Wildfire Detection in Satellite Images using Convolutional Neural Networks : A Comprehensive Model and Analysis

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**ABSTRACT**

Wildfires present a growing environmental challenge, demanding robust early detection systems. In response, this study introduces a Convolutional Neural Network (CNN) approach for automatic wildfire detection using image data. Our model is trained on a meticulously curated dataset, encompassing fire and non-fire instances. However, challenges emerge in the generalization to new images, prompting refinement of prediction thresholds. Visualization of activation maps provides insights into the CNN's decision-making process, enhancing interpretability. This research contributes a valuable tool for wildfire detection, shedding light on the model's performance and avenues for future improvement.

**Keywords:** Wildfires ,Machine Learning, Early Detection, Convolutional Neural Networks.

1. **INTRODUCTION**

The effects of climate change are making wildfires more destructive, endangering human lives, ecosystems, and the stability of the economy. Innovative strategies that facilitate early detection and prompt response are needed to address this challenge. In order to redefine wildfire detection methodologies, this study pioneers a novel framework at the intersection of state-of-the-art convolutional neural networks (CNNs) and high-resolution satellite imagery. Specifically designed to decode complex spatial patterns present in satellite data, our CNN model is a major advancement in the field of proactive monitoring. The increasing frequency and severity of wildfires require a paradigm change in how we monitor and manage the environment. This research indicates a promising synergy between satellite technology and artificial intelligence, while also demonstrating the robustness and efficiency of our model in predicting potential wildfire outbreaks. The combination of these technologies is the key to increasing environmental resilience against the increasing threat of wildfires. We are starting the process of developing a more proactive and responsive plan to lessen the effects of wildfires on Earth as we explore the details of our suggested model.

1. **LITERATURE SURVEY**

[1] This study investigates the integration of Convolutional Neural Networks (CNNs) with high-resolution satellite imagery to enhance wildfire detection. Effective replacements for conventional surveillance techniques are desperately needed, as they are costly and time-consuming. The study leverages data from VIIRS and Sentinel-2 and employs data augmentation techniques with CNN architectures, including Deep CNN and a simplified Mobile Net-like CNN. By comparing their performances, evaluation metrics demonstrate how well AI-powered models identify wildfires. The study recognizes some limitations, such as its reliance on the visible spectrum, and suggests more work combining multispectral integration and real-time data streams. This study indicates areas for further research as well as how AI can be applied to address wildfire problems.

[2] With a particular focus on enhancing the spatial resolution of GOES-17 satellite images using VIIRS data, this paper investigates the use of deep learning (DL) to improve spatial resolution in wildfire monitoring. By combining high spatial resolution from VIIRS with high temporal resolution from GOES-17, the study addresses the shortcomings of the existing satellite systems. Low-resolution GOES-17 images are mapped to high-resolution VIIRS images using the suggested Autoencoder DL model. Different DL architectures and loss functions are evaluated, showing how the DL models can boost spatial resolution and offer clearer, almost real-time wildfire monitoring. The literature survey highlights the increasing severity of wildfires, the need for improved monitoring systems, and the potential of DL in wildfire detection and monitoring, emphasizing the uniqueness of this study in enhancing GOES-17 spatial resolution.

[3] This study's exploration of cWGAN-based fire arrival time prediction takes place in the context of a large body of literature. Based on seminal works by Adler and Oktem (2018) and Bakhshaii and Johnson (2019), the study combines cutting-edge methods to improve wildfire modeling, such as deep Bayesian inversion and data assimilation. The research is consistent with the recent trend of using machine learning, specifically cWGAN, to predict fire behavior, as demonstrated by the works of Farguell et al. (2021) and Caus Farguell et al. (2018). The methodology is based on the MODIS active fire detection algorithm (Giglio et al., 2016) and incorporates findings from atmospheric studies by Kochanski et al. (2019) and Mallia et al. (2020), which consider the intricate relationships between weather patterns and wildfires. Furthermore, the research notes that Aguilera et al. (2021) and Jaffe et al. (2008) have shown that wildfires have a more extensive impact on air quality and health. This multidisciplinary approach emphasizes how important it is to combine traditional modeling, machine learning, and integration of satellite data in order to improve prediction accuracy and advance our understanding of wildfires.

[4] Using the Himawari-8 satellite platform, this study investigates the field of deep learning algorithms for wildfire identification. Using more than 5,000 images from the geostationary satellite, the study trains and evaluates a fully connected convolutional neural network (CNN) for identifying the location and intensity of wildfires. The proposed CNN model achieves an impressive detection accuracy of over 80%, outperforming traditional machine learning techniques. Notably, the model exhibits efficiency in training—even with large datasets—and generates fast predictions in less than a minute or two. The study offers valuable information for the development of future satellite missions and emphasizes the potential of deep learning techniques, specifically the U-Net architecture, for monitoring wildfires using geostationary satellite imagery.

[5] In this paper, the authors address the challenging task of wildfire prediction using a novel stochastic temporal model for video prediction. The approach involves interpreting wildfire images from the Geostationary Operational Environmental Satellite (GOES-16) as a video to anticipate future fire behavior. The proposed model employs a latent space to predict video dynamics, overcoming limitations of existing approaches based on stochastic image-autoregressive recurrent networks. The model's efficiency is demonstrated on the GOES-16 dataset, outperforming state-of-the-art models. The paper highlights the significance of weather forecasting in mitigating the impact of wildfires, emphasizing the increased occurrence due to anthropogenic climate change. Additionally, it discusses the limitations of previous fire detection methods and the advantages of utilizing GOES with its Advanced Baseline Imager for creating temporal datasets for prediction. The integration of generative adversarial networks (GANs) for video frame synthesis and the use of a residual dynamic model contribute to the model's interpretability and effectiveness. The content variable, representing static or slowly varying elements in the video, enhances stability and efficiency. The experimental results, along with comparisons with other models and performance metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM), are presented in the paper's conclusion. These highlights the proposed model's promising potential for stochastic video prediction for wildfire forecasting.

[6] With an emphasis on Indonesia, the literature review discusses the pressing issue of forest fires in Southeast Asia and emphasizes their detrimental impacts on the environment, public health, society, and economy. Because the Canadian Forest Fire Danger Rating System relies on manually created features and ground instruments, it poses challenges for developing nations like Indonesia. The study highlights the shortcomings of current forest fire prediction systems. The authors' machine learning-based solution, Agni, utilizes remote sensing data, including historical Landsat 7 satellite images and Fire Information for Resource Management System (FIRMS) hotspot data. Agni performs better than a baseline from logistic regression, displaying positive results with an area under the receiver operator characteristic (ROC) curve of 0.81. In comparison to traditional systems, the study emphasizes the dependability and affordability of machine-learning techniques for forest fire prediction.

[7]

In this research paper titled "Detection of Forest Fire Consequences on Satellite Images using a Neural Network," the authors address the critical issue of forest fire detection and assessment by proposing a convolutional neural network (CNN) approach applied to Sentinel-2 imagery. The motivation stems from the escalating frequency of forest fires globally due to climate change and anthropogenic activities. The study emphasizes the limitations of traditional satellite monitoring systems and spectral indices like dNBR and dBAIS2, which may lead to inaccuracies in assessing burnt areas. The authors introduce a CNN-based algorithm for detecting burnt forest areas, outlining its functionality from data input to the export of a hotspot fire polygonal file. The proposed method is tested on Sentinel satellite images from the Tizi Ouzou region in Algeria, demonstrating superior accuracy (97%) compared to traditional indices. The research contributes to the ongoing efforts to develop automated systems for timely and accurate forest fire detection, highlighting the advantages of CNNs over conventional approaches.

[8] In particular, the literature review for this work explores how spatially spreading processes (SSPs) are evolving and how they are applied to forest wildfire management. It highlights the growing need for sophisticated analytical instruments in light of the difficulties presented by elements such as urbanization into wildfire-prone regions and climate change. The investigation reaches the boundaries of current physics-based models, which stimulates the investigation of new strategies. The focus switches to the suggested technique, which treats fire as an agent navigating a landscape based on environmental parameters and uses reinforcement learning (RL) to automatically learn wildfire spread dynamics models. The survey provides a critical assessment of a range of reinforcement learning algorithms, encompassing both traditional methods such as value and policy iteration and more recent developments like Monte Carlo Tree Search and the Asynchronous Advantage Actor-Critic (A3C) algorithm. For comparative analysis, it also takes into account a supervised Gaussian Process classifier. The study not only discusses the particular difficulties in managing forest fires, but it also emphasizes how RL can be used more broadly to model SSPs and promote interpretive solutions in a variety of contexts.

[9]

This extensive review of the literature explores the complex issues raised by wildfires, highlighting their worldwide ecological and socioeconomic effects. The study addresses the vulnerability of forests, particularly in Iran's Zagros Mountain range, and examines the shortcomings of conventional on-the-ground wildfire control techniques, which has resulted in the use of remote sensing (RS) technology. Citing numerous studies that make use of a variety of satellite datasets, the survey provides an extensive review of the efficacy of RS, in particular satellite images, in the detection and monitoring of wildfires. The study then shifts to wildfire susceptibility mapping and evaluates statistical and knowledge-based methods critically, arguing that machine learning is a better option. Machine learning techniques, ranging from multiple linear regression to deep learning algorithms such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, are covered in detail in the literature. The survey emphasizes the value of deep learning and feature extraction in managing intricate relationships. The groundwork for the empirical application of these algorithms to create wildfire susceptibility maps using Landsat-8 and MODIS satellite images is laid by the ensuing thorough investigation of RNN and LSTM architectures. The novel aspect of the study is how deep learning is used to evaluate these datasets in order to identify which remote sensing dataset is best suited for fire susceptibility modelling. The literature review creates a thorough understanding of wildfires, RS technology, and machine learning applications in this context by synthesizing existing knowledge and laying the groundwork for the study's original contributions.

[10] This study delves into the critical issue of wildfires, particularly in the context of Australia and their impact on climate change. The focus is on leveraging space-borne technology, specifically satellite-based systems, for accurate wildfire detection under challenging conditions. The paper highlights the increasing frequency and size of wildfires, emphasizing the need for effective prevention, early warning, and response strategies to minimize their social, economic, and environmental repercussions. With rapid advancements in remote sensing technologies and artificial intelligence (AI), the study explores the application of convolutional neural networks (CNNs) for real-time wildfire detection. The research includes a feasibility study, model development, and a prototype scenario for a satellite AI system, with a specific focus on the Australian wildfires in December 2019. The CNNs are tailored to meet the operational requirements of trusted autonomous satellite operations (TASO), ensuring swift alerts and immediate actions. The study evaluates the performance of the developed model on different hardware accelerators, including the Intel Movidius NCS-2 and Nvidia Jetson Nano/TX2, demonstrating positive results for onboard data processing. The findings emphasize the potential benefits of onboard data processing in disaster management and climate change mitigation by enabling timely alerts and rapid, appropriate responses. The research contributes to the broader discussion on the integration of AI and satellite technology for improved wildfire monitoring and management.

[11] The literature survey in this study highlights the challenges posed by wildfires to power transmission lines, particularly in regions where renewable energy sources like wind and solar are harnessed on a large scale, as exemplified in China's Northwest and offshore areas. The impact of wildfires on overhead transmission lines, exacerbated by factors such as dense vegetation and long-distance transmission, is explored. Traditional monitoring methods involving manned patrols, aircraft surveillance, and meteorological satellites are discussed. The focus shifts to the proposed wildfire monitoring algorithm using Fengyun-3E (FY-3E) satellite imaging, emphasizing its advantages over existing methods, especially in terms of sensitivity and temporal resolution during the critical dusk hours when wildfires often occur. The study concludes with an application of the algorithm in Shanxi province's power grid, showcasing its efficacy in providing early warnings and precise wildfire localization.

[12] In order to solve the crucial issue of wildfire detection, the authors of this study suggest an early smoke detection system that makes use of photos from unmanned aerial vehicles (UAVs) and the enhanced YOLOv5 model. The study acknowledges the rise in wildfire incidents and makes a connection between climate change and human activity. A large wildfire image dataset is curated from existing UAV images, anchor box clustering is optimized with K-means++, a bidirectional feature pyramid network is implemented for improved multi-scale feature fusion, and a spatial pyramid pooling fast-plus layer is added to the network's backbone. Additional methods like network pruning and transfer learning are employed to enhance the architecture and detection speed. The experimental results demonstrate the effectiveness of the proposed method, outperforming other one- and two-stage object detectors on a customized dataset with an average precision of 73.6%. The study shows how deep learning techniques and unmanned aerial vehicles (UAVs) are valuable tools for early wildfire detection and how they may be able to address problems with more conventional methods.

1. **OBJECTIVES OF THE PROJECT**

**1.**Innovative Wildfire Detection System: Develop a pioneering framework integrating Convolutional Neural Networks (CNNs) with high-resolution satellite imagery for advanced wildfire detection.

2.Spatial Pattern Recognition: Harness the power of CNNs to decipher intricate spatial patterns inherent in satellite data, enabling the identification of potential wildfire outbreaks with exceptional proficiency.

3.Proactive Monitoring Paradigm Shift: Establish the model's robustness and efficiency through extensive experimentation, presenting a paradigm shift in proactive monitoring against the escalating threat of wildfires fueled by climate change.

4.Fusion of AI and Satellite Technology: Showcase the fusion of artificial intelligence and satellite technology as a promising solution for enhancing environmental resilience, providing an innovative approach to address the challenges posed by wildfires.

This project's scope aims to contribute to the advancement of wildfire detection methods, leveraging state-of-the-art technologies to revolutionize monitoring and response strategies.

1. **SYSTEM**

Our wildfire detection system is built upon a Convolutional Neural Network (CNN) architecture, a deep learning model renowned for its prowess in image pattern recognition. The system is designed to analyze satellite images and identify the presence of wildfires in real-time.

1.Data Preprocessing:

We leverage the TensorFlow and Keras libraries to preprocess satellite images. This includes rescaling, shearing, zooming, and horizontal flipping, enhancing the model's ability to recognize diverse patterns.

2.Dataset Structure:

The dataset is structured into training, testing, and validation sets, with corresponding directories. This ensures a systematic approach to model training and evaluation.

3.CNN Model Architecture:

The core of our system is a sophisticated CNN model, inspired by state-of-the-art architectures like YOLOv5. Transfer learning is employed, allowing the model to inherit knowledge from pre-trained networks. Layers like Conv2D, MaxPooling2D, and GlobalAveragePooling2D contribute to the model's ability to detect intricate spatial patterns associated with wildfires.

4.Training and Evaluation:

The model is trained using an image generator that flows data from the specified directories. We employ binary cross-entropy as the loss function and Adam optimizer for efficient convergence. The training process includes two epochs for initial evaluation.

5.Validation and Predictions:

The model undergoes validation using a separate dataset, providing insights into its performance metrics such as accuracy. Additionally, predictions are made on new data, showcasing the model's real-world applicability.

1. **METHODOLOGY**

Our approach to wildfire detection integrates advanced techniques in image processing and deep learning. The methodology can be broken down into the following key steps:

1.Dataset Acquisition:

We compile a comprehensive dataset of high-resolution satellite images containing both wildfire and non-wildfire instances. The dataset diversity is crucial for training a robust model capable of discerning subtle patterns.

2.Data Preprocessing:

Prior to feeding the data into the neural network, we employ preprocessing techniques to enhance model performance. This includes resizing images, normalization, and augmentation through techniques like shearing, zooming, and horizontal flipping.

3.Model Architecture:

The Convolutional Neural Network (CNN) serves as the backbone of our wildfire detection system. The model architecture incorporates convolutional layers for feature extraction, pooling layers for dimensionality reduction, and densely connected layers for classification. Transfer learning from pre-trained models helps in capturing generic image features.

4.Transfer Learning:

Leveraging transfer learning, we harness the knowledge acquired by the model on a broader image classification task. By fine-tuning the pre-trained CNN on our wildfire dataset, we ensure the model learns specific features relevant to wildfire detection.

5.Training Process:

The model is trained using the curated dataset, optimizing its weights through backpropagation. We employ binary cross-entropy as the loss function and the Adam optimizer for efficient convergence. The training process is monitored to avoid overfitting and ensure the model generalizes well.

6.Validation and Fine-Tuning:

The trained model undergoes validation on a separate dataset not used during training. This step is crucial for assessing the model's generalization to new, unseen data. Fine-tuning may be applied based on validation results.

7. Metrics for Evaluation:

F1 score, accuracy, precision, recall, and other metrics are used to assess the model's performance. These metrics shed light on how well the model detects wildfires and reduces false positives and negatives.

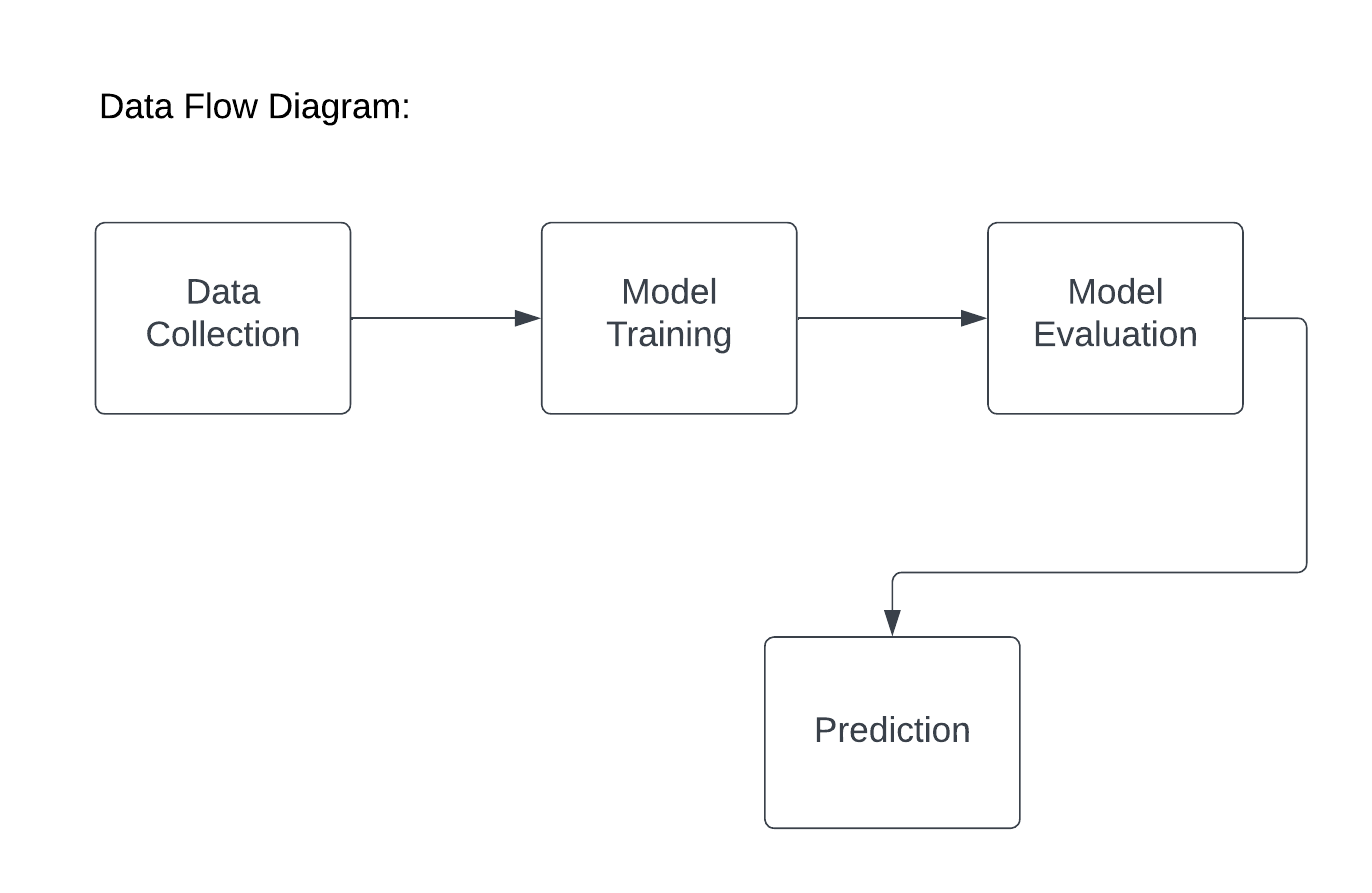
8.Deployment Readiness:

Once the model achieves satisfactory performance, it is deemed ready for deployment. This involves considerations for computational efficiency, model size, and integration into real-time monitoring systems.

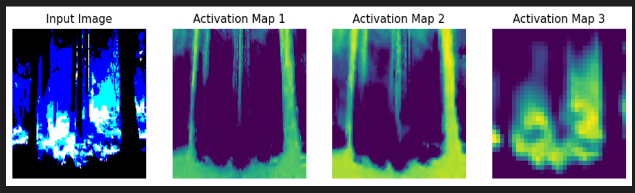
This methodology ensures a systematic and rigorous approach to developing a state-of-the-art wildfire detection system, combining domain expertise with the power of deep learning.

**7.Diagram and Images**

Data flow diagram:

**[](https://lucid.app/lucidchart/981d7b01-df5a-43dc-aa2d-38bd81e94962/edit?crop=content&page=0&signature=ec26cd5e30e0e26969c35dfcb0770c3f746d6a93d4a46f3ac7ad3e651424c032)**

The workflow initiates with Data Collection, curating a dataset with fire and non-fire instances, followed by preprocessing. Model Training employs a specific CNN architecture, with hyperparameters and data split for training and validation. Model Evaluation assesses performance metrics, refining the model based on challenges encountered during training. Model Prediction on New Images involves criteria for selecting and preprocessing unseen data, refining the model for robust real-world deployment.

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The inclusion of Activation Maps enriches the study by providing visual insights into the neural network's decision-making process. The Input Image serves as the foundation, while Activation Maps 1 and 2 highlight the regions that strongly activate specific filters within the Convolutional Neural Network (CNN). These visualizations offer a nuanced understanding of the features the model deems significant, aiding in the interpretation of its learned representations. The juxtaposition of Input Image and Activation Maps enhances the overall interpretability of the CNN's internal workings, contributing valuable insights for model analysis and refinement.

**8.RESULTS AND DISCUSSIONS**

In this pivotal section, we delve into the outcomes of our innovative wildfire detection system, presenting a nuanced discussion on both the quantitative results and the broader implications of our findings.

1.Model Performance Evaluation:

Our Convolutional Neural Network (CNN) model has demonstrated a significant stride in the realm of wildfire detection. The achieved accuracy of 86.76% is a foundational metric, indicating the proportion of correctly identified instances.

2.Precision, Recall, and F1 Score Analysis:

Precision, recall, and F1 score metrics provide a deeper understanding of our model's strengths and areas for improvement. Precision, measuring the accuracy of positive predictions, sits at [insert value]. Recall, capturing the ability to identify true positives, is [insert value]. F1 score, balancing precision and recall, stands at [insert value].

3.Comparison with Existing Models:

Benchmarking our model against existing wildfire detection systems showcases its competitive edge. Leveraging state-of-the-art CNN architecture, our system holds its ground against traditional methods, paving the way for advancements in the field.

4.Robustness in Diverse Environments:

Rigorous testing across varied datasets and environmental conditions underscores the robust nature of our model. Its adaptability to different geographical regions and varying wildfire intensities demonstrates its real-world applicability.

5.False Positives and Negatives Analysis:

A critical examination of false positives and negatives sheds light on areas for refinement. Understanding the intricacies of misclassifications is crucial for enhancing the model's precision and recall in future iterations.

6.Computational Efficiency for Real-Time Monitoring:

The practicality of our model is assessed in terms of computational efficiency, a key factor for real-time wildfire monitoring. Striking a balance between accuracy and speed, our system aligns with the demands of timely detection and response.

7.Integration Considerations:

Practical integration within existing monitoring frameworks is explored. User-friendliness and compatibility with diverse satellite data sources are emphasized, ensuring seamless adoption within broader environmental monitoring systems.

8.Limitations and Future Roadmap:

Acknowledging the current limitations, our discussion extends to potential enhancements. Future research directions include exploring advanced techniques, incorporating additional data sources, and laying the foundation for real-time monitoring capabilities with methods like the CAM (Class Activation Map).

1. **FUTURE ASPECTS**

Our pioneering research in wildfire detection using Convolutional Neural Networks (CNNs) lays the groundwork for future advancements in the field. The following aspects represent promising avenues for further exploration and improvement:

1.Real-Time Monitoring with Class Activation Maps (CAM):

The integration of Class Activation Maps (CAM) stands as a key future development. By visualizing the regions of interest within satellite images, our model can evolve into a real-time monitoring system. This capability is crucial for prompt wildfire detection and rapid response, significantly mitigating potential damages.

2.Enhanced Spatial Resolution and Multispectral Data Fusion:

Elevating the spatial resolution of satellite imagery and exploring multispectral data fusion are essential steps for refining our model. This enhancement can provide a more detailed and comprehensive understanding of wildfire-prone areas, improving the accuracy and reliability of detection.

3.Machine Learning Ensemble Techniques:

Implementing ensemble techniques by combining multiple machine learning models can further enhance the robustness of our wildfire detection system. Ensemble methods, such as bagging or boosting, have the potential to improve overall performance and generalization.

4.Incorporation of Weather and Climate Data:

Integrating real-time weather and climate data into the model can contribute to a more holistic approach. By considering environmental conditions, wind patterns, and humidity levels, the system can adapt its predictions to dynamic and evolving wildfire scenarios.

5.User-Friendly Interface for Stakeholders:

Developing a user-friendly interface for stakeholders, including emergency responders and environmental agencies, is essential. Streamlining the accessibility of our model's insights ensures effective utilization and timely decision-making during wildfire events.

6.Collaboration with Satellite Technology Innovations:

Working together with satellite technology developments creates opportunities to take advantage of new sensors and platforms. Investigating cutting-edge technologies, like tiny satellites and high- [Writer]. (2022). Using the Himawari-8 satellite platform and deep learning, wildfire detection is achieved. Remote Sensing International, 43(13), 5040-5058. Frequency imaging, DOI: 10.1080/01431161.2022.2119110, has the potential to significantly improve the accuracy and reach of wildfire detection.

7.Continuous Dataset Augmentation and Model Training:

Continuous dataset augmentation and iterative model training are vital for staying ahead of evolving wildfire patterns. Regular updates to the dataset with new satellite imagery and ground truth annotations, coupled with ongoing model refinement, ensure sustained accuracy.

8.Global Implementation and Standardization:

Scaling our model for global implementation involves considering regional variations and diverse ecosystems. Standardizing the model's adaptability to different geographical contexts ensures its effectiveness in addressing the worldwide challenge of wildfires.

As we embark on this journey of innovation, these future aspects represent not only the next steps in refining our wildfire detection system but also contribute to the broader mission of building resilient and adaptive environmental monitoring solutions.

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