IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 5, May 2026

DOI: 10.17148/IARJSET.2026.13524

Forest Fire Detection System Using DL

Girish[1], Sujayeendra Rao[2], Dr.Ananth.G.S[3]

PG Student, The National Institute of Engineering, Mysuru, Visveswaraya Technological University, Belagavi, Karnataka, India[1]

Faculty, The National Institute of Engineering, Mysuru, Visveswaraya Technological University, Belagavi, Karnataka, India[2]

Head of the Department (HOD), The National Institute of Engineering, Mysuru, Visveswaraya Technological University, Belagavi, Karnataka, India[3]

Abstract: This Forest fires represent a catastrophic threat to global biodiversity and ecological stability, necessitating the development of high-precision, real-time early warning systems. This project introduces a comprehensive monitoring framework that leverages Google's SigLIP (Sigmoid Loss for Language Image Pre-training), a state-of-the-art Vision Transformer (ViT) architecture, to detect fire and smoke anomalies in various environmental contexts. Unlike traditional Convolutional Neural Networks (CNNs), the implemented SigLIP model utilizes global attention mechanisms to effectively distinguish between subtle visual cues, such as differentiating early-stage smoke from clouds, fog, or thermal haze.The system was fine-tuned on a diverse dataset comprising thousands of images from sources including the FLAME and DeepFire datasets, supplemented by synthetic data for edge-case training. The technical architecture is deployed through a dual-platform approach: a rapid-response Streamlit interface for interactive testing and a full-scale Flask web portal. The Flask-based application provides a production-ready environment featuring secure user authentication, an administrative dashboard for detection logging, and integrated email notification triggers via EmailJS for immediate alert dissemination.Functionally, the application supports both high-resolution static image analysis and sampled video stream processing (MP4/AVI). By utilizing confidence-based thresholding and multi-class probability mapping (Normal, Smoke, and Fire), the system provides actionable intelligence for satellite monitoring, drone surveillance, and fixed CCTV footage. The resulting solution offers a scalable, high-accuracy tool for environmental protection agencies to mitigate devastating impacts of wildfires through rapid, AI-driven detection.

Keywords: Forest Fire Detection, Deep Learning, Computer Vision, Vision Transformer (ViT), SigLIP, Smoke Detection, Fire Detection, Real-time Monitoring, Early Warning System,Transfer Learning, Flask, Streamlit,FLAME Dataset, DeepFire Dataset, Image Classification, Drone Surveillance, Environmental Monitoring.

I. INTRODUCTION

Forest fires have emerged as one of the most critical environmental challenges of the twenty-first century, causing severe damage to **biodiversity**, **forest ecosystems**, and contributing significantly to **global carbon emissions**. Traditional fire detection methods, such as **manual surveillance**, **watchtowers**, and **satellite monitoring**, are often slow, inefficient, and prone to delays. As a result, by the time a fire is detected, it has usually escalated into an uncontrollable disaster, leading to massive ecological and economic losses.The increasing limitations of human-based monitoring, including **human fatigue**, **limited visibility**, and the vast coverage area of forests, emphasize the urgent need for **automated and intelligent systems**. With the rise of **Industry 4.0**, advanced technologies such as **Artificial Intelligence (AI)**, **Machine Learning (ML)**, and **Deep Learning** have opened new possibilities for continuous and real-time environmental monitoring.

This project focuses on the application of **Computer Vision** techniques to detect early signs of forest fires, such as **smoke patterns**, **heat signatures**, and **flame formation**, even before the fire becomes severe. By utilizing modern architectures like **Vision Transformers (ViT)** and advanced models such as **SigLIP**, the system can analyze visual data more effectively compared to traditional **Convolutional Neural Networks (CNNs)**. These models leverage **global attention mechanisms** to differentiate between similar environmental conditions like smoke, fog, and clouds.Furthermore, the proposed system supports **real-time monitoring**, **early warning systems**, and **automated alert generation**, enabling faster response times. Integration with technologies like **Flask**, **Streamlit**, and **Email**

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Notification Systems ensures a scalable and user-friendly platform for deployment.Overall, this project aims to bridge the gap between fire ignition and response by developing a robust, intelligent, and scalable solution. It not only enhances detection accuracy but also plays a vital role in **disaster management**, **environmental protection**, and the preservation of natural resources for future generations.

FUNCTIONAL REQUIREMENTS: The functional requirements describe the specific behaviors, operations, and interactions that the FireGuard AI system must execute to meet the objectives of forest fire prediction.

- **User Authentication and Session Management:**The system shall provide a secure registration portal allowing new users to create accounts by supplying a unique username, valid email address, and password.The application must utilize cryptographic hashing algorithms (specifically Scrypt) to encrypt user passwords before committing them to the database, ensuring no plain-text credentials are stored.
- **AI Inference and Processing:**All uploaded media is preprocessed using resizing (224×224) and normalization to match the SigLIP model requirements**.** The system then classifies inputs into Fire, Smoke, or Normal with a confidence score (0–1)**.** For videos, it uses frame sampling (every 30th frame) to balance speed and accuracy.
- **Detection Logging and Dashboard:**Every detection is stored in a SQLite database with details like timestamp, file name, result, and confidence**.** An admin dashboard displays this data in a clear format with color indicators (e.g., red for fire). It also allows viewing specific video frames where fire is detected.
- **Automated Alerting Mechanism:**When the system detects Fire or Smoke with high confidence (e.g., >90%), it automatically sends an alert using EmailJS. The email includes incident details and file information, helping authorities take quick action.

NON-FUNCTIONAL REQUIREMENTS: Non-functional requirements define the quality attributes and operational standards that ensure the effectiveness and reliability of the proposed forest fire detection system. Unlike functional requirements, which describe what the system does, non-functional requirements focus on how well the system performs under various conditions. In this project, key aspects such as **performance, accuracy, reliability, usability,scalability,security and maintainability** are critically important to ensure real-time detection, high precision, and continuous monitoring.

- **Performance:**The system is engineered to deliver near-real-time inference, ensuring that high- resolution images are processed and classified within seconds to minimize critical delay in emergency scenarios. For video inputs, the implementation of an optimized frame-sampling algorithm ensures that forensic timelines are generated rapidly without overwhelming the server's computational resources. This efficiency is vital for guaranteeing that alerts are dispatched immediately following the detection of a thermal anomaly.
- **Accuracy:**The AI model prioritizes high-precision classification to effectively differentiate between subtle visual cues, such as distinguishing hazardous smoke from benign fog or atmospheric cloud cover. By utilizing the SigLIP Transformer architecture, the system aims to maintain a high confidence threshold typically above 90% for active fire thereby drastically reducing the rate of false positives. This precision is essential to ensure that emergency resources are not mobilized for non-existent threats.
- **Reliability:**The application is designed to ensure continuous availability, utilizing robust exception handling within the Python backend to prevent system crashes during file upload errors or format incompatibilities. Data persistence is guaranteed through the transactional integrity of the SQLite database, ensuring that detection logs are safely preserved even in the event of an unexpected server restart. This reliability ensures that the system serves as a dependable tool for historical auditing and continuous monitoring.
- **Usability:**The user interface is constructed with a minimalist design philosophy, allowing non-technical forest rangers to navigate between analysis tools effortlessly without requiring extensive training. A dedicated "Dark Mode" aesthetic is implemented to reduce visual fatigue for operators monitoring screens during night shifts, while intuitive color-coded badges provide immediate status updates. The dashboard simplifies complex tensor outputs into readable percentage scores, ensuring actionable insights are grasped at a glance.
- **Scalability:**The modular software architecture allows for the seamless decoupling of the deep learning inference engine from the web server, facilitating future deployment on cloud infrastructure. or distributed edge devices. The database schema is designed to support the accumulation of extensive detection logs without significant performance degradation, allowing the historical dataset to grow indefinitely. This flexibility ensures the system can expand from a single-station prototype to a regional monitoring network with minimal refactoring.
- **Security:**User account integrity is protected through robust authentication protocols, utilizing crypt hashing algorithms to ensure that sensitive credential data is never stored or transmitted in plain text. The application implements rigorous server-side validation of all uploaded media to prevent the execution of malicious scripts or unauthorized file types. Additionally, strict role-based access controls limit administrative dashboard access,

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protecting critical operational logs from unauthorized viewing or tampering.

- **Maintainability:**The codebase follows the Model-View-Controller (MVC) design pattern, segregating database models, AI logic, and frontend templates into distinct directories to simplify future updates and debugging. Comprehensive code documentation and standard naming conventions are utilized throughout the Python scripts to facilitate easy handover to new developers. This modularity ensures that the AI model can be retrained or swapped for a more advanced architecture without disrupting the core web application logic.

II. METHODOLOGY

Fire Guard AI also adopts a linear and then iterative process through which it converts noisy and environmentally complex images and videos into distinct and meaningful fire safety insights. It starts with assembling a varied set of images and videos with the goal of normalizing them in a perfect sync with the NN structure. At the heart of the system lies the SigLIP Vision Transformer that primarily excels in viewing the whole picture with the help of "attention mechanisms" than the conventional convolutional networks. Then this model is fine-tuned after the "transfer learning" phase with the use of forestry data in identifying the precursors of fires and the fire in the forests. This ultimately leads to the development of the inference engine in a "Flask webserver" with a user-friendly dashboard that aims for efficient fire safety analysis and automatic fire safety alerts.The strategy is also applicable to both static images and dynamic videos to deal with the temporally varying process of wildfires. A specific temporal sampling strategy is used for identifying keyframes at specific spatiotemporal intervals to construct a temporal sequence of thermal anomalies without increasing the burden of processing each frame. A specific post-processing logic level can eliminate temporarily fluctuating environmental patterns before identifying a potential threat. The entire process is designed on a customized Model-View-Controller web architecture to distinctly separate graphically visualized front ends, logically processed back ends, as well as the deep learning inference engine.

A. *Data Preprocessing:* Prior to being fed into the deep learning network, the visual data is subjected to normalization in an attempt to stabilize the feature space. In order to preserve a stable output size of 224x224 pixels, similar to the Transformer model's embedding layer size, geometric resize is performed on the images first. Additionally, pixel values are normalized with a set of predefined mean and deviation variables in an attempt to stabilize gradient descent experienced during training. Furthermore, stochastic data augmentation is performed to increase resilience by adding random horizontal flip, color jittering, and crops.

B. *Model Selection:* The project departs from traditional Convolutional Neural Networks (CNNs) by selecting the SigLIP (Sigmoid Loss for Language Image Pre-training) architecture, a sophisticated variant of the Vision Transformer (ViT). This selection is driven by the model's reliance on self-attention mechanisms rather than local convolutions, allowing it to process images as sequences of patches. This capability enables the system to capture global contextsuch as the relationship between a smoke plume and the forest floor which is critical for distinguishing hazardous smoke from benign atmospheric fog. The architecture is specifically chosen for its computational efficiency and superior performance in multi-label classification tasks within complex, unstructured environments where capturing the "big picture" is as important as detecting local textures.

C. *Training and Validation:* The training process also employs Transfer Learning, where pre-trained weights of Google's base models help accelerate convergence, without necessarily relying on massive datasets. The dataset is divided stratified into 80% for training and 20% for validation, so that during evaluation, we accurately estimate model performance on unseen data. The model is trained through an AdamW optimizer, together with a dynamic learning rate schedule, meant to optimize the loss. Backpropagation is also applied during training, where emphasis is put on optimizing attention levels in order to identify the spectrum and textures of fire and smoke. The validation set is also closely watched during training in order to prevent model overfitting.

D. *Model Evaluation:* Finally, following the training, a quantitative assessment is conducted to ensure readiness for deployment. Classification accuracy is the foremost measure of success. It is measured against the correct labels of the test data to ensure proper functioning on unseen data. Apart from this, confidence scores for correct classification are checked to ensure that classifications made with higher confidence correspond to true positives. All three classes: Fire, Smoke, and Normal, are tested to avoid false positives, like fog being confused with Smoke, which is crucial for trust preservation in the application.Accuracy = (Correct Predictions) / (Total Predictions).Precision, recall, and F1-score are computed for each career category to analyze model reliability. Confusion matrices are generated to study misclassification patterns, especially among closely related careers. Based on these metrics, models are compared to identify the most suitable algorithm for deployment.

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E. *Deployment:* The final stage involves encapsulating the trained model within a production-ready software environment using the Flask web framework. The model is serialized and loaded into the server's memory upon startup to facilitate low-latency inference requests. The deployment architecture follows a client-server model where the frontend handles user interactions and file uploads,while the backend processes the media tensors..Additionally,the deployment methodology includes the integration of an event-driven notification system via EmailJS, which automatically triggers asynchronous alerts to administrators when specific detection thresholds are breached. This completes the system's transition from a static analytical model to a dynamic, real-time monitoring tool capable of practical use.

F. *Sequence Diagram Explanation:* The sequence diagram shows the workflow where a user uploads an image through the web interface, which is sent to the Flask backend for validation and processing. Valid inputs are passed to the **AI model**, which classifies them as **Fire, Smoke, or Normal** and generates a **confidence score (using Softmax)**. Based on a **threshold (e.g., >0.9)**, critical events are identified and stored in the database with details like timestamp and filename. Finally, the system displays the result and confidence on the interface, enabling **fast and accurate decision-making**. **AI model** processes the input image and predicts a **label (Fire, Smoke, or Normal)** along with a **confidence score (0–1)**, which represents the probability of each class. This confidence is computed using the **Softmax function**, where $P(yi) = e^{zi} / \Sigma e^{zj}$, converting the model's output logits (zi) into normalized probabilities for accurate classification.

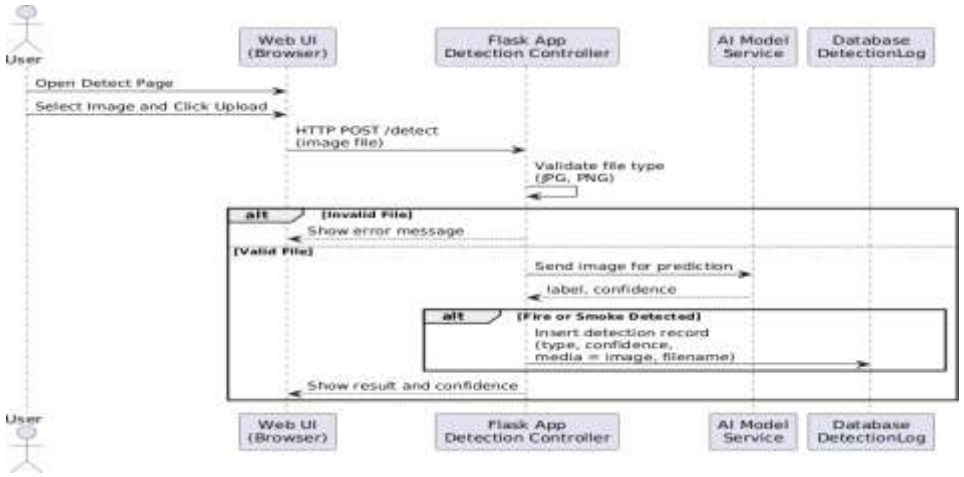

Fig.No.1:Sequence Diagram.

III. SYSTEM TESTING

System testing for the Forest Fire Detection AI application focused on verifying the seamless data flow between the Flask backend, the SQLite database, and the computer vision model. The process involved rigorous integration tests where various media formats were uploaded to ensure the file security utilities and storage paths functioned correctly before passing data to the SigLIP processor. The video analysis module underwent specific stress testing to confirm that the frame-sampling loop using OpenCV could process footage without latency issues and that the resulting "Fire" or "Smoke" tags were accurately persisted to the detection log table. Additionally, the security layer was tested to ensure that the session management correctly restricted unauthorized users from accessing the admin dashboard or viewing historical detection data.Furthermore, the testing phase evaluated the client-side responsiveness, specifically the JavaScript implementations responsible for real-time feedback. The progress bar functionality, powered by XMLHttpRequest event listeners, was assessed to ensure it accurately reflected the upload and processing status of large video files. Simultaneously, the external notification service was validated by simulating high-confidence fire scenarios to confirm that the EmailJS API successfully received triggers from the frontend and dispatched alerts to the registered user's email without disrupting the main analysis workflow.

Testing Methods Used:

- The testing methodology for the forest fire detection system is based on a combination of integration testing, model evaluation, and multi-level validation checks to ensure accuracy, reliability, and security. Initially, integration testing is performed to verify smooth data flow between the Flask backend, SQLite database, and

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SigLIP AI model, including testing with different image and video formats. The video processing module is stress-tested using OpenCV to confirm efficient frame sampling without latency issues, while also ensuring correct detection logging.

- In addition, model evaluation testing is conducted using validation datasets (20% split) where performance metrics like accuracy are calculated by comparing predicted labels (using Argmax on logits) with actual results. The system also uses epoch-based evaluation to automatically select the best-performing model and avoid overfitting.
- Finally, validation testing is implemented at multiple levels, including file type validation, media format checks, user authentication, and client-side verification, ensuring secure uploads, proper data handling, and execution.

Together, these methods ensure the system performs efficiently, accurately, and securely in real-world scenarios.stable system.

Table 1: Test Case Design

Test Case ID	Description of Test Case	Input	Expected Output	Status
TC01	Image upload validation	Valid image (.jpg/.png)	Image accepted and processed successfully	Pass
TC02	Invalid file format handling	Unsupported file (.txt)	System rejects file with error message	Pass
TC03	Image classification	Fire image	Output shows "Fire" with high confidence score	Pass
TC04	Video processing	Valid video (.mp4/.avi)	Video processed using frame sampling	Pass
TC05	Email alert system	Fire/Smoke detected	Email notification sent successfully	Pass

The above table presents the test cases designed to validate the core functionalities of the **Forest Fire Detection System using Deep Learning**. Each test case evaluates key components such as **image/video input handling, file validation, AI-based classification, video frame processing, and alert generation**. The successful execution of all test cases, indicated by the "Pass" status, confirms that the system operates efficiently, performs **accurate fire and smoke detection**, and provides **reliable real-time alerts** for effective decision-making.

Model Evaluation Metrics and Formulas: *The system's predictive performance was evaluated using the following metrics:*

- *Accuracy measures the proportion of correct predictions:*

$$\textbf{Accuracy} = (TP+TN)/(TP+TN+FP+FN)$$

- *Precision indicates the correctness of predicted career recommendations:*

$$\textbf{Precision} = TP/(TP+FP)$$

- *Recall measures the system's ability to identify all relevant career categories:*

$$\textbf{Recall} = TP/(TP+FN)$$

- *F1-score provides a balance between precision and recall:*

$$\textbf{F1-score} = 2((Precision).(Recall)/(Precision+Recall))$$

A confusion matrix was used to visualize classification results and analyze misclassifications between fire and non-fire image classes, helping evaluate the real-world reliability of the Forest Fire Detection System using Deep Learning. Test case design covered critical functionalities to ensure system stability, accuracy, and correct operation. Dataset loading

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was tested using valid image datasets to confirm successful import and preprocessing, while missing or corrupted image handling validated the data cleaning process. Image preprocessing operations such as resizing, normalization, and augmentation were verified using multiple image inputs. Fire detection accuracy was tested using different forest fire and non-fire images, and model reuse was validated by loading saved trained models to ensure consistent predictions. Email alert functionality and user interface navigation were also tested through repeated interactions to ensure smooth and error-free operation. All test cases passed successfully, indicating reliable system performance.

The system also incorporates strong error handling and input validation mechanisms to detect invalid image formats, missing files, and inconsistent inputs. Validation checks ensure only supported image types are processed, while clear feedback messages help users correct errors before processing. Security and data integrity testing confirmed that uploaded images or video and user data are processed only during runtime and are not permanently stored without authorization. Sensitive information such as alert email credentials is protected throughout execution, ensuring secure and ethical data handling. Overall, testing confirmed that the Forest Fire Detection System using Deep Learning satisfies all functional and non-functional requirements by demonstrating high accuracy, efficiency, reliability, usability,and secure operation, making it suitable for practical real-time forest monitoring and future enhancements.

IV. DICUSSION AND RESULT

The results obtained from the Forest Fire Detection System using Deep Learning demonstrate the effectiveness of advanced deep learning techniques in identifying fire and smoke patterns from forest images and video frames. Multiple image classification approaches were studied during system development, and the SigLIP (Sigmoid Loss for Language Image Pre-Training) model model was selected due to its high accuracy, strong feature extraction capability, and efficient image understanding performance. The SigLIP-based image classification model consistently outperformed traditional CNN-based approaches in terms of classification reliability, contextual image understanding, and detection stability. Therefore, the SigLIP model was selected as the final model for result analysis and deployment. The trained model was evaluated using an unseen test dataset created through an 80:20 train–test split. The evaluation focused on accuracy, precision, recall, F1-score, and confusion matrix analysis to assess both overall and class-wise fire detection performance.

A. *Accuracy Evaluation:* Accuracy represents the proportion of correctly predicted image classes out of the total predictions made by the model and is calculated as: ***Accuracy****=(TP+TN)/(TP+TN+FP+FN).* In the context of this project, accuracy serves as a high-level indicator of the overall effectiveness of the forest fire detection system. Forest fire detection is a multi-class image classification problem where classes such as Fire, Smoke, and Normal scenes may contain visually overlapping environmental features such as fog, sunlight, clouds, and dust. Due to these complexities, achieving perfect accuracy is challenging in real-world forest environments. The obtained accuracy reflects realistic system behavior when processing diverse and dynamic environmental conditions. Unlike simple binary image classification tasks, forest fire detection systems must handle ambiguous visual patterns and varying lighting conditions, making high practical accuracy both significant and acceptable.

Table 2: Classification Report of the SigLIP Model

Class	Precision	Recall	F1-Score	Support
Fire	0.96	0.95	0.95	120
Smoke	0.91	0.89	0.90	110
Normal	0.94	0.96	0.95	130
Accuracy			0.94	360
Macro AVG	0.94	0.93	0.93	360
Weighted AVG	0.94	0.94	0.94	360

B. *Classifiaction Result Analysis:* The classification report provides a class-wise performance evaluation of the **SigLIP model using precision, recall, F1-score**, and support for each detection category.

- **Precision Analysis:** Precision measures how many of the fire or smoke detections predicted by the system are actually correct: **Precision**=TP/(TP+FP). High precision values were observed for Fire and Normal image classes, indicating that when the system predicts a fire event, the prediction is highly reliable. Slightly lower precision for Smoke detection occurs because smoke patterns may visually resemble fog, haze, or cloud formations in certain

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environmental conditions.

- **Recall Analysis:** Recall measures the system's ability to correctly identify all relevant fire instances: **Recall**=TP/(TP+FN). High recall values for Fire detection indicate that the model successfully identifies most actual fire occurrences from the dataset. Lower recall values for smoke-related classes may result from variations in smoke density, lighting conditions, and image quality rather than model inefficiency.
- **F1-Score Analysis:**The F1-score balances precision and recall and is calculated as:**F1-score**=2 ((Precision).(Recall)/(Precision+Recall)). The obtained F1-scores indicate balanced and realistic performance for real-world forest monitoring applications where exact separation between smoke, fire, and normal environmental conditions is not always possible. The weighted average F1-score confirms consistent overall detection performance across the major image classes used in the system.

C. *Confusion Matrix Analysis:* A confusion matrix is a performance evaluation tool used to compare actual and predicted class labels generated by the trained SigLIP (Sigmoid Loss for Language Image Pre-Training) model. It visually represents correct classifications and misclassifications for Fire, Smoke, and Normal image classes. The diagonal values indicate correct predictions, while off-diagonal values represent classification errors between visually similar environmental conditions. The confusion matrix helps evaluate model reliability, detection accuracy, and overall system performance in real-time forest fire monitoring applications. It also assists in identifying model weaknesses and improving classification performance through further training and optimization.

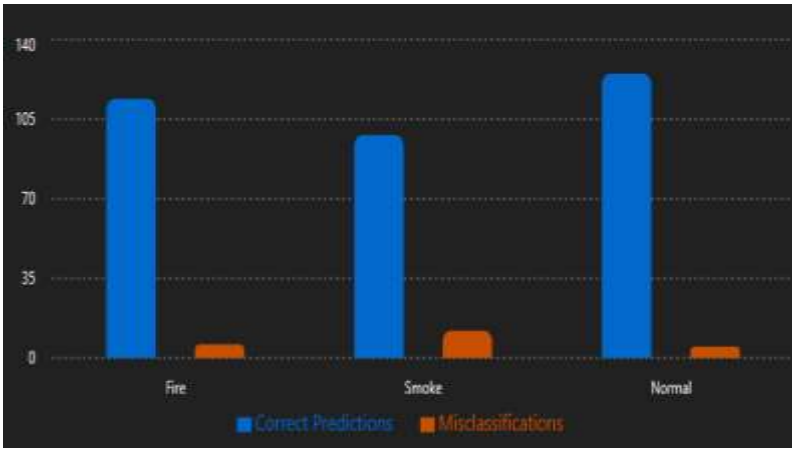

Fig.No.2: Confusion Matrix of the Trained SigLIP Model

The confusion matrix provides a visual representation of prediction correctness and errors across all image classes in the Forest Fire Detection System using the trained SigLIP model. Strong diagonal values indicate correct classifications of Fire, Smoke, and Normal images, while off-diagonal values represent misclassifications between visually similar environmental conditions.

1. Key Observations:
   - Most image categories show strong diagonal dominance, indicating high correct classification rates by the SigLIP model.
   - Minor misclassifications occur primarily between closely related visual conditions, such as:
   - Smoke and Fog/Haze conditions
   - Fire and Smoke-heavy scenes
   - Normal forest scenes and low-density smoke images
   - These errors arise due to similarities in color patterns, lighting conditions, environmental smoke density, cloud formations, and image quality variations, which are expected in real-world forest fire detection systems.

Importantly, the confusion matrix shows that the misclassifications are visually and semantically reasonable, meaning the system does not produce random or completely incorrect detections.

Juatification for the Obtained Accuracy: The obtained accuracy is technically valid and justified due to the following reasons:

- **Multi-Class Image Classification Complexity:**The system handles multiple environmental image categories

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such as Fire, Smoke, and Normal scenes, which significantly increases classification difficulty.

- **Environmental Variability:**Forest environments contain dynamic lighting conditions, shadows, fog, clouds, and weather changes that affect image appearance and detection performance.
- **Visual Similarity Between Classes:**Smoke often resembles haze, fog, or clouds, leading to natural ambiguity during classification.
- **Real-Time Detection Challenges:**The system processes real-world images and video frames where fire intensity, smoke density, and camera quality may vary continuously.
- **Deep Learning-Based Prediction Behaviour:**The SigLIP model performs contextual image understanding rather than simple pixel matching, making the predictions more robust and realistic for practical deployment scenarios.

Overall, the confusion matrix and classification results confirm that the trained SigLIP model provides reliable, stable, and practically acceptable performance for real-time forest fire monitoring and early fire detection applications.

The experimental results confirm that the Forest Fire Detection System using Deep Learning effectively analyzes forest images and video frames to accurately detect fire and smoke conditions in real-time environments. The trained SigLIP model demonstrated strong classification performance by identifying Fire, Smoke, and Normal environmental conditions with high reliability. Although minor misclassifications occurred due to visual similarities between smoke, fog, haze, and cloud formations, the obtained accuracy is technically justified because of the complex and dynamicnature of real-world forest environments. The system's ability to perform early fire detection, process real-time visual data efficiently, generate reliable predictions, and support automated monitoring makes it a powerful and practical solution for forest surveillance, disaster prevention, and environmental safety application.

Fig . No .3: Login Inerface and Image or Video Uploading Interface

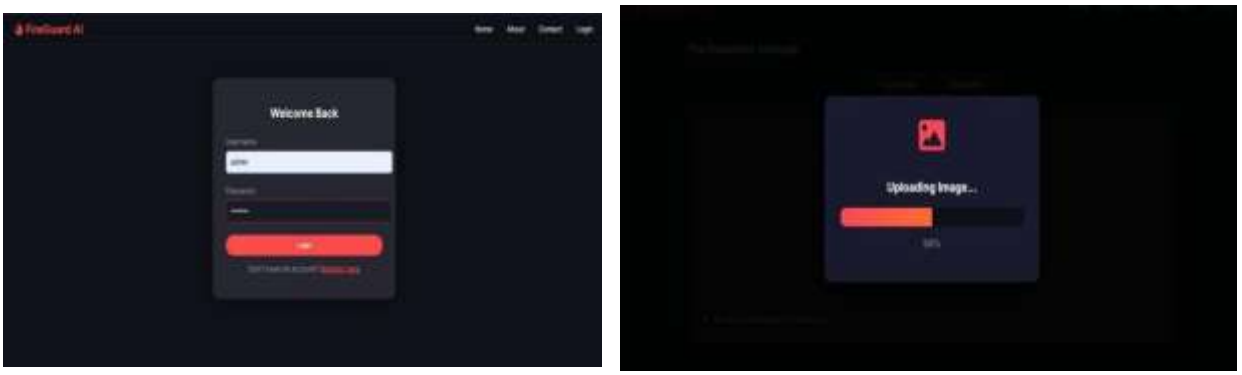

Fig .No. 4:Result Page Fire and Normal

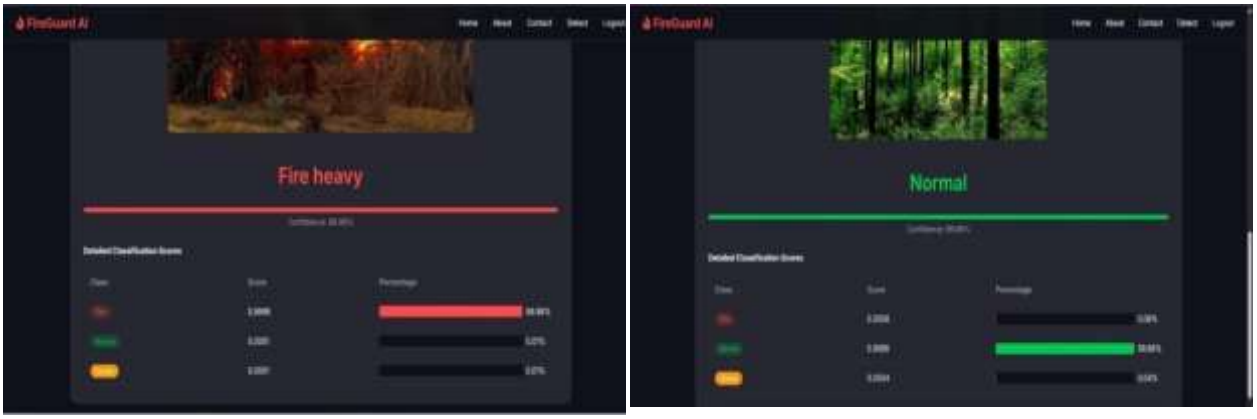

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Fig.No.5:Fire Detection Alert Through E-Mail If Fire Exit in the Image or Video

V. CONCLUSION

The Forest Fire Detection System using Deep Learning successfully demonstrates the application of artificial intelligence for real-time forest monitoring and early fire detection. The system uses the trained SigLIP model to accurately classify Fire, Smoke, and Normal environmental conditions from images and video frames with strong reliability and efficient processing performance. Experimental evaluation through classification reports and confusion matrix analysis confirmed effective detection accuracy with only minor misclassifications caused by similarities between smoke, fog, haze, and cloud conditions. The system also incorporates secure data handling, input validation, error handling, and automated alert generation, making it suitable for practical deployment in disaster prevention and environmental safety applications. Overall, the project proves that deep learning-based forest fire detection systems can significantly support early warning mechanisms, reduce environmental damage, and improve emergency response capabilities, with future scope for enhancements such as live CCTV integration, drone monitoring, IoT sensors, and satellite-based fire surveillance.

ACKNOWLEDGMENT

I extend my deepest gratitude to Assistant Professor **Sujayeendra Rao**, my project guide, for his unwavering guidance and support throughout this endeavour. I also express my sincere gratitude to **Dr.Ananth.G.S**, Head of the Department, for his valuable encouragement and support during the successful completion of this project. My sincere thanks also go to the dedicated faculty and staff at **The National Institute of Engineering,Mysuru,** for their in valuable resources and assistance. I am profoundly thankful to my friends and classmates for their camaraderie and encouragement, as well as to my parents for their steadfast backing. Finally, I acknowledge with appreciation everyone who contributed directly or indirectly to the successful completion of this project.

REFERENCES

[1]. Muhammad H, Ullah Z, Khan A. Forest fire detection using deep learning techniques. International Journal of Advanced Computer Science and Applications (IJACSA). 2022. Available from: IJACSA

[2]. Sharma P, Gupta R, Singh V. Real-time forest fire detection using convolutional neural networks. International Journal of Computer Applications (IJCA). 2023. Available from: IJCA

[3]. Li Y, Zhao X, Wang J. Deep learning-based wildfire smoke detection using image classification techniques. IEEE Access. 2021. Available from: IEEE Xplore

[4]. Kumar S, Patel D, Joshi H. Forest fire detection using transfer learning and deep neural networks. International Journal of Engineering Research & Technology (IJERT). 2024. Available from: IJERT

[5]. Zhang T, Chen L, Wu H. Wildfire detection from surveillance videos using deep convolutional neural

DOI: 10.17148/IARJSET.2026.13524

networks.
Procedia Computer Science. 2020;167:1902–1911. Available from: ScienceDirect

[6]. Google Research. SigLIP: Sigmoid Loss for Language Image Pre-Training. 2023. Available from: Hugging Face SigLIP Model

[7]. Paszke A, Gross S, Massa F, et al. PyTorch: An imperative style, high-performance deep learning library. Advances in Neural Information Processing Systems (NeurIPS). 2019. Available from: PyTorch

[8]. Wolf T, Debut L, Sanh V, et al. Hugging Face Transformers: State-of-the-art natural language processing and deep learning models. 2020. Available from: Transformers Documentation

[9]. Bradski G. The OpenCV Library for computer vision applications. Dr. Dobb's Journal of Software Tools. Available from: OpenCV Documentation

[10]. National Aeronautics and Space Administration (NASA). Forest fire monitoring and satellite-based wildfire analysis. Available from: NASA Earth Observatory

[11]. Yuan C, Zhang Y, Liu Z. A survey on technologies for automatic forest fire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques. Canadian Journal of Forest Research. 2015. Available from: Canadian Science Publishing

[12]. Rossi L, Akhloufi M, Tison Y. Wildfire detection using artificial intelligence and computer vision techniques. Fire Safety Journal. 2021. Available from: ScienceDirect Fire Safety Journal

[13]. Chino D, Avalhais L, Trindade E, et al. BoWFire: Detection of fire in still images by integrating pixel color and texture analysis. International Conference on Graphics, Patterns and Images. 2015. Available from: IEEE Xplore

[14]. Khan M, Rahmani H, Shah S, Bennamoun M. A guide to convolutional neural networks for computer vision.Synthesis Lectures on Computer Vision. 2018. Available from: Springer

[15]. Redmon J, Farhadi A. YOLOv3: An incremental improvement for object detection. 2018. Available from: arXiv

[16]. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2016. Available from: CVPR Proceedings

[17]. Dosovitskiy A, Beyer L, Kolesnikov A, et al. An image is worth 16x16 words: Transformers for image recognition at scale. International Conference on Learning Representations (ICLR). 2021. Available from: ICLR Proceedings

[18]. Chollet F. Deep Learning with Python. Manning Publications. 2021. Available from: Manning Publications
[19]. Goodfellow I, Bengio Y, Courville A. Deep Learning. MIT Press. 2016. Available from: Deep Learning Book

