aiming to demystify the decisions made by AI systems. A systematic review [12] of XAI literature reveals a growing discourse on the necessity of explanation in AI, highlighting four key debates central to the 'black-box' problem. This research suggests an urgent need for a unified conceptual understanding within XAI, emphasizing the importance of generating trust through transparency, ensuring compliance with regulations, promoting social responsibility, and establishing accountability. The review calls for empirical studies that address diverse stakeholder needs, aiming to measure XAI's true efficacy in making AI more comprehensible and trustworthy for all. Reference [13] complemented by exploration of convolutional neural networks in various industrial technologies, underscoring the versatility and potential of these models in diverse applications.

Highlighting the major contributions and novelty, this study presents the following key advancements in the field of wildfire detection and management:

- **Innovative Integration of Techniques:** FireDetXplainer (FDX) uniquely combines transfer learning, fine-tuning methodologies, and the Learning without Forgetting (LwF) framework to address catastrophic forgetting, enhancing the model's ability to retain knowledge while learning new information.
- **Utilization of MobileNetV3:** FDX leverages the pre-trained MobileNetV3 model, known for its efficiency in image classification, to achieve exceptional accuracy in wildfire imagery classification. This marks a significant advancement in applying pre-trained models to environmental challenges.
- **Advanced Model Adaptation:** The research introduces strategic adaptation and augmentation techniques, including convolutional blocks and advanced image preprocessing, to improve the model's capability in identifying complex patterns specific to wildfire imagery.
- **Integration of Explainable AI (XAI) Tools:** FDX incorporates Explainable AI tools like Grad-CAM and LIME, making it one of the first models in wildfire detection to offer transparent and understandable explanations for its predictions, thereby increasing user trust and model interpretability.
- **Robust Testing Across Diverse Datasets:** By leveraging datasets from Kaggle and Mendeley, the model demonstrates unparalleled adaptability and robustness, showcasing its potential for real-world application across various conditions and scenarios.
- **Setting a New Benchmark:** FDX represents a paradigm shift in the use of deep learning for environmental applications, combining high accuracy, adaptability, and explainability in a way that sets a new benchmark for future research in the field.

Looking ahead, our research paves the way for significant advancements in detecting wildfires more accurately and responsively. Building on the solid foundation laid by the current study, future efforts will focus on refining our model to distinguish fires from similar phenomena more precisely. This will involve integrating a broader spectrum of data, including varied weather conditions and temperature changes, to train the model to identify actual fires amidst everyday natural occurrences like clouds or sunsets [14]. The ambition is to develop a highly precise detection tool that can quickly alert to forest fires, enabling swift action to mitigate damage and protect communities [15]. By harnessing cutting-edge technologies and expanding our dataset to cover a wider array of wildfire scenarios, we aim to create a comprehensive solution for early wildfire detection and management. This future work will not only enhance the model's accuracy and reliability but also its applicability across different environments, setting a new standard in the field of wildfire management [16].

II. LITERATURE REVIEW

Wildfires present a growing global challenge, and the race to detect them early is on. Aiming to improve response times and mitigate damage, a study has harnessed the continuous stream of hyperspectral satellite data. Their deep learning model showcases an impressive capability to detect wildfires rapidly and accurately, promising a significant leap forward in the domain of remote sensing and disaster prevention.

Recent research [17] leveraged hyperspectral satellite imagery for early wildfire detection, utilizing deep learning to pinpoint fires at the pixel level. A novel system outperformed baselines, yielding a 94% F1-score and faster detection by 1.5 times, despite challenges like night-time fires. This method, tested on GOES-16 data, also integrated an interactive dashboard for detailed regional analysis, marking progress in the field of remote sensing for fire identification. Building on the imperative for early detection of forest fires, a novel study [18] implemented a deep learning model using Himawari-8 satellite data, aimed at reducing detection latency. This model, leveraging both spatial and temporal data, improved detection times significantly, achieving an average initial detection time of just 12 minutes. The convolutional neural network (CNN) method outshined traditional random forest (RF) approaches, showcasing its spatial pattern recognition capabilities. It demonstrated an overall accuracy and F1-score of 0.98 and 0.74, respectively, with the added advantage of robust performance under diverse environmental conditions. The CNN's swift detection ability marks a notable advancement in the utilization of geostationary satellite data for timely forest fire monitoring.

Tackling the significant environmental threat posed by forest fires, researchers [19] have developed a deep learning system designed to quickly detect fires and alert authorities. Utilizing a Convolutional Neural Network (CNN) model, this system processes images from a custom dataset, achieving commendable detection accuracies of 93% in training and 92% during testing. The system, supported by a Raspberry Pi setup, not only identifies fires but also sends notifications through various channels. With its high accuracy and real-time alert capabilities, this model presents a practical solution for early fire detection, potentially limiting the damaging impact of wildfires on ecosystems.

In the face of escalating forest fires, [20] have developed a deep learning-based system designed for early detection and classification. This system capitalizes on the Inception-v3 convolutional neural network's transfer learning capabilities, enhanced by Radial Basis Function Networks (RBFNs) with Rapid and Accurate Image Super Resolution (RAISR). The proposed model outshines previous CNN models with a notable accuracy of 97.55% and an F-Score of 93.33%, showcasing its effectiveness in identifying fire and non-fire images. It also utilizes the water wave optimization technique for image feature selection and enhancement. This method sets a new precedent for forest fire categorization, promising to aid in developing strategic responses to such disasters. While utilizing the capabilities of unmanned aerial vehicles (UAVs), a groundbreaking wildfire detection system was crafted, employing deep convolutional neural networks for heightened accuracy in identifying fires from aerial photos [21]. Through rigorous testing, GoogLeNet and a modified VGG13 network demonstrated superior performance, with GoogLeNet achieving an impressive 99.0% accuracy.

The modified VGG13, tailored for the specific task of fire detection, also showed promising results with a 96.9% accuracy rate. These networks, by swiftly processing vast quantities of high-resolution UAV imagery, provide a crucial tool in the early detection and monitoring of wildfires, potentially saving lives and reducing economic losses.

The study [1] introduces a Dynamic Equilibrium Network (DENet) to enhance fire detection across varied domains, specifically targeting data from spaceborne, airborne, and terrestrial sensors. Tested on the Flame And Smoke Detection Dataset (FASDD) and the FLAME dataset, DENet showcased a remarkable balance in learning, evidenced by a 7.71% improvement in mean average precision (mAP) over the PODNet model on existing datasets. It maintained strong performance on new datasets, achieving an mAP of 97.55% on older datasets and 92.20% on newer datasets. This model represents a significant advancement in the domain-incremental learning field, providing a robust framework for fire detection in integrated space-air-ground observation networks.

The study [22] examines efficient CNN architectures for real-time fire detection, proposing two compact models: NasNet-A-OnFire and ShuffleNetV2-OnFire. These architectures are optimized for computational efficiency and speed, with ShuffleNetV2-OnFire achieving a 2.3× speed increase for binary classification and a 1.3× speed increase for superpixel localization, at 40 fps and 18 fps, respectively. The models demonstrate robust performance, with NasNet-A-OnFire and ShuffleNetV2-OnFire both achieving 95% accuracy for full-frame classification and 97% for superpixel localization. Notably, the ShuffleNetV2-OnFire architecture is over six times more compact than previous works, with around 0.15 million parameters, while still maintaining high accuracy. This advancement demonstrates the potential for deploying these models on low-powered devices, like the Nvidia Xavier-NX, which reached 49 fps, highlighting their suitability for real-world applications.

In the research [5], the effectiveness of LIME, SHAP, and CAM, three explainable AI methods, was put to the test for image classification. LIME came out on top, closely matching human decision-making by identifying key image segments with an Intersection Over Union (IOU) score of 0.566. Although CAM wasn't as precise, it was the fastest, processing images in just 0.012 seconds. This comparison highlights the balance between accuracy and speed needed for real-time AI applications. The study suggests more work is needed to further enhance these methods for broader uses.

In a study [8] exploring wildfire detection in Southern Europe, an XAI framework using a Random Forest model was employed to interpret wildfire occurrence. The framework's accuracy in predicting wildfire-prone regions was impressive, with an area under the curve (AUC) of 81.3%. The study's performance metrics showed an accuracy of 69.7%, an F1 score of 62.0%, and a high sensitivity of 78.7%, indicating its effectiveness in detecting wildfire occurrences. Despite these promising results, the precision was relatively modest at 50.9%, suggesting a balance between correctly predicting wildfires and avoiding false alarms is needed. This research underlines the potential of XAI in aiding forest management and disaster mitigation strategies. The FireXplainer model [2] has marked a significant step forward in the detection and interpretation of wildfires. This innovative approach employs advanced techniques like transfer learning and the Learning without Forgetting (LwF) method, enhancing the precision of wildfire classification. The usage of the XAI Grad-CAM method also adds a layer of transparency, pinpointing the exact image regions influencing the model's decisions. The model's performance is impressive, boasting a 99.1% precision and a 99.3% recall, leading to an overall F1 score of 99.0%. These figures not only surpass previous state-of-the-art models but also offer

TABLE 1. Overview of recent studies in wildfire detection and classification using deep learning techniques.

Paper	Problem	Methodology	Results
[1]	Cross-domain fire detection	DENet model	mAP: 97.55% on old dataset, 92.20% on new dataset
[2]	Wildfire detection and interpretation	Transfer learning, LwF methodology, XAI Grad-CAM	99.1% precision, 99.3% recall, 99.0% F1 score
[9]	Forest fire/smoke detection	CNNs, transfer learning on VGG16, InceptionV3, Xception	Xception: 98.72% accuracy; LwF: 91.41% and 96.89%accuracy on different datasets
[10]	Wildfire image classification	Lightweight CNN model (LW-FIRE)	LW-FIRE1504x2: TPR 0.980, ACC 0.944
[11]	Early wildfire detection using satellite imagery	Deep learning architecture on satellite images	94%F1-score, 1.5x faster detection
[18]	Early wildfire detection using satellite data	CNN on Himawari-8 data	Avg. detection time: 12 minutes, Accuracy: 98%, F1-score: 0.74
[19]	Wildfire detection and alert system	CNN model, Raspberry Pi setup	Training acc: 93%, Testing acc: 92%
[20]	Early detection and classification of forest fires	Inception-v3 with RBFNs and RAISR	Accuracy: 97.55%, F-Score: 93.33%
[21]	Wildfire detection from UAV imagery	GoogleNet, Modified VGG13 CNNs	GoogleNet: 99% accuracy, Modified VGG13: 96.9% accuracy
[22]	Real-time fire detection	NasNet-A-OnFire, ShuffleNetV2-OnFire CNN models	Both models: 95% accuracy for full-frame and 97% for superpixel localization
[23]	Wildfire severity classification	U-Net models with different loss functions	BCE-MSE approach: RMSE of 0.54
[24]	Multi-sensor fire detection	Recurrent Trend Predictive Neural Network (rTPNN)	96% accuracy, 92%+ True Positive/Negative rates, 11s alarm trigger time
[25]	Detection of fire-affected areas using satellite data	CNN based on U-Net architecture	Sentinel-2: 0.83 F1 score, 92% detection

an interpretable framework that could significantly aid in wildfire management and response strategies.

This research [9] delves into the crucial task of forest fire and smoke detection through AI and deep learning. It tackles the challenge of identifying such calamities early on, aiding in prompt disaster management. The study employs Convolutional Neural Networks (CNNs) and explores the efficiency of transfer learning on pre-trained models like VGG16, InceptionV3, and Xception. Remarkably, the Xception model shines with an accuracy of 98.72%. When applying the Learning without Forgetting (LwF) technique, Xception demonstrates robust performance on both new and original datasets, showing a remarkable adaptability without losing its initial detection capabilities. The research confirms that these advanced models, with LwF, set a new benchmark in the field, enhancing the precision of detecting forest fires and contributing significantly to environmental conservation efforts.

In the study [23], the researchers improved the classification of wildfire severity from satellite imagery by experimenting with different loss functions in deep learning U-Net models. They found that the Binary Cross-Entropy (BCE) coupled with Mean Square Error (MSE) loss function produced better results than the conventional Dice-MSE approach. For severity classes 2 and 3, the IoU-SoftIoU configuration showed the best outcomes, but it underperformed for other severity levels. On average, the BCE-MSE approach achieved a Root Mean Square Error (RMSE) of 0.54, outperforming the Dice-MSE's RMSE of 0.65, indicating a more accurate prediction of wildfire-affected areas.

The recent study [10] has revealed the efficacy of a new lightweight wildfire image classification model, LW-FIRE, which has been meticulously tested across several datasets. The model has been evaluated against existing state-of-the-art methods and has shown promising results. Particularly notable is the model's performance on the LW-FIRE1504 $\times$ 2 configuration, where it achieved an impressive True Positive Rate (TPR) of 0.980, a False Positive Rate (FPR) of 0.091, and an Accuracy (ACC) of 0.944. Additionally, LW-FIRE1001 $\times$ 2 excelled with a TPR of 0.966 and an ACC of 0.951. Moreover, LW-FIRE1504 $\times$ 2 outperformed its counterparts with a TPR of 0.976 and an ACC of 0.973. These results showcase the model's robustness and its potential as a reliable tool for real-time wildfire detection and classification.

In the innovative study [24] of multi-sensor fire detection, the proposed Recurrent Trend Predictive Neural Network (rTPNN) has significantly advanced the field. The rTPNN model showcases remarkable accuracy, achieving a 96% success rate in fire detection. Its unique architecture allows it to predict fire trends swiftly, outperforming traditional methods like Linear Regression and Support Vector Machines. Notably, rTPNN excels in real-time responsiveness, triggering fire alarms in a mere 11 seconds, substantially faster than alternative models. Its robust design ensures low false positive and negative rates, affirming its potential as a reliable solution for urgent fire detection scenarios.

In the study [25] examining wildfire detection using multi-sensor satellite imagery and deep learning, the findings were noteworthy. The Sentinel-2 model excelled in clear conditions, achieving an F1 score of 0.83 with 92% of fire perimeters detected, while the Sentinel-1 model struggled, with only a 0.46 F1 score and 26% detection rate. The fusion of Sentinel-2 and Sentinel-3 data yielded the highest detection accuracy in clear conditions, significantly improving results with an F1 score reaching 94%. When cloud cover was a factor, combining Sentinel-1 and Sentinel-2 data proved advantageous, showcasing the potential for enhanced detection capabilities in adverse weather conditions. These outcomes underscore the efficacy of employing deep learning for analyzing complex satellite data, thereby offering a robust tool for early wildfire detection and management. To wrap up, the latest researches shows that using deep learning and detailed images from satellites is changing how quickly and accurately we can spot wildfires. These modern methods are a big step forward, as they can catch fires early and help keep people and the environment safer. Tools like LW-FIRE and rTPNN have shown that with the right technology, we can react to wildfires much faster than before. The work done here is not just about new gadgets; it's about making a real difference in fighting fires and maybe even saving lives and homes. This is just the beginning, and the hope is that these smart systems will be used more widely to tackle wildfires everywhere. A comparative overview of recent studies in wildfire detection and classification using different methodologies is shown in the Table 1.

III. PROPOSED METHODOLOGY

In this section of FireDetXplainer study, we apply MobileNetV3 for transfer learning and detail image preprocessing for training efficiency. We also incorporate Explainable AI (XAI) techniques, such as Grad-CAM and LIME, to enhance the model's transparency and decision-making clarity.

A. DATASETS

The FireDetXplainer study utilizes a comprehensive dataset to train and evaluate its wildfire detection model. This dataset comprises a total of 3,520 images, with 2,216 categorized as 'fire' images and 1,304 as 'no-fire' images. The dataset contains images captured in clear weather conditions, both during the day and at night. This selection ensures the model's accuracy in accurately differentiating fire and non-fire cases with maximum visibility. The data assembled by the model covers diverse landscapes comprising dense forests, open fields and even fringes of urban regions. These images are sourced from multiple online platforms, including Kaggle and Mendeley [26], ensuring a diverse and representative collection of visual data. The dataset is curated to provide a balanced representation of wildfire scenarios, enhancing the model's ability to accurately identify and classify fire occurrences in various environmental conditions. This rich dataset forms the foundation of the study's deep learning approach, enabling robust training and validation of the FireDetXplainer model. As illustrated in Table 2, the distribution of images across the datasets is balanced, offering an equal number of fire and non-fire images from Mendeley, while Kaggle provides a larger proportion of fire images.

TABLE 2. Distribution of image types across datasets used in the study.

Datasets	Fire Images	Non-fire Images
Mendeley	950	950
Kaggle	1266	354

B. FIREDETXPLAINER ARCHITECTURE

The FireDetXplainer (FDX) model, an innovative framework in wildfire detection, represents a significant stride in leveraging cutting-edge machine learning for environmental safety. The architecture of FDX is carefully designed to combine advanced neural network capabilities with the pressing need for accurate and efficient wildfire detection and classification. Central to the FDX model is the integration of MobileNetV3 for transfer learning, emphasizing not just on high performance but also on computational efficiency, making it suitable for real-time applications. This section delves into the core components of FDX's architecture, highlighting its unique approach in handling the complex task of wildfire detection. Figure 1 presents a detailed illustration of the FireDetXplainer (FDX) architecture, clearly outlining its components and workflow. This algorithm in Table 3 outlines a machine learning process for wildfire image analysis, involving data loading, preprocessing, and splitting. It employs a pre-trained MobileNetV3 model, adjusted for feature extraction and fine-tuning with wildfire data. The model is trained, evaluated, and integrated with Explainable AI techniques like Grad-CAM and LIME for insightful visualizations and interpretability, culminating in the aggregation of performance metrics and trained models.

C. TRANSFER LEARNING WITH MOBILENETV3

1) OPTIMIZING MOBILENETV3 INTEGRATION

- **Integration:** The FireDetXplainer (FDX) model integrates MobileNetV3, recognized for its efficiency and effectiveness in image classification tasks. MobileNetV3's design is particularly advantageous for applications where computational resources are limited, making it an ideal choice for real-time wildfire detection.
- **Adaption:** FDX capitalizes on the pre-trained MobileNetV3, which has been trained on extensive datasets. This allows the model to effectively identify

TABLE 3. Algorithm of fireDetXplainer.

Algorithm of FireDetXplainer

Initialize: $list, trainedModelList$
for $dataset \in \{\text{Kaggle}, \text{Mendeley}\}$ **do**
    $fireImages, noFireImages \leftarrow load(dataset)$
    $processedData \leftarrow preprocess(fireImages, noFireImages)$ using techniques like ellipse morphing, sharpening, and ROI segmentation
    $trainedModelList.append(processedData)$
end for
$trainSet, valSet, testSet \leftarrow split(processedData, 0.8, 0.1, 0.1)$
$pretrainedModel \leftarrow initializeModel(\text{MobileNetV3})$
$freezeLayers(pretrainedModel)$ for feature extraction
$fineTuneLayers(pretrainedModel, wildfireData)$
$model \leftarrow train(pretrainedModel, trainSet, valSet)$
if early stopping criteria met **then**
    break
end if
$performanceMetrics \leftarrow evaluate(model, testSet)$
$importantFeatures \leftarrow extractFeatures(model, testSet)$
$incorporateXAI(model, testSet, importantFeatures, \text{Grad-CAM}, \text{LIME})$
$display(importantFeatures, \text{Grad-CAM})$
$apply(model, \text{LIME})$ to provide interpretability on test images
$aggregate(trainedModelList, performanceMetrics)$

and interpret unique patterns in wildfire images, leveraging its deep learning capabilities.

- **Preservation and Adaptability:** A key aspect of FDX's approach is the preservation of MobileNetV3's initial layers. These layers are kept frozen to retain their fundamental image processing skills. Meanwhile, the latter layers of the model are fine-tuned to focus specifically on the unique characteristics of wildfire images. This dual strategy ensures that FDX maintains a solid foundation in general image recognition while being highly effective in identifying wildfire-specific features.

2) FINE TUNING TECHNIQUES

Fine-tuning in the FireDetXplainer (FDX) architecture involves selectively training the top layers of the MobileNetV3 model. This process is crucial for adapting the model to recognize and classify new data - specifically, images related to wildfires. The aim of this fine-tuning is to strike a balance between general and specific learning:

- **Selective Training:** The process targets the top layers of the model, which are most adaptable to new types of data. By refining these layers, FDX becomes attuned to the nuances of wildfire images.
- **Balanced Learning:** This approach ensures that while the model remains versatile enough to process a variety of image types, it also becomes proficient in identifying critical features indicative of wildfires. The underlying principle is to retain the model's broad image recognition capabilities while enhancing its ability to detect specific elements characteristic of wildfires.

The fine-tuning process of the MobileNetV3 model involves adjusting the top layers of the pre-trained network to better suit wildfire detection tasks. Initially, the model, trained on a large and diverse dataset, possesses general image recognition capabilities. During fine-tuning, the final layers are selectively retrained on the wildfire dataset, allowing the model to specialize in recognizing fire and non-fire images. This step involves a lower learning rate to make small, precise updates to the weights, ensuring the model adapts to the specifics of wildfire imagery without losing its pre-learned general knowledge.

3) HYPER-PARAMETER OPTIMIZATION

In the FireDetXplainer (FDX) model, hyper-parameter optimization is a critical process aimed at refining the model's performance. This optimization includes:

- **Optimization Strategy:** The model undergoes a detailed process where key parameters such as learning rate, batch size, and the number of training epochs are carefully adjusted. These parameters significantly influence the model's learning ability and overall accuracy.
- **Balancing Act:** The goal of this optimization is to find the ideal balance that prevents the model from over-fitting (being too narrowly adjusted to the training data) or under-fitting (failing to capture the underlying trends in the data). Achieving this balance ensures that the model performs reliably across various scenarios and datasets.

4) LEARNING WITHOUT FORGETTING (LWF) METHODOLOGY

The Learning without Forgetting (LwF) approach in FireDetXplainer (FDX) focuses on dual objectives:

- **Dual Focus:** LwF is crucial for ensuring the model retains its original capabilities, even as it learns new tasks. In the context of FDX, this means maintaining the model's general image processing skills while adapting to the specific requirements of wildfire detection.
- **Retaining Core Knowledge:** This methodology is vital for preserving the foundational strengths of the model. It allows FDX to keep its initial learned behaviors intact, ensuring a solid base of knowledge is always present,

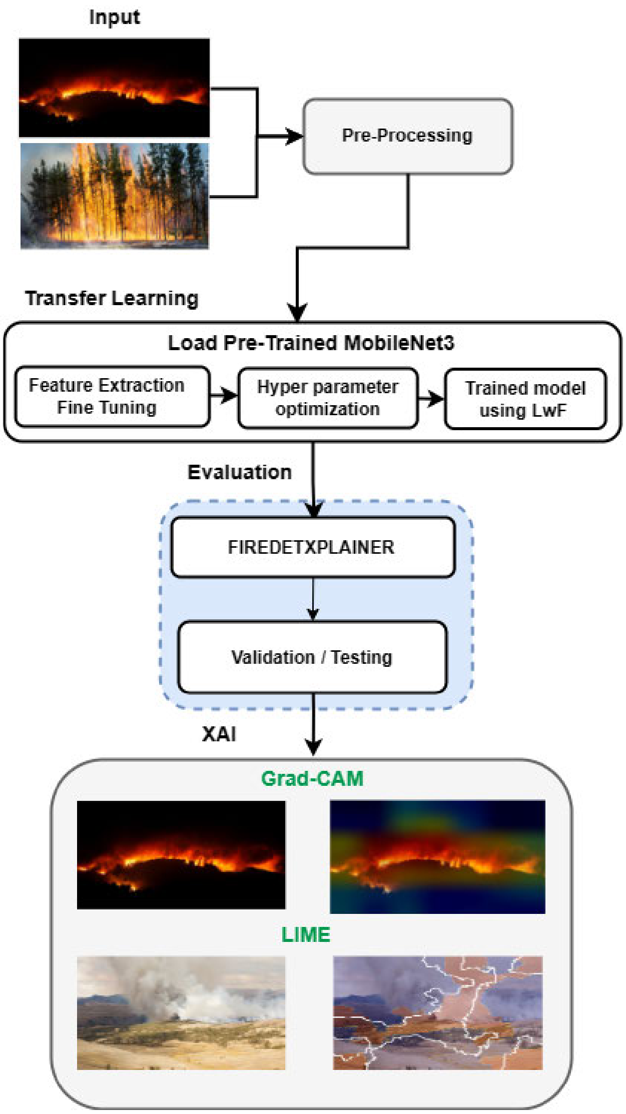

FIGURE 1. Detailed Architecture of FireDetXplainer.

even as the model evolves to handle the complex task of identifying wildfires.

5) PREPROCESSING TECHNIQUES

In the FireDetXplainer (FDX) architecture, preprocessing plays a pivotal role in preparing the data for optimal model training:

- **Data Augmentation:** This involves employing a variety of image manipulation techniques, such as rotations, flips, and color adjustments. By artificially expanding the dataset, FDX can better understand and generalize from the training data to real-world wildfire scenarios, enhancing its detection capabilities.
- **Normalization and Standardization:** These processes are essential for maintaining consistent image quality and format. By standardizing the input data, FDX can more effectively learn and recognize patterns, which is critical for accurate wildfire detection. This step ensures that variations in image brightness, contrast, or color do not hinder the model's learning and performance.

6) TRAINING PROCESS

The FireDetXplainer (FDX) employs a sequential training approach to optimize wildfire detection:

- **Methodical Learning:** The training process is designed to be systematic, enabling the model to incrementally learn from the enriched dataset. This approach combines the pre-learned knowledge from MobileNetV3 with new patterns specific to wildfire imagery, creating a robust learning environment.
- **Focus on Efficacy and Efficiency:** The core objective of this training phase is to ensure the model is not just learning effectively but also efficiently. This means optimizing the use of computational resources while ensuring the model achieves high accuracy in detecting wildfires. The process is fine-tuned to strike a balance between rapid learning and depth of understanding, making the model proficient in recognizing a wide range of fire scenarios.

In the development of the FDX model, the transfer learning and the framework is Learning without Forgetting (LwF) which is brought to combination with the use of the pre-existing knowledge to keep the model adaptable to new data while forgetting what previously has been learned not forgotten. At first, Transfer Learning is involved with using MobileNetV3 architecture, which is trained up on large-scale data set. That way FDX can begin with already well-trained feature-set, which in turn speeds up the training process and make results of fire detection tasks better.

In parallel with the usage of LwF technique, there is also a mechanism that is integrated to tackle with likely scenario of catastrophic forgetting - the scenario of learning new information that will make previously learnt knowledge forgotten. LwF applies the structure where the sub-net is preserved for the pre-learned tasks but yet the other sub-nets would be modified by the new data. Such an approach will guarantee that FDX realizes their efficiency in the already mastered tasks and increases the new knowledge simultaneously, making a harmonious process where former and new stones are constantly interacting with one another.

Through reconciliation of transfer learning with LwF, FDX thrives due to the robust feature extraction competences of a pre-trained model and it can constantly adapt to a particular wildfire detection problems during its lifespan. This integrative scheme is the fundament of the architecture of the model and gives it the capacity of high precision and adaptability in fastening fire risk in different environments and weather conditions.

D. MODEL TRAINING

In this phase of the research on FireDetXplainer, the training process is meticulously outlined in alignment with the data provided in the code. The dataset is initially segregated into distinct subsets for training, validation, and testing, following an 80:10:10 ratio which is a common practice to ensure the model is exposed to a variety of data while also being able to validate and test its predictions accurately. In the splitting of data in this fashion, a model is tested in a way that is not only on the data it has already been exposed to but also on other unseen data of which it has no prior acquaintance. This would improve its capability to generalize.

Hyper-parameter tuning is a pivotal aspect of training deep learning models, essential for achieving optimal performance. In this research, critical parameters such as the learning rate, batch size, and number of epochs were meticulously fine-tuned. Specifically, the learning rate was set to a low value of 0.0001, carefully chosen to ensure gradual and precise adjustments to the model's weights during training, thus minimizing the risk of overshooting. The batch size, affecting the model's convergence and its ability to generalize, was optimized at 32, striking a balance between computational efficiency and effective learning. Furthermore, the model underwent training for 100 epochs, a decision driven by the need to provide sufficient iterations for the network to learn from the entire dataset without falling into the trap of over-fitting. These choices in hyper-parameter settings underscore the meticulous approach taken to fine-tune the model's learning process, where the learning rate influences the magnitude of weight updates, the batch size impacts the model's learning granularity, and the epochs determine the depth of exposure to the training data.

An early stopping strategy is employed to prevent over-fitting, which is a condition where the model performs well on the training data but fails to generalize to unseen data. This technique monitors the model's performance on the validation set and halts the training once the performance ceases to improve, thus saving computational resources and time.

The code segment uses TensorFlow and Keras libraries, which are popular for building and training deep learning models. The training leverages callbacks like ReduceLROnPlateau for dynamic learning rate adjustments, and EarlyStopping for halting the training at the optimal moment. After training, the model's performance is evaluated using metrics like accuracy, precision, recall, and F1-score, which provide insights into the model's classification prowess.

The training process is powered by Google Colab's GPUs, which are highly efficient at performing the matrix and vector operations central to deep learning. Using such hardware accelerates the training process, allowing for more extensive experimentation with hyper-parameters and larger datasets.

IV. RESULTS

The FireDetXplainer (FDX) model showcases an impressive performance that sets it apart in the realm of wildfire detection. Its precision of 99.88% and recall of 99.97% reflect an exceptional ability to correctly identify both fire and non-fire scenarios with minimal errors. The F1-score of 99.93% further solidifies its accuracy, indicating a balanced precision-recall trade-off. This is particularly significant as

TABLE 4. Comparison of the state of art models based on evaluation metrics.

Model	No. of parameters	Precision	Recall	F1-Score	Accuracy
ShuffleNetV2-OnFire [19]	0.15 M	94.0	94.0	95.0	N/A
LW-FIRE [10]	1.1 M	N/A	N/A	97.2	N/A
LwF and CNN [9]	N/A	94.4	96.5	98.7	N/A
FireXplainer [2]	5.3 M	99.1	99.3	99.0	N/A
FireDetXplainer	**6.5 M**	**99.88**	**99.97**	**99.93**	**99.91**

it ensures reliable fire detection while minimizing false alarms, which is crucial in emergency response scenarios. Table compares the FireDetXplainer results with state of the art model based on evaluation matrices. The model's high accuracy rate of 99.91% stands as a testament to its robustness and efficiency in real-world conditions. Such a high accuracy rate is indicative of the model's comprehensive learning from the training data and its ability to generalize this learning to new, unseen data. This level of accuracy is rarely achieved in wildfire detection models, highlighting the advanced capabilities of FDX. Table 4 shows a comparison of FireDetXplainer with state of the art models in terms of evaluation matrices such as precision, recall, f1-score and accuracy score. Furthermore, the model's complexity, represented by its 6.5 million parameters, is well-justified by its performance metrics. This complexity enables the model to capture intricate patterns and nuances in the data, which is essential for accurate wildfire detection. Despite the large number of parameters, the model remains computationally efficient, as evidenced by its relatively low training and validation losses (0.0107 and 0.0084, respectively). These losses indicate that the model is not over-fitting and is well-tuned to the problem at hand. While the model's intricate design is crucial for detecting wildfires accurately, this complexity, with its 6.5 million parameters, inherently brings challenges, particularly in computational resource requirements. Such a sophisticated model may demand more memory and processing power during real-time analysis, posing potential constraints for deployment on less powerful systems or in mobile applications where efficiency is paramount. Developing strategies to optimize the model for faster inference without compromising accuracy is essential for broadening its applicability across various platforms.

The FireDetXplainer (FDX) model's training showcases its ability to effectively learn from the dataset without over-fitting, as evidenced by a training loss of 0.0107. Coupled with this, the model demonstrates exceptional generalization to unseen data, indicated by a validation loss that significantly decreases to 0.0084. This reduction in validation loss is critical, reflecting the model's precision in making accurate predictions on new data. This indicates that the model has effectively learned general patterns and features from the training data, which are essential for accurate classification, without over-fitting. Over-fitting is a common issue in machine learning where a model becomes too attuned to the training data and loses its ability to generalize to new, unseen data. These low values in loss metrics are indicative of a well-optimized model that is capable of making accurate predictions. Moreover, the model achieves a noteworthy milestone by maintaining a 100% validation accuracy from an early stage, which is maintained throughout the training process. This perfect validation accuracy, alongside the low validation loss, provides a compelling narrative of the model's robustness and its reliable performance across various conditions. The balanced combination of low training and validation losses, together with impeccable validation accuracy, underscores the FDX model's optimized and effective approach in wildfire detection, ensuring its applicability and effectiveness in real-world scenarios.

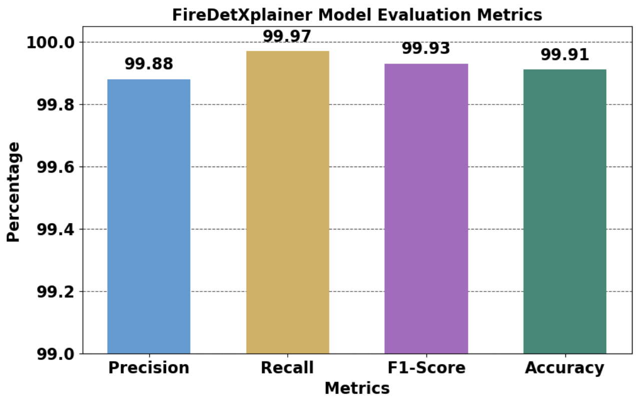

FIGURE 2. Visualization of Evaluation Metrics of FireDetXplainer Model, Highlighting Scores in Precision, Recall, F1-Score, and Accuracy.

In summary, the FireDetXplainer model's exceptional performance metrics - precision, recall, F1-score, and accuracy - combined with its efficient learning as indicated by its loss metrics, clearly demonstrate its superiority over existing models. The balance between a large number of parameters and computational efficiency, along with the outstanding accuracy, positions the FDX model as a significant advancement in the field of wildfire detection and management. As illustrated in Figure 2, the FireDetXplainer model achieved remarkable performance across all key evaluation metrics, with precision, recall, F1-score, and accuracy score. These results underscore the model's robustness and reliability in fire detection and explanation tasks.

V. EXPLAINABLE AI (XAI)

To improve the interpretability of our model, we incorporate two distinct Explainable AI (XAI) techniques: Gradient-weighted Class Activation Mapping (Grad-CAM) and Local Interpretable Model-agnostic Explanations (LIME).

A. GRAD-CAM

Grad-CAM is a technique that helps to understand the decision-making process of convolutional neural networks. It generates a "heatmap" or a visual explanation that highlights the regions of the image that were most influential in the model's prediction. This heatmap is created by capturing the gradients flowing into the final convolutional layer of the network, which indicates the importance of each pixel in the image for the classification task. The result is a visual overlay that can be placed on the original image to show which parts contributed most to the decision, such as identifying specific areas of fire in an image when the task is to detect wildfires. This method is particularly useful for validating the focus of the model and ensuring that it aligns with human interpretation and domain knowledge.

In this research, Grad-CAM plays a pivotal role in enhancing the interpretability of wildfire detection. By applying Grad-CAM, we can visualize which parts of an image the neural network focuses on when predicting the presence of wildfires. This is crucial for confirming the model's reliability and ensuring it bases its decisions on relevant features, such as the actual flames or smoke, rather than on irrelevant background features.

In the Grad-CAM processed image Figure 3, this technique highlights the areas in the image that led to the model's prediction of fire. The warmer or more intense the coloration on the heatmap, the more significant that region was for the model's decision. This visualization allows for an intuitive understanding of the model's functioning, ensuring that the model is paying attention to the right cues in the image, such as the bright, fiery areas that typically represent a wildfire, which are prominently marked in the image. This not only builds trust in the model's predictions but also provides insights into potential improvements for further model training.

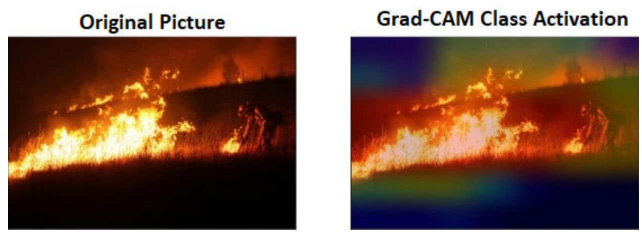

FIGURE 3. Visualization of Original wildfire image and Grad-CAM processed image.

B. LIME

LIME, which stands for Local Interpretable Model-agnostic Explanations, is a technique used to explain the predictions of machine learning models. It works by approximating the model locally with an interpretable one, such as a linear model or decision tree. LIME perturbs the input data and observes the corresponding changes in the output, allowing it to identify which features significantly influence the model's predictions. Besides these, a LIME-based approach emerged and proved to have an powerful degree of interpretability through diverse fields. More specifically, the outcomes of AIPs-SnTCN, iAFPsEnC-GA, and cACP-DeepGram have indicated LIME as a model which improved a understanding of a predictive models of biomedical research.

AIPs-SnTCN employs LIME in the context of predicting anti-inflammatory peptides, combining word embedding techniques with a self-normalized temporal convolutional network to achieve high predictive accuracy and interpretability [27].

iAFPs-EnC-GA integrates LIME for antifungal peptide prediction, utilizing a genetic algorithm-based ensemble classifier and showing the interpretive contribution of features to model predictions [28].

cACP-DeepGram applies LIME to anticancer peptide prediction, leveraging deep neural network models and demonstrating improved interpretability and prediction accuracy [29].

In this research, LIME provides a detailed explanation of individual wildfire predictions made by the model. By highlighting the specific features within an image that contribute to the model's classification decision, LIME offers a granular view of the model's reasoning process. This can help researchers and practitioners understand and trust the model's decisions and identify any biases or areas for improvement.

The LIME processed images further elucidate this point. For example, in Figure 4, LIME highlights areas of smoke and regions with a particular color or texture that the model associates with fire. It outlines these regions, showing their contribution to the model's prediction. In Figure 5, LIME illustrates how certain patterns in the landscape, such as specific terrain features, are weighted by the model in its decision-making process. These visual explanations are instrumental in validating the model's performance and ensuring that it makes predictions based on relevant and accurate features.

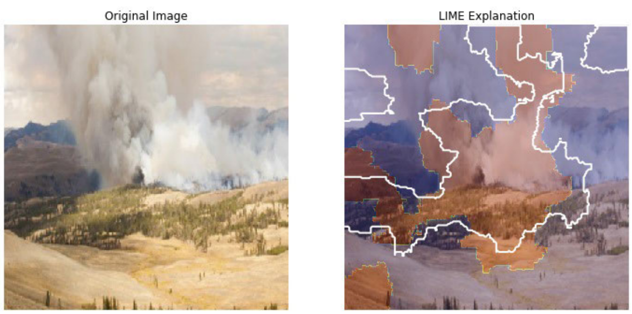

FIGURE 4. Visualization of Original wildfire image and LIME processed image.

VI. DISCUSSION

In discussing the FireDetXplainer model, we focus on its strengths in wildfire detection through deep learning. The model's integration of advanced neural network architectures like MobileNetV3, coupled with Explainable AI (XAI) techniques, allows for a high degree of accuracy and transparency. Our results underscore the model's capability, with precision and recall rates both exceeding 99%, presenting a significant leap from traditional methods. The F1-score, a balanced measure of the model's accuracy, stands at 99.93% and 99.91% respectively, indicating a robust performance in identifying fire-affected areas.

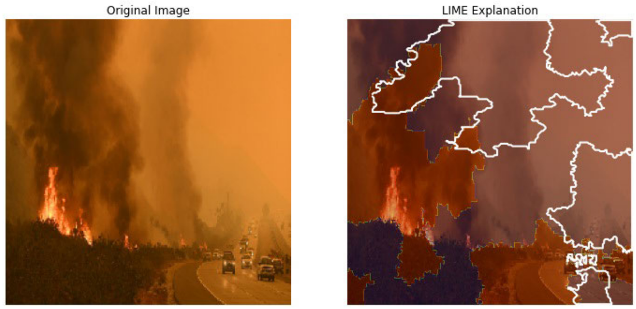

FIGURE 5. Visualization of Original wildfire image and LIME processed image.

The model benefits from the Learning without Forgetting (LwF) methodology, ensuring that it remains adept at its original tasks while adapting to new challenges. Through Grad-CAM visualizations, we can pinpoint which aspects of the image most inform the model's predictions. LIME further elucidates the model's reasoning by highlighting influential features. These XAI methodologies not only provide a deeper understanding of the model's inner workings but also pave the way for potential enhancements. The discussion also contemplates the model's training efficiency, reflected in the stability of its learning curves over time. The curves showcase the model's ability to maintain high performance, even with the introduction of new data during the learning process. This adaptability is critical for real-time applications in diverse and unpredictable environmental conditions.

Lastly, the integration of XAI enhances the user's trust in the model by offering clear and interpretable insights into its decision-making process. Such transparency is vital for the deployment of AI in critical sectors like wildfire management, where understanding the rationale behind algorithmic decisions can have significant implications.

Figure 6, the accompanying graph illustrates these points, with the accuracy curve plateauing at high levels, confirming the model's reliable performance. The loss curve's decline suggests that the model has effectively minimized errors throughout its training. These visual metrics serve as tangible proof of the model's efficacy and the successful application of its learning strategies.

While the FireDetXplainer (FDX) model demonstrates significant advancements in wildfire detection through high accuracy and interpretability, it is important to acknowledge its limitations and identify areas for further improvement. One notable limitation is the dependency on the quality and diversity of the training data. Despite the model's robust performance in current test scenarios, its effectiveness may vary in real-world conditions that were not adequately represented in the training dataset. This underscores the need for continuous expansion and diversification of the dataset to encompass a wider range of wildfire scenarios, including different vegetation types, weather conditions, and fire behaviors.

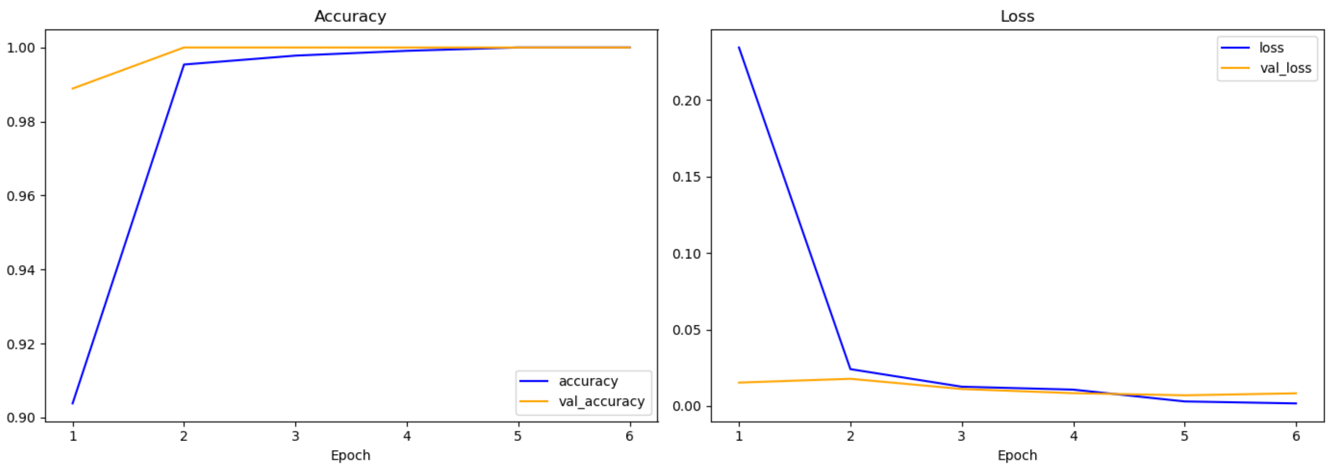

FIGURE 6. Visualization of FireDetXplainer model's training accuracy and loss convergence over epochs.

VII. ETHICAL CONSIDERATIONS IN AI DEPLOYMENT FOR WILDFIRE MANAGEMENT

In this study, the emphasis will be on using AI to improve the process of wildfire detection and accuracy. Fest covers the role of critical side in avoiding any case of bias in training data for machines to not favour any scenario over others. With a demand for parity being a major factor in AI system adoption, it is imperative to make the AI algorithms suitable for all living areas and climates.

It is recommended nowadays for AI decision making transparency tools to be built-in. Providing our systems with such transparency is vital for creating trust in AI systems, specifically in critical applications such as wildfire detection that carry many issues for communities and the environment.

The significance of human oversight in AI deployment is emphasized. Accuracy of AI and fast processing of data is undoubtedly superior; nevertheless, humans must involve with AI making the final decision-making. This approach ensures that AI serves as a support tool, not replacing critical human decision-making processes. Building a rapport with a broad range of stakeholders, including emergency managers, scientists, and neighborhood harms are inevitable factors at the AI design and refinement stages. Their insights and feedback ensure the AI system is effective, equitable, and trustworthy.

The next step is the consideration of these aspects, which main purpose is ensuring that AI will be utilized ethically and beneficial in wildfire management. Also the goal is to develop such system, which don't introduce new challenges.

VIII. CONCLUSION

In summarizing the research, we begin with the challenge of accurately detecting wildfires, a problem compounded by the similar visual characteristics of fire, smoke, and other natural elements. The approach of this research relies on using transfer learning. It makes use of the MobileNetV3 model, which is carefully adjusted and fine-tuned to improve accuracy in identifying different types of images. The results, anchored by an impressive accuracy rate of 99.91%, underscore the efficacy of the model, further enhanced by Explainable AI techniques like Grad-CAM and LIME, which clarify the model's decision-making process. These XAI tools not only provide transparency but also point towards areas for potential refinement. The research concludes with reflections on future work, suggesting avenues to differentiate between fire-related images and other environmental textures more effectively. This could potentially involve developing more nuanced models or incorporating additional sensory data to reduce false positives and increase reliability in diverse conditions. The goal remains to advance the model's practical application in real-time wildfire detection and prevention.

IX. FUTURE WORK

For future works, the actions of the current study would be extended to the wildfire detection model improvement to the point when the model makes a right discrimination between fire and similar natural phenomena. This can be accomplished through the use of more data, such as different weather variables and temperature changes, to teach the model to distinguish a fire from uneventful things like clouds or sunsets thereby ascending the precision of the model. The primary intent is to design a tool that can precisely detect forest fires with immediate reaction, therefore addressing the issue early, and minimizing harm. Such remediation aims to employ the most advanced technologies for wildfire detection, response, and effective community protection.

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