Enhancing Wildfire & Smoke Detection with Deep Learning: A Fast AI-Based Approach

Aparna Reghu
Dept. of CSE
College of Engineering Kidangoor Kottayam, Kerala, India aparnareghu55@gmail.com

Ciya Joe
Dept. of CSE
College of Engineering Kidangoor
Kottayam, Kerala, India
ritaciya2003@gmail.com

Deepa Mariam Thomas
Dept. of CSE
College of Engineering Kidangoor
Kottayam, Kerala, India
deepamariamt2003@gmail.com

Geethu K
Dept. of CSE
College of Engineering Kidangoor
Kottayam, Kerala, India
geethuk520@gmail.com

Marion Punnen Kurien
Dept. of CSE
College of Engineering Kidangoor
Kottayam, Kerala, India
marionpunnen2004@gmail.com

Rekha K. S.
Dept. of CSE
College of Engineering Kidangoor Kottayam, Kerala, India rekhaks@ce-kgr.org

***Abstract*— Wildfires are a significant environmental threat, causing extensive damage to ecosystems, infrastructure, and human life. Traditional detection methods, such as satellite imaging and sensor-based systems, often suffer from delays, high costs, and limited coverage, making early intervention challenging. This project proposes a deep learning-based wildfire, smoke, and fog detection system using FastAI to enable real-time and accurate identification of hazardous conditions. The model is built on a convolutional neural network (CNN) and trained using a labeled dataset containing images of fire, smoke, fog, and non-hazardous scenarios. To improve generalization, data preprocessing techniques such as data augmentation and normalization were applied. The model leverages transfer learning to achieve higher accuracy with reduced computational resources, making it feasible for real-world deployment. Performance evaluation was conducted using accuracy, precision, recall, and F1-score for fire, smoke, and fog classification, demonstrating reliable detection capabilities. The system can be integrated with real-time surveillance sources such as CCTV cameras, drones, and satellite feeds, allowing early detection and rapid response to potential wildfire and visibility hazards caused by fog. Compared to conventional methods, this approach offers a cost-effective, scalable, and automated solution for environmental monitoring. By leveraging deep learning and real-time image analysis, the proposed system enhances disaster preparedness and prevention efforts. Future work will focus on expanding the dataset, optimizing the model for real-time processing, and integrating it with cloud-based deployment for large-scale applications. This study highlights the potential of AI-driven fire, smoke, and fog detection in improving disaster response, visibility monitoring, and wildfire mitigation.**

***Index Terms*— Wildfire Detection, Smoke Detection, Fog Detection, Convolutional Neural Networks (CNNs), Real-Time Fire Monitoring**

I. INTRODUCTION

Wildfires pose a severe environmental and economic threat, causing large-scale destruction of forests, biodiversity loss, and air pollution. The increasing frequency and intensity of wildfires in recent years have been largely attributed to climate change, deforestation, and prolonged droughts. In addition to fires, smoke and fog reduce visibility, creating hazardous conditions for transportation, aviation, and public safety. Early detection of such incidents is crucial for preventing widespread destruction, improving emergency response, and minimizing economic losses. However, traditional wildfire detection methods, such as satellite imaging, thermal sensors, and human surveillance, suffer from delayed response times, high operational costs, and scalability limitations. These challenges highlight the need for real-time, automated, and cost-effective fire, smoke, and fog detection systems.

Recent advancements in artificial intelligence (AI) and deep learning have introduced novel methods for real-time image-based wildfire detection. AI-driven models can analyze large-scale image datasets, detect fire and smoke patterns with high accuracy, and significantly reduce false alarms. Among various deep learning approaches, Convolutional Neural Networks (CNNs) have demonstrated state-of-the-art performance in image classification tasks, making them an ideal choice for wildfire and smoke detection. However, deep learning models typically require large labeled datasets and high computational power, making their deployment challenging in resource-constrained environments such as edge devices and drones.

This project proposes an AI-driven wildfire, smoke, and fog detection system using FastAI, an optimized deep learning framework built on PyTorch. FastAI simplifies model training and leverages transfer learning to achieve high accuracy with minimal computational cost. The proposed system is designed to analyze images from CCTV cameras, drones, and satellite feeds, ensuring real-time detection and rapid response. The CNN-based model is trained on a diverse dataset containing fire, smoke, fog, and non-fire images, with preprocessing techniques such as data augmentation and normalization applied to improve model generalization. The system is evaluated using accuracy, precision, recall, and F1-score, demonstrating its effectiveness in real-world deployment.

Compared to traditional fire monitoring techniques, this AI-driven approach offers a cost-effective, scalable, and automated solution for wildfire prevention and hazard monitoring. By integrating real-time image processing with deep learning, the system enhances disaster preparedness, reduces detection delays, and minimizes false alarms. Future improvements will focus on enhancing model robustness, integrating cloud-based deployment for large-scale monitoring, and optimizing real-time processing on edge devices. This research contributes to the advancement of AI-based wildfire detection and provides a practical solution for mitigating fire-related disasters and visibility hazards caused by smoke and fog.

II. LITERATURE SURVEY

Wildfire detection has evolved significantly over the years, transitioning from traditional observation techniques to AI-driven automated systems. Early methods primarily relied on satellite imaging, thermal sensors, and human surveillance, which often resulted in delayed detection and limited accuracy. Recent advancements in machine learning and deep learning have introduced efficient models capable of real-time fire and smoke detection, significantly improving response times and reducing false alarms. Several studies have explored the integration of AI with remote sensing, IoT-based monitoring, and edge computing to enhance wildfire detection capabilities. Gonc¸alves et al. [1] investigated a deep learning-based wildfire detection system, utilizing a convolutional neural network (CNN) trained on real-world datasets. Their findings highlighted the effectiveness of CNN models in identifying wildfire patterns; however, the system struggled with environmental variations, leading to occasional misclassifications. Jadon et al. [2] proposed FireNet, a lightweight fire detection model optimized for IoT-based applications. Their study demonstrated the potential of low-power AI models for embedded systems, though challenges remained in detecting fires under complex backgrounds and low-visibility conditions.

In another study, Muhammad et al. [3] explored AI-driven fire detection in dynamic environments, emphasizing the need for adaptive feature extraction techniques. While their approach improved detection accuracy, false positives were still an issue when analyzing smoke patterns in uncertain weather conditions. Aslan et al. [4] introduced a novel method using generative adversarial networks (GANs) to improve fire detection accuracy. The study demonstrated that GAN-generated synthetic images could significantly enhance model training, particularly when real-world fire data was limited.

Hossain et al. [5] proposed a feature-based fire detection model utilizing texture and shape analysis. Their approach effectively reduced misclassifications caused by non-fire elements like sunlight reflections, but performance dropped when detecting fire at long distances. Similarly, Zhang et al. [6] experimented with synthetic data augmentation using Faster R-CNN models, showing that artificially generated datasets enhanced model generalization, particularly in low-light conditions. Their research provided insights into overcoming data scarcity challenges, which remain a limitation in wildfire detection research.

Mahdi et al. [7] conducted a comparative study evaluating multiple machine learning models, including decision trees, support vector machines (SVMs), and neural networks. Their findings suggested that ensemble learning techniques could significantly improve detection accuracy while reducing false alarms. Meanwhile, Al-Smadi et al. [8] focused on real-time smoke detection using YOLO models, concluding that YOLOv4 and YOLOv5 provided an optimal balance between speed and accuracy. However, the study acknowledged the computational limitations of real-time AI inference, particularly in edge computing environments.

Frizzi et al. [9] explored semantic segmentation for fire localization, demonstrating that pixel-wise classification allowed for precise identification of fire and smoke regions. Their research highlighted the importance of segmentation techniques in reducing false positives, though high computational requirements remained a drawback. Finally, Mahmud et al. [10] investigated the use of Unmanned Aerial Systems (UAS) for wildfire surveillance, combining drone imagery with deep learning-based fire detection. Their study demonstrated the effectiveness of aerial monitoring in remote and inaccessible areas, but noted challenges related to battery life, weather conditions, and real-time data transmission.

Despite these advancements, several research gaps remain. Many AI models struggle with false positives due to environmental variability, while real-time deployment remains a challenge due to high computational costs. Additionally, the limited availability of diverse wildfire datasets affects model training and generalization. Future research should focus on optimizing lightweight AI models for edge computing, improving multi-sensor integration, and expanding training datasets through synthetic data generation. By addressing these challenges, wildfire detection systems can become more reliable, efficient, and scalable, ultimately contributing to faster disaster response and mitigation efforts.

III. METHODOLOGIES

The proposed wildfire and smoke detection system utilizes FastAI, a deep learning framework built on PyTorch, to develop an automated and real-time detection mechanism. The methodology consists of multiple stages, including data collection, preprocessing, model training, evaluation, and deployment. The system is designed to analyze images from CCTV cameras, drones, and satellite feeds to detect fire and smoke patterns, enabling early intervention and disaster mitigation.

A. Data Acquisition and Preprocessing

The effectiveness of a deep learning model heavily relies on the quality and diversity of training data. The proposed system collects wildfire and smoke images from multiple sources, including publicly available datasets, real-time surveillance cameras, satellite imagery, and UAV (drone) footage. Open-source datasets such as FlameNet, FireNet, and SmokeNet are used to ensure a wide variety of environmental conditions, including different terrains, lighting conditions, smoke densities, and weather variations. Additionally, images from government fire departments and NASA's satellite imagery archives are incorporated to increase dataset robustness. To enhance model performance, data preprocessing and augmentation techniques are applied. Images are resized and normalized to ensure uniformity, reducing computational overhead. Data augmentation techniques such as random cropping, horizontal flipping, contrast adjustments, rotation, and noise addition are employed to simulate real-world conditions where wildfire images may appear in different orientations and lighting environments. This augmentation improves the model's ability to generalize well to unseen data.

Fig. 1. Images in our dataset

Each image in the dataset is carefully labeled into three categories: fire, smoke, and non-fire images. Labeling ensures that the model can accurately classify different wildfire scenarios and differentiate them from visually similar but non-hazardous elements like fog, clouds, or industrial emissions.

B. Model Selection and Training

To develop an efficient wildfire detection system, a Convolutional Neural Network (CNN) is used as the base model for image classification. CNNs are well-suited for detecting spatial patterns in images, making them ideal for fire and smoke recognition. To optimize training efficiency and improve accuracy, transfer learning is employed. Pre-trained models such as ResNet-50, MobileNetV2, and EfficientNetB0 are used as feature extractors. These models, previously trained on large-scale datasets like ImageNet, already possess strong feature extraction capabilities, significantly reducing the amount of training data required for high accuracy.

The training process involves fine-tuning the CNN model using adaptive learning rate scheduling, dropout layers, and batch normalization. Dropout layers prevent overfitting by randomly disabling neurons during training, ensuring that the model does not memorize specific features but instead generalizes well. Batch normalization speeds up training and stabilizes learning by normalizing input distributions for each layer. The dataset is split into 80% for training and 20%

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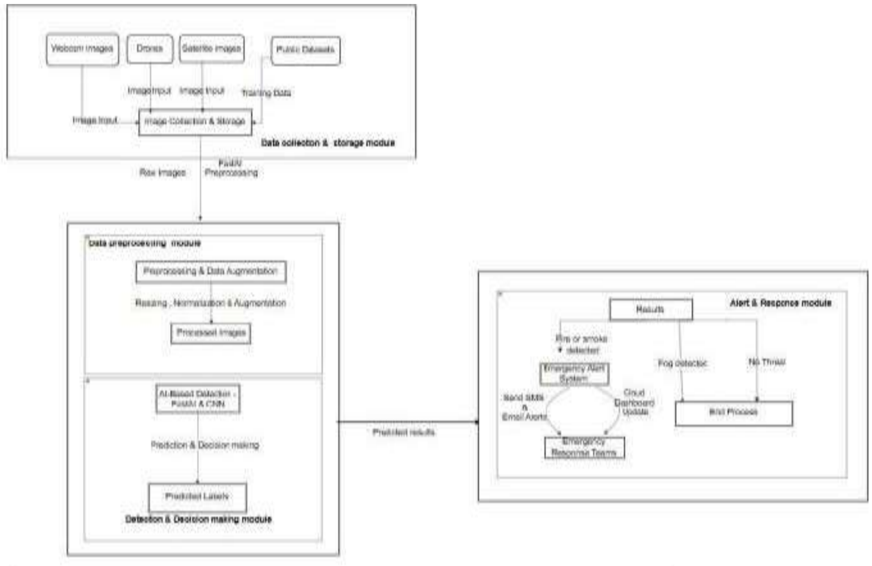

Fig. 2. System architecture

for validation, ensuring a balanced approach to learning and performance evaluation.

epoch	train_loss	valid_loss	accuracy	time
0	1.312640	0.359814	0.894872	05:10

epoch	train_loss	valid_loss	accuracy	time
0	0.391985	0.171635	0.933333	06:12
1	0.218180	0.126245	0.956410	07:36
2	0.137307	0.145678	0.961538	09:37
3	0.088115	0.116467	0.964103	08:11
4	0.056741	0.114172	0.966667	11:31

Fig. 3. Training Progress of FastAI Model

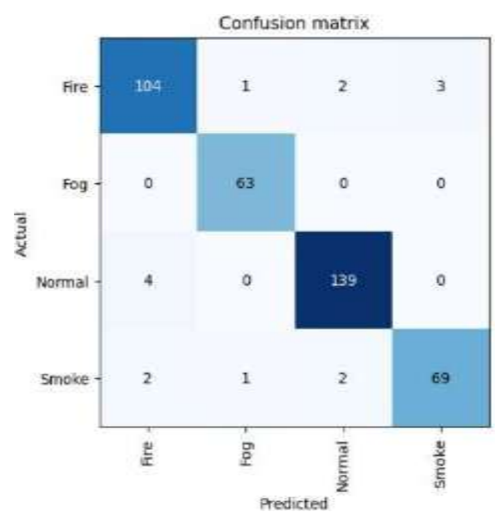

Fig. 4. Confusion Matrix for Fire, Fog, Smoke, and Normal Classification

A key challenge in wildfire detection is minimizing false positives and false negatives. To address this, the model is trained with cross-entropy loss as the objective function, which effectively differentiates between fire and non-fire categories. The Adam optimizer is used for efficient weight updates, ensuring fast convergence during training.

C. Model Evaluation

To ensure the reliability and effectiveness of the proposed wildfire and smoke detection system, the trained model is evaluated using multiple performance metrics. These metrics help assess the accuracy of predictions, minimize false positives and negatives, and ensure that the system performs well under different environmental conditions. The evaluation process involves testing the model on a validation dataset consisting of fire, smoke, and non-fire images, which were not used during training.

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Fig. 5. Prediction vs. Actual Classification with Loss and Probability

Fig. 6. Prediction : Fire

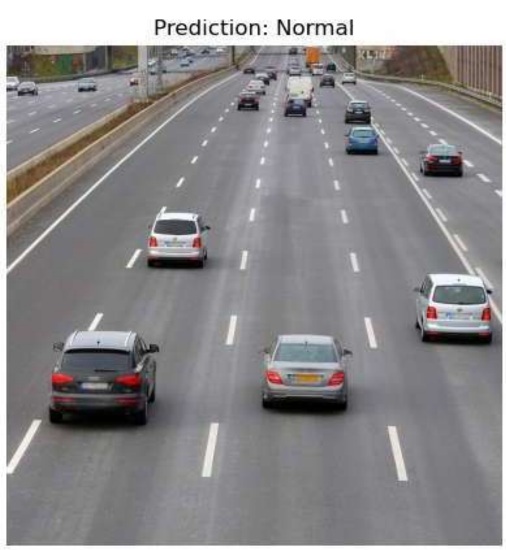

Fig. 9. Prediction : Normal

Fig. 7. Prediction : Smoke

Fig. 8. Prediction : Fog

One of the primary metrics used is accuracy, which measures the overall correctness of the model's predictions. However, accuracy alone is insufficient, especially in imbalanced datasets where fire occurrences are less frequent than non-fire images. To address this, precision and recall are also analyzed. Precision determines how many of the predicted fire cases are actual fires, reducing false alarms, while recall ensures that most actual wildfire cases are detected, minimizing missed detections. The F1-score, a harmonic mean of precision and recall, provides a balanced measure of the model's effectiveness in distinguishing fire and smoke from non-fire elements.

To further analyze the model's performance, a confusion matrix is generated. This matrix visually represents the number of true positives (correct fire detections), true negatives (correct non-fire classifications), false positives (incorrectly classifying non-fire as fire), and false negatives (failing to detect fire when present). A low false positive rate is crucial to avoid unnecessary alerts, while a low false negative rate ensures that no real fire incidents go undetected.

Additionally, a Receiver Operating Characteristic (ROC) curve is used to evaluate the model's discrimination ability between fire and non-fire images. The Area Under the Curve (AUC) value from the ROC curve provides an overall measure of how well the model can differentiate between fire and non-fire conditions. A higher AUC value indicates a better-performing model, capable of making reliable predictions across various environmental settings.

The evaluation results help in fine-tuning the model by adjusting hyperparameters such as learning rate, dropout rate, and batch size to further improve performance. If the model exhibits signs of overfitting or underfitting, additional training iterations or data augmentation techniques are applied to enhance generalization. These evaluation techniques ensure that the wildfire detection model is not only accurate and efficient but also robust enough for real-world deployment in challenging conditions.

D. Real-Time Detection and Deployment

Once trained and evaluated, the model is deployed in a real-time detection system, allowing it to process images from CCTV cameras, drones, and satellite feeds. The deployment pipeline includes image acquisition, pre-processing, model inference, and alert generation.

E. Future Enhancements

While the proposed system provides real-time, automated wildfire detection, several enhancements can further improve its efficiency. Multi-sensor fusion can be integrated by combining IoT-based temperature, humidity, and CO sensors with the vision-based model to reduce false positives by correlating multiple environmental factors. Additionally, real-time video analysis instead of static image processing can enhance fire tracking and movement prediction, leading to more dynamic and responsive detection. A hybrid cloud-edge deployment approach, where cloud computing is used for large-scale processing while edge AI handles real-time local inference, can optimize detection speed and computational resource utilization. Furthermore, autonomous UAV integration can be implemented, where drones equipped with AI-assisted navigation and onboard fire detection models can be deployed for automated surveillance in remote and inaccessible wildfire-prone regions, enhancing monitoring capabilities and early intervention. These improvements will ensure that the system is more robust, scalable, and capable of minimizing fire-related disasters effectively.

IV. RESULTS

The following images and outputs illustrate the system's functionality, including data processing, model inference, and threat classification results. The detection model was evaluated using real-time and uploaded image data, with logs and categorized threat levels generated based on the identified fire, smoke, or fog patterns

Fig. 10. Home page

Fig. 11. Upload Image page

Fig. 12. Sign in page

Fig. 13. Otp verification page

Fig. 14. Predictions page

Fig. 15. Detection Result - Fire

Fig. 16. Detection Result - Smoke

Fig. 17. Detection Result - Fog

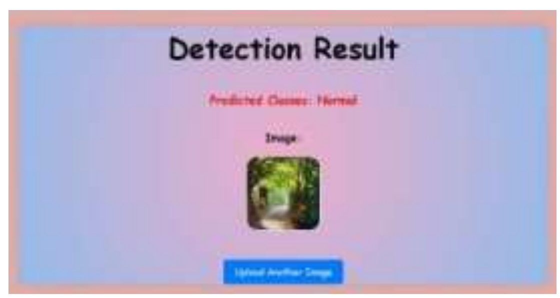

Fig. 18. Detection Result - Normal

Fig. 19. Detection Result - Fire

Fig. 20. Alert generated for fire detection

Fig. 21. Alert generated for smoke detection

V. CONCLUSION

Our project presents a deep learning-based wildfire, smoke, and fog detection system using FastAI, addressing the limitations of traditional fire monitoring methods. The proposed approach leverages Convolutional Neural Networks (CNNs) with transfer learning to achieve accurate and real-time classification of fire-related hazards. The system is designed to process images from CCTV cameras, drones, and satellite feeds, enabling automated detection and rapid response. Data preprocessing and augmentation techniques were employed to improve model robustness, ensuring reliable performance in diverse environmental conditions.The effectiveness of the model was evaluated using standard performance metrics, demonstrating high detection accuracy. The system's deployment feasibility was explored through cloud-based and edge AI implementations, optimizing computational efficiency. The results indicate that AI-driven wildfire detection offers a scalable, cost-effective, and automated solution for disaster management.

Future enhancements include multi-sensor fusion, real-time video analysis, and UAV-assisted fire surveillance to further improve detection accuracy and reduce false positives. Additionally, hybrid cloud-edge deployment can enhance real-time processing capabilities, making the system adaptable to large-scale applications. This research contributes to the advancement of AI-powered fire detection, providing a proactive approach to mitigating wildfire-related disasters and improving overall emergency response efficiency.

VI. REFERENCES

[1] Gonc¸alves, A. M., Brando, T., Ferreira, J. C. (2024). Wildfire Detection with Deep Learning: A Case Study for the CICLOPE Project. IEEE Access.

[2] Jadon, A., Omama, M., Varshney, A., Ansari, M. S., Sharma, R. (2019). FireNet: a lightweight specialized fire smoke detection model for real-time IoT applications. arXiv preprint arXiv:1905.11922.

[3] Muhammad, K., Khan, S., Elhoseny, M., Ahmed, S. H., Baik, S. W. (2019). Efficient fire detection for an uncertain surveillance environment. IEEE Transactions on Industrial Informatics, 15(5), 3113-3122.

[4] Aslan, S., Gu¨du¨kbay, U., To¨reyin, B. U., Cetin, A. E. (2019, May). Early detection of wildfire smoke based on motion-based geometric image transformation and deep convolutional generative adversarial networks. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP) (pp. 8315-8319). IEEE.

[5] Hossain, F. A., Zhang, Y., Yuan, C., Su, C. Y. (2019, July). Fire and smoke detection using static image features and an artificial neural network. In 2019 1st international conference on industrial artificial intelligence (iai) (pp. 1-6). IEEE.

[6] Zhang, Q. X., Lin, G. H., Zhang, Y. M., Xu, G., Wang, J. J. (2018). Wildland forest fire smoke detection based on faster R-CNN using synthetic smoke images. Procedia engineering, 211, 441-446.

[7] Mahdi, A. S., Mahmood, S. A. (2022, May). Analysis of Deep Learning Methods for Early Wildfire Detection Systems. In 2022 5th International Conference on Engineering Technology and its Applications (IICETA) (pp. 271-276). IEEE.

[8] Frizzi, S., Bouchouicha, M., Ginoux, J. M., Moreau, E. Sayadi, M. (2021). Convolutional neural network for the semantic segmentation of smoke and fire. IET Image Processing, 15(3), 634-647.

[9] Al-Smadi, Y., Alauthman, M., Al-Qerem, A., Aldweesh, A., Quaddoura, R., Aburub, F., ... Alhmiedat, T. (2023). Early detection of wildfire smoke using different yolo models. Machines, 11(2), 246.

[10] Mahmud, K. R., Wang, L., Liu, X., Jiahao, L., Hassan, S. (2024, June). Deep Learning-Based Wildfire Smoke Detection Using Uncrewed Aircraft System Imagery. In 2024 21st International Conference on Ubiquitous Robots (UR) (pp. 580-587). IEEE.