



SMART WILDFIRE DETECTION SYSTEM USING IMAGE PROCESSING AND REDUCED DEEP CNN MODELS

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ABSTRACT

Forest wildfires pose a serious risk to ecosystems and human safety, making early and accurate detection essential. Machine Vision, which integrates artificial intelligence with digital image processing, provides an effective solution to this challenge. This paper presents a comprehensive experimental study that combines image processing, machine learning, and deep learning techniques for wildfire detection, aiming to develop a system that is both easy to understand for educational purposes and effective for practical applications. A modified Reduce-VGGNet model is proposed for classifying wildfire and non-wildfire images, with a workflow that includes data collection, preprocessing, model training, and performance evaluation. The study also addresses key challenges such as varying lighting conditions, smoke patterns, and background similarities, while demonstrating how deep learning improves the identification of fire and smoke compared to traditional methods. By enhancing detection accuracy and reducing false alarms, this work highlights the potential of Machine Vision in enabling faster and more reliable wildfire detection. Additionally, the model is designed to be computationally efficient, making it suitable for real-time implementation in resource-constrained environments. The experimental results validate the robustness and consistency of the proposed approach across different scenarios. The system can also be integrated with surveillance and monitoring platforms for continuous observation of forest regions. Overall, this paper contributes to the development of intelligent and scalable wildfire detection systems for future applications.

Keywords: Machine Vision, Wildfire Detection, Deep Learning, Image Processing, Reduce-VGGNet

I. INTRODUCTION

Forest wildfires represent one of the most severe environmental hazards, posing serious threats to ecosystems, wildlife, and human communities. Conventional detection approaches, including manual surveillance and satellite-based monitoring, often suffer from delays, high operational costs, and limited real-time effectiveness. With the growing intensity and frequency of wildfire incidents, there is an urgent need for automated and intelligent systems capable of providing early warnings. Machine Vision, which integrates artificial intelligence, computer vision, and image processing techniques, presents a promising solution to this problem. In particular, deep learning methods have demonstrated strong capabilities in image recognition and pattern analysis, making them highly suitable for detecting fire and smoke. The adoption of these advanced technologies can significantly improve detection precision, minimize false alerts, and enable quicker response to wildfire events. Furthermore, such systems can be designed to operate continuously with minimal human intervention, enhancing monitoring efficiency. They can also be integrated with real-time alert systems to support rapid decision-making by authorities. Overall, these advancements contribute to building more resilient and proactive wildfire management strategies.



Figure.1: Visual Representation of Wildfire in Dense Forest Region

Conventional wildfire detection methods, including satellite imaging and sensor-based systems, often face challenges such as delayed response, restricted coverage, and high implementation costs. To address these issues, deep learning-based vision systems have emerged as powerful alternatives, offering enhanced capabilities in image recognition, pattern analysis, and automated decision-making. By utilizing Convolutional Neural Networks (CNNs) and advanced architectures, machine vision systems can efficiently detect smoke, flames, and heat-related anomalies from images or video streams in real time. Furthermore, models such as YOLO, ResNet, and Efficient Net have shown remarkable success in object detection and classification tasks. In this context, the present work proposes an experimental framework that integrates machine vision techniques using a modified Reduce-VGGNet model for effective wildfire detection. The objective is to bridge academic learning with practical implementation, providing a system that is both educationally valuable and applicable to real-world wildfire monitoring and management.

II. LITERATURE REVIEW

Author(s) & Year	Method/Model Used	Key Contribution	Limitations
Abhila Anju O., Jayasree M., et al. (2025)	CNN Variants	Comparative study showing improved accuracy using deep learning models for wildfire detection	High computational complexity
Peer Mohamed Appa M. A. Y., Jones A. E., et al. (2025)	FireNet (CNN)	Effective wildfire classification using satellite imagery	Limited performance in complex environments
Elias Corbin, Linnea Weller (2025)	YOLO-based Framework	Efficient wildfire detection in remote sensing images	May produce false positives in smoke-like patterns
Pandu Wicaksono, Rezki Yunanda, et al. (2024)	YOLOv8	Real-time wildfire detection with high precision and recall	Requires large annotated datasets
Malladi L. A., et al. (2025)	VGG16 CNN	High accuracy in wildfire classification tasks	Not optimized for real-time use
Jonnalagadda A. V., et al. (2024)	VGG-based CNN	Comparison of custom and transfer learning models	Model complexity

The literature highlights that deep learning models, particularly CNN-based architectures such as VGG, YOLO, and FireNet, have significantly improved the accuracy and efficiency of wildfire detection systems compared to traditional methods. These approaches enable real-time detection and robust classification of fire and smoke patterns from images and remote sensing data.

III EXISTED SYSTEM

In the existing system, the project relies on conventional methods such as manual observation, satellite imagery analysis, and basic image processing techniques for wildfire detection. These methods, while commonly employed, may suffer from limitations in efficiency and accuracy. Furthermore, they incorporate algorithms such as thresholding, edge detection, and color segmentation to process and analyze the imagery data. Existing wildfire detection systems are mainly based on traditional monitoring techniques and basic image processing methods. These systems rely on human observation, satellite monitoring, or conventional algorithms to detect fire events. The existing system performs wildfire detection using techniques such as manual surveillance, satellite imagery analysis, and simple image processing algorithms. These approaches attempt to identify fire by analyzing visual characteristics such as colour intensity and smoke patterns. However, these traditional methods often struggle to provide reliable results due to environmental variations and complex forest conditions.

IV PROPOSED SYSTEM

The proposed system integrates digital image processing, machine learning, and deep learning techniques to enhance wildfire detection accuracy and efficiency. It includes the Reduce- VGGnet algorithm for precise wildfire image classification. Leveraging advancements in deep learning, this algorithm significantly improves detection accuracy. The proposed system consists of several stages including data collection, image preprocessing, model training, and prediction. Each stage plays an

important role in ensuring accurate wildfire detection.

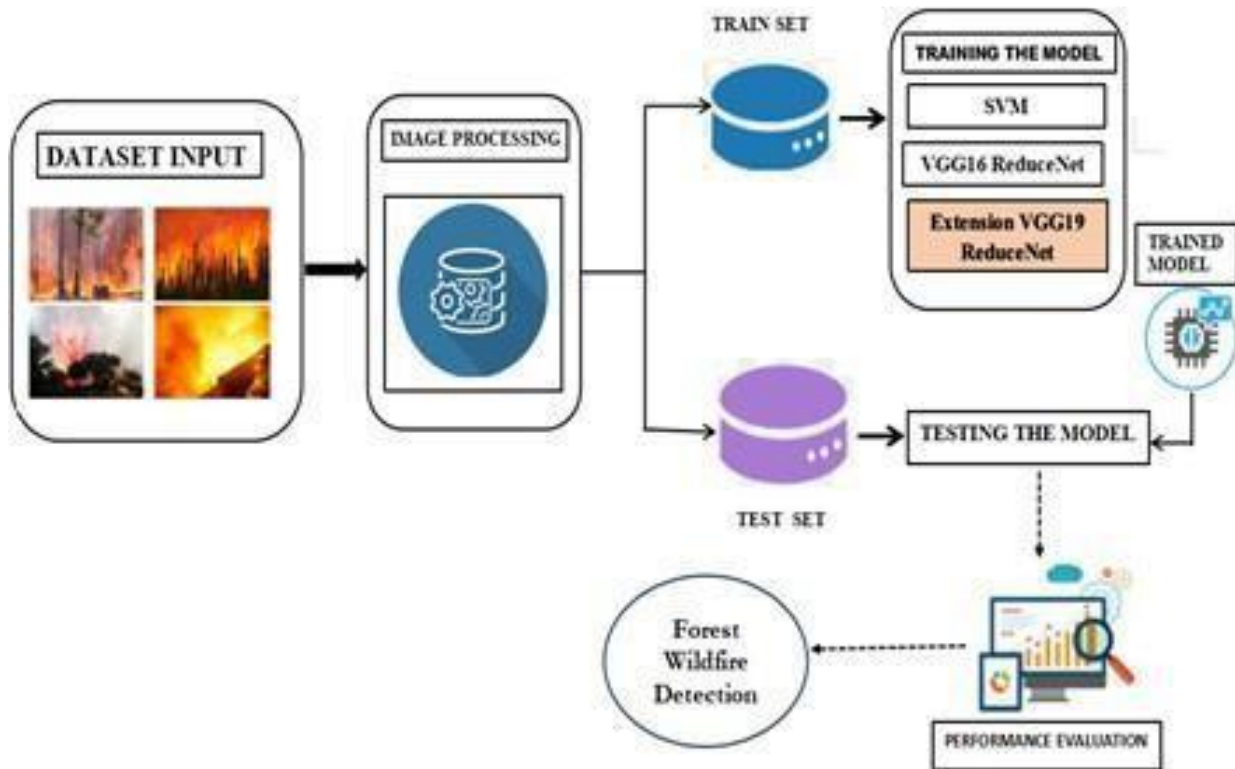
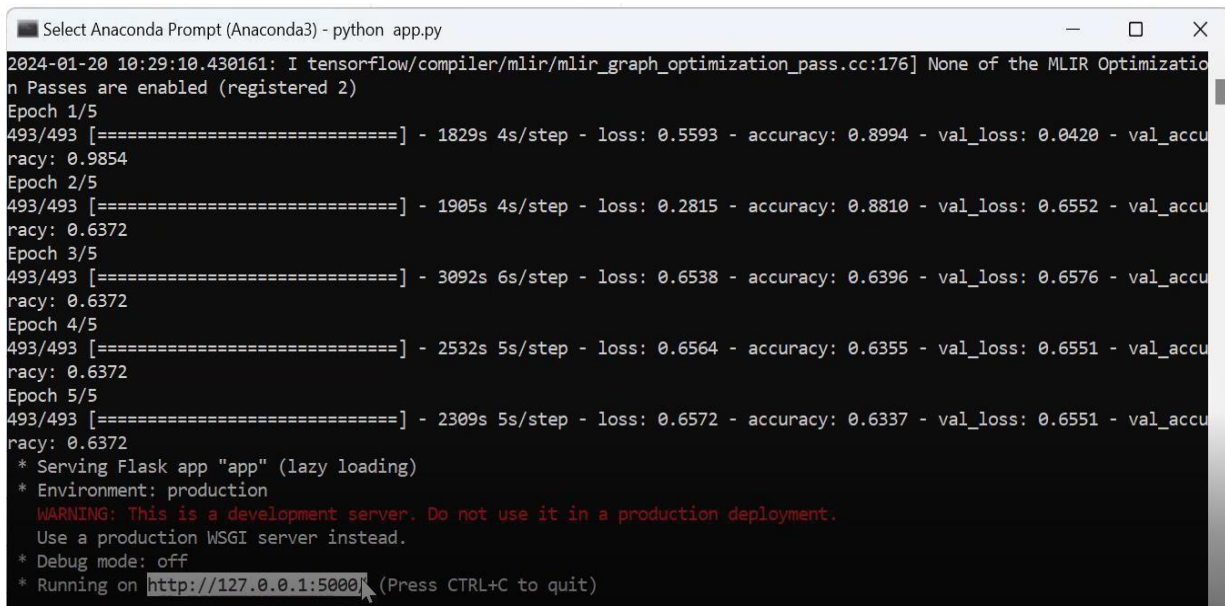


Figure 2: Proposed Framework for Forest Wildfire Detection Using Deep Learning Models

Figure 2 shows the overall workflow of the proposed forest wildfire detection system. It begins with the dataset input, which consists of wildfire and non-wildfire images collected for analysis. The images then undergo preprocessing and image processing to enhance quality and extract important features. After processing, the dataset is divided into training and testing sets for model development. The training phase involves machine learning and deep learning models such as SVM, VGG16, and an extended VGG19 Reduce Net architecture. These models learn patterns and features associated with wildfire occurrences. The trained model is then evaluated using the test dataset to assess its performance. Finally, the system provides accurate forest wildfire detection results along with performance evaluation metrics, ensuring reliable classification of fire and non-fire scenarios. It also improves decision-making by providing timely detection and analysis of wildfire risks. The framework supports efficient monitoring and can be further enhanced for real-time wildfire surveillance applications.

V RESULTS



```
Select Anaconda Prompt (Anaconda3) - python app.py
2024-01-20 10:29:10.430161: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:176] None of the MLIR Optimization
n Passes are enabled (registered 2)
Epoch 1/5
493/493 [=====] - 1829s 4s/step - loss: 0.5593 - accuracy: 0.8994 - val_loss: 0.0420 - val_accu
racy: 0.9854
Epoch 2/5
493/493 [=====] - 1905s 4s/step - loss: 0.2815 - accuracy: 0.8810 - val_loss: 0.6552 - val_accu
racy: 0.6372
Epoch 3/5
493/493 [=====] - 3092s 6s/step - loss: 0.6538 - accuracy: 0.6396 - val_loss: 0.6576 - val_accu
racy: 0.6372
Epoch 4/5
493/493 [=====] - 2532s 5s/step - loss: 0.6564 - accuracy: 0.6355 - val_loss: 0.6551 - val_accu
racy: 0.6372
Epoch 5/5
493/493 [=====] - 2309s 5s/step - loss: 0.6572 - accuracy: 0.6337 - val_loss: 0.6551 - val_accu
racy: 0.6372
* Serving Flask app "app" (lazy loading)
* Environment: production
WARNING: This is a development server. Do not use it in a production deployment.
Use a production WSGI server instead.
* Debug mode: off
* Running on http://127.0.0.1:5000 (Press CTRL+C to quit)
```

Figure 3: Training and Validation Performance Output of the Proposed Wildfire Detection Model in Anaconda Prompt

Figure 3 shows the training and validation performance output of the proposed wildfire detection model executed in the Anaconda Prompt environment. It displays epoch-wise results including loss and accuracy values for both training and validation phases. The gradual changes in these metrics indicate how well the model is learning and generalizing over iterations. Additionally, the output confirms successful deployment of the model using a Flask application running on a local server.

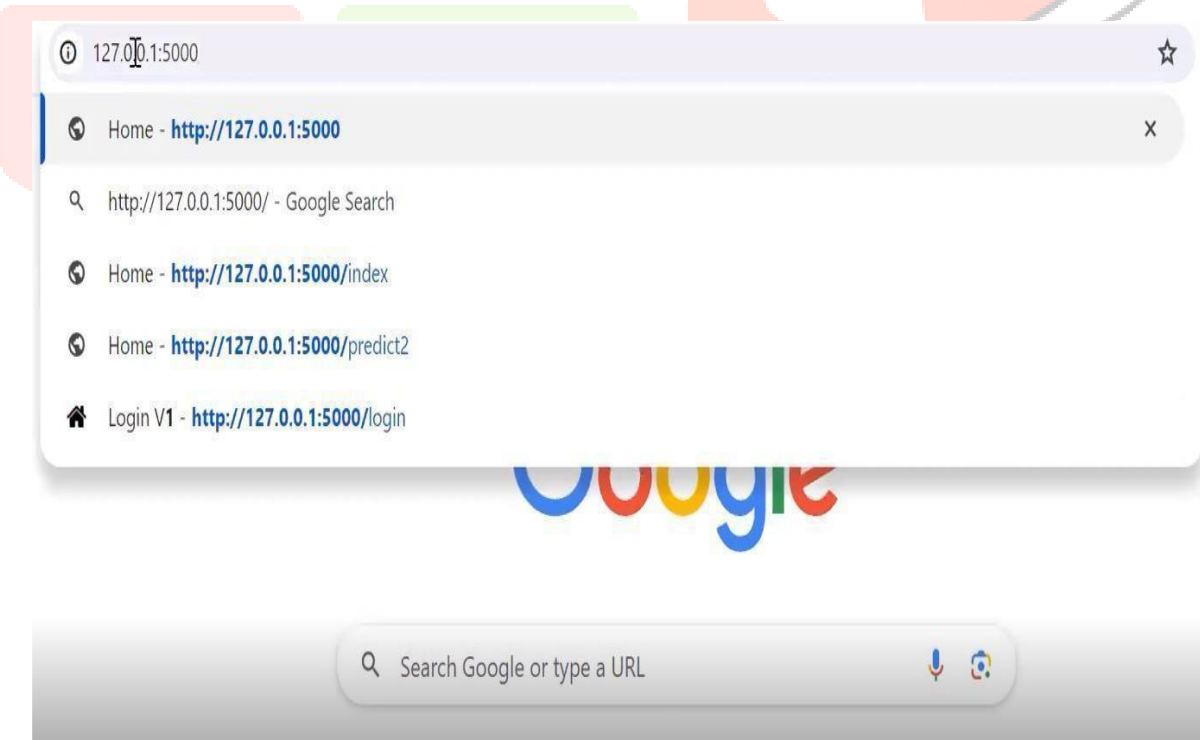


Figure 4: Local host Web Interface Access for Wildfire Detection System Using Flask Server

Figure 4 shows the local host web interface access of the proposed wildfire detection system using a Flask server. It displays the browser navigation with URLs such as home, index, predict, and login pages. The interface allows users to interact with the deployed model through different endpoints. This setup confirms successful integration of the model with a web-based application for user access.



Figure 5: Dashboard Interface of Deep Learning-Based Forest Wildfire Detection System

Figure 5 shows the dashboard interface of the deep learning-based forest wildfire detection system. It presents the main homepage with a clear title describing the application and its purpose in wildfire detection using machine vision. The interface includes navigation options such as home and signup for user interaction. This dashboard provides an entry point for users to access and utilize the system’s features efficiently.

Figure 6: User Registration Interface for Forest Wildfire Detection System

Figure 6 shows the user registration interface of the forest wildfire detection system. It includes input fields such as username, name, email, mobile number, and password for creating a new account. The form allows users to securely register and access the system’s features. This interface ensures proper user management and authentication within the application.

Log In

username
admin

password
.....

Remember me [Forgot Password](#)

Log In

Register here! [Sign Up](#)

Figure 7: Authentication Module of Smart Wildfire Detection System

Figure 7 shows Authentication Module of Smart Wildfire Detection System, which provides a secure login interface for users to access the application. It includes fields for username and password along with options such as “Remember Me” and password recovery for enhanced usability. This module ensures that only authorized users can interact with the wildfire detection system and its functionalities.

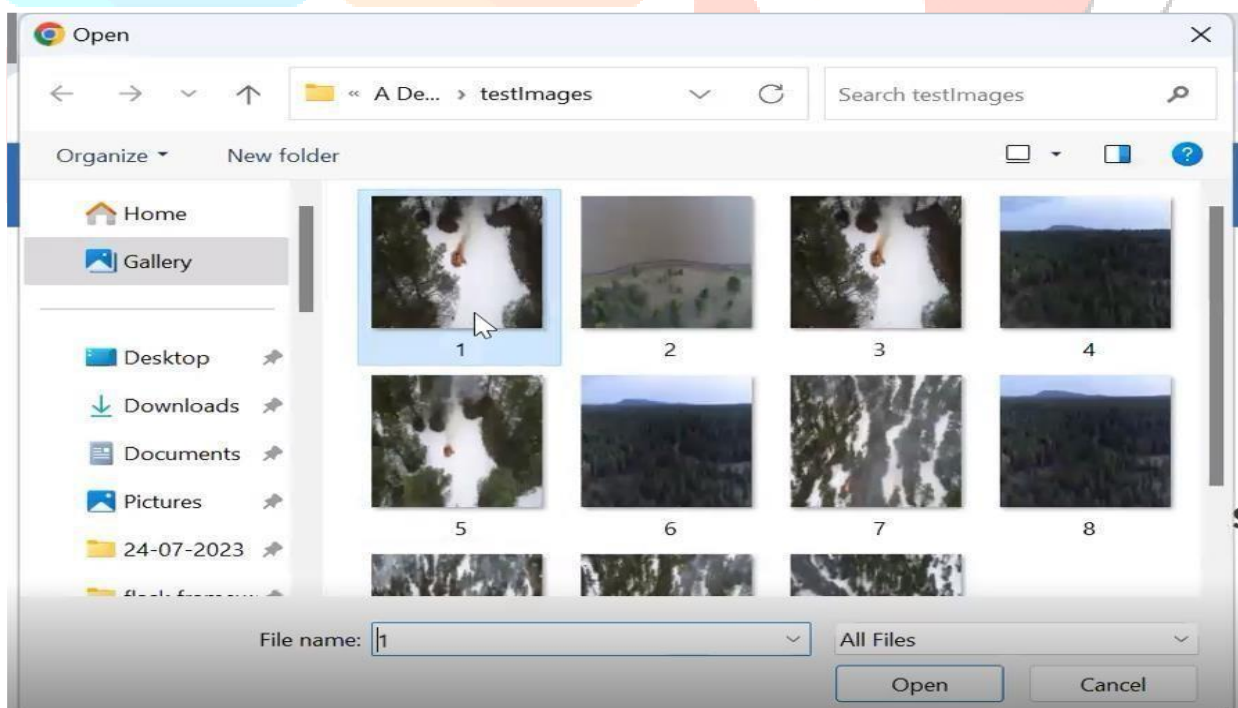


Figure 8: Dataset Image Selection Interface for Forest Wildfire Detection System

Figure 8 shows Dataset Image Selection Interface for Wildfire Detection System, where users can browse and choose test images from the dataset for analysis. The interface displays multiple image samples, enabling easy selection of input data for processing. This step allows the system to load images that will be further analyzed using image processing and deep CNN models for wildfire detection.



Figure 9: Wildfire Detection Output with Identified Fire Regions

Figure 9 shows Wildfire Detection Output with Identified Fire Regions, where the system highlights detected fire areas using bounding boxes on the input image. The prediction output indicates the presence of fire through labeled regions, enabling visual interpretation of detection results. This demonstrates the effectiveness of the reduced deep CNN model in accurately identifying wildfire-affected areas.



Figure 10: Detected Fire Regions in Forest Image Using CNN Model

Figure 10 shows Detected Fire Regions in Forest Image Using CNN Model, where the system identifies and marks fire-affected areas using bounding boxes. The prediction output clearly indicates fire presence within the selected regions of the image. This result highlights the model's capability to accurately localize wildfire instances in complex forest environments.

VI PERFORMANCE EVALUATION

Algorithm Name	Precision	Recall	Accuracy	F1-Score
Existing SVM	99.765569	99.71384 6	99.7587 30	99.739609
Propose VGG16 Reduce Net	99.808233	99.80823 3	99.822222	99.808233
Extension VGG19 Reduce Net	99.733381	99.71864 7	99.746032	99.726006

Table.1: Performance Metrics of Wildfire Detection Algorithms

Table 1 shows the performance comparison of existing SVM and proposed reduced deep CNN models for wildfire detection. The evaluation is carried out using key metrics such as precision, recall, accuracy, and F1-score. The existing SVM model demonstrates high performance with precision and recall values close to 99.7%. However, the proposed VGG16 Reduced Net achieves slightly higher accuracy and balanced performance across all metrics. It records the highest accuracy among the compared models, indicating better classification capability. The Extension VGG19 Reduced Net also performs competitively but shows slightly lower values compared to VGG16. Overall, the reduced CNN models outperform the traditional SVM approach in most evaluation aspects. The results highlight the effectiveness of deep learning techniques for accurate wildfire detection. This comparison validates the proposed model's superiority in handling complex image-based detection tasks.

VII CONCLUSION

This paper concludes with the success of Reduce-VGG-Net, a modified VGG16 algorithm, in achieving superior accuracy for forest fire detection compared to existing methods. The integration of spatial and temporal features into Reduce-VGGNet is highlighted as a crucial enhancement, improving the algorithm's ability to detect fire accurately based on both foreground features and changes in frame sequences. The two-model approach, combining fire classification and region-based annotation through Reduce-VGG-Net, is acknowledged for its success in providing a comprehensive solution for both static and dynamic data without manual intervention. Comparative evaluations consistently show the proposed algorithm's superiority, demonstrated through metrics like accuracy, precision, recall, and F-score, reinforcing its effectiveness. Utilizing the VGG19 Reduce-Net model as an extension achieves 99% accuracy in wildfire region detection. Integration of a user-friendly Flask interface with secure authentication enhances the testing experience and data input process.

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