Real-Time Fire Object Detection System Using Machine Learning

Venkata Bhargavi. Akuthota[1,*], *Khadar Basha*. Syed[2], *Dhanush*. Ramineni[3], and *Vikram*.Guduru[4]

[1,2,3,4]Department of CSE, Vignan's Foundation for Science, Technology and Research Vadlamudi, Guntur, Andhra Pradesh, India

Abstract. The spread of forest fires presents one of the major concerning ecosystems, human security, and property. This paper introduces a fire object detection system that employs machine learning algorithms to enhance early detection of fire breakout and response to the same. The computer vision and deep learning algorithms allow the system to identify features related to fire objects and actions in images and video feeds. This set of scenarios under various fire conditions, environmental conditions, and backgrounds was curated for training a CNN. In terms of evaluating the model's robustness in real applications across various settings, the metrics were defined by accuracy, precision, recall, and F1 scores. The proposed system is designed for alerting emergency responders within time so that quicker intervention may be made to possibly mitigate the devastating effects of wildfires. Future research will be the integration of the system into real-time surveillance systems and exploring added sensory data to increase the detection capabilities.

1 Introduction

A general review of current forest fire detection methods-that focus more on recent advancements in image processing and deep learning-are in fact mentioned. Wildfires are an area of significant environmental as well as economic threats, therefore, early detection is very important to manage and mitigate fires efficiently This paper covers some of the state-of-the-art models and technologies on one's agenda that have an objective to become a tool

*Email; akuthotabhargavi864@gmail.com

in enhancing early warning systems as well as minimizing damages caused by wildfires. [1].The project will ensure a real-time fire detection system that utilizes the power of machine learning algorithms and computer vision techniques in order to enhance the efficacy of fire detection. This shall be achieved by integrating advanced algorithms such as Convolutional Neural Networks and Support Vector Machines. [2]. Since these fire detection systems act to avoid the utmost devastating consequences of wildfires and urban fires, authors want to overcome the shortcomings of traditional approaches by applying sophisticated deep learning models. Their solution is an architectural style-based CNN type that enhances accuracy, speed, and reliability in real-time fire detection scenarios. The proposed model analyzes large amounts of image data so that it can recognize fire outbreaks more efficiently than by conventional methods. Paper Topics: Deep Learning is Important to Automate Fire Detection. It Applies for modern smart cities and industrial environments. [3]. C.P. Kala discusses the environmental and socioeconomic implications of forest fires bringing the immediate call for multilateral cooperation and management interventions. Forest fires possess significant threats to biodiversity and ecosystems as well as human livelihoods, thus destroying vast areas in regions around the world. The paper describes how those fires not only cause habitat loss and carbon emissions but also disrupt local economies and communities dependent upon forest resources. [11]. Using a machine learning approach and deep learning models involving object detection frameworks such as YOLO (You Only Look Once) and Faster R-CNN (Region-Based Convolutional Neural Networks). These models find great popularity in real-time fire detection as these models have the potential to recognize the fire region within an image with very high accuracy and high efficiency.

The fire region annotations done by the authors are structured, which increases the robustness of the training datasets used in these models toward the applications of fire surveillance. [13]Fire detection systems are the critical ingredient for mitigating the environmental, economic, and human impacts of fires. Thus, research is continually directed toward improvement for enhancing reliability, scalability, and integration with intelligent surveillance to support better fire management and prevention

2 LITERATURE REVIEW

Fire detection systems are the critical ingredient for mitigating the environmental, economic, and human impacts of fires. Thus, research is continually directed toward improvement for enhancing reliability, scalability, and integration with intelligent surveillance to support better fire management and prevention.

Özel, Alam [1] The authors pointed out that traditional methods such as satellite monitoring and infrared sensors were difficult because they lagged into time and gave false alarms. The authors have successfully shown how the deep models, CNNs specifically, are very efficient in the real-time detection of fire patterns from different sources. It should be stressed that frameworks such as YOLO (You Only Look Once) and Faster R-CNN are also more powerful, and enhancements in accuracy and speed of the systems increase the reliability of the systems. the innovations in these technologies are critical in providing efficient improvement for early fire detection and management. In this machine algorithm. Naive Bayes Classifier gives a Best

Accuracy is 99 percent

Shahi Dost, S., Shabbir, M [2] Outlier classification for mining evolutionary communities have explained several approaches which are biased towards machine learning techniques to identify anomalies in dynamic data sets. Traditional statistical methods do not perform well at the task of anomaly identification on complex, dynamic data and hence the requirement of sophisticated algorithms. The authors have discussed SVM and Logistic Regression as effective tools to be applied in such a scenario and illustrated its performance on Azure Machine Learning.

Mohit Dua; Mandeep Kumar; Gopal Singh Charan; Parre Sagar Ravi [3] Dua et al. approach such a concept by building from the previous works that already employed the use of machine learning for fire outbreak detection in different settings. Studies have pointed out the fact that even the most traditional fire detection techniques like smoke detectors and infrared sensors fail in accuracy and response time in complex settings. The authors have stated that Convolutional Neural Networks can be implemented to scan large databases of images to enhance fire detection capabilities. As the authors propose an improved deep learning approach to the problem, this contributes to all the efforts into finding reliable and efficient fire detection systems due to their adaptability in changing and challenging environments. This study calls for advancing and perfecting machine learning techniques for improving safety responses and strategies in fire-prone places.

FatmaM. Talaat, Hanaa ZainEldin [4] Talaat and ZainEldin use some of the leading-edge deep learning models particularly in the case model YOLO-v8 for enhancing precision in detection while looking forward to providing a response time by their work in this research regarding the fire detection for smart cities. They discuss the efficiency of applying transfer learning whereby pre-trained models are tailored and adjusted to other applications which have reduced the demand in terms of data to be trained. Furthermore, they focus on the algorithm assembling in fire detection and IoT systems in smart cities, further expediting alerts and managing the resources better too. This work is part of contributions towards making improvements in fire safety for cities with new technologies

Md. Ashif Mahmud Joy, 3Ayesha Siddiqua, Md. Nurul Islam, Dr. Fuad Hasan Khan Chowdhury [5] The author, joy et al. of this paper, has presented the study carried out for the existing fire detection systems and identified some of the primary limitations inherent in traditional methods Some of the primary limitations inherent in the traditional methods include the high level of false alarm rates and delayed response times in densely populated as well as forested areas. There is much concern among researchers regarding the integration of sophisticated technologies, including machine learning and image processing capabilities, which would enhance detection capabilities. This research also has a contribution associated with discussion that continues towards improving fire detection technology and also advocating a more integrative approach suited specifically for diverse scenarios

Marwa Jamal et al. [6] The approach proposed this architecture by combining the YOLOv5, an effective yet efficient method for real-time object detection, with the U-Net architecture, used for fire segmentation. This enhances the systems’ capacity to do precise fire detection in complex environments. Hybrid models of this type are better than earlier approaches that centred on standalone models, such as CNNs or traditional image processing techniques. Besides, in this work, the authors stress the training using different datasets to learn robustness when applied to different fire conditions.

Yanık et al [7] The paper an architecture for smoke and fire detection was proposed by Yanık et al. through a lightweight deep learning model known as

Mobile Net. Because it is efficient, Mobile Net can be applied to real-time processing on drones. Such drones are limited to their computational resource so this is advantageous to the drones to inspect the remote or inaccessible areas for early fire detection. This hence presents another advantage in the deployment of AI models on resource-constrained devices as it explicitly posits the potential for real-time aerial surveillance in the fire-prone regions

Chandak [8] Using the streams of real-time data, the possible issues which can be criticized are high ingress and continuous streams that appear under usual scenarios of fire detection systems-deployed either in the forest, or inside buildings, even in the industrial sites. For instance, dealing with concept drift, handling imbalanced data, and using the big data tools such as Apache Spark, the system of detecting fire can work more effective, accurate, and scalable toward prompt responses and results in a case concerning security and safety issues.

A.S. Shamsoshoara, F. Afghah, A. Razi, L. Zheng, P.Z. Fulé, and E. Blasch**,** [9] This work identifies pile burns using aerial imagery and deep learning. It incorporates the "Flame Dataset," which is a specialized dataset, and hence, enhances the features to identify flames in complex scenarios. Earlier methods of fire detection on aerial imagery relied heavily on the old computer vision approach that performed poorly in terms of accuracy under dynamic conditions. Improved methodology using deep learning significantly enhances the precision of detection and minimizes false positives. Such a research goes to show the potential of using AI within surveillance from an aerial perspective as well as in dealing with wildland fires

de Venâncio et al [10]de Venâncio et al. in 2023 proposes a fire detection system which amalgamates YOLOv5 with time analysis to improve the accuracy in the fire event detection. This approach reduces false positives by considering the temporal behaviour of fire and smoke. Where the previous research work most probably used still images, there is need for temporal analysis such that there can be a difference between fire elements and non-fire elements based on changes in the environment

C.P. Kala [11] The C.P. Kala, 2023 emphasizes environmental and social implications of forest fires, where multilateral cooperation should be promoted along with efficient management interventions. And it is significant in respect to functions of forest fires in terms of the progress of deforestation, loss of biodiversity, and economic disruption in fire-prone regions. The research project underscores the inadequacy of the prevailing fire management practices worldwide and calls for a more sustainable and inclusive fire damage mitigation in the world.

Lu P, Zhao Y, Xu Y [12] They proposed a two-stream CNN model that detects the region of flames with adaptive receptive field adjustments to promote the accuracy in the detection. In this regard, it focuses on interesting features at varying scales and hence detects flames more effectively for differing surroundings Earlier methods typically possessed a static receptive field, which limited their potential flexibility in terms of accepting sizes and intensities of flames variations.

Wahyono, A. Dharmawan, A. Harjoko, Chrystian, F.D. Adhinata [13] (2022) is focused work on region-based annotation for fire images to support intelligent surveillance systems. Their machine learning models are required to be trained, and that requires a certain dataset or set of images of fire accidents. The annotated dataset matters in improvement for model training since most the previous works on fire detection did not have a relevant and usable dataset, and it will make improvements in training models very challenging, especially in scenarios that deploy images like surveillance.

Bahhar, C. Ksibi, A. Ayadi, Jamjoom, M. Ullah, [14] (2023) a wildfire and smoke detection system based on a staged YOLO model that is combined with an ensemble of CNNs. The staged YOLO model aims at improving the wildfire detection mechanism since it deciphers the various stages involved in the wildfire and smoke occurrence, thus capturing early and developed fire events. This paper contributes toward the technologies involved in fire detection and presents an effective multi-stage solution for real time wildfire surveillance.

X. Song, S. Gao, C. Che, [15] It is going to make use of features fusing multispectral techniques to detect pedestrians. Although the main subject of this work is to primarily focus on pedestrian detection, the ideas can be borrowed for fire detection systems, mainly on feature fusion and robustness in detection.
With multispectral feature fusion, deep learning models, and big data frameworks all combined, it is thereby feasible to create a system that is less only correct in detecting fires but also reliable, with concern for false positives, novel fire patterns, and other such challenging environmental conditions

3 Methodology

3.1 Data Collection

Data Collection: The dataset contains environmental data such as temperature, humidity wind speed, and many more fire weather indices like FFMC, DMC, ISI, etc., and size of areas of burnings of forest fires.

– Data Annotation: It provides labels to the data consisting of features of relevance enough to predict the probability of its happening and the extent of fire along with a chance of using supervisions in the process of training.

3.2 Data Preprocessing

Feature Encoding: The categorical variables like month and day need to be changed to numerical ones so that it learns how to process it appropriately.
Normalization: Continuous variable temperature, wind, and humidity are converted so that features lie in a different scale so training the model is more efficient.

3.3 Dataset Splitting

This divides the dataset into three parts - training, testing, and validation. That will mean 80Model Design: It involves models applied with the paper for machine learning, which are Decision Trees, Random Forest, SVM, Logistic Regression, Naive Bayes, Boost, and K-Nearest Neighbours (KNN) as they can be designed to learn features of the environment beforehand pertaining to their ability to predict fire occurrences Model Compilation I compile every model with a loss function-tuned to either regression or classification-specific mean squared error in case of regression or categorical cross-entropy in case of classification

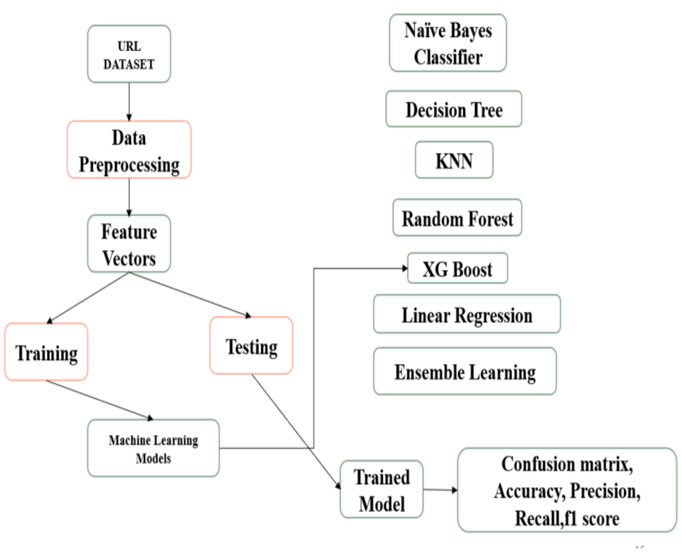

Fig. 1. Flowchart of Machine Learning Pipeline for Fire Object Detection.

3.4 Model Training

This stage involves training the preprocessed dataset on the trained models for some fixed number of epochs. Here, in this process, they tend to learn retrieval of patterned information from environmental data that could cause fire, thereby changing their parameters inside to reduce prediction errors.

Validation: The validation set was intended to train; thus the correct fine-tunings in this regard, including the hyperparameters tuning or early stopping to avoid overfitting

3.5 Model Evaluation

– Testing: Trained models are tested on the test dataset. Accuracy, precision, recall, and F1 score are calculated so as to find how accurate areas prone to fires can be predicted.

The above (Fig:1) shows a Project flow diagram shows the process for a predictive analysis for forest fire detection using machine learning models. It begins with cleaning the URL dataset by data preprocessing and transforming data into feature vectors. The dataset is split into training and testing sets, and various machine learning models, i.e., naïve bayes, logistic regression, K-NN, Decision trees, Random Forest, XG Boost, including individual and ensemble models, are trained. Predictions from these models are evaluated using metrics like confusion matrix, accuracy, precision, recall, and F1-score to determine detection of forest.

3.6 Objective

This project will construct an efficient machine learning model by essembling various classifiers, namely Logistic Regression, Naive Bayes, and KNN, SVM Putting all these together would allow the ensemble to exploit the best strengths of each classifier in enhancing any possible overall accuracy, precision, recall, or more performance metrics. Variations are handled more robustly as well, and it also forms a point of comparison among the different models. The idea is to design a classification model that is at once reliable and high-performing on complex data sets which can impact real-life decision-making accuracy.

3.7 Feature selection

Integrated IoT device and Drones for real-time monitoring Use of real-time video processing to enhance live feed detection of fire Ensemble Learning with Transfer learning for better accuracy of the model Weather and environmental data for enhanced prediction Suppress false alarms via Advanced filtering Integrated Emergency Response systems for providing timely alerts The selected features are normalized with namely KNN and Logistic Regression, which depend on the magnitude-based computation and therefore would
yield different results. Finally, Voting Classifier combines various classifiers, including Logistic Regression, Naive Bayes, and KNN-trained on the clean, pre-processed feature set: This approach combines both feature-level voting and individual model insights, thus improving the robustness of phishing detection relating to patterns in feature extraction that always predict phishing activity across models. Thus, it supports high-performance phishing detection, like methodologies adopted in similar studies.

4 Results and discussion

Features obtained using deep learning models have been experimented upon. The accuracy of different classifiers varied at an enormously broad scale. It was seen that for the KNN classifier, the accuracy was 52 percent, SVM obtained 53 percent, Naïve Bayes Classifier

showed a brilliant 99 percent, Random Forest obtained 57 percent, Decision Tree 53 percent, Logistic Regression 49 percent,
CNN obtained 56 percent, and XGBoost 58 percent. Naïve Bayes per- formed much better than all other algorithms, while XGBoost only managed to attain modest improvement at 58 percent accuracy. Although some algorithms perform rather modestly, the overall results clearly confirm that Naïve Bayes is one heck of a performer and XGBoost stands in good promises of further tuning.

Overall, the performance difference among the classifiers emphasizes that algorithms are more appropriate for some distributions over data and some feature spaces than for others. The high 99 percent accuracy of Naive Bayes suggests that the conditional independence assumption may be valid here; the probabilistic nature of this model must be an asset when given cleaner, smaller datasets. On the other hand, Logistic Regression and KNN algorithms which are based on linear dependencies or proximity have been unsuccessful because the relationship between the variables in the data set is non-linear.

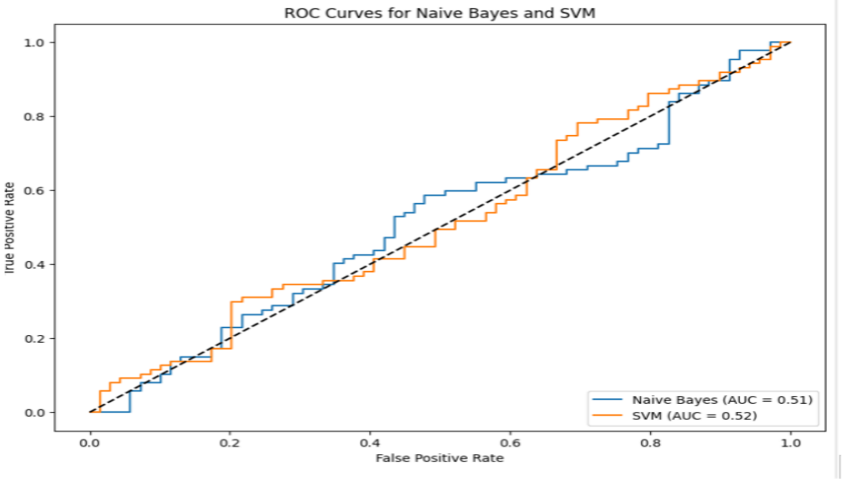

Fig. 2. ROC Curve for Naive Bayes and SVM

The above (Fig:2) ROC curve depicted in the figure compares the performance of two classification models: Naive Bayes and Support Vector Machine . Both models are evaluated using their ROC curves,
which plot the True Positive Rate against the False Positive Rate at different threshold levels.

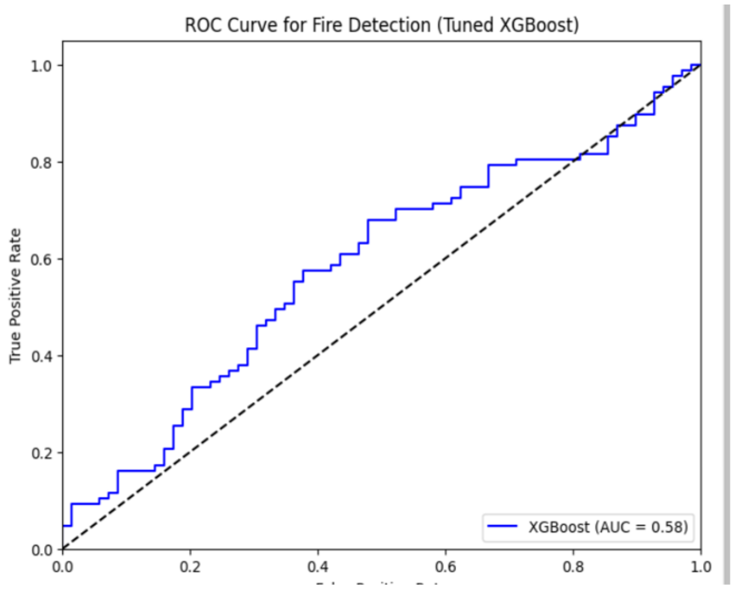

Fig. 3. ROC curve for XG Boost

The above (Fig:3) represent an ROC (Receiver Operating Characteristic) curve for a fire detection model using the XGBoost algorithm. The AUC (Area Under the Curve) value of 0.58 suggests that the model is performing slightly better than random guessing (an AUC of 0.5).

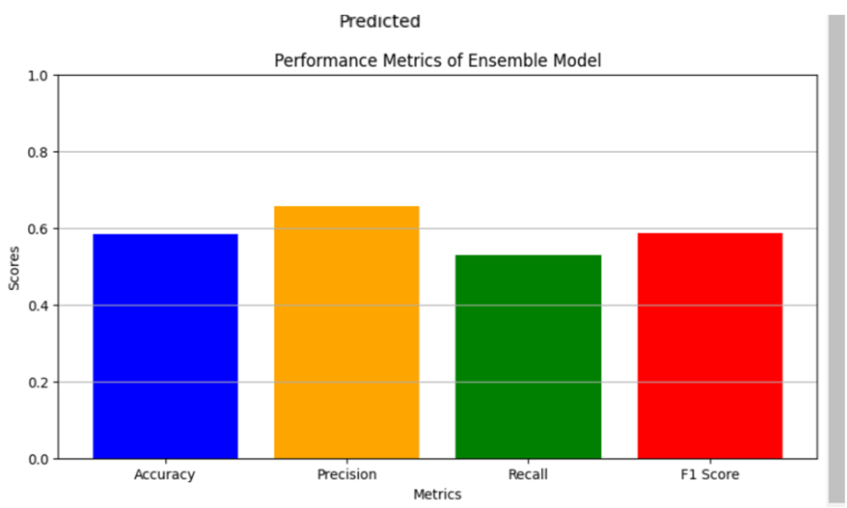

Fig. 4. Performances Metrices of Ensemble Model

The above (Fig:4) represents a bar chart displaying the performance metrics of an ensemble model. The metrics typically used to evaluate the effectiveness of a classification model include Accuracy, Precision, Recall, and the F1 Score

5 Conclusion

The fire detection system mainly employs algorithms based on machine learning to identify probable fire hazards by considering various input data. This should train the model on historical datasets of fire occurrences, so it is able to recognize patterns and conditions which usually precede an outbreak of fire. Feature selection includes temperature, wind speed, humidity, and rainfall, to ensure that the model incorporates all those important environmental factors so that it can be applied with versatility and reliability in various regions and conditions. With constant learning, the model could evolve from time to time, responding well to changing climate conditions and getting better by time and hence achieving more robust- ness in fire-prone areas. Finally, as machine learning becomes integrated with IoT sensors or satellite data, the system is not only improved but basically gives a better real-time view of actual environmental conditions. With the effect of cumulative data from various sources, the model may refine its prediction and provide fire alerts that are even more accurate.

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