AN EXTENSIVE INVESTIGATION ABOUT THE DEVELOPMENTS OF LEARNING ALGORITHMS FOR FOREST FIRE PREDICTION AND TRACKING

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Abstract
Forest fires, which cause significant harm to both the environment and the economy, are becoming more frequent worldwide. This underscores the urgent need for early prediction and detection. Various technologies and techniques have been proposed to anticipate and detect forest fires, with artificial intelligence emerging as a critical enabler. Specifically, machine learning (ML) techniques have garnered considerable interest for their potential in predicting and assessing the risk of forest fire-induced damage. This article reviews the machine learning methods used for identifying and forecasting forest fires. Choosing the optimal forecasting model remains a challenge, as each ML algorithm has its own strengths and weaknesses. Our primary objective is to identify research gaps and recent studies that leverage machine learning techniques in the study of forest fires. By selecting the most suitable ML techniques based on specific forest characteristics, current research enhances predictive accuracy.
Keywords: Forest Fire Prediction, Machine Learning, Early Fire Detection, Artificial Intelligence, Environmental Impact and Risk Assessment.

1. Introduction

Forest fires are a common and essential aspect of the Earth's system, occurring throughout the year globally. According to current estimates, the annual global area affected by fires is approximately 420 million hectares, surpassing the size of India. Grasslands and savannas are particularly susceptible to these fires. Human activities are responsible for over 90% of forest fires, with lightning strikes accounting for the majority of the remaining ignitions. The impacts of forest fires on humans can be severe, including direct effects like fatalities and community destruction, and indirect effects such as smoke and ash inhalation. Furthermore, forest fires contribute to global warming and threaten the survival of various plant and animal species.

Early prediction and detection of fires are crucial to minimizing damage and reducing firefighting efforts. Significant amounts of money are invested annually in fire management to mitigate or prevent forest fires. Therefore, understanding the causes of forest fires and improving prediction methods are essential for effective forest fire management. Preventive measures include predicting the likelihood of fire incidents by analyzing factors like fuel content and weather conditions, and detecting and locating active fires to provide early warnings before they spread uncontrollably.

Figure 1: Aerial view of forest fired image

Fire activity may be observed on ranges ranging from millimeters to kilometers and seconds to millennia, but there are limits. Mechanistic models may accurately reflect burning and fire mechanisms. Input quality of information and ability to resolve critical physical steps constrain these models. Physical models are not necessarily suitable for large-scale, near-real-time research and fire prevention due to existing computing constraints. As a result, forest fire management and research depend largely on the development of theoretical and mathematical approaches capable of handling complicated and complicated relations among variables, as well as accessibility to data and quality, particularly for meso-, synoptic-, strategic-, and global-scale events. Forest fire surveillance and tracking have advanced thanks to remote-sensing technologies, despite the complexity of forest fire and modeling issues. NASA's TERRA and AQUA have detected fires instruments like as the Comprehensive Very High-Resolution Radiometer (AVHRR), Visible Infrared Imaging Radiometer Suite (VIIRS), and Moderate Resolution Image Spectroradiometer. These sensors continuously track vegetation patterns and changes. Advances in numerical weather prediction and simulations of climate give greater geographical resolutions and longer prediction timeframes, which may improve severe fire-related forecasts. These developments make a data-driven strategy to woodland fire modeling a natural next step for numerous scientific problems, provided there is sufficient evidence. The use of machine learning (ML) techniques to research and woodland fire control has so gained traction in recent years.

Though there is no official definition, we define ML as the study of computer algorithms that learn by doing. This methodology is intrinsically data-driven, since machine learning algorithms' efficacy is contingent upon the caliber and volume of relevant data at hand. Recently, machine learning (ML) has made significant strides in the fields of computers and data analysis, usually leading to the intelligent operation of apps. Scientists studying artificial intelligence seek to comprehend and produce sentient objects that can behave in accordance with their objectives and conditions, change with their surroundings, and gain knowledge from past experiences. The advantages of using AI to study forest ecosystems, including disturbances brought on by illnesses, insects, and forest fires, have been shown in earlier studies. It has been proposed that ML techniques may accurately model intricate ecological issues. Current evaluations in geosciences, severe weather estimation, woodland ecology, prediction of floods, statistically scaling down, satellite imagery, and water management show ML models' usefulness. Additionally, persuasive arguments have been made recently for the use of deep learning to studies of Earth systems and to halt climate change. Studies to combine the several ML approaches used to handle the range of difficulties in forest fire research are still necessary, however.

2. Artificial Intelligence & MLs in fire prediction

New technologies are generally developed to make processes more manageable, precise, faster, or cost-effective. They also enable us to accomplish tasks or develop solutions that were previously unattainable. One of the most rapidly growing scientific procedures for practical applications in recent years has been artificial intelligence (AI).

Machine learning (ML) is a subset of AI where algorithms, trained on data, create intelligent systems. Over the last decade, AI and ML have surged in popularity due to major advancements in computer technology. This surge has led to significant improvements in the ability to collect and analyze vast amounts of data.

2.1 ML based methodology

Machine learning is the umbrella term for a range of approaches, instruments, and programs that let computers interpret, decipher, and find patterns in data so they can predict the future. The ultimate objective of machine learning is to remove the need for direct programming by enabling self-learning via data. Machines that have been trained on datasets may make more accurate projections by applying the patterns that they have learnt to fresh data. Main machine learning approaches include reinforcement learning, supervised learning, and unsupervised learning.

- **Supervised learning**: Machines are trained to solve problems with human assistance, where humans collect and label data before feeding it into the systems. A computer is given specific data features to analyze in order to detect patterns, classify items, and evaluate the accuracy of its predictions.

- **Unsupervised learning**: These methods focus on grouping or clustering unclassified data. In this category, machines learn to identify patterns and trends in unlabeled data without human oversight.

- **Reinforcement learning**: In this method, models solve problems in an unfamiliar environment through trial and error. Machines receive penalties for mistakes and rewards for correct actions, similar to scenarios in many games. This approach helps them learn to find the optimal solution.

2.2 ML stages for tracking

A number of processes are involved in the typical machine learning analysis process (Figure 2): gathering data, choosing relevant characteristics, creating mathematical models, and assessing the target systems. Data is essential for good ML models and all machine learning techniques. It is well accepted that data amount matters, and that having more data improves the accuracy of machine learning models. Although this is often the case, the accuracy of information is equally important and has to be taken into account. Inadequate or poor-quality datasets (such as those with large mistakes or hard-to-reproduce data) may result in inaccurate machine learning predictions, which can skew how the findings are interpreted. Thus, the creation of a dataset that appropriately represents the topic under investigation is the first stage in building a trustworthy machine learning model.

Preparing raw data for processing and analysis involves a number of important steps, including cleansing and transformation. Reformatting, editing, and combining datasets to enhance their information are often part of this step. Data purification and enhancement of features (including selecting and feature extraction) may turn the initial information into samples for ML model training. The modeling phase then concentrates on the main machine learning goals, which include creating a model that employs an exceptional data set with appropriate characteristics to accomplish the goals of the venture.

This stage begins with Algorithm Selection, Hyperparameter Optimization, and Training. A framework is built using a machine learning algorithm that is selected, setup, and performed. The Combined Algorithms Search and Hyperparameter Optimisation or Full Model Selection are the names given to these steps performed together. Often, this method takes several rounds, necessitating further dataset adjustments. Illustrations of iterations need data preparation-modeling feedback loops.

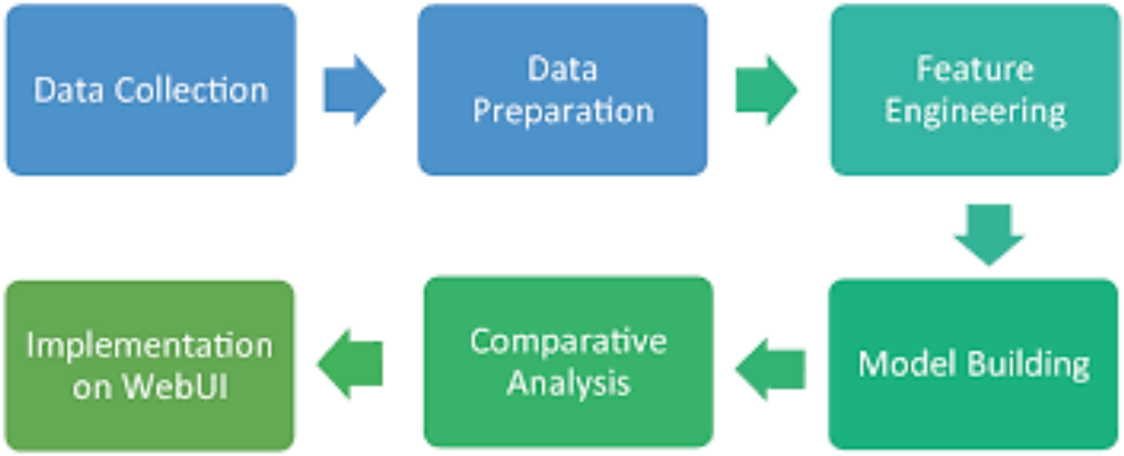

Figure 2. Machine Learning Process

Diagnostics bridge the gap between a model's performance and interpretability, ensuring that domain specialists can understand ML project outcomes. In the end, these kinds of models may be used by experts and scholars to guarantee that the results are understandable. Deployment is the process of making the final model accessible to the users of the program.

2.3. Deep Learning (DL) in forestry fire prediction

The architecture of the human brain, also known as artificial neural networks, serves as the model for deep learning, a type of machine learning. Creating computer systems that can identify patterns and draw conclusions from data in order to make judgments or predictions that are similar to those made by humans is its main goal. Different from standard machine learning techniques, deep learning uses numerous layers. Every layer functions as a data-trained model, and the output from one layer becomes the input for the one after it. Deep learning algorithms are able to recognize intricate patterns and extract more profound meaning from data than traditional machine learning techniques because of this tiered approach.

CNNs, RNNs, and GANs are a few examples of the different DL techniques. In example, CNNs are widely utilized in fire detection systems, particularly for detecting flames in photos. CNNs are often used in the deep learning approach to address this particular problem in the field of forest fire prediction systems [30].

3. Review of ML Technologies & their usage in Forest Fire Science

Numerous studies in the literature examine the application of machine learning in the field of forest fire science . In this review, we evaluate publications that explore and utilize machine learning techniques across various aspects of forest fire research.

3.1. Detection of Fire range

Numerous studies have focused on the early detection of fires in forest fires due to the significance of fire detection. There has been an increasing interest in leveraging advanced technologies such as Ml & DL for fire detection. Some of the methods proposed by research works include:
The purpose of [34] was to develop a system that would reduce the number of false alarms by analyzing data from a variety of sources, such as information from visible and infrared cameras, information from meteorological geography, and other sources. In order to achieve a detection rate

of over 98% and a false alarm rate of 1.93%, many techniques were utilized. These techniques included Wireless Sensor Networks (WSN), Backpropagation Neural Networks (BPN), Radial Basis Function Networks (RBFN), Dynamic Learning Vector Quantization (DLVQ), and Multilayer Perceptrons (MLP).

In [35], ionization and photoelectric CO gas sensors were utilized in order to conduct an analysis of the features of forest fires and residential fire temperatures, as well as the Canadian Fire Weather Index (FWI). Through the utilization of both distributed Artificial Neural Networks (ANN) and Naive Bayes, they were able to reach a detection accuracy of 81% for home fires and a detection accuracy of 92% for forest fires.

In order to identify forest fires from aerial photographs taken by unmanned aerial vehicles (UAVs), [36] utilized a Convolutional Neural Network (CNN) to obtain an accuracy of detection of 83%.

Using the Decision Tree (DT) approach, [37] evaluated meteorological data and successfully created self-organized and fault-tolerant WSN models for forest fire detection. However, it was unsuccessful in detecting approximately 45 percent of the probable failures.

In the study [38], the Fuzzy Unordered Rule Induction Algorithm (FLURIA), One Rule (OneR), and Neural Network (NN) classifiers were utilized to analyze 17 fire films in order to identify instances of fire in videos. The results of their investigation showed that the Support Vector Machine (SVM) had an accuracy of 90.9%.

A study that was quite similar to the one that was referred to in [36] was carried out by [39], which utilized aerial 360-degree imagery to identify forest fires with a greater performance accuracy of 94%.

The detection of forest fires was accomplished by [40] by employing a Multilayer Neural Network (NN) on thermal camera data obtained from unmanned aerial vehicles (UAVs), however particular findings were not published.

For the purpose of real-time forest fire identification, [41] utilized MLP in conjunction with WSN to perform an analysis of data pertaining to relative temperature, humidity, smoke, and wind acceleration. According to the findings of their experiment, the communication load ratio ranged from 2.5% to 8%, regardless of whether or not the NN method was utilized.

Utilizing temperature, humidity, light, and carbon monoxide data from wireless sensor network (WSN)-based fire detection systems, [42] conducted an evaluation of data mining approaches such as FURIA, NN, and OneR. FURIA had an accuracy rate of 87.6%, OneR had a rate of 71.6%, and NN had a rate of 93.8% when it came to fire detection.

A comparative analysis of a data fusion system that can identify fires by combining data on temperature, CO, humidity, and light intensity was carried out by [43]. They did not give anyone with the results of their study.

[44] was able to attain F-measure rates of 0.89, 0.98, 0.98, and 94.3% for accuracy, precision, recall, and dependability by utilizing CCTV security camera analysis to develop a CNN camera-based fire detection model. This was accomplished by doing the analysis on the CNN camera.

A rule-based image processing method was used to analyze movies of fire and fire-like objects. The results showed that the system achieved a recall rate of 93.13%, an accuracy rate of 92.59%, an F-score of 92.86%, and a false detection rate of less than 40% or less.

With the intention of detecting fires through the utilization of fuzzy logic and a home monitoring system, [46] conducted an analysis of temperature, humidity, carbon monoxide, and smoke in the WSN approach. There were 6.67 percent of errors in the study.

The goal of [47] was to implement a multi-sensor WSN in order to detect forest fires. When evaluating temperature, humidity, smoke, and light sensors, the Naive Bayes method was utilized as the method of choice. In their investigation, they discovered that the accuracy rate was 94%.

An investigation was conducted by [48] using photos captured by UAVs for the aim of detecting fires. Through their investigation, they were able to achieve a performance accuracy of more than 95%.

An MLP classifier was utilized by [49] in order to evaluate temperature, carbon dioxide (CO_2), smoke, and several other characteristics in an effort to ascertain the main combustion phase in real time. In their research, they found that the accuracy rate was 82.5%.

Deep CNN and SVM were utilized by [50] in order to analyze fire photographs in order to determine the extent of fire events. There was a 92.2% accuracy rate for the SVM, a 93.2% accuracy rate for the CNN, and a 90% accuracy rate for the deep CNN.

3.2. Fire Forecasting

Forecasting forest fires is essential to disaster preparation. The control of forest fires might be enhanced by the use for sophisticated forest fire prediction technologies. Deep learning techniques as well as machine learning have been effectively applied to this field. Several approaches recommended by studies consist of:

Following the examination of socioeconomic, infrastructural, and topological data, Arpaci [51] utilized a Random Forest (RF) predictor in order to take precautions against fire. In their research, they had a success rate of 78%.

There were 0.68% false positives and 0.028% false negatives, according to the findings of a Bayesian investigation of visual data [52].

A logistic regression analysis was performed by [53] to forecast the occurrence of fires by analyzing the topography, the types of plants, the climate, the weather, and the activities of humans. The accuracy percentage that they obtained from their research was 85.7%.

The multi-sensor data, which included temperature, CO volume, and smoke density, was examined by [54] utilizing MLP and fuzzy mathematical techniques in order to estimate the likelihood of a fire occurring. After doing their inquiry, they came up with the wrong result of 10-4.

The probability of forest fire initiation was predicted using a model that analyzed raster geographic information system (GIS) data, which included the date, geographic coordinates, cause, land use, and burnt areas [55]. The MLP and logistic regression procedures were the experimental methods that were utilized in order to evaluate these data. The results of their investigation showed that the artificial neural network (ANN) had an accuracy rate of 75.5% when ignition was present and

87.8% when ignition was absent. On the other hand, the logistic regression had an accuracy rate of 78.8% when ignition was present and 74% when ignition was absent.

A subset of human, biotic, and abiotic factors that influence the activity of forest fires was the subject of research that was carried out by publication number 56. A MODIS satellite fire dataset was subjected to Bayesian neural network (BNN) analysis using the technique. According to the findings of their investigation, the accuracy of their findings was 0.961, the specificity was 0.72, and the recall was 0.963.

employed the CNN technique to evaluate the weather, different types of fuel, and landscaping in order to estimate the time-resolved geographical development of a forest fire [57]. From their research, they were able to determine that the F-value was 93%, the sensitivity was 92.5%, and the mean precision was 97%.

With an accuracy rate of 90.9%, [58] was able to forecast the size of forest fires by utilizing the LSTM classifier and utilizing meteorological and fire data.

When weather, location, and time were taken into consideration, a fuzzy inference system for forest fire prediction achieved an accuracy rate of 75% [59].

Through the utilization of the CART methodology, [60] conducted an assessment of the terrain, the state of the vegetation, accessibility, the history of fire, and various other environmental characteristics in an effort to identify the existence of fire in particular models. They found that their investigation was accurate 88.39% of the time.

Multilayer Feedforward Networks (MLFN) were utilized in [61] in order to classify NDVI composite MODIS data in order to estimate high-risk fire hazard based on multi-temporal satellite image pixels. They were able to get a mean squared error (MSE) of 0.07 and an accuracy rate of 90% through their analysis.

Through the utilization of 37 variables derived from a variety of sources, [62] utilized Random Forest (RF) and Multiple Linear Regression (MLR) to estimate the probability of fires and the factors that contributed to them. For the fire season, the accuracy of the RF classifier was 93.31%, whereas for the no-fire season, it was 179%. [63] utilized logistic regression modeling to analyze meteorological data, geographical factors, and previous observations of daily fires in order to investigate fires that were caused by humans through the use of modeling. 49.193 metrics were reported for the no-fire season variable, while 22.15 metrics were reported for the fire season variable, according to their findings. Depending on the results of their investigation, the overall percentage of fires that were correctly predicted ranged anywhere from 47.4% to 82.6%. The risk of forest fires was evaluated with the use of a boosted regression tree classifier [64]. On the basis of two satellite photographs (OLI and MODIS), they achieved an accuracy of 0.89.

The techniques of RF, BRT, and GAM were utilized in order to conduct an investigation into the development of forest fire susceptibility. [65] utilized these techniques in order to examine topographical, meteorological, and geophysical information. There were errors of 87 and 70 for GAM, 72 and 79 for RF, and 80 and 74 for BRT, according to their research.

A study [66] analyzed fire occurrence forecasts by employing the auto-learn architecture to assess meteorological data. The results showed that the predictions were accurate 87% of the time.

[67] investigated socioeconomic data, business activity, and fire-causing capabilities (logistic regression, support vector machine, and random forest) in order to ascertain the frequency of forest fires that were caused by humans. As a whole, their research had an accuracy rate of 74.6 percent. Using a number of different machine learning models, a study conducted by [68] was able to forecast the behavior and spread of forest fires by using data that was collected from open data collections maintained by the Brazilian government. According to the results of their study, the following findings were correct: There was a significant increase in the use of AdaBoost models (91%), support vector machines (81%), random forests (88%), and artificial neural networks (86%).

For the purpose of predicting the fire weather index, [69] utilized meteorological measurements in conjunction with a neural network predictor. The result was a performance error rate of one percent.

By conducting an examination of a global dataset of burned areas on a monthly basis for the year 2015, [70] was able to make predictions regarding the frequency and extent of forest fires. Multilayer perceptrons, logistic regression, linear regression, random forest, and XGBoost were some of the machine learning models that were utilized in their research. Other models that were utilized included random forest. A 94% accuracy rate was achieved by XGBoost, an 81% accuracy rate was achieved by logistic regression, an 89% accuracy rate was achieved by random forest, and a 90% accuracy rate was achieved by multilayer perceptrons.

[71] used BT, RF, logistic regression, naïve Bayes (NB), and SVM to forecast forest fires using GIS, multi-temporal MODIS, and meteorological ALADIN data. Based on the findings, it was discovered that the accuracy of BT, RF, logistic regression, NB, and SVM was 84.9%, 82.5%, 83%, and 81%, respectively.

In [72], a different predictor, the DFP-MnBpAnn, was utilized to anticipate the danger of forest fires. The data used in [72] were identical to those used in [59]. They achieved an accuracy rate of 89% through their investigation.

A study project on forecasting the relevance of the components in a fire start hazard scheme was conducted by [73], which involved the analysis of data pertaining to meteorological, vegetation, and topological human presence utilizing multilayer perceptron (MLP) and BPA technique. Their findings included 24-hour rainfall (35.9%), temperature (1028.7%), fuel moisture (10 hours) (60.3%), aspect (16.9%), principal road network (17.3%), and month of the year (14.3%).

In [74], a comparison was made between the efficiency of artificial neural network (ANN) models and logistic regression-based models for fire prediction systems that are caused by humans. Logistic regression (RBFN) was utilized in order to assess the data that was obtained from a Geographic Information System that was geographically differentiated. Their research revealed an ANN's 85% accuracy in correctly predicting no-fire situations.

A research by [75] used the locally weighted learning (LWL) algorithm with ensemble learning methods such Cascade Generalization (CG), Bagging, Decorate, and Dagging to forecast forest fire vulnerability in Pu Mat National Park, Nghe An Province, Vietnam. At 0.993 for the area under the receiver operating characteristic curve (AUC), the CG-LWL and Bagging-LWL models showed the best training performance. With an AUC of 0.983, the Dagging-LWL ensemble model fared better than the other models.

3.3. Mapping on Fire

Machine Learning (ML) methods have only recently been introduced in fire mapping studies compared to other fields, but they have quickly become integrated into various research areas. Below are some of the methods and findings from research studies:

[76] achieved a performance accuracy of 89% by mapping the severity of fires using imagery captured by unmanned aerial vehicles (UAVs) and the Random Forest Classifier.

Logistic regression was used in conjunction with geographic information system (GIS) data in [77] to evaluate the risk of fire ignition based on human activity and presence characteristics. According to the findings of their research, the global accuracy was 79.8%, and the ignition forecast accuracy ranged from 78.2% to 82.7%.

The SVM approach was utilized by [78] in order to locate burned areas through the analysis of meteorological data. According to the findings of their investigation, the MAD and RMES predictions were 13.07 and 64.7, respectively, with a performance error rate of 12.7% on average.

Evaluation of GIS-based data and mapping of forest fire susceptibility were both accomplished through the application of the Backpropagation Neural Network (BPN) in [79]. A 78% agreement rate was discovered as a result of their research.

For the purpose of mapping the severity of the fire at the research location, [80] utilized Sentinel satellite imagery in conjunction with a Random Forest classifier, attaining an accuracy rate of 98%.

With the use of SVM and nine additional classifiers, [81] was able to map burned regions using Landsat Thematic Mapper (TM) images. This resulted in a performance accuracy of more than 93%.

For the purpose of mapping burned regions, [82] evaluated spectral bands derived from MODIS data by employing a supervised minimum distance classifier, achieving an accuracy rate of 90%.

Using the MARS-DFP classifier, [83] conducted an analysis concerning the weather, vegetation, and infrastructure, which resulted in a study that had an accuracy rate of 86.5%. [84] developed five hybrid machine learning algorithms to map forest fire susceptibility in northern Morocco: Frequency Ratio-Multilayer Perceptron, Frequency Ratio-Logistic Regression, Frequency Ratio-Classification and Regression Tree, Frequency Ratio-Support Vector Machine, and Frequency Ratio-Random Forest. The highest performance model was the Frequency Ratio-Random Forest, with an AUC of 0.989, followed by the Frequency Ratio-Support Vector Machine with an AUC of 0.959.

3.4. Evaluation of the information from Forest Fires

Because datasets make it possible to assess and compare model performance, they have played a crucial role in the advancement of machine learning (ML) research. As large-scale forest fire statistics become more widely available, there are many opportunities to use machine learning (ML) and deep learning (DL) techniques to efficiently extract pertinent characteristics from the data. The following papers provide examples of how different datasets and machine learning techniques are used to forest fires: A research study conducted by [85] utilized the CNN methodology in order to assess the IRIS dataset; however, the findings of this study were not published.

The R-CNN method was utilized in order to evaluate the data from the ConFoBi project. In their research, they were able to get a recall rate of 92.4% and an accuracy rate of 43.4%.

The CNN method was also utilized by [87] in order to evaluate photographs taken by drones; however, the conclusions of this research were not made public.

An evaluation of drone footage was performed by [88] using the YOLOv3 method, and the results showed an accuracy of 82%, a recall of 79%, and an F1 score of 81%.

A research study conducted by [89] utilized the Bi-CNN methodology to evaluate the YUPENN, BUAA, and Maryland datasets. The results of this study demonstrated an average accuracy of 93%.

Comparing drone photographs, open-source photographs, and the Kaggle UAV dataset was accomplished by [90] through the utilization of the DenseNet121, Resnet52, and MobilNetv2 networks. According to their research, the accuracy of DenseNet was 93.1%.

[91] conducted an analysis of the COCO dataset by employing DenseNet121, Resnet52, and MobilNetv2, which resulted in an accuracy of 87.5% for MobileNet.

Pictures that were created with DenseNet and CycleGan were evaluated by [92], which provided results with an accuracy of 98.27%, a precision of 99.38%, and an F1 score of 98.16%.

A CNN and RNBFE technique was used to evaluate the UCM and WHU RS datasets. The results showed that the WHU dataset had an accuracy of 97%, while the UCM dataset had an accuracy of 97.84%.

An evaluation of the FLAME dataset was carried out by [94] utilizing CNN and UNet methodologies. The results of this evaluation included an F1 score of 87.75%, a CLA accuracy of 76.23%, a SEG recall of 83.88%, and a precision of 91.99%.

UNet++ and UNet approaches were applied by [95] in order to evaluate the forest fire data that was gathered from Andong, Republic of Korea. The results generated specificities of 91.77% and 83.11% respectively.

Images from MSCOCO were evaluated by [96] utilizing MobileNet V3 and YOLOv4, which resulted in a recall of 99.21%, a precision of 99.21%, an accuracy of 99.57%, and a reduction in inference time of 75.68%.

[97] evaluated 2096 photos obtained from the internet using MobileNet v2, CNN, FireNet, and AlexNet techniques, which resulted in an accuracy of 99.3% after 2.5 million parameters were taken into consideration.

[98] used FireNet to analyze photos from Google on Baida and the AInML lab dataset (DCNN), and the results showed that 88% of the images were accurate.

The accuracy of the drone photographs that were analyzed by [99] using the author's model was 81.97% based on the results.

In a study by [100], seven ML approaches were employed to assess active fire pixels obtained from MODIS monthly MCD14ML composites, including Logistic Regression, SVM, Linear Discriminant Analysis, and ensemble algorithms, such as eXtreme Gradient Boosting, Random Forest, Gradient Boosting, and AdaBoost (AB). The AUC values ranged from 0.817 to 0.879, while accuracy scores ranged from 0.734 to 0.812. The Random Forest model outperformed the other methods across all performance metrics.

4. Discussion

Integrating machine learning (ML) and forest fire science, as well as highlight several research priorities for the future. The adoption of powerful, efficient ML methods in forest fire science and management holds promise, and we review considerations such as data handling, model selection, and accuracy, and examine various forest fire domains where these methods have been applied.

- To enhance forest fire resilience, it's crucial to emphasize the importance of big data measurement and analysis connected to fire occurrences and forecasts. A more robust framework involving government and local communities residing near fire-prone areas is essential. There is a need for further research into such frameworks, potentially leveraging community social media interactions and crowdsourced event sensing.

- Cloud computing platforms have been developed to provide computational and data storage solutions for managing vast datasets, particularly remote sensing data. The large volume, high spatial-temporal resolution, and complexity of these data have presented challenges. Data processing and management are vital in making the most of extensive geographic datasets. Google Earth Engine (GEE) offers a promising and practical solution for analyzing remote sensing big data. It provides access to multi-temporal remote sensing data and cloud-based computational power for geospatial data analysis, facilitating the rapid processing of data without the need to download them to local computers [101,102].

- GEE provides various remote sensing algorithms for image enhancement, image classification, and cloud masking, allowing improved image quality and accuracy. These algorithms are customizable and accessible via JavaScript or Python APIs, eliminating many time-consuming preparatory steps required in traditional remote sensing methods [103–106].

- Machine learning (ML) is a data-centric approach that can detect patterns in data. It works best with sufficient high-quality data, but issues like data scarcity and human error can be problematic. One solution is to generate synthetic data instances where training a forest fire detection model using synthetic datasets can enhance model performance [107].

- In forest fire domains, remote sensing plays a crucial role in data collection, with advancements in remote sensing increasing the availability of large spatiotemporal datasets. However, not all satellite images have high resolution, and weather can be unstable, resulting in noisy images. Unmanned Aerial Vehicles (UAVs) can collect high-resolution images of the forest, providing more frequent and precise images of the forest canopy than ground-based imaging at a lower cost. This allows for more accurate fire location detection compared to satellite imagery. Thus, integrating UAVs with machine learning offers a promising solution for early-stage forest fire detection, and for transmitting critical information to relevant authorities via efficient communication technologies [109,110].

- Deep learning algorithms have gained popularity in the last decade due to their superior performance in spatial feature recognition, enhancing fire behavior identification and prediction. These algorithms can learn multiple layers of data representation, capturing the complex structure of data and improving pattern recognition compared to conventional machine learning approaches.

5. Conclusions

This study examined several investigations that include machine learning methods into the field of forest fire science. According to the studies we studied, creating sophisticated systems using artificial intelligence is a potential strategy for predicting important environmental concerns and supporting public policies aimed at averting forest fires. However, there are disadvantages to machine learning in the study of forest fires. In order to be taught, machine learning algorithms often need a large quantity of data, which is frequently unavailable during forest fires. These systems also need a lot of processing power, which may be expensive and challenging to scale. Furthermore, it might be difficult to assess the precision of ML predictions in practical situations. Even though machine learning (ML) models are capable of autonomous learning, meaningful modeling of fire dynamics at different scales requires knowledge of forest fire research. Because of their intricacy, several machine learning techniques need extensive and specialized expertise to use. The goal of this research is to provide academics with a thorough grasp of the state-of-the-art in forest fire threat assessment, an area that is still ripe for investigation.

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