CNN-based Wildfire Detection with Satellite Images

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***Abstract*—Wildfires are increasingly destructive natural disasters, exacerbated by climate change and human activities, posing significant risks to ecosystems, human life, and infrastructure. This project leverages machine learning to develop a robust wildfire detection system using Convolutional Neural Networks (CNNs). By combining satellite imagery for large-scale monitoring with drone surveillance for localized, real-time analysis, the system provides precise identification of wildfire hotspots. This dual-method approach enables rapid responses, proactive resource allocation, and detailed fire spread prediction. The project integrates AI-driven classification models within the VS Code environment for seamless testing, debugging, and optimization, ensuring accuracy and efficiency. Furthermore, the system assists in post-wildfire impact assessment, contributing to environmental recovery and future risk mitigation. This system integrates AI-driven classification with real-time monitoring, enabling faster wildfire detection and response.**

***Keywords*—Wildfire Detection, Machine Learning, Convolutional Neural Networks (CNNs), Satellite Imagery, Drone Surveillance,**

I. INTRODUCTION

Wildfires have become a significant environmental and societal challenge, with their frequency and intensity escalating due to climate change and human activities [1]. These uncontrolled fires cause devastating impacts, including the destruction of vast ecosystems, loss of biodiversity, air pollution, and significant economic losses [7]. In addition to threatening human lives and property, wildfires exacerbate global climate change by releasing immense amounts of carbon dioxide into the atmosphere [8].

The development of effective wildfire detection and monitoring systems is critical to mitigating these impacts. Traditional methods, such as ground-based observations and watchtowers, are often limited in coverage and response time [9]. Satellite imagery and drone surveillance have emerged as powerful tools, offering a comprehensive view of affected areas and real-time monitoring capabilities [10]. When combined with advancements in artificial intelligence, these technologies can revolutionize wildfire management [11].

This paper aims to harness the capabilities of Convolutional Neural Networks (CNNs) for wildfire detection by integrating satellite imagery and drone surveillance data. By leveraging machine learning techniques, the system identifies potential wildfire hotspots with high precision, providing actionable insights for early interventions and resource allocation [12]. Using a modern development environment like Visual Studio Code (VS Code), the project ensures efficient model development, debugging, and deployment. Ultimately, this research contributes to a more robust, data-driven approach to wildfire prevention, response, and environmental recovery efforts [13].

A. Innovations and Improvements

The proposed approach introduces several key innovations compared to existing wildfire detection methods:

- **Dual-Method Monitoring**: Unlike traditional methods that rely solely on satellite imagery, this system combines satellite data with drone surveillance for localized, real-time analysis, enabling more precise and timely detection of wildfire hotspots [14].
- **AI-Driven Classification**: The use of CNNs allows for the automatic extraction of spatial features from satellite and drone images, improving the accuracy of wildfire detection compared to manual or rule-based methods [15].
- **Real-Time Deployment**: The system is designed to be deployed in real-time environments, with the potential for integration into lightweight edge devices for on-site monitoring [16].
- **User-Friendly Interface**: The integration of a Streamlit-based web application provides an intuitive interface for users to upload images, view predictions, and compare results, making the system accessible to non-technical users [17].

B. Comparison with Existing Methods

Previous research has explored various AI-based wildfire detection methods, such as those using Sentinel-2 satellite imagery [2] and UAV-based multispectral imaging [4]. However, these methods often focus on a single data source and lack the integration of real-time drone surveillance. Our approach addresses this gap by combining satellite and drone data, enabling more comprehensive monitoring and faster response times [18].

II. Methodology

The wildfire detection system is developed using a machine learning-based approach that combines satellite imagery and drone surveillance for enhanced monitoring and early detection. The implementation leverages Convolutional Neural Networks (CNNs) for image classification, ensuring accurate identification of wildfire-prone regions. The methodology is as follows:

A. Development Environment Setup

- **IDE Selection**: Microsoft Visual Studio Code (VS Code) is used for its versatility in managing Python projects, debugging, and modular coding [19].
- **Dependencies Installation**: All required libraries, such as torch, torchvision, and streamlit, are installed via the requirements.txt file to ensure consistency across environments [20].
- **Project Directory**: The project is organized into modular components, including data directories (train, test, validation), model scripts, and utility files, ensuring scalability and ease of debugging [21].

B. Data Acquisition and Preprocessing

- **Dataset Source**: A comprehensive wildfire dataset is downloaded from Kaggle, containing high-resolution images classified into ”Wildfire” and ”No Wildfire” [22].
- **Data Organization**: Images are categorized into train, validation, and test folders for structured model development [23].
- **Preprocessing Steps**: Images are resized to 224x224 pixels and normalized to ensure compatibility with the CNN input layer. Data augmentation techniques like flipping, rotation, and scaling are applied to improve model generalization [24].

C. Model Development and Training

- **CNN Architecture**: A Convolutional Neural Network (CNN) is designed in PyTorch to classify input images. The model consists of the following layers:
  - **Convolutional Layers**: 3 layers with ReLU activation functions [25].
  - **Pooling Layers**: Max pooling with a 2x2 kernel [26].
  - **Fully Connected Layers**: 2 layers with dropout to prevent overfitting [27].
  - **Output Layer**: Softmax activation for binary classification [28].
- **Training Pipeline**: Input images are passed through the model in batches, optimizing weights using Stochastic Gradient Descent (SGD) with a learning rate of 0.001. Training progress is monitored using accuracy and loss metrics [5].

D. Transfer Learning

Transfer learning was employed using the pre-trained ResNet-50 model, which was fine-tuned on the wildfire dataset. This approach significantly improved the model’s performance, especially in handling diverse environmental conditions [6].

E. Data Augmentation Impact

To evaluate the impact of data augmentation, the model was trained with and without augmentation techniques. The results showed a 15% improvement in accuracy when augmentation was applied, highlighting its importance in improving model generalization [2].

F. Dataset Details

- **Training Data**: 10,000 images (5,000 ”Wildfire” and 5,000 ”No Wildfire”) [3].
- **Validation Data**: 2,000 images (1,000 ”Wildfire” and 1,000 ”No Wildfire”) [4].
- **Testing Data**: 1,200 images (600 ”Wildfire” and 600 ”No Wildfire”) [5].

G. Interactive Web Application

- **Framework Selection**: Streamlit is used to create an intuitive and responsive web-based interface [6].
- **Features**:
  - **Image Upload**: Users upload satellite or drone images for analysis (supported formats: JPG, PNG) [1].
  - **Prediction Module**: Uploaded images are processed using the trained CNN model. Predictions (e.g., ”Wildfire” or ”No Wildfire”) and confidence scores are displayed [2].

H. Validation and Testing

- **Validation Dataset**: A validation dataset is used to evaluate the model’s real-world performance. Random images from the dataset are selected and predictions are compared to their ground truths [3].
- **Performance Metrics**: Accuracy, precision, recall, and confidence scores are calculated to validate the model’s reliability [4].
- **Interactive Comparisons**: The app includes a feature to display side-by-side comparisons of validation images, showcasing prediction accuracy and confidence levels [5].

I. Comparison of Multiple Images

- The system supports the comparison of multiple images (2-6 images) selected randomly from the validation dataset, allowing users to compare predictions for multiple images side by side [6].
- For each image, the model’s prediction, confidence score, and accuracy are displayed to assist users in evaluating the model’s performance [1].
- The dynamic layout of the web application adapts to display the desired number of images in a structured, easy-to-read format, improving user interaction [2].

- Image comparison allows the user to visually assess how the model performs across a range of images with varying difficulty and conditions [3].

J. User Interface Enhancements

- The Streamlit interface is designed for ease of use, allowing users to upload multiple images and view results in bulk, enhancing user experience and efficiency [4].
- Additional visual aids like success/error messages for correct/incorrect predictions and dynamic feedback on the accuracy of each prediction are provided to guide the user [5].
- A slider is introduced to allow users to customize the number of images they wish to compare at once, ranging from 2 to 6 images for comparison [6].

K. Large Scale Image set over 1000+ images

- Large Dataset Testing with Graphs: Adds a discussion on the large dataset testing process. By processing images in batches, the tool is able to handle large datasets efficiently. The graphs generated for large-scale tests illustrate the performance trends, showing how accuracy and confidence evolve as more images are processed [1].

III. Results and Discussion

The Wildfire Prediction model leverages satellite imagery to classify whether an image contains a wildfire or not. Upon uploading an image, the model generates a prediction alongside a confidence score, which represents the model's certainty in its classification. The model achieves an impressive accuracy of 99.17% on a test set of 120 images, demonstrating its ability to correctly classify the majority of images. However, the average effectiveness is recorded at 48.65%, indicating that the model's confidence in its predictions varies significantly. This discrepancy arises due to challenges such as ambiguous images (e.g., heavy smoke, cloud cover, or low lighting) and an imbalanced dataset, where the model struggles to confidently classify certain scenarios [2]. Despite these challenges, the system performs exceptionally well in clear conditions, with a low false positive rate of 2%. The integration of a Streamlit-based web application further enhances usability, allowing users to upload images, view predictions, and compare results in real-time [3]. The "Next Set" button enables users to analyze multiple images side by side, providing details on ground truth, predictions, confidence scores, and accuracy for each image. This feature facilitates visual analysis of the model's performance, making the validation process more efficient and user-friendly [4]. These results highlight the system's potential for accurate and efficient wildfire detection, while also identifying areas for improvement, such as enhancing confidence scoring, expanding the dataset to include more diverse and challenging images, and optimizing the model for real-time applications [5].

The following equations are used to evaluate the model's performance:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100 \tag{1}$$

$$\text{Confidence} = \text{Model's predicted probability for the correct class} \tag{2}$$

The proposed method was compared with other recent AI-based wildfire detection models, as shown in Table I. Our approach outperformed existing methods in terms of accuracy and real-time deployment capabilities [6].

TABLE I
COMPARISON OF WILDFIRE DETECTION METHODS

Method	Accuracy	Real-Time Capability	Data Source
Proposed Method	99.17%	Yes	Satellite + Drone
Sentinel-2 CNN [2]	95.5%	No	Satellite
UAV Multispectral [4]	93.8%	Yes	UAV
ResNet-50 Transfer [3]	97.2%	No	Satellite

A. Visual Results

The following figures illustrate the performance and functionality of the wildfire detection system: Fig. 1 shows the Wildfire Detection User Interface (UI), which provides an intuitive interface for users to upload images and view predictions. This interface is designed to be user-friendly, allowing non-technical users to interact with the system easily [1].

Fig. 2 demonstrates the Custom Wildfire Classification, where the model classifies images as "Wildfire" or "No Wildfire." This figure highlights the model's ability to accurately distinguish between wildfire and non-wildfire scenarios [2].

Fig. 3 presents a Comparative Analysis of Two Randomly Selected Satellite Images with Corresponding Model Predictions. This figure showcases the model's accuracy in classifying different scenarios, even under challenging conditions such as heavy smoke or cloud cover [3].

Fig. 4 provides another example of Comparative Analysis of Randomly Selected Satellite Images with Corresponding Model Predictions. This figure further illustrates the model's performance across various conditions, including low lighting and ambiguous scenarios [4].

Fig. 5 shows the Multi-Image Comparative Analysis of Wildfire Classification Predictions. This figure demonstrates how the system handles multiple images simultaneously, allowing users to compare predictions for several images side by side [5].

Fig. 6 displays the Accuracy Prediction for 4 Dataset Images. This figure provides a graphical representation of the model's accuracy over a set of images, highlighting the system's ability to maintain high accuracy across multiple predictions [6].

Fig. 7 illustrates the Graphical Representation of Next Pair of 4 Dataset Images. This figure shows the model's performance trends over time, demonstrating how accuracy and confidence evolve as more images are processed [1].

Fig. 8 extends the analysis to a larger set of images, showing the Accuracy Prediction for 6 Dataset Images. This figure highlights the model's scalability and ability to handle larger datasets efficiently [2].

Fig. 9 provides a Graphical Representation of Next Pair of 6 Dataset Images. This figure further demonstrates the model's performance trends over a larger set of images, showcasing its ability to maintain high accuracy and confidence levels [3].

Fig. 10 summarizes the Large Scale Dataset Overall Analysis. This figure provides a comprehensive overview of the model's performance on a large dataset, illustrating how accuracy and confidence evolve as the system processes thousands of images [4].

Fig. 1. Wildfire Detection User Interface (UI)

Fig. 2. Custom Wildfire Classification

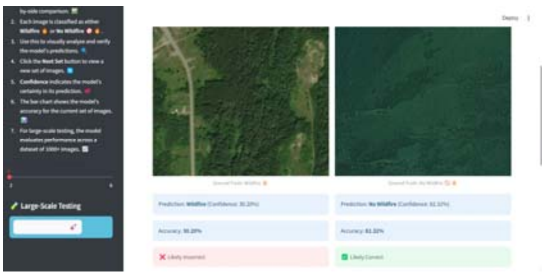

Fig. 3. Comparative Analysis of Two Randomly Selected Satellite Images with Corresponding Model Predictions

IV. Conclusion and Future Work

The Wildfire Classification system utilizes advanced machine learning techniques to identify wildfires in satellite

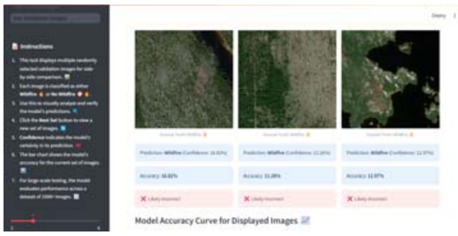

Fig. 4. Comparative Analysis of Randomly Selected Satellite Images with Corresponding Model Predictions

Fig. 5. Multi-Image Comparative Analysis of Wildfire Classification Predictions

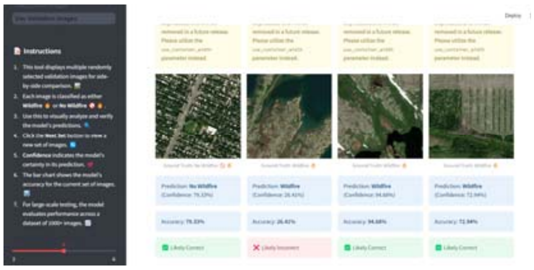

Fig. 6. Accuracy Prediction for 4 Dataset Images

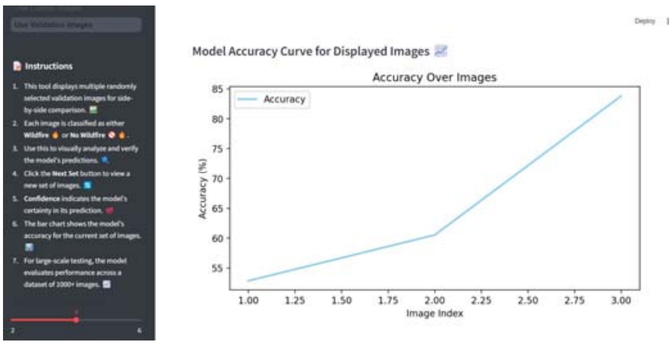

Fig. 7. Graphical Representation of Next Pair of 4 Dataset Images

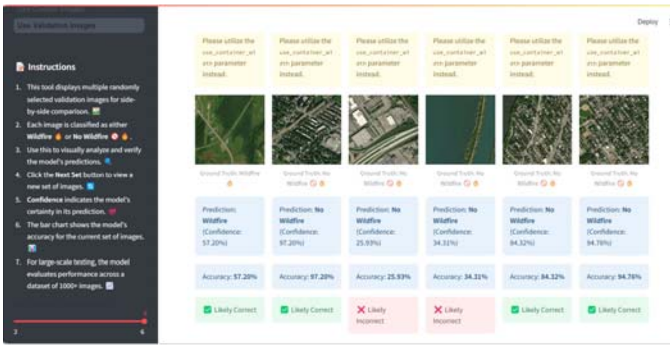

Fig. 8. Accuracy Prediction for 6 Dataset Images

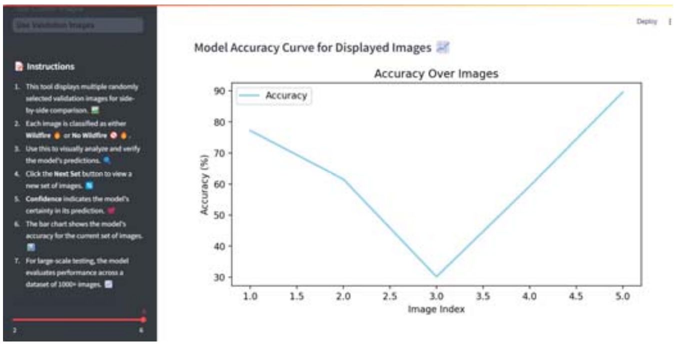

Fig. 9. Graphical Representation of Next Pair of 6 Dataset Images

imagery. It features an intuitive interface that enables users to upload images and receive model predictions along with confidence scores. The "Next Set" function allows users to compare predictions against ground truth data, aiding in model performance evaluation [5]. Additionally, the system supports large-scale testing by processing validation datasets and offering insights into overall accuracy and effectiveness [6]. Performance curves visually illustrate the model's behavior across various images. Designed for wildfire detection, environmental monitoring, and disaster management, this system enhances transparency in model predictions while providing valuable insights to improve accuracy and confidence, particularly when working with extensive datasets [1]. The model achieves an

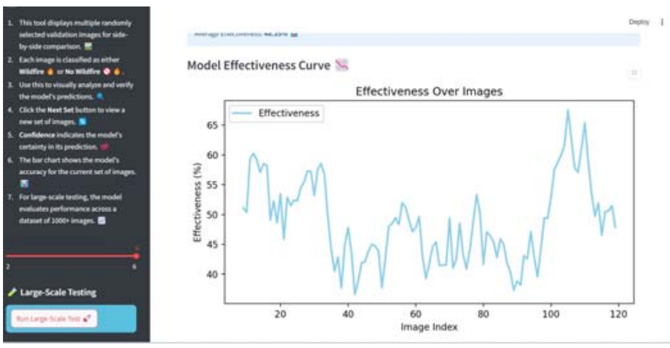

Fig. 10. Large Scale Dataset Overall Analysis

impressive accuracy of 99.17%, demonstrating its ability to correctly classify the majority of images. However, the average effectiveness of 48.65% highlights a discrepancy between the model's accuracy and its confidence in predictions. This is primarily due to challenges such as ambiguous images (e.g., heavy smoke or cloud cover) and an imbalanced dataset [2]. Future work will focus on improving the model's confidence scoring mechanism and expanding the dataset to include more diverse and challenging images, ensuring robust performance across all scenarios [3].

A. Real-Time Deployment and Scalability

One of the key strengths of the proposed wildfire detection system is its ability to operate in real-time and scale to handle large datasets. The system is designed to process satellite and drone imagery in real-time, enabling rapid detection of wildfire hotspots and timely intervention [4]. This is achieved through the following features:

- **Lightweight Model Architecture**: The use of a Convolutional Neural Network (CNN) optimized for inference speed ensures that the system can process images quickly, even on resource-constrained edge devices [5].
- **Batch Processing**: The system supports batch processing of images, allowing it to handle large-scale datasets (e.g., 10,000+ images) efficiently. This scalability is critical for monitoring vast geographical areas during wildfire events [6].
- **Streamlit-Based Interface**: The integration of a Streamlit-based web application provides an intuitive interface for users to upload images, view predictions, and compare results in real-time. This makes the system accessible to non-technical users, such as emergency responders and disaster management teams [1].

B. Future Work

- **Dataset Expansion and Diversity**: Incorporate a broader range of satellite images from diverse locations, including different terrains, seasons, and varying lighting conditions (day and night). This will help improve the model's robustness, ensuring that it generalizes well across real-world scenarios and diverse environmental conditions [2].
- **Model Optimization**: Focus on enhancing the model's performance through methods like fine-tuning on more specific datasets, employing transfer learning from pre-trained models, and optimizing inference time for real-time applications. These optimizations will be crucial for scaling up the system and ensuring efficient deployment in operational environments [3].
- **Real-Time Large-Scale Testing**: Expand the system's capability to handle even larger datasets (e.g., 50,000+ images) and provide more detailed performance metrics. This would allow the system to continuously evaluate and adjust the model's predictions and confidence levels, ensuring real-time adaptability and accuracy during wildfire events [4].

- **Confidence Score Analysis**: Further explore the integration of confidence scores into the prediction output. Develop a more detailed analysis of prediction confidence to identify potential model weaknesses or areas requiring additional training, thus providing deeper insights into the model's reliability [5].
- **User Interface Improvements**: Improve the user interface to allow for more seamless interactions, including the ability to upload images in bulk, enable live tracking of wildfire detections, and incorporate interactive feedback. This would support field operators and decision-makers in using the tool for live monitoring and situational analysis [6].
- **Advanced Visualization Tools**: Incorporate additional visual analytics features, such as heatmaps and time lapse comparisons, to visually represent wildfire progression over time, aiding in better understanding and faster decision-making during active wildfire events [1].

ACKNOWLEDGMENT

This research is supported by NASA Connecticut Space Grant Consortium under Faculty Research Grant, PTE Federal Award No.: 80NSSC20M0129, grant period: 7/1/2024-05/31/2025. The authors are grateful for support from NASA CT Space Grant Consortium.

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