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Research Article

Cutting-Edge AI Trends In Emerging Technologies Improving Forest Fire Management: Early Detection Through Image Classification And Predictive Modeling

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ABSTRACT

Forest fires pose a significant threat to ecosystems, wildlife, property, and human lives worldwide. Leveraging advancements in artificial intelligence and machine learning, our research presents a comprehensive approach to forest fire detection and management. We employ a state-ofthe-art image classification model, YOLOv8, to swiftly identify fire occurrences within forest imagery, achieving high accuracy rates. Concurrently, we develop a predictive model using logistic regression to forecast the likelihood of fire outbreaks based on environmental factors. Integration of these technologies holds promise for proactive forest fire management. Future prospects include the integration of our YOLOv8 model with UAVs for real-time monitoring and early detection of fire occurrences, thus enhancing environmental conservation and safety measures.

Keywords—Forest fires, artificial intelligence, machine learning, image classification, YOLOv8, fire detection, predictive model, logistic regression, environmental factors, proactive management, UAVs, real-time monitoring, early detection, environmental conservation, safety measures

I. INTRODUCTION

Forest fires stand as one of the most pressing threats to the delicate balance of ecosystems, wildlife habitats, human infrastructure, and lives worldwide. The ferocity and unpredictability of these infernos demand swift detection and effective response mechanisms to mitigate their catastrophic impact. In recent years, the intersection of technology and environmental stewardship has paved the way for innovative approaches to forest fire management, with particular emphasis on leveraging artificial intelligence (AI) and machine learning (ML) techniques. Our research endeavours to push the boundaries of forest fire detection and management by presenting a comprehensive framework that combines image classification and predictive modelling methodologies. The urgency of addressing forest fire risks cannot be overstated. Not only do these conflagrations result in substantial ecological damage, but they also pose significant threats to human safety and livelihoods. As climate change intensifies, the frequency and severity of forest fires are on the rise, necessitating proactive measures to safeguard vulnerable ecosystems and communities. In this context, technological innovations offer a ray of hope, promising to enhance early detection capabilities and streamline response efforts. At the forefront of our research lies the deployment of advanced image classification techniques, with a specific focus on YOLOv8 (You Only Look Once version 8). This state-of-the-art model represents a quantum leap in image recognition capabilities, renowned for its accuracy, efficiency, and real-time object detection capabilities. By harnessing the power of YOLOv8, we aim to develop a robust system capable of swiftly identifying fire occurrences within forested regions with unparalleled precision and reliability. The significance of rapid fire detection cannot be overstated. Early intervention is critical in containing fires before they spiral out of control, minimizing damage to ecosystems and human infrastructure.

Traditional methods of fire detection, while effective to some extent, often suffer from limitations such as delayed response times and reliance on human observers. By integrating YOLOv8 into our detection system, we seek to overcome these limitations, enabling authorities to deploy resources swiftly and effectively in response to emerging fire threats. However, forest fire detection is not merely about identifying flames in imagery; it also entails predicting the likelihood of fire outbreaks based on a multitude of environmental factors. In this regard, our research takes a multifaceted approach, incorporating predictive modelling techniques to forecast fire-prone regions. By analysing variables such as longitude, latitude, temperature, humidity, wind speed, and vegetation type, we aim to discern patterns and correlations that can inform proactive fire management strategies. The integration of image classification and predictive modelling represents a
paradigm shift in forest fire detection and management. By fusing these complementary technologies, we aspire to create a synergistic system capable of not only identifying fire occurrences in real-time but also predicting potential fire outbreaks before they occur. This proactive approach holds immense potential for mitigating the impact of forest fires, empowering stakeholders to take preemptive measures to protect ecosystems and communities. In this paper, we delve into the intricacies of our methodology, detailing the experimental setup, and presenting the results of our research. By elucidating the potential implications for forest fire prevention and management strategies, we aim to contribute to the ongoing discourse on wildfire management and environmental conservation. Through the fusion of AIdriven image analysis and predictive modelling techniques, we envision a future where proactive measures are the cornerstone of forest fire management, safeguarding biodiversity and human livelihoods against the ravages of infernos.

II. OBJECTIVES

Our research endeavours are anchored in the development of a comprehensive forest fire detection system, amalgamating advanced technologies to enhance prediction accuracy and response efficiency. Our primary objective entails the creation of an image classification model utilizing YOLOv8. This model serves as the cornerstone of our detection system, swiftly identifying fire occurrences within forest imagery with precision and reliability. By leveraging the real-time object detection capabilities of YOLOv8, we aim to expedite the detection process, enabling early intervention and mitigation efforts to curb the spread of forest fires. Concurrently, we embark on a parallel trajectory focused on predictive modelling, harnessing environmental variables such as longitude, latitude, temperature, humidity, wind speed, and vegetation type to forecast the likelihood of fire outbreaks. Through the application of statistical techniques, notably logistic regression, we seek to discern patterns and correlations within the data to accurately predict fire-prone regions. By integrating YOLOv8 with predictive modelling, we aim to fortify our detection system's predictive capabilities, enabling it to proactively identify high-risk areas and issue timely alerts to relevant authorities. Through this synergistic integration of image analysis and predictive modelling, our overarching objective is to furnish stakeholders with a robust and reliable toolset for forest fire detection and management, fostering proactive measures to safeguard ecosystems and communities against the ravages of forest fires.

II. LITERATURE REVIEW

TABLE I. REVIEWED PAPERS ON FOREST FIRE DETECTION

Sr. No.	Paper Name	Description	Accuracy
1	Early Detection of Forest Fire Using Mixed Learning Techniques and UAV	This work presents an automatic forest fire detection system using image processing methods, leveraging brightness and motion clues alongside histogram-based segmentation. Key techniques include optical flow for motion analysis, ViBe method for background extraction, and a combination of deep learning models like YOLOv4.	85.36%
2	Forest Farm Fire Drone Monitoring System Based on Deep Learning and Unmanned Aerial Vehicle Imagery	The proposed forest fire monitoring system integrates a drone equipped with a high-definition camera and a remote monitoring terminal to provide early warnings using video-based fire detection. The drone follows a preset patrol route, transmitting real-time video and images to ground software. Integrates a deep learning-based forest fire monitoring system with a CUIM600 drone.	81%
3	Computer Vision-Based Wildfire Smoke Detection Using UAVs	This work presents a comprehensive dataset of various smoke images and videos from different scenarios for training the SSD Inception-V2 model for real-time fire detection. The model's parameters are tuned for optimal performance, and its effectiveness is tested on wildfire smoke videos and images under diverse conditions.	Not provided

4	Early Forest Fire Detection Using Drones and Artificial Intelligence	The proposed platform uses a fixed-wing drone for constant high-altitude patrol and a rotary-wing drone for close inspection to confirm fire alarms, minimizing false positives. Equipped with optical and thermal cameras, the drones operate autonomously with onboard processing and AI capabilities for real-time fire detection. The system aims to enhance early warning, timely responses, and cross-border cooperation for wildfire management in the Balkan-Mediterranean area.	Not provided
5	Forest Fire detection using Machine learning	This paper presents the use of convolutional neural networks (CNNs) and the YOLOv2 model for detecting fire and smoke in both indoor and outdoor environments through live video footage. It highlights the enhanced accuracy and efficiency of YOLOv2 over its predecessor for real-time object detection, with applications including UAV-based forest fire monitoring. The proposed methods aim to reduce false positives and improve early fire detection using advanced neural network techniques.	93%

6	Forest Fire Detection Method Based on Deep Learning	A novel, computationally efficient fire detection system has been developed, leveraging a modified YOLOv5 architecture. This streamlined model is designed to operate in real-time on resource-constrained devices. The approach begins with pretraining on the COCO dataset, followed by fine-tuning on specialized flame detection data. This transfer learning strategy mitigates overfitting and enhances the model's generalization capabilities.	83.9%
7	A Forest Fire Detection System Based on Ensemble Learning	This paper addresses the challenge of early forest fire detection, highlighting the limitations of traditional methods such as sensors, infrared/ultraviolet detectors, and satellite remote sensing. It proposes an advanced ensemble learning model combining YOLOv5 and EfficientDet object detectors with EfficientNet for holistic image analysis, significantly enhancing detection accuracy and reducing false positives by leveraging deep learning techniques on a comprehensive dataset.	99%
8	Forest fire flame and smoke detection from UAV-captured images using fire-specific color features and multi-color space local binary pattern1	This paper introduces a novel fire detection method leveraging texture and color features from aerial images and an ANN classifier suitable for UAVs. It utilizes multi-space LBP features from YCbCr and HSV color spaces to enhance flame and smoke texture detection. Additionally, the incorporation of maximum pixel values alongside mean pixel values significantly improves small flame pixel detection and robustly distinguishes between flame and smoke.	Not provided
9	Forest fire image recognition based on convolutional neural network	This paper proposes a hybrid method that combines conventional image processing and CNNs to segment candidate flame areas based on color features before using CNNs for training, thus enhancing the recognition rate of forest fire images. The approach includes adaptive pooling within the CNN architecture to further improve detection performance amidst complex backgrounds.	80.4% to 90.7% depending on the dataset used.
10	Fire Detection Method Based on Depth-wise Separable Convolution and YOLOv3	This innovative fire detection approach employs a two-phase strategy for analyzing video input. The initial phase utilizes a classification system based on depthwise separable convolutional neural networks (DS-CNN) to determine the presence or absence of fire in each frame. Following this, the second phase comes into play for frames identified as containing fire. This phase leverages YOLOv3's target regression capabilities to pinpoint the exact location of the fire within the image. For frames where no fire is detected in the first phase, the system immediately produces an output without further processing. This dual-stage methodology combines efficient classification with precise localization,	98%

		offering a comprehensive solution for fire detection in video streams.	
11	Forest Fire Smoke Detection Based on Deep Learning Approaches and Unmanned Aerial Vehicle Images	This research proposes a UAV-based system utilizing an enhanced YOLOv7 model for detecting forest fire smoke, integrating advanced attention mechanisms and feature fusion techniques for improved performance. The system uses a comprehensive dataset of UAV-captured forest fire smoke images, leading to a fully automated smoke detection model that can effectively reduce natural disaster impacts. Key enhancements include the incorporation of CBAM and BiFPN modules, which significantly improve the model's sensitivity and accuracy in identifying small-scale smoke features.	Not provided
12	Forest Fire Detection and Monitoring	This paper highlights the critical role of remote sensing (RS) and geographic information systems (GIS) in forest fire detection and monitoring, emphasizing their integration with modern satellite technologies like MODIS and UAVs. It discusses the development of forest-fire risk maps using various statistical models and machine learning techniques, crucial for effective fire management and mitigation strategies worldwide, including	Not provided
		Nepal.	
13	Desert/Forest Fire Detection Using Machine/Deep Learning Techniques	This paper explores the performance of SVM, ResNet-50, Xception, and MobileViT for fire classification using a novel Utah Desert Fire dataset. It proposes modified transfer learning approaches for ResNet-50 and Xception and compares their performance against existing solutions on the DeepFire dataset.	98%
14	Forest fire detection system using wireless sensor networks and machine learning	This paper proposes an early forest fire detection system using a wireless sensor network and a machine learning regression model. The system, powered by rechargeable batteries and solar energy, is designed for prolonged, standalone operation in harsh environments. Real-world trials in tropical forests demonstrated its effectiveness and lower latency in fire alerts compared to existing systems.	81%
15	Forest fire and smoke detection using deep learning-based learning without forgetting	This research focuses on using AI-based computer vision techniques, specifically Convolutional Neural Networks (CNNs), for early forest fire and smoke detection from images. Transfer learning with learning without forgetting (LwF) was applied to pre-trained models like VGG16, InceptionV3, and Xception, achieving high accuracy on both new and original datasets.	96.89%

We have conducted an extensive review of current forest fire detection techniques, as summarized in the Table I. This survey encompassed a wide range of approaches, from UAV-based systems and deep learning models to wireless sensor networks and computer vision algorithms. By studying these diverse methodologies and their reported accuracies, we gained valuable insights into the state-of-the-art in forest fire detection. Building upon this foundation, our research presents a novel two-stage approach to forest fire detection and prevention. Our approach combines elements from several reviewed papers, particularly those utilizing machine learning for risk assessment (such as paper #14) and deep learning models for imagebased fire detection (like papers #1, #5, and #6). However, our two-stage methodology offers a unique integration of risk prediction and active monitoring, potentially improving the efficiency and effectiveness of forest fire detection systems.

IV. METHODOLOGY

A. Model

The YOLO (You Only Look Once) model leverages the PyTorch framework and incorporates new features and enhancements to improve performance and facilitate training. YOLOv8 processes an entire image in a single forward pass of a convolutional neural network. It comes pre-trained on the ImageNet dataset, utilizing an image resolution of 224 for training purposes.

TABLE II. COMPARISON OF VARIOUS YOLOV8 IMAGE CLASSIFICATION MODELS

Model	size (pixels)	acc top1	acc top5	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	params (M)	FLOPs (B) at 640
YOLOv8n-cls	224	69.0	88.3	12.9	0.31	2.7	4.3
YOLOv8s-cls	224	73.8	91.7	23.4	0.35	6.4	13.5
YOLOv8m-cls	224	76.8	93.5	85.4	0.62	17.0	42.7
YOLOv8l-cls	224	76.8	93.5	163.0	0.87	37.5	99.7
YOLOv8x-cls	224	79.0	94.6	232.0	1.01	57.4	154.8

It can be seen from Table II, in the latest YOLOv8 model performance test, based on the open source COCO dataset, YOLOv8n-cls model has small model size and input resolution, making it suitable for deployment on resource-constrained devices in remote forest environments. It has exceptionally fast inference speed of 12.9 ms on a CPU, enabling real-time forest fire detection and rapid response. It has high efficiency with a low parameter count of 2.7M and low FLOPs of 4.3B, allowing for power-efficient operation and broader hardware compatibility. It has a balanced validation accuracy of 69.0% on the COCO dataset, which is sufficient for the forest fire detection task, while maintaining the model's small size and fast inference capabilities. The trade-off between model size, speed, and accuracy is well-balanced in the YOLOv8n-cls model. Therefore, this paper selects YOLOv8n-cls model for training the image data.

B. Network Structure The YOLOv8 architecture, building upon the YOLOv7 ELAN concept, incorporates a refined backbone network and neck module to facilitate robust feature extraction. Departing from the prevalent C3 modules of YOLOv5, YOLOv8 adopts the C2f module, introducing additional skip connections and split operations to enhance feature extraction capabilities. Although these enhancements offer advantages in feature representation, their inclusion may impact deployment efficiency. Notably, the adjustment of the first convolutional layer's kernel size from 6x6 to 3x3 alters the initial feature representation learned by the network, underscoring the significance of seemingly minor architectural modifications.

In the neck module, YOLOv8 streamlines its design by shedding two convolutional connection layers and restructuring the block from 3-6-9-3 to 3-6-6-3. These changes potentially influence the flow of information within the network. Moreover, YOLOv8's backbone design incorporates scaling factors tailored for different model sizes (N/S/M/L/X), with deviations observed in the channel counts of S/M L backbone networks from strict adherence to scaling factors. This design choice suggests a departure from a one-size-fits-all approach, mirroring similar design principles observed in YOLOv7.

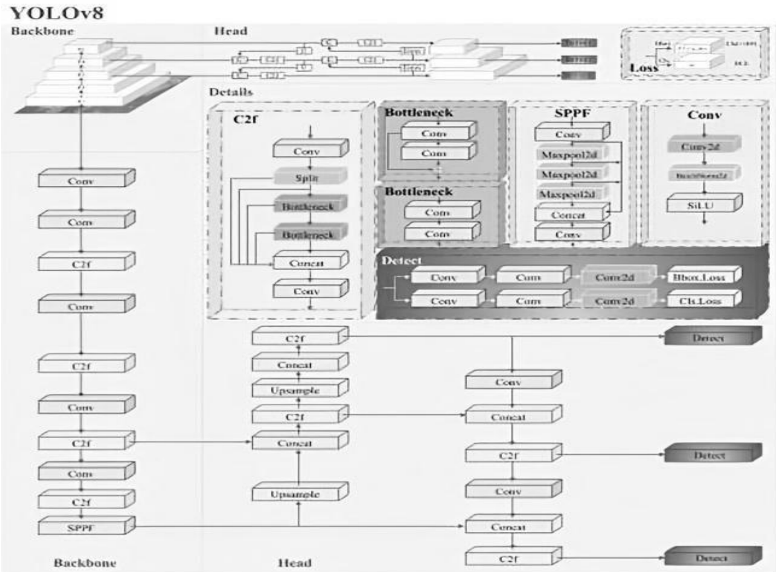

Fig. 1. Network architecture of the YOLOv8 model. Adapted from "Improving Detection Capabilities of YOLOv8-n for Small Objects in Remote Sensing Imagery: Towards Better Precision with Simplified Model Complexity," by R. Bai, F. Shen, M. Wang, J. Lu, & Z. Zhang, 2023, (https://doi.org/10.21203/rs.3.rs-3085871/v1). Copyright 2023 by Ruihan Bai et al.

The most significant architectural evolution in YOLOv8 lies within its head module. Transitioning from a coupled structure to a decoupled design separates the classification and detection heads, aligning with contemporary trends in object detection architectures. Furthermore, YOLOv8 adopts an Anchor-Free approach, discarding the objectness branch and retaining only the decoupled classification and regression branches. The regression branch adopts the integral form representation introduced by the Distribution Focal Loss (DFL), signaling a departure from traditional object detection methodologies.

In the loss calculation process, YOLOv8 leverages the TaskAlignedAssigner strategy for sample assignment, assigning positive samples based on a weighted combination of predicted classification scores and Intersection over Union (IoU) metrics. The loss calculation incorporates Binary Cross-Entropy (BCE) Loss for classification and a combination of DFL and CIoU Loss for regression, weighted by specific ratios to compose the final loss function. The matching strategy of TaskAlignedAssigner can be summarized as follows: positive samples are selected based on the weighted scores of classification and regression.

$$t = s^{\alpha} \times u^{\beta} \quad (1)$$

where, $\boldsymbol{s}$ is the prediction score corresponding to the ground truth category, $\boldsymbol{u}$ is the IoU of the prediction bounding box and the gt bounding box.

Data augmentation in YOLOv8 closely resembles that of YOLOv5, with a notable modification introduced during the final 10 training epochs. Following the YOLOX approach, Mosaic data augmentation is discontinued to mitigate potential performance impacts from artifact introduction. The intensity of augmentation varies based on model scale, with larger models integrating techniques like MixUp and CopyPaste to enhance training data diversity.

In the inference and post-processing stages, YOLOv8 largely mirrors the workflow of YOLOv5. Notably, decoding integral representation bounding boxes generated by DFL requires conversion into standard 4dimensional bounding box formats. The post-processing pipeline encompasses decoding bounding boxes, dimensional transformation, and subsequent steps to ensure efficient object detection.

V. IMPLEMENTATION

A. Image Classification Dataset

For training the YOLOv8 image classification model, we collected a dataset consisting of 3871 samples, including 1762 images of fire class and 2109 images of non-fire class, obtained from Google Images. We ensured that the training and testing data were non-overlapping to maintain the integrity of the model evaluation process. The dataset was divided into training and testing sets, with 799 samples used for testing. The model was trained over 40 epochs, with an image size factor set to 64 to optimize performance. During training, the YOLOv8n model in YOLOv8 architecture was utilized.

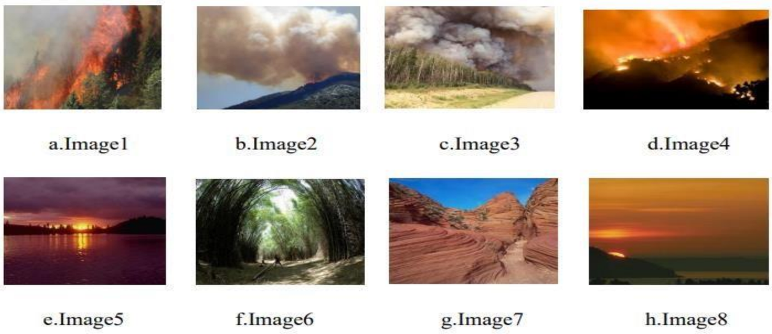

Fig. 2. Example of training pictures

B. Forest Fire Susceptibility

Dataset

In parallel, we developed a machine learning model to predict the likelihood of forest fires based on environmental factors such as longitude, latitude, temperature, humidity, vegetation type, and wind speed. The dataset used in this study comprises 77 samples for training and 52 samples for testing, contributing a total 129 sample-dataset. The dataset was obtained from an undisclosed source and lacks comprehensive documentation regarding its origin and collection details. However, an analysis of the latitude and longitude value ranges suggests that the data was likely collected from regions across the western United States and potentially northern Mexico. Specifically, the latitude values range from approximately 21°N to 54°N, encompassing areas from southern Mexico up through the western and central United States. The longitude values span from around 88°W to 128°W, covering the western half of the United States from roughly the Rocky Mountains westward to the Pacific coast. This includes states and regions such as California, Oregon, Washington, Nevada, Idaho, Utah, Arizona, New Mexico, Colorado, Montana, and

Wyoming, as well as western portions of Texas. Various classification models like Logistic Regression, Random Forest Classifier, Decision Tree Classifier, Support Vector Classifier and KNN Classifier were trained on 40 samples of class 0 (less prone to forest fires) and 37 samples of class 1 (more prone to forest fires), with 24 samples of class 0 and 28 samples of class 1 utilized for testing.

TABLE III. FIRST FEW SAMPLES OF TRAINING DATASET

longitude	latitude	temperature	humidity	vegetation type	wind speed	forest_fire
112.23	34.45	90	10	2	15	1
100.67	29.82	85	20	3	10	0
98.33	32.77	100	5	0	20	1
122.41	47.62	75	35	1	5	0
105.81	44.3	80	15	4	12	1
114.6	35.11	95	8	2	18	1
104.59	30.38	90	12	3	11	0
92.33	45.51	70	40	1	4	0
111.7	33.52	105	3	0	22	1
121.95	37.42	60	50	4	3	0
106.23	32.77	85	15	3	13	1
100.51	43.58	75	25	1	7	0
95.59	30.97	65	35	3	2	0
125.68	49.17	55	45	0	1	0

As in Table III., the dataset provided contains several key environmental variables measured across different locations. The longitude and latitude values are reported in degrees, the standard units for geographic coordinates, while temperature is expressed in degrees Fahrenheit, a common temperature scale. Humidity is measured as a percentage (%) to indicate the moisture content of the air.

The vegetation type column represents the dominant plant life in each location, encoded as integer values corresponding to specific vegetation categories, such as dry shrubland, grassland, coniferous forest, deciduous forest, and mixed forest, denoted as 2,3,0,1 and 4 respectively in the training dataset.

Additionally, the wind speed is quantified in miles per hour (mph), a standard unit for air movement. Importantly, the forest_fire column denotes the presence (1) or absence (0) of forest fire risk or occurrence in each location, providing a binary classification of this critical environmental factor.

VI. RESULTS

A. Image Classification Dataset Upon testing, the YOLOv8n model exhibited an impressive accuracy of 98.49% on the testing data, showcasing its efficacy in classifying forest fire images with high precision and recall. The trained YOLOv8 model achieved excellent performance metrics, with a precision of 0.98, recall of 0.99, and F1 score of 0.98 on the test data. These results indicate that the model effectively distinguishes between fire and non-fire images, with minimal false positives and false negatives.

Fig. 3. Results given out by the test batch 1

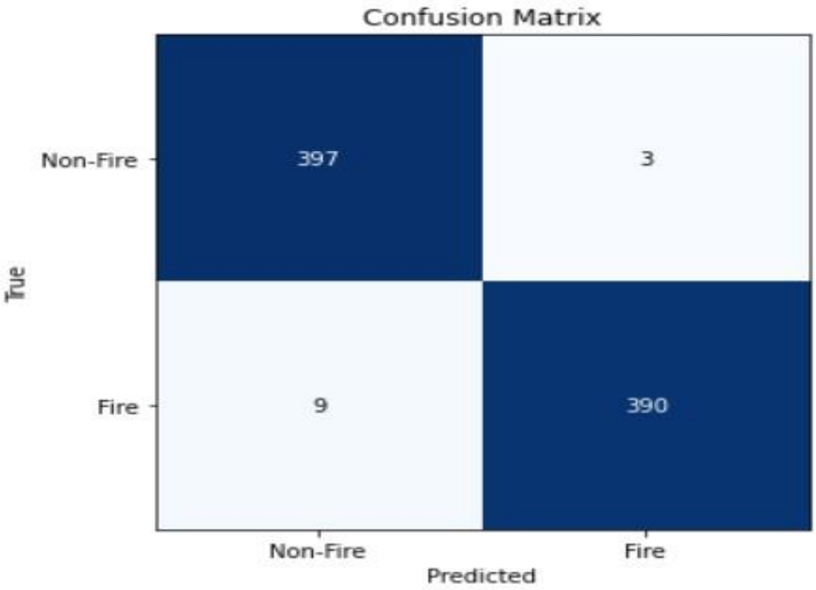

Fig. 4. Confusion Matrix for Test Dataset

As in Fig. 4., the confusion matrix illustrates the performance of the YOLOv8 model on the testing data. The matrix shows that out of the total test instances, the model correctly classified 390 fire cases and 397 non-fire cases. However, it misclassified 3 non-fire instances as fire (false positives) and 9 fire instances as non-fire (false negatives).

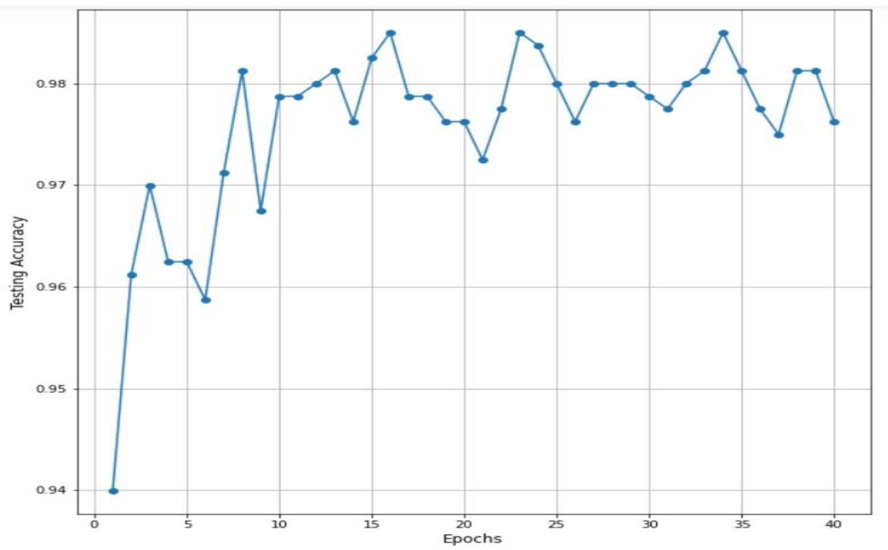

Fig. 5. Testing accuracy variation over epochs

As in Fig. 5., the graph illustrates the variation of testing accuracy over 40 epochs during the training of the YOLOv8 model. The accuracy curve exhibits fluctuations, which is a common pattern observed in deep learning model training. The initial epochs show a steep increase in accuracy, indicating that the model is learning the relevant features rapidly. However, as the training progresses, the accuracy curve becomes more volatile, with occasional dips and peaks, suggesting that the model is fine-tuning its parameters to capture more intricate patterns and generalize better. Despite the fluctuations, the overall trend demonstrates that the model achieves a reasonably high testing accuracy, maintaining a level around 0.98 throughout the later epochs.

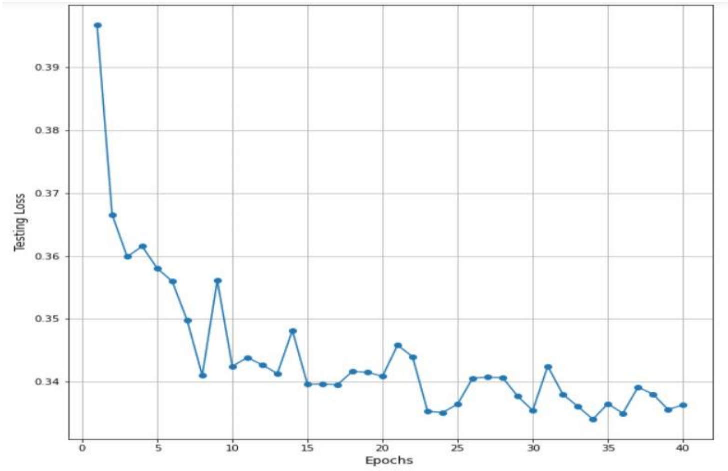

Fig. 6. Testing loss variation over epochs

As in Fig. 6., the graph depicts the testing loss curve over 40 epochs during the training of the YOLOv8 model. Initially, the loss decreases steadily, indicating effective learning. Subsequently, the curve exhibits volatility with occasional spikes, suggesting the model is adapting to complexities in the data. Despite fluctuations, the overall trend remains relatively low, signifying the model's ability to generalize and minimize errors on unseen data. Occasional increases in loss are not uncommon as the model may overfit or struggle with certain instances temporarily during training.

TABLE IV. COMPARISON OF MODELS USED BASED ON EVALUATION METRICS

Model Name	Testing Accuracy (in %)	Precision Score	Recall Score	F1 Score
YOLOv8	98.49	0.98	0.99	0.98
ResNet-50	88.36	0.50	0.50	0.49
VGG19	95.74	0.51	0.51	0.51
GoogLeNet	96.75	0.51	0.50	0.50

As in Table IV., the comparison table presents the performance metrics of different image classification models on the same test data. YOLOv8 outperforms the other models by a significant margin, achieving a testing accuracy of 98.49% and impressive precision (0.98), recall (0.99), and F1 (0.98) scores. This indicates that YOLOv8 is highly effective in correctly classifying fire and non-fire instances while maintaining a good balance between precision and recall. The other models, ResNet50, VGG19, and GoogLeNet have lower testing accuracies and relatively poorer precision, recall, and F1 scores compared to YOLOv8.

B. Forest Fire Susceptibility

Dataset The Logistic Regression model achieved the highest accuracy of 98.08% on the test data, indicating its capability to accurately predict forest fire susceptibility based on the input environmental factors. The logistic regression model demonstrated excellent performance, with precision, recall, and F1 score values of 1.0, 0.96, and 0.98, respectively. These results underscore the model's effectiveness in accurately classifying forest areas into low and high susceptibility categories.

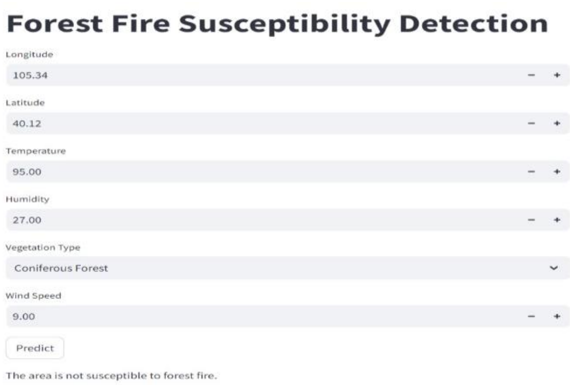

Fig. 7. Output given on an input set by Logistic Regression Model

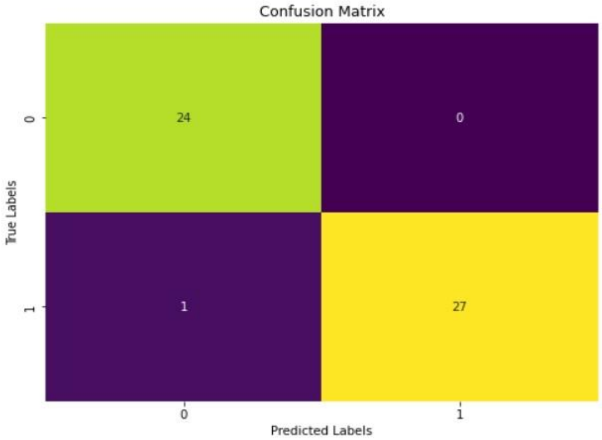

Fig. 8. Confusion Matrix for Test Dataset

As in Fig. 8., the confusion matrix shows the performance of a logistic regression model on test data for forest fire prediction. The model correctly predicted 24 instances where there was no fire (represented by the value 0) and 27 instances where there was fire (represented by the value 1). There were 0 instances where the model incorrectly predicted fire (false positives), and 1 instance where the model incorrectly predicted no fire (false negative).

TABLE V. COMPARISON OF MODELS USED BASED ON EVALUATION METRICS

Model Name	Testing Accuracy (in %)	Precision Score	Recall Score	F1 Score
Logistic Regression	98.08	1.0	0.96	0.98
Random Forest Classifier	92.31	1.0	0.86	0.92
Decision Tree Classifier	90.38	1.0	0.82	0.90
Support Vector Classifier	92.31	0.96	0.89	0.92
KNN Classifier	90.38	0.96	0.86	0.90

As in Table V., the comparison table presents the performance of various machine learning models on the same test data. Logistic Regression achieves the highest testing accuracy of 98.08% along with a perfect precision score of 1.0 and a high recall score of 0.96, resulting in an impressive F1 score of 0.98. This indicates that Logistic Regression is highly effective in predicting the likelihood of forest fires based on the given features. Random Forest Classifier and Support Vector Classifier also performed reasonably well, with testing accuracies of 92.31% and high precision scores. However, their recall scores are slightly lower compared to Logistic Regression, suggesting a potential trade-off between precision and recall in these models.

VII. CONCLUSION AND PROSPECTS

Our research presents a robust and comprehensive approach to forest fire detection and management through the integration of advanced technologies such as image classification using YOLOv8 and predictive modelling. The results demonstrate the efficacy of our methodology, with the YOLOv8n model achieving high accuracy rates in classifying forest fire images and the logistic regression model accurately predicting forest fire susceptibility based on environmental factors. These findings underscore the potential of leveraging artificial intelligence and machine learning for proactive forest fire prevention and timely intervention. Moreover, the integration of UAVs or drones holds great promise for enhancing our detection system's capabilities further. By integrating our YOLOv8 model with UAVs, these drones can continually scan forest areas identified as highly susceptible to fires by our predictive model, enabling real-time monitoring and early detection of fire occurrences. This proactive approach can significantly aid forest authorities in deploying timely intervention measures to mitigate the impact of forest fires, thereby safeguarding ecosystems, wildlife, and human lives. Looking ahead, the integration of our YOLOv8 model with UAVs opens up exciting possibilities for the future of forest fire management. By equipping UAVs with our detection system, they can autonomously patrol forest areas identified as high-risk based on our predictive model. Continuously scanning the terrain from above using onboard cameras, these drones can swiftly detect any signs of fire presence in the imagery. Upon detection, they can promptly transmit alerts to forest authorities, enabling rapid response and intervention. Furthermore, the combination of our YOLOv8 model with UAV technology can facilitate dynamic monitoring of large and inaccessible forest regions, providing comprehensive coverage and timely detection of fire outbreaks. This proactive approach not only enhances the efficiency of forest fire management but also minimizes the potential damage to ecosystems and communities. Therefore, the future integration of our YOLOv8 model with UAVs represents a promising direction for advancing forest fire detection and response capabilities, ultimately contributing to enhanced environmental conservation and safety measures.

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