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Technique for anomaly based wild fire outbreak prediction in forest environment

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Abstract
One of the most important ecological resources in the world is forests. However, forest fires (FFs), which harm the ecosystem and have an effect on species and economy, pose a serious threat to them. More precise prediction techniques are desperately needed due to the rising incidence of FFs worldwide. The accuracy and scalability of traditional FF forecast methods, which depend on meteorological data and human knowledge, are frequently constrained. This research review various current techniques for the prediction of forest fire, with detailed analysis of their processes, challenges, effectiveness and weaknesses. Covering research published between 2018 to 2025, 25 out of 140 papers were selected for in-depth investigations analysis. These findings show that machine learning is mostly adopted for the prediction of FF, followed by recurrent convolutional neural network algorithms. Models or processes such as neural network clustering were also deployed. Furthermore, python programming language and pytorch simulation tool were mainly adopted for the implementation and experimentation of the existing algorithms. The research outcome also shows that misclassification, high false positive rate and spatio-temporal differences were the common weaknesses of the algorithms, which may lead to further research directions. Also, integrating human activity data is still understudied. Closing this gap could improve Deep Learning and machine learning models' usefulness for the prediction of wild Fire in Forest environment.

Keywords: Wide fire, anomaly, deep learning, machine learning and simulation tool

Introduction

Approximately 4 billion hectares, or 30% of the world's area, are covered by forests alone. Global biodiversity preservation depends on the preservation of forests (Ball *et al.,* 2021) [23]. Destructive occurrences like wildfires have the potential to negatively alter the planet's equilibrium and endanger our future. Long-term catastrophic impacts of wildfires on ecosystems include the destruction of land covers, greenhouse gas emissions, vegetation dynamics, and wildlife habitat (Barmpoutis, *et al.,* 2020) [13]. Minimizing the loss of life and property from flames requires early identification and quick extinguishment (Ezeh *et al*., 2014) [35]. According to the National Interagency Fire Center (NIFC), the number of acres burned by wildfires in the United States of America has risen from about 3 million acres in the 1990s to over 8 million acres in recent years (Giannakidou *et al.,* 2024) [9].

Globally, there are now more wildfires due to climate change-induced greater temperatures and more frequent droughts, which has had serious effects on the economy, the environment, and society. In this regard, reducing the effects of wildfires requires efficient fire management techniques that use the newest technical developments, such as artificial intelligence (Avaorao and Ezeh, 2010) [36]. A number of studies have studied the impact of wildfires and the relevance of good fire management strategies. For example, a study by the NIFC expected the total direct and indirect costs of wildfires in the US to exceed $20 billion in 2020 (National Interagency Fire Center, 2020).

According to a different study published in the International Journal of Wildland Fire, the cost of wildfires to the world economy was assessed at $126 billion in 2015 and is expected to rise to $230 billion by 2030 (Bowman *et al.,* 2019). These results emphasize how crucial it is to spend money on efficient fire management techniques.

Natural catastrophes like wildfires can have catastrophic effects on infrastructure, communities, and the environment (Edje *et al*., 2022). In order to lessen the effects of these occurrences, effective prevention and preparedness measures are essential. In this context, wildfire prevention and preparedness models are important because they offer useful data to aid in fire management and planning initiatives (Pereira *et al.,* 2022) [26]. These models forecast the probability of a wildfire in a given area by combining fuel, weather, and human activity data.

The models also examine the behaviour of the fire once it has started, including its rate of spread and the potential area that may be affected (Edje and ABD Latiff, 2021) [37]. This information is vital in driving decision-making processes, including resource allocation, reaction planning, and the development of effective mitigation methods (Subramanian and Crawley, 2017) [27]. These models take into account social factors like land use, population density, and human behavior in addition to physical elements, which might affect the probability and intensity of a wildfire (Noonan-Wright *et al.,* 2022) [6]. The combination of these factors into the models improves their accuracy and the efficiency of the policies implemented from their outcomes.

Machine Learning (ML) is one of the most widely utilized models for predicting and preventing forest wildfires. In order to predict the likelihood of wildfires, the course of fire expansion, or the fire susceptibility of certain places, machine learning algorithms may be able to identify patterns and correlations in data (Yao *et al.,* 2018) [29]. These forecasts can then help with reaction action planning, managerial decision-making, and policy considerations. Among the most popular machine learning techniques for modeling wildfires are decision trees, random forests, and support vector machines (Kim *et al.,* 2024) [32]. Artificial Neural Networks (ANNs) are another approach that has been used in wildfire forest prediction. ANNs have been used to detect fire severity, identify possible ignition sources, and model the behavior of fire spread. Additionally, ANNs are capable of processing large amount of data from several sources, including weather forecasts and satellite photos, and producing predictions in real time (Mohajane *et al.,* 2021) [28].

Methodology

The current study was carried out using the research methods employed in previous literature reviews, which were written by Agboi *et al*. (2024) and Adigwe *et al*. (2024) [33, 34]. The research methodology aims to help understand the overall impact of using diverse algorithms for the prediction of anomaly based fire outbreak in forest environment.

The main Research Questions (RQ) that were developed in order to look into and carry out the current study are listed below.

- What functionalities and attributes do the algorithms have?
- What are the privileges and challenges of the existing algorithms for identifying anomaly based fire outbreak in forest environment?
- What methods do the existing algorithms used to identify anomaly based fire outbreak in forest environment?
- What programming languages and simulation environments adopted for implementing the algorithm and performance assessment?
- Which studies have been published on algorithms for predicting anomaly based fire outbreak in forest environment?

For pertinent publications that will support the study, a search was conducted across five major electronic research repositories: IEEE Xplore, Elsevier, Springer, Wiley Online Library, and Science Direct. However, a few papers from MDPI and Hindawi that are marginally related to the subject are also included in this analysis. We specified the following keywords for the search process: "anomalies detection," "health sensor-cloud," and "anomalies detection Health sensor-cloud" in the context of the research domain in order to do an automated in-depth text search by search engine screening and manual screening. The investigation was carried out utilizing Boolean operators with the preset keywords and within the parameters of the developed research questions to categorize pertinent articles using the table of contents for these keywords. Additionally, the following inclusion criteria were used to screen, filter, and order the articles in this study:

- The paper's relevance to the application of anomaly based fire outbreak detection techniques in forest environment.
- The papers published from 2018 until 2024
- English should be used as the primary language, and only primary studies from pertinent research should be chosen.
- Based on the developed research questions, the article should provide a thorough knowledge.

To ensure that all pertinent papers were located and gathered with a focus on the predefined keywords, a time limit was set for the search in compliance with the inclusion criteria. To make the discovered research papers smaller and easier to handle, the paragraphs were further scanned using the keywords. During the first stage, an estimated 140 articles covering the years 2018–2025 [5] were collected. In the subsequent round, 80 articles in total were eliminated through screening based on titles and keywords. The next step was filtering the remaining articles based on the abstract using the Boolean AND operator and the predefined searching criteria. Taking into consideration each of the indicated research issues, the researchers completed and selected the final 25 papers for further investigation and analysis based on the inclusion criteria. Thanks to the thorough screening procedure, which is shown in Fig 1 from the first to the last stage.

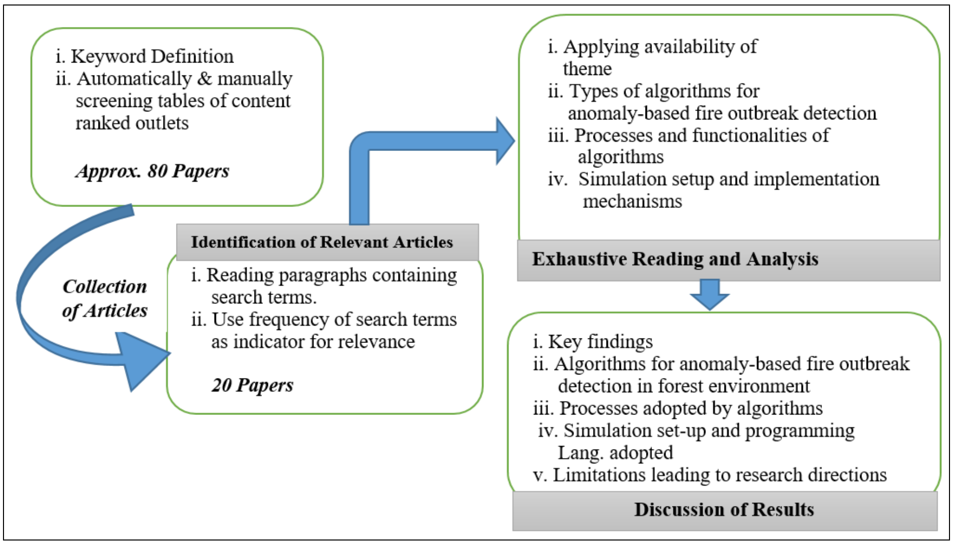

Fig 1: Research Methodology Structure

A table and statistical graphic tools will be used to assess the results of the research questions (RQ) as stated above. The table will list and illustrate the several methods that currently in use, procedures. Simulation and programming tools used for the methods' implementation and testing, and their drawbacks. Tools for statistical charts will be used to visually represent and compare performance-based findings.

Results and Discussion

This section presented a detailed analysis of current studies that adopted various techniques used for the prediction of wildfire breakout in forest environment and the outcome of the research.

Analysis of the Existing algorithms deployed for the prediction of fire outbreak in forest environment

A statistical learning models were proposed for outlier detection in fire forest outbreak monitoring (Nesa *et al*., 2018) [7]. It adopted four different statistical Classification models namely Regression Trees (CART), Random Forest (RF), Gradient Boosting Machine (GBM), and Linear Discriminant Analysis (LDA), to detect the occurrence of both errors and events outliers in a forest environment. Additionally, temporal and spatial data dependencies were also considered. The models can successfully identify both types of outliers with up to 100% accuracy for error detection and 98.51% accuracy for event identification, according to simulation results. Consequently, the results show that the prediction accuracy, which was shown to rise from 81.68% to 96.53% utilizing RF, can be positively impacted by the use of spatial and temporal characteristics in event detection. Uremek, *et al*., (2024) [33] presented an efficient outlier detection model in forest fires through low power environmental data monitoring and artificial intelligent. To assure accuracy, one of the main components of this model is the comparison of local environmental data in real time with environmental data retrieved from meteorological service. A feedback loop that enhances the model's predicted accuracy is informed by this comparison. In order to determine the optimal times for communication and to predict future occurrences, the study also explores in-depth time series analysis using the Autoregressive Integrated Moving Average (ARIMA) model. Finally, a decision tree approach is adopted for thorough evaluation of fire risk because of its easy use and clarity.

A classification model was proposed for outlier detection in fire forest monitoring to reduce the impact fire outbreak in an environment (Rajagopal *et al*., 2018) [40]. Firstly, the dataset generated from wireless sensor devices are preprocessed to discard excessive noise or irrelevant data points. After which they are classified as either outliers or inliers using Support Vector Machine (SVM) algorithm. Fig 2 demonstrate the processes of the proposed model architecture. The firefighter department is notified about the predicted outliers which symbolizes the outbreak of fire for prompt response so as to minimize human lives and loss properties.

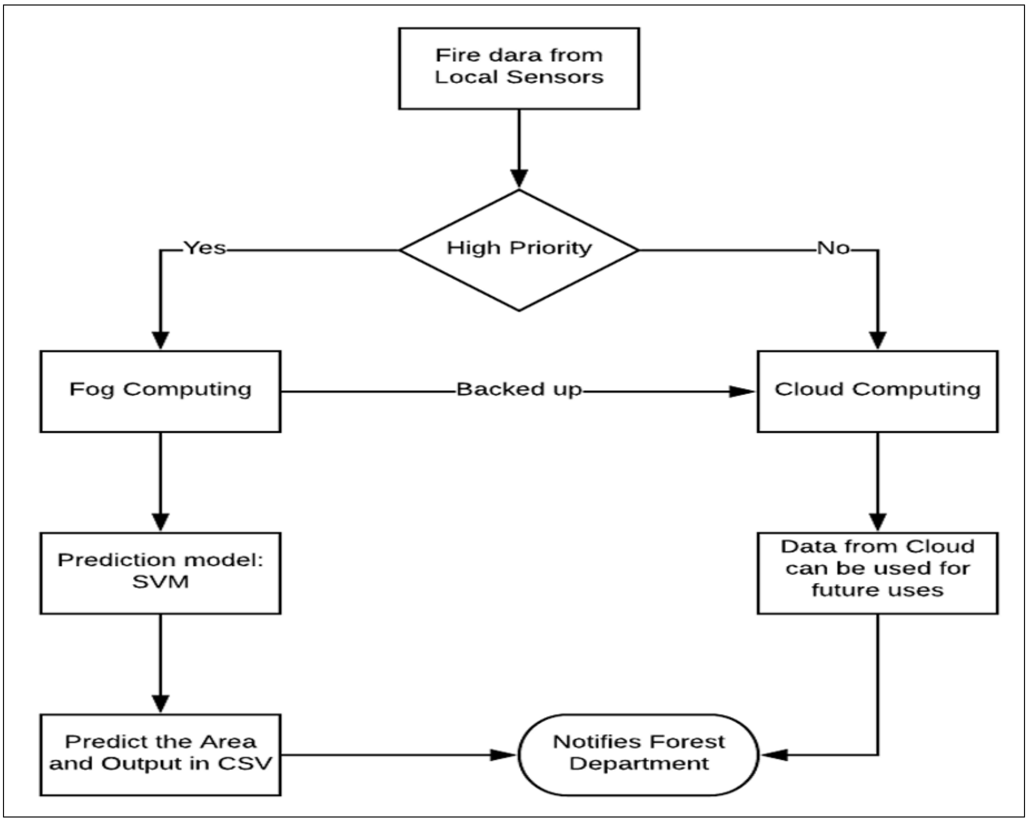

Fig 2: Architecture of Outlier based Fire Forest Prediction

An energy efficient clustering approach was presented for the detection of outlier based wildfire outburst in forest (Bharany *et al*., 2022) [10]. It utilizes an effective clustering technique to address energy and routing issues in order to prolong the life of an unmanned aerial vehicle (UAV) during forest fires. The proposed EE-SS algorithm, controls sensor node energy consumption while accounting for several aspects, including the characteristics of a fire disaster area. Dataset which comprises of the fire outburst, generated by sensor nodes are classified into discrete clusters in order to combat them. Also, it lowers the routing cost and boosts system efficiency by selecting the best fit cluster heads (CHs).

A Bayesian Network information fusion-enabled Deep Neural Network model is proposed for outlier detection in fire forest monitoring environment (Kim and Lee, 2021) [11]. Firstly, Long Short-term memory (LSTM) is used to determine the possibility of a fire in a limited term period by extracting the local features inside the bounding boxes. Thereafter, the Majority-voting approach of the limited term decisions is computed to ensure long term reliability. Then, the outlier which happens to be fire/smoke is detected using the Bayesian Network classifier.

Conversely, Ghali *et al*., (2021) [8] proposed a Deep Vision Transformers model for the prediction of outlier based fire forest and monitoring. There are two various types of transformers namely TransUNet and MedT frameworks, tailored to the unstructured environment, which were assess with different backbones and optimize for the segmentation of forest fires. Both frameworks performed better than the previous approaches, after rigorous evaluation, with an F1-score of 96.0% for the MedT architecture and 97.7% for the TransUNet architecture. Furthermore, Ghali *et al*., (2022) [14] proposed a Deep Learning and transformer approaches for outlier based wildfire detection and segmentation. the Transformer utilized the TransUNet and TransFire methods to segment the wildfire region, while the deep learning combines both the EfficientNet-B5 and DenseNet-201 models to predict and classify fire on aerial dataset (images). Experimental result shows that the proposed model outperformed the existing approaches with an accuracy of 85.12%, and demonstrated its capacity to categorize wildfires, even those with small fire region. Also, its segmentation strength outperformed other current models with an F1-score of 99.9% for the TransUNet framework and 99.82% for the TransFire framework.

An artificial Bee Colony-enabled Conversion Matrix model is presented for outlier based fire forest detection (Toptas and Hanbay, 2020) [12]. A new feature matrix was created by combining the pixel values of images with and without flames. At random, a conversion matrix was produced. The feature matrix was used to multiply the conversion matrix. The K-means clustering technique was used to determine the inaccuracy of this multiplication result. The artificial bee colony approach was used to update the conversion matrix until the desired performance was achieved. All of the photos in the dataset were moved to a new color space at the conclusion of the updating process by multiplying the updated conversion matrix by the total number of images. Binary pictures were created from the final images. Binary pictures were obtained using the Otsu technique. The relevant ground truth images in the dataset were contrasted with these binary images. Finding the two photos' similarity ratio is the goal of this comparison. The degree of preservation of the original image features is indicated by this ratio, as demonstrated in Fig 3.

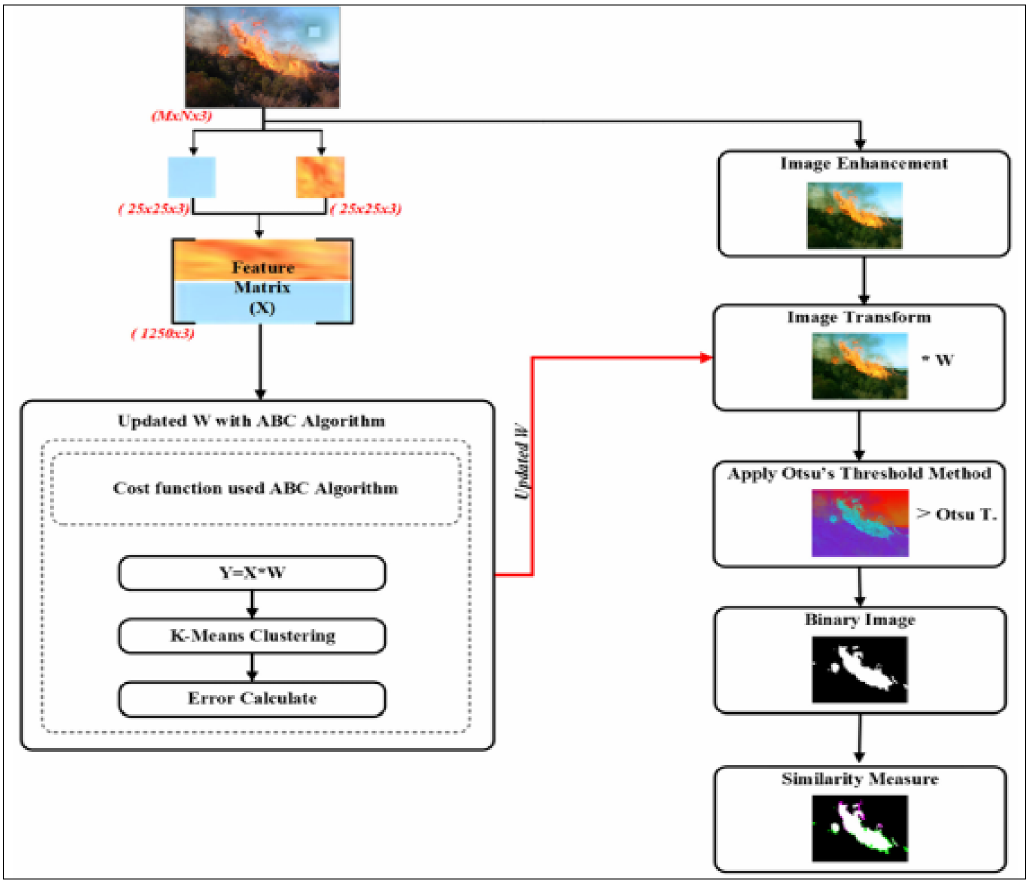

Fig 3: Architecture of the Proposed artificial Bee Colony-enabled Conversion Matrix model

A deep Convolution Neural Networks-based Exploitation of Fire Dynamic Textures (DCNN-EFDT) Model was developed for the forecasting of fire forest environment (Barmpoutis *et al.*, 2020) [13]. After an RGB 360-degree camera installed on an unmanned aerial vehicle captures optical 360-degree raw data, the raw data is converted to stereographic images. Following that, two DeepLab V3+ networks are used to segments smoke and flames, respectively. A new post-validation adaptive technique is then suggested, which lowers the false-positive rates by taking use of each test image's ambient look as demonstrated in Fig 4. A dataset, known as the "Fire detection 360-degree dataset," comprising 150 infinite field of view photos with both artificial and actual fire was produced in order to assess the effectiveness of the proposed approach.

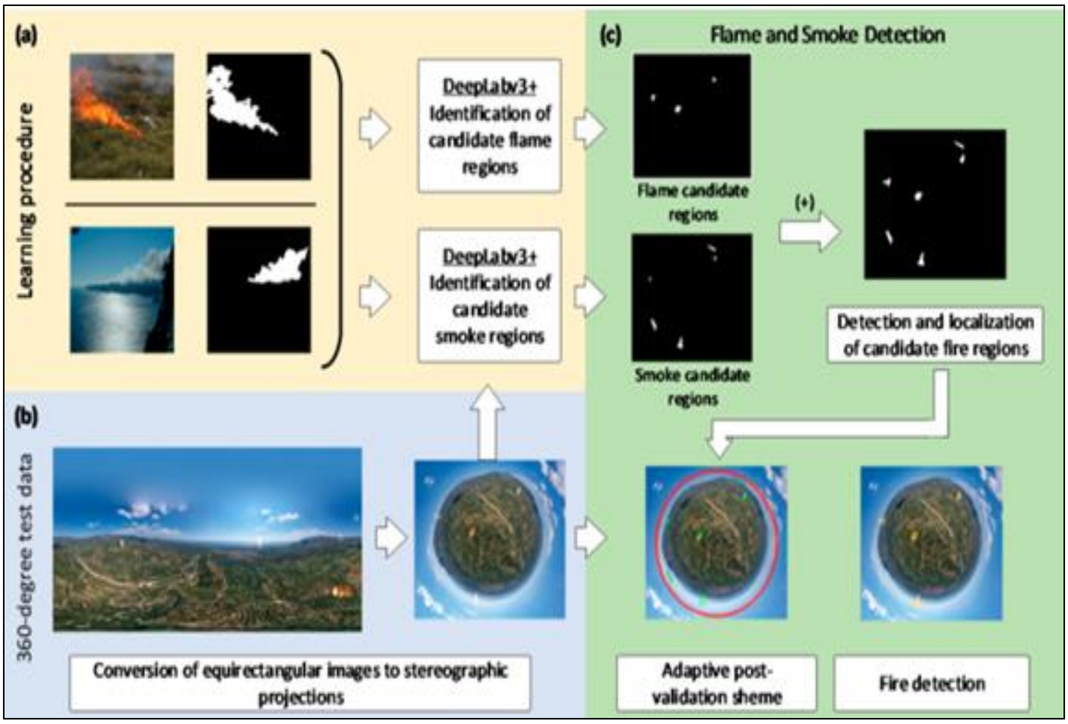

Fig 4: Architecture of the Proposed DCNN-EFDT Approach

A forest fire outlier detection using Ensemble Learning Technique was developed by Xu *et al*., (2021). First, two separate algorithms, Yolov5 and EfficientDet are integrated together for a comprehensive fire detection process. Secondly, in order to prevent false positives, EfficientNet approach is deployed for learning global datasets. Lastly, the detection outcome is achieved based on the decisions of the three approaches. Simulation results shows that, without adding any latency, the proposed technique minimizes false positives by 51.3% and enhances detection performance by 2.5% to 10.9%. Furthermore, Zhang and Zhang (2022) [16], proposed a systematic approach using Convolutional Neural Network (CNN) for the prediction of outlier based wildfire breakout in forest environment. It comprises of two strategies, the first strategy uses a model server framework and a novel machine learning technique to validate and feed wildfire images (datasets) sorted by time of day using convolutional neural network models trained for day and night. One large CNN model is said to be trained on all wildfire datasets images (dataset), day or night. An automated wildfire detection in real time, is achieved by integrating the innovative machine learning technique with social media platforms and existing forest response systems through alerting APIs, as demonstrated in Fig 5.

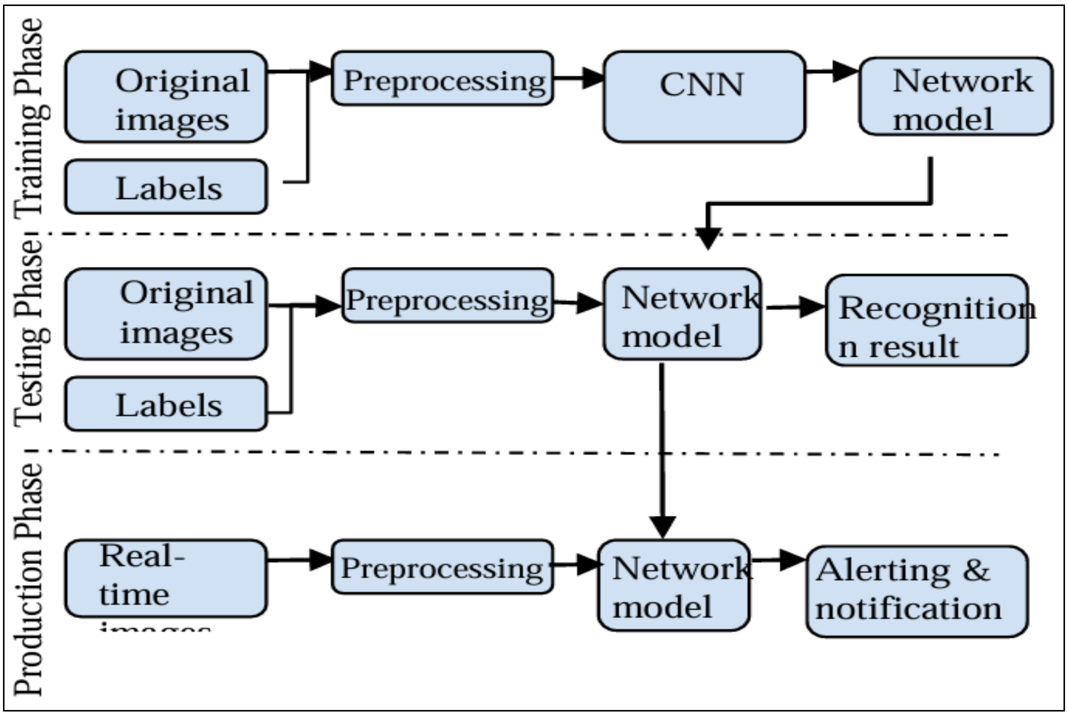

Fig 5: The Architecture of the Proposed Systematic based CNN Approach

An Adaptive Spatial Feature Fusion (ASFF) model was developed for the prediction of real time outlier based forest fire (Lin *et al.,* 2023) [17]. At the initial stage, CNN is deployed for feature extraction in conjunction with the Transformer encoder, which has a strong global modeling capability and a self-attention mechanism. Thereafter, the Coordinate Attention (CA) technique is used to improve the classification of datasets for accurate detection of outlier based forest fires outbreak. The model is better able to discover and identify forest fire targets due to the fact that CA takes direction-related location information into account in addition to inter-channel information. Also, the model can effectively fuse features to minimize the influence of complex backgrounds in the forest area for detection and automatically filter out irrelevant information from other layers thanks to integrated adaptively spatial feature fusion (ASFF) technology.

An intelligent Smoke Detection algorithm was proposed for wildfire-monitoring cameras ecosystem (Shi *et al.,* (2020) [19]. Firstly, Local binary patterns and a dense optical estimator method is used to process the original datasets (video frames). Then, generated features are fed into a lightweight deep convolutional neural network, which acts as a binary classifier to identify smoke. Consequently, Peruzzi *et al.,* (2023) [18] proposed a Machine Learning models approach for the detection of outlier based fire forest. The main outcome is that, although the two models' performances are comparable when used independently, the integration of both models, yields a higher accuracy, precision, recall, and F1 score (96.15%, 92.30%, 100.00%, and 96.00%, respectively. The ML models use audio samples and images as their respective inputs, enabling timely fire detection.

A Co-occurrence of Local Binary Pattern Variants technique was developed for the prediction of wildfire in foerest environment (Prema, *et al.,* 2022) [20]. Initially, the smoke-colored areas are divided based on colour at the YUV color locality. Then the irrelevant frame is used to partitioned the smoke area from the smoke-colored areas. Then, the candidate individual features in the smoke area are extracted using Co-occurrence of Local Binary pattern (CoLBP) and Co-occurrence of Hamming Distance based Local Binary pattern (CoHDLBP). Finally, the ELM classifier is adopted for selecting the features from the smoke area, which leads to the actual wildfire detection.

A hybrid deep learning model was proposed for the detection of forest fire in the study conducted by Ghosh and Kumar (2022) [21]. It integrates convolutional neural networks (CNN) and recurrent neural networks (RNN) for feature extraction, and for final classification by deploying two fully connected layers. The CNN's final feature map was flattened before being supplied to the RNN as an input. While CNN extracts a variety of high-level and low-level characteristics, RNN extracts a variety of sequential and dependent features.

A neural architecture search-enable object system was implemented for the prediction of anomaly based fire forest (Tran *et al.,* 2023) [31]. The object-detection models were trained and evaluated on a massive fire dataset consisting of about 400,000 images. Then, a Bayesian neural network (BNN)-based approach was deployed for estimating the damaged area as a regression model (i.e. the actual anomalies (fire occurrence)). Conversely, Mashraqi *et al.,* (2022) [22] proposed a drone imagery forest fire detection using the combination of classifier and deep learning (DIFFDC-MDL) model. The purpose of the DIFFDC-MDL model is to identify and categorize forest fires in drone footage, by generating feature vectors. It then utilizes recurrent unit model for classifying forest fires. The shuffling frog jump algorithm is utilized to further enhance the categorization results.

An intelligent deep learning model was proposed for the detection of outlier based wild fire forest and alarm system (Almasoud, 2023) [31]. The major datasets source for the proposed model is an Integrated Sensor System (ISS), which integrate a variety of sensors. Then, to explore and identify the presence of risk associated with fire, the attention-based convolution neural network with bidirectional long short term memory (ACNN-BLSTM) model is used. Also, the prediction performance is improved by using the bacterial foraging optimization (BFO) approach for hyperparameter modifying of the ACNN-BLSTM model. Ultimately, the Global System for Mobiles (GSM) modem notifies the authorities to take the necessary measures as soon as the fire is discovered, as demonstrated in Fig 6.

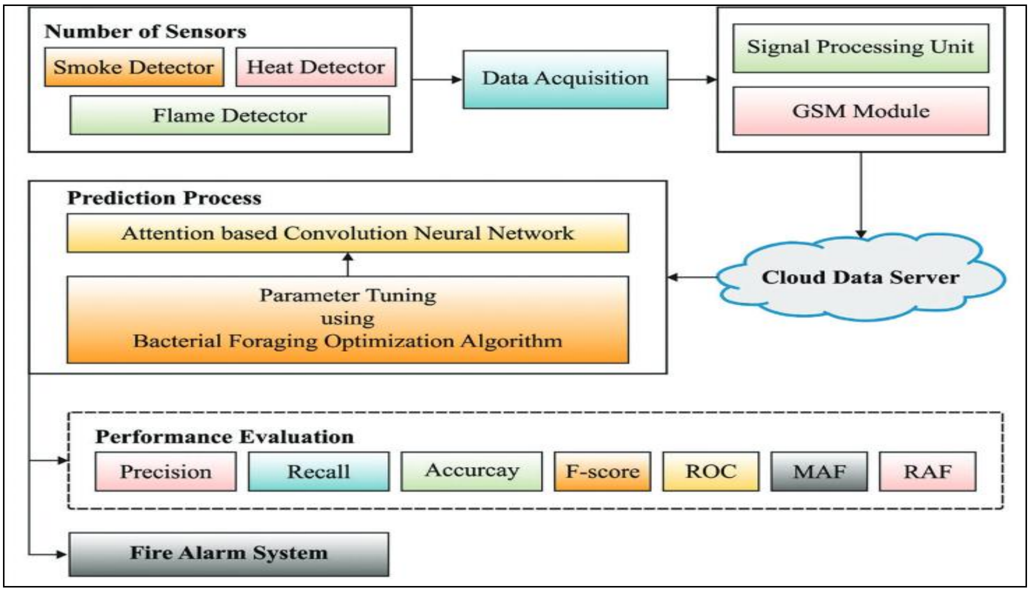

Fig 6: The Proposed Deep Learning Model

A Recurve Feature Elimination based Support Vector Machine model was developed to predict the occurrences of wild fire outbreak in forest environment (Barzani *et al*., 2024) [32]. It identifies important fire causes (e.g. smoke, high temperature) by integrating machine learning models, particularly Support Vector Machine (SVM) and Random Forest (RF), with recursive feature elimination (RFE). Firstly, significant fire factors were detected using the RFE models consisting of Extra Trees, Gradient Boosting, and AdaBoost. The RFE model's main elements in Forest Fire Susceptibility Mapping (FSM) were first applied to all factors, and then the SVM and RF models were applied to those factors. Cross-validation was used to assess the model's performance after training and testing data were split tenfold. The outcome of the assessment shows that the model improves performance rates based on accuracy, precision recall and F-score than other models. Consequently, Hiremath and Kannan (2024) [1], presented anomaly detection of wild fire in forest environment. The meteorological characteristics was identified to carry important information about the likelihood of a fire the following day using the mutual information approach. The random forest technique was then used to predict whether there would be a fire or not the following day using the top nine parameters. The class imbalance in the fire data class was addressed by using SMOTE and weighted data sampling. Given the climatic data from the preceding days, both methods performed a good job of accurately classifying fire episodes.

An early prediction of forest fire outbreak techniques was investigated to advert potential ecological disaster (Bera *et al*., 2025) [5]. Three distinct machine learning algorithms—random forest, extreme gradient boost, and support vector machine—were assessed. The models contained sixteen driving factors, including meteorological, topographic, anthropogenic, and forest health data, and were trained using almost 2000 ground-based fire observations gathered between 2017 and 2022 [20]. With Random Forest exhibiting the best overall performance and all models having over 80% accuracy in 5-day early predictions, findings show the critical elements impacting fire occurrences. The research conducted by Shahzad *et al*., 2025 [3], utilizes multi-layer stacking ensemble Machine Learning (ML) approach for mapping forest fire susceptibility. For comparative analysis, we used a number of benchmark models, such as Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), and K-Nearest Neighbor (KNN). Satellite and ground hotspot data, as well as pertinent influencing elements, were used in the creation of an extensive fire inventory database. Accuracy, area under the curve (AUC), precision, recall, and F1 score evaluation measures were used to analyze and validate the fire probability indices from the six models. The multi-layer stacking ensemble model yields the greatest results in terms of accuracy (96.24%), AUC (99.43%), precision (97.81%), recall (94.59%), and F1 (96.17%), according to the Performance Evaluation Outcomes.

A hybrid spatial machine learning-enabled neural network model is developed for the prediction of fire outbreak in forest (Sharma and Khanal, 2024) [4]. Several machine learning and neural network techniques, such as Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Convolutional Neural Network (CNN), were used to build the final fire prediction model using feature importance analysis. The final fire danger map was created utilizing a correlation test and correlation coefficient analysis. The DT model outperformed other models with the maximum accuracy of 90.58%, according to the assessment of predictive performance based on accuracy ratings. However, the correlation test produced a superior fire danger map than any other machine learning or neural network method that used feature importance based on the kernel density map of the fire data from 2000 to 2023 [31]. All models, however, were able to forecast with more than 80% accuracy. Consequently, Koitsa *et al*., 2025, presented a feature construction-enabled artificial intelligent techniques for the prediction of wild fire outbreak in the forest ecological system. The feature constructs include Principal Component Analysis (PCA), Minimum Redundancy Maximum Relevance (MRMR), and Grammatical Evolution. The Hellenic Fire Service's highly detailed and publicly accessible symmetrical datasets for the years 2014–2021 [37] was obtained for this purpose. It was further enhanced with meteorological information that corresponded to the conditions at the beginning and end of each wildfire event. The study came to the conclusion that weather phenomena may offer and surpass other approaches in terms of stability and accuracy, and that the Feature Construction strategy, which uses Grammatical Evolution, integrates both symmetrical and asymmetrical conditions.

The table below contain more insight regarding the process types, challenges resolved, performance measurement (Metrics), experimentation setup, benchmark and the weaknesses of the existing algorithms.

Results

Table 1 presents a thorough analysis and discussion of the findings from this research. In order to improve representations and get additional understanding, these data were further assessed using statistical tools. The sorts of algorithms or techniques used, the procedures followed, the problems solved, the results, the simulation packages, the benchmark, the metrics, and the limitations of the aforementioned current methodologies are all highlighted in the table.

Categories of Algorithms and models/Processes Adopted by existing Algorithms

According to the literature review's findings, machine learning algorithms were mostly used prediction of wild fire in forest environment than other types of algorithms, as shown in Fig 7.

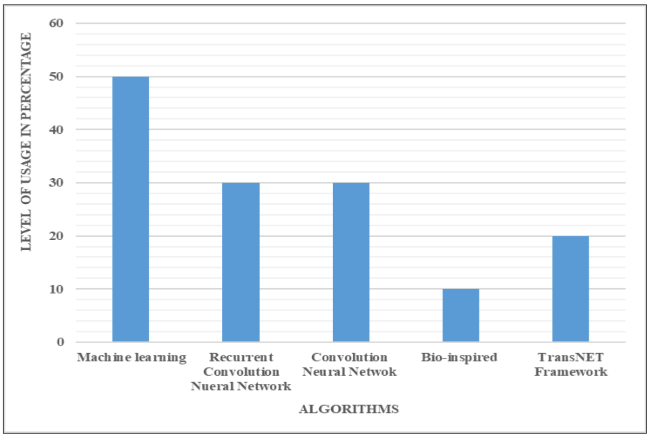

Fig 7: Adoption Level of Algorithms

Table 1: The properties of the existing algorithms

S/N	Article Title	Algorithm	Processes	Challenges Resolved	Outcome	Simulation Package	Benchmark	Metrics	Weaknesses
1	Outlier Detection in Sensed Data using Statistical Learning Models for IoT (Nesa *et al*., 2018) [7]	Regression Trees (CART), Random Forest (RF), Gradient Boosting Machine (GBM) and Linear Discriminant Analysis (LDA)	Classification	Contaminated data due to sensor malfunctioning	Event and error outlier were successfully detected.	MATHLAB using statistical boxes	Not Specified	Accuracy, Recall, False Positive Rate (FPR), Specificity, Precision and F-score	Inefficient feature extraction from dataset.
2	ASystem for Efficient Detection of Forest Fires through Low Power Environmental Data Monitoring and AI (Uremek, *et al*., 2024) [39]	Autoregressive Integrated Moving Average (ARIMA) and Decision Tree (DT)	Clustering and Classification	Inaccurate prediction of outlier based fire forest outbreak	Improved accuracy rate of outlier detection based fire forest outbreak		Not Specified	Risk prediction Rate and Target Risk Prediction Rate	Inability to validate the fire detection components
3	Data mining approach to predict forest fire using fog computing (Rajagopal *et al*., 2018) [40]	Support Vector Machine (SVM)	Classification	Inconsistent prediction of fire outbreak	Improved the rate of outlier fire forest detection.	Python and Visual Studio IDE	Principal Component Analysis (PCA)	Accuracy, Root Mean Squared Error (RMSE)	Misclassification of data points leading to inefficiency of data classification.
4	Wildfire Monitoring Based on Energy Efficient Clustering Approach (Bharany *et al*., 2022) [38]	EE-SS Clustering Algorithm	Clustering	Inadequate identification of fire prone environment	Improved prediction rate of fire prone region	NS 3	LEACH, SEED, PSO-HAS and LEACH-C	Energy Consumption Rate, Clustering Lifetime and Building time	Still prone to high energy usage.

Table 1: Continue

S/N	Article Title	Algorithm	Processes	Challenges Resolved	Outcome	Simulation Package	Benchmark	Metrics	Weaknesses
5	ABayesian Network-Based Information Fusion Combined with DNNs for Robust Video Fire Detection (Kim and Lee, 2021) [11]	Long Short Term Memory, Majority Voting and Bayesian Network Classifier	Neural Network and Classifier	Inconsistency and unreliable outlier based fir forest detection in long term period	Improved accuracy detection rate and reliability	Python and Sklearn packages	CNN, Motion-Flicker-Based Dynamic Features and Deep Static Features (MFDF-DSF) and	Accuracy, False Positive Rate and Reliability	Prone to Gathering of domain knowledge needed to improve performance
6	Wildfire Segmentation Using Deep Vision Transformers (Ghali, *et al*., 2021) [8]	TransUNET and MedT Framework	Framework	Challenged with limited relationship between features due to locality of convolution operators	Improved detection rates with 97.7% FI-score	Python	Deep CNN^{2}U-Net, U-Net and EfficientSeg	FI-Score, Recall, Precision and Inference Time	Not Considering the Spatiotemporal differences in fire outbreak detection outlier
7	A new artificial bee colony algorithm-based conversion matrix for fire/flame detection (Toptas and Hanbay, 2020) [12]	Artificial Bee Colony and Conversion Matrix Approaches	Optimization and Statistical Process	Misclassification and identification of outlier fire outbreak	Improved classification rate for outlier detection	Python	PSO	FI-Score, Sensitivity and Specificity	Still trail with inaccurate and reliability
8	Early Fire Detection Based on Aerial 360-Degree Sensors, Deep Convolution Neural Networks and Exploitation of Fire Dynamic Textures (Barmpoutis *et al*., 2020) [13]	DCNN and Exploitation Fire Dynamic Textures	Neural Networks	Misclassification of outliers in large datasets	Improved classification and outlier detection rates	Python	DeepLab v3+, Faster R-CNN	FI-Score and Mean Intersection Over Union	False positive rate still on the high side.

Table 1: Continue

S/N	Article Title	Algorithm	Processes	Challenges Resolved	Outcome	Simulation Package	Benchmark	Metrics	Weakness
9	Deep Learning and Transformer Approaches for UAV-Based Wildfire Detection and Segmentation (Ghali *et al*., 2022) [20]	EfficientNet-B5, DenseNet-201, TransNet Framework and TransFire Framework	Neural Networks and Framework	Unreliable outlier detection of fire outbreak in small dataset	Improved Outlier detection rates both on small and large dataset	Python	MobileNetV3-Small, InceptionV3 and Xception	Accuracy, FI-Score and Inference Time	Not Specified
10	A Forest Fire Detection System Based on Ensemble Learning (Xu *et al*., 2021)	Yolov5, EfficientDet and EfficientNet	Framework	High false positive rates that leads to inaccurate outlier detection	Improved outlier detection performance rate with minimum latency	Python	SSD and YOLOV3-SPP	Frame Accuracy, False Positive Rate, Average Precision and Average Recall	Not Specified
11	Real-Time Wildfire Detection and Alerting with a Novel Machine Learning Approach (Zhang and Zhang, 2022) [16]	Fast R-CNN and Machine earning	Neural Network and Learning	Inadequate real time outlier detection rate	Improved detection rates in real time	Pytorch	Not Specified	Accuracy, Precision and Recall	Prone to inaccurate classification in big dataset
12	A Semi-Supervised Method for Real-Time Forest Fire Detection Algorithm Based on Adaptively Spatial Feature Fusion (Lin *et al*., 2023) [17]	Coordinate Attention, CNN and ASFF	Neural Network and Fusion	Inability to automatically captured big data labels in real time	Improved detection rates while automatically labeling data features	Pytorch	YoLOv5 and YOLOv5+Transformer	Precision, Recall, Average Precision and Mean Average Precision	Inadequate Semantic segmentation of feature extraction

Table 1: Continue

S/N	Article Title	Algorithm	Processes	Challenges Resolved	Outcome	Simulation Package	Benchmark	Metrics	Weakness
13	Fight Fire with Fire: Detecting Forest Fires with Embedded Machine Learning Models Dealing with Audio and Images on Low Power IoT Devices (Peruzzi *et al*., 2023) [17]	Neural Network	Learning		Improved fire outbreak detection	Coretex Micro-controller	Not Specified	Accuracy, Recall, Precision and FI-Score	Still prone to misclassification issues
14	Optimal Placement and Intelligent Smoke Detection Algorithm for Wildfire-Monitoring Cameras (Shi *et al*., 2020) [19]	Local Binary Patterns and Dense Optical Flow Estimator, Light weight deep convolutional neural network.	Neural Network and statistics	Inappropriate detection of wildfire in forest environment	Improved wildfire detection rate	MobileNetV2	Baseline	True Positive Rate, False Positive Rate, Positive Predictive Value	Not Specified
15	A Novel Efficient Video Smoke Detection Algorithm Using Co-occurrence of Local Binary Pattern Variants (Prema *et al*., 2022) [20]	CoHDLBP, CoLBP and Extreme Learning Machine	Framework and Classification	High false positive rate	Improved fire forest detection rate with minimum false positive rate	Pytoch And Python	Principal Component Analysis (PCA) and Support Vector Machine (SVM)	False Positive Rate, recall, Accuracy and FI-Measure	Still prone with misclassification on Large dataset.
16	A hybrid deep learning model by combining convolutional neural network and recurrent neural network to detect forest fire (Ghosh and Kumar, 2022) [21]	CNN and RNN	Deep Learning	High false positive rate	Improved detection rates with minimum false positive rate	Pytoch and Python	Not specified	Accuracy, False Postive Rate, Recall and Precision	Prone to misclassification issues

Table 1: Continue

S/N	Article Title	Algorithm	Processes	Challenges Resolved	Outcome	Simulation Package	Benchmark	Metrics	Weakness
17	Forest-Fire Response System Using Deep-Learning-Based Approaches With CCTV Images and Weather Data (Tran *et al.,* 2022)	DetNAS	Deep learning	Challenged with early detection forest fire	Improved early fire detection with optimal accuracy	Python and MATLAB	Not Applicable	Accuracy, Recall and FI-Measure	Not Specified
18	Drone imagery forest fire detection and classification using modified deep learning model (Mashraqi *et al*., 2022) [20]	Recurrent Unit Model, Shuffled Frog Leap Algorithm.	Deep learning	Challenged with local minima problem in small dataset	Improved fire detection rates with low false positive rate	Python	ResNet50, VGG16, Inception and LSTM	Accuracy, Sensitivity, specificity F-measure	Issues with irregularities in classifying large dataset.
19	Intelligent Deep Learning Enabled Wild Forest Fire Detection System (Almasoud, 2023) [31]	Attention-based CNN, Bidirectional LSTM and Bacterial Foraging Optimization	Deep learning and Optimization	Not Consideration spatiotemporal differences	Improved fire forest detection rate with respect to time and space	Python	BeyesNet, J48, Decision Tree and RBF-Network	Precision, Recall, Accuracy and F-Score	Misclassification of possible outliers and computation complexity
20	Evaluating the Impact of Recursive Feature Elimination on Machine Learning Models for Predicting Forest Fire-Prone Zones (Barzani *et al*., 2024) [32]	Recursive Feature Elimination, Random Forest and SVM	Classification and Clustering	Inaccurate detection of forest fire susceptibility mapping	Improved detection rates with high accuracy	Python	SVM and Random Forest	Recall, Precision, F-Score, AUC	

Table 1: Continue

S/N	Article Title	Algorithm	Processes	Challenges Resolved	Outcome	Simulation Package	Benchmark	Metrics	Weakness
21	Early Warning System and Anomaly Detection for Forest Fires (Hiremath and Kannan, 2024) [39]	Weighted data Sampling and SMOTE	Neural	Misclassification issues	Accurate classification that leads to optimal prediction	Python/Pytorch	Not Applicable	FI-score, Accuracy, Recall,	High Positive Rate
22	Early prediction of forest fire events integrating multi-sensor datasets and machine learning techniques (Bera *et al*., 2025) [5]	. Random Forest, Extreme gradient boost, support vector.	Classification/Clustering	Neglecting the dynamic nature of climates dataset	Optimal Accurate fire forest prediction with climatic conditions	Python		Area Under Curve, Accuracy, Root Mean Squared Error	Misclassification of data records in the dataset
23	A forest fire prediction: A multi-layer stacking ensemble model approach (Shahzad *et al*., 2025) [5]	Multi-layer stacking ensemble Machine Learning	Classification/Clustering	Unrelaible fire outbreak prediction in forest	Reliable and Efficient prediction of fire outbreak in forest environment.	Python	Random Forest, Extreme Gradient Boosting nd Logistic Regression	Area Under Curve, FI-Score, Precision Recall	High False Positive Rate
24	Predicting Forest Fires Using Spatial Machine Learning and Neural Networks (Sharma and Khanal, 2024) [32]	Decision Tree and CNN	Classification, Deep Learning	Overfitting issues	Reduction of data imbalance with optimal prediction	Pytorch		Accuracy	Spatio-Temporal Difference
25	Monitoring the duration of a Forest Fire Using Feature Construction Methods Enhanced with Meteorological Information (Constantina Kopista *et al*., 2025) [5]	Principal Components Analysis, Minimum Redundancy Maximum Relevance (MRMR)	Classification and Clustering	Inability of detecting anomalies in symmetrical and asymmetrical dataset	Accurate prediction of fire outbreak in forest with minimal root mean error.	Python	BAYESNN, ADAM and DNN	Accuracy Root Mean Squared Error, Average Execution time	Inconsistency in identification of relevant data features

However, as shown in Fig 8, neural network model performs better than other types of processes/models used by the current methodologies. While the classification process is mainly intended to identify anomalies in a given dataset, the clustering process is primarily used to pick and extract relevant features from the dataset. Optimization process is mainly used to speed up the dataset training/testing operations, that leads to optimal performance.

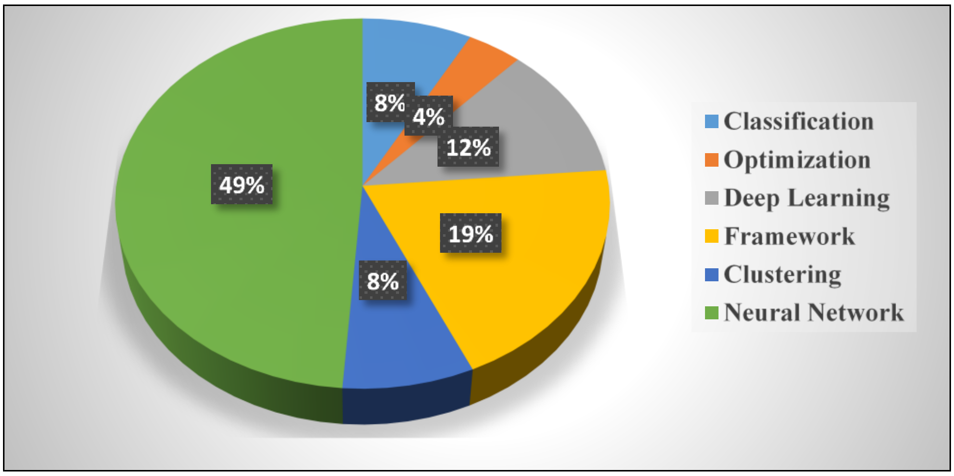

Fig 8: Adoption Level of Model/Processes

Programming languages and Simulation Tools adopted

Additionally, Python programming language and pytorch simulation tool were majorly deployed for the implementation and simulation of the existing algorithms as demonstrated in Figs 9a and 9b.

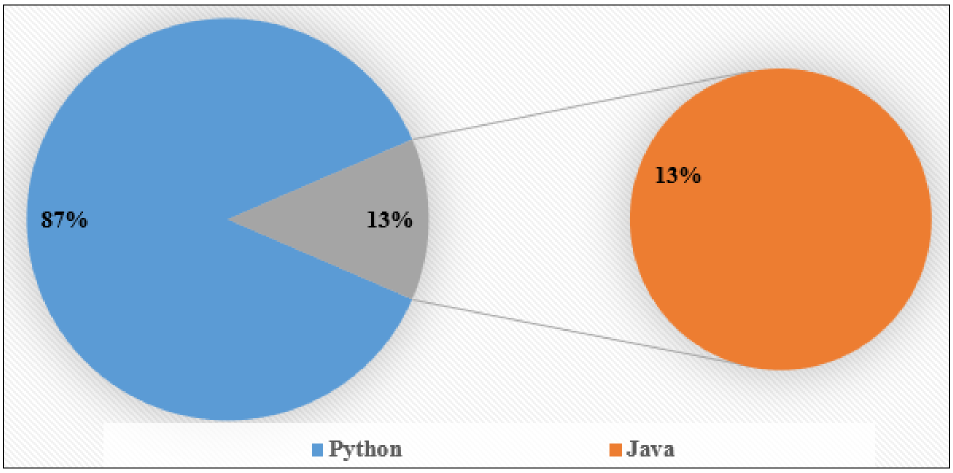

Fig 9a: Usage Level of Programming Lang.

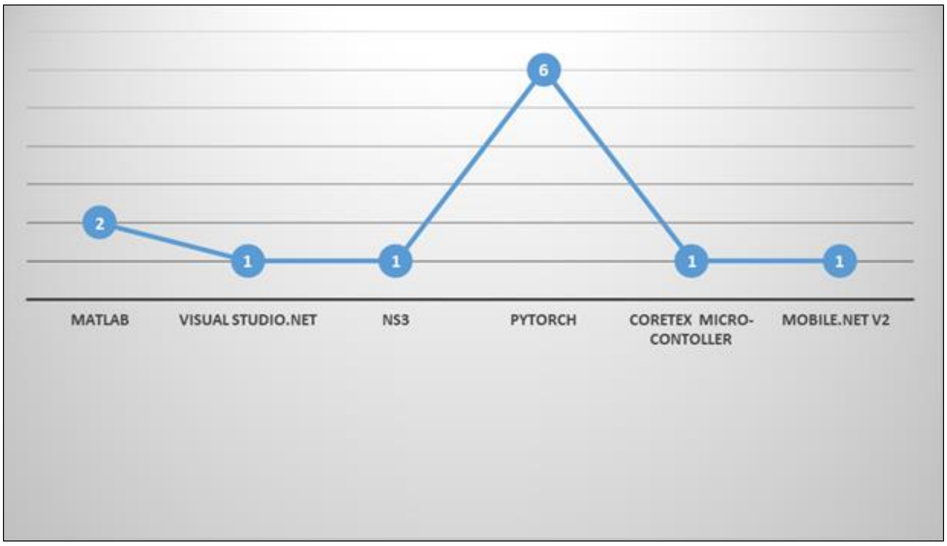

Fig 9b: Usage Level of Simulation Tool

A programming language called Python can be used to construct software, automate procedures, analyze and visualize data, and build websites. On the other hand, Pytorch is an open-source machine learning and deep learning framework. Researchers and developers utilize it extensively to develop, train, and implement artificial intelligence models.

Weaknesses of the Existing Algorithms

Even though the performance of the existing algorithms were improved to acceptable level of operations, they are still vulnerable to certain issues that may lead to future study. Most of the existing algorithms are challenged with segmentation irregularities, misclassification, high false positive rate high energy usage and spatio-temperance differences are some of the challenges algorithms. It was discovered that misclassification is the prevailing issues of the existing algorithms as depicted in Fig 10. Due to its substantial environmental impact and impact on power grids, the high energy consumption of data training—especially for large-scale Artificial Intelligence (AI) and machine learning models—has emerged as a major concern. Over the course of several months, training a single large AI model can use as much energy as hundreds of households. Thousands of Graphics Processing Units (GPUs) or Tensor Processing Units (TPUs) must operate in parallel for weeks or months in order to process billions of parameters through repeated computations during training. Up to 40% of the energy used in data centers can be attributed to cooling systems because of the enormous amount of heat produced by intensive computation. The models developed specially CNN and RNN models need to be updated and retrained frequently, which increases energy consumption.

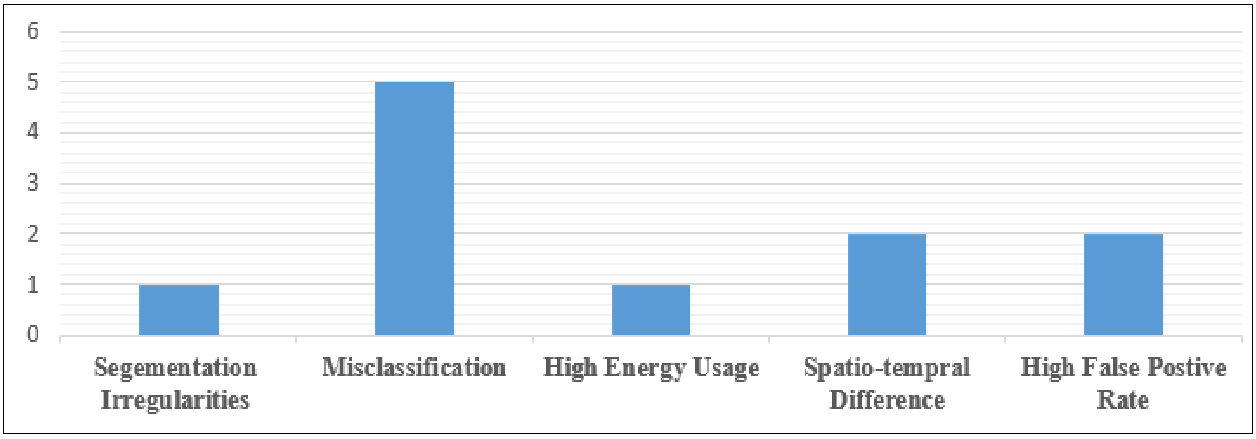

Fig 10: Weaknesses of the Existing Algorithms

When a data point is erroneously assigned to an unsuitable category by a model or analysis, this is known as misclassification of data points, and it directly lowers the accuracy and dependability of the model. These mistakes, which include false positives and false negatives, are brought about by faulty data, class overlaps, or inadequate model training. Variations in phenomena, like temperature, disease, or human activity, across various geographic places (spatial) and discrete, changing time periods (temporal) are referred to as spatiotemporal disparities. These variations are essential for mapping regional variations in dataset during training and testing processes.

Images with non-uniform, complicated, or arbitrarily formed objects that pose a challenge to conventional computer vision models are referred to as irregular segmentation in datasets. High bounding box overlaps, extreme aspect ratios, and a large number of disconnected components are characteristics of datasets such as iShape (which includes six actual and synthetic subsets) that handle this issue. Significant class imbalance (e.g., small cracks vs. vast pavement background) and high-density overlapping boxes are frequently caused by or suffer from irregular objects (e.g., cracks, thin lines, complicated textures). A high false positive rate occurs when a test, model, or system incorrectly flags legitimate, negative instances as positive, creating a high volume of false alarms. It signifies low specificity, wasting resources, causing user alert fatigue, and destroying trust in automated systems, such as in cybersecurity, medical screening, and financial fraud detection.

Conclusion

The transformative potential of machine learning and Neural Network models in Fire Forest prediction is demonstrated by this comprehensive review, which highlights its interdisciplinary applicability in artificial intelligence and environmental research. Machine learning, Convolutional neural and recurrent convolutional neural network models are the most widely employed models, according to the study, with recurrent convolutional neural network being particularly good at processing geographical data and machine learning for capturing temporal relationships. These models show a growing tendency toward combining several methods to improve prediction accuracy. It also was discovered python programming language was mostly used for the development of the existing models. Clustering and classification processes were mainly used to select or extract relevant features for onward classification to actualize meaningful prediction outcomes. Publication activity trends show the research field's expansion, especially in 2020–2023, which was fueled by improvements in machine learning and neural network models. But a drop in research output in 2025 [2] draws attention to unsolved issues such data heterogeneity, variations in data formats, spatio-temporal, high false positive rate, data imbalance, misclassification and the absence of common data integration procedures, Hence, these can further be investigated in the future.

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