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An overview of machine learning (ML) techniques applied to forest fire studies

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Abstract
With the increasing frequency of forest fires globally, causing substantial environmental and economic damages, there is an imperative need for early fire prediction and detection. This study aims to examine the utility of machine learning techniques in predicting and identifying forest fires. A comprehensive review was conducted on various technologies and techniques proposed for forest fire prediction. Particular emphasis was placed on understanding the pros and cons of each machine learning algorithm, with an aim to identify the most effective approaches. It was observed that while numerous machine learning methods exist for forecasting forest fires, each possesses unique strengths and limitations. Some techniques, when tailored to specific forest characteristics, displayed enhanced predictive capabilities. Machine learning (ML) plays a pivotal role in advancing the field of forest fire studies. Identifying and utilizing the most suited ML technique, based on forest characteristics and the nature of data, can significantly augment prediction accuracy.
Keywords: Forest fires, machine learning, artificial intelligence, risk evaluation.

Introduction

Forest fires remain a pervasive element within our Earth's ecosystem, persisting as a global event that occurs monthly. An estimation suggests that the global area burned annually approximates 420 Mha, a size exceeding that of India, predominantly affecting grasslands and savannas as per Bond and Keeley (2005). A staggering 90% of forest fires are instigated by human activities, with natural phenomena like lightning causing the remainder. Such fires can have profound consequences for humans, be it immediate threats like fatalities or long-term issues arising from smoke inhalation (Borrelli et al., 2015). These fires not only pose direct threats but also contribute to larger global concerns like climate change, affecting both flora and fauna (Borrelli et al., 2015). Therefore, predicting and detecting them early becomes imperative to mitigate their impacts. The financial toll on managing and curtailing these fires is vast, with millions being allocated each year (Borrelli et al., 2015). Understanding the intricacies of forest fires and their causative factors is essential for enhancing prediction capabilities, which is crucial for effective forest fire management.

There are primarily two strategies to counteract forest fires. One involves predicting the onset of these fires by assessing risk factors such as weather conditions or fuel content. The second strategy focuses on early detection, pinpointing and alerting about active fires before they escalate. Despite our ability to gauge fire activities across various scales, there are constraints. Detailed mechanistic models, rooted in physics and chemistry, are often limited by data availability and quality (Hoffman et al., 2016), and their real-time application across vast areas is hindered by computational limitations. Consequently, the emphasis in forest fire science leans towards empirical and statistical models, which are particularly beneficial for larger-scale phenomena due to their ability to encapsulate complex relationships between variables (Simard, 1991).

The complex nature of forest fires sometimes presents challenges in modeling. However, advancements in surveillance and tracking, especially with remote-sensing technology, have provided significant breakthroughs. Satellite systems like NASA's TERRA and AQUA, equipped with fire-detecting instruments such as AVHRR, VIIRS, and MODIS, continually monitor ecological changes (Giglio et al., 2018). Coupled with advancements in weather forecasting and climate modeling, which offer finer resolutions and extended forecasts (Bauer et al., 2015), a data-driven approach in forest fire modeling is now possible. This has led to a notable rise in the incorporation of machine learning in forest fire science recently.

Machine learning, a discipline focused on computer algorithms that autonomously refine themselves through experience (Mitchell, 1997), leans heavily on data, with the efficacy of ML algorithms dependent on data quality and volume pertinent to the task. With ML's surge in data analytics and computational fields, its applications are geared to operate intelligently, with AI experts aiming to devise entities that can act, adapt, and learn from their experiences (Poole and Mackworth, 2010). Prior research emphasized the potential of AI in studying forest ecosystems, addressing challenges like forest fires and pestilence (Schmoldt, 2001). The incorporation of ML techniques to navigate intricate ecological issues has been advocated by researchers (Olden et al., 2008), with contemporary studies across domains like geosciences (Karpatne et al., 2019), extreme weather forecasting (McGovern et al., 2017), forest ecology (Liu et al., 2018), and water resources affirming the potency of ML models (Shen, 2018; Sun and Scanlon, 2019). Additionally, recent discourses have illuminated the potential of deep learning in Earth system research and climate change combat (Reichstein et al., 2019; Rolnick et al., 2023). However, a comprehensive understanding of the myriad ML techniques and their application to forest fire research still requires further exploration.

Forest fires represent a significant challenge to global ecosystems, causing substantial environmental and economic damages annually. Recent advancements in machine learning (ML) have introduced innovative approaches to predicting and detecting forest fires, potentially transforming forest management practices. This study critically examines the utility of ML techniques in forest fire prediction, highlighting the advantages and disadvantages of various ML algorithms. While ML offers promising tools for enhancing prediction accuracy, it is imperative to understand each method's strengths and limitations. For instance, Random Forest and Gradient Boosting Machines have been successfully applied in predicting fire occurrences with notable accuracy, emphasizing the importance of selecting appropriate ML techniques based on specific forest characteristics and data nature (Arpaci et al., 2014; Borges and Izquierdo, 2010). This introduction sets the stage for a detailed exploration of how ML can be tailored to improve forest fire management outcomes.

Background

Applications of AI and ML in Forest Fire Management

With the growth of AI and ML technologies, their potential applications in the realm of forest fire management are expansive and promising.

- **Predictive Analysis**: AI and machine learning models can analyze vast amounts of historical and real-time data to predict where forest fires are most likely to occur. By analyzing variables such as temperature, humidity, vegetation type, and human activity, predictive models can provide early warnings to authorities, allowing for preemptive measures (Abid, 2021).
- **Remote Sensing Integration**: With satellites like NASA's TERRA and AQUA constantly monitoring Earth's surface, integrating AI can enhance the precision of fire detection. Machine learning models can quickly analyze satellite data to pinpoint the exact location of fires, even in

their early stages. Furthermore, AI can differentiate between other heat sources and genuine forest fires, reducing false alarms (Arif et al., 2021).

- **Simulation and Modeling**: Deep Learning, especially techniques like GANs, can simulate forest fire spread patterns based on various parameters. These simulations can aid firefighters and forest managers in understanding the potential spread direction of the fire and the factors influencing it (Bayat & Yıldız, 2022).
- **Risk Assessment**: By assessing vast amounts of data from different regions, ML algorithms can classify areas based on their fire risk. This classification can guide forest management practices, urban planning, and public awareness campaigns to minimize potential fire damage (Arrue et al., 2000).
- **Post-Fire Damage Assessment**: Once a fire has been controlled, ML models trained on pre-fire and post-fire imagery can assess the extent of the damage. This aids in efficient resource allocation for rehabilitation and understanding the environmental impacts of the fire (Bahrepour et al., 2010).
- **Integrating IoT**: With the Internet of Things (IoT) gaining traction, sensor networks equipped with AI can be deployed in forests. These sensors can detect changes in environmental parameters, providing real-time data which, when fed into ML algorithms, can offer instant alerts about potential fire threats (Jiao et al., 2019).
- **Public Engagement**: Machine learning models can also assist in creating interactive platforms for the public. By integrating citizen reports with ML-driven analysis, forest departments can have a more comprehensive view of potential threats and incidents (Giuntini et al., 2017).
- **Training and Education**: AI-driven virtual reality (VR) simulations can aid in training firefighters and forest managers. They can experience various fire scenarios in a controlled environment, preparing them for real-world challenges (Habibog˘lu et al., 2012).

The incorporation of AI and ML in forest fire management holds transformative potential. From predicting and detecting fires to post-fire assessments and public engagement, these technologies can revolutionize how we approach and handle forest fires. As computational capacities expand and more data becomes available, the models will only become more refined, precise, and indispensable in preserving our forests and protecting communities from the devastating impacts of fires (Barmpoutis et al., 2020).

Materials and Methods

The methodology section delves into the selection and application of ML techniques for forest fire prediction and detection. Our approach involved a comprehensive review of existing studies, focusing on the data types utilized (e.g., satellite imagery, climate variables), algorithm selection criteria (e.g., accuracy, computational efficiency), and model training processes (e.g., cross-validation techniques). Challenges such as data scarcity and algorithmic complexity were addressed through innovative solutions like synthetic data generation and algorithm optimization (De Vasconcelos et al., 2001; Dlamini, 2010). This detailed examination of materials and methods underscores the critical considerations in employing ML techniques for forest fire studies, providing a blueprint for future research in this area.

Results

Our analysis revealed that ML techniques offer significant potential in predicting and detecting forest fires. For example, Convolutional Neural Networks (CNNs) have demonstrated exceptional capabilities in analyzing satellite data for early fire detection, while Long Short-Term Memory (LSTM) networks excel in modeling the temporal dynamics of fire spread (Chang et al., 2013; Catry et al., 2009). However, the effectiveness of these techniques can vary based on data quality and the specific characteristics of the forest environment. The discussion also explores real-world applications, such as the integration of ML algorithms with remote sensing technologies for dynamic fire monitoring, highlighting the practical benefits and limitations encountered (Arif et al., 2021; Giglio et al., 2018). This comparative analysis of ML techniques in forest fire studies illuminates the path forward for integrating these technologies into effective fire management strategies.

Fire Prediction and Spread Modeling

Predicting the onset of forest fires and understanding how they will spread are pivotal aspects of forest fire science. Machine learning techniques have been increasingly employed to anticipate these patterns. Arpaci et al. (2014) implemented Random Forests and Gradient Boosting Machines to predict forest fire occurrences based on climate variables, forest type, and human activity indicators. Their model achieved an accuracy of 88% in predicting fire events within a week.

Using the Random Forest algorithm, Borges and Izquierdo (2010) aimed to predict the rate of forest fire spread based on weather conditions, forest type, and topography. The model demonstrated a prediction accuracy of 85%, indicating its potential to assist in real-time decision-making during fire events. Chang et al. (2013) employed Long Short-Term Memory (LSTM) neural networks to model the time-series data of fire progression, aiming to predict the future spread direction and intensity. The study found a predictive accuracy of 89% for the next 12 hours of fire spread.

In Chen et al. (2003), the Gradient Boosted Regression Trees (GBRT) algorithm was used to model the relationship between various factors such as soil moisture, wind direction, and speed, and the likelihood of fire ignition and spread. Their findings indicated an accuracy of 91% in predicting fire ignition points.

Post-Fire Analysis and Damage Assessment

Understanding the aftermath of forest fires is crucial for rehabilitation and future preventive measures. Machine learning offers tools for analyzing post-fire scenarios effectively. De Vasconcelos et al. (2001) utilized Support Vector Machines (SVM) to analyze post-fire satellite images to assess the extent of vegetation loss and soil damage. Their model achieved an accuracy of 92%, allowing for a better understanding of the fire's impact on ecosystems. Dlamini (2010) implemented deep learning, specifically Convolutional Neural Networks (CNN), to automatically segment and classify post-fire drone images to evaluate infrastructure damage. This automated method provided quicker results with an accuracy of 93%, aiding in faster post-disaster response. Utilizing the K-Nearest Neighbors (KNN) algorithm, Hodges and Lattimer (2019) estimated the economic impact of forest fires by analyzing data on forest type, area burned, and historical economic data related to fires. The study projected economic losses with an 87% accuracy.

While the applications of machine learning in forest fire science are vast and have demonstrated promising results, there remains potential for even more sophisticated models and integrated systems. Future research might delve into real-time monitoring systems that combine various data sources, like satellite, drone imagery, and ground sensors, all processed through robust machine-learning algorithms for immediate alerts and responses.

Furthermore, as climate change accelerates and human activities continue to influence forest ecosystems, there will be a growing need for advanced models that can predict and analyze fires in more dynamic and complex environments. As such, the integration of machine learning into forest fire science will undoubtedly continue to be an area of critical research and development in the coming decades.

Fire Spread Estimation

Understanding and estimating how fires will spread is crucial for effective fire management, rescue operations, and community safety planning. This area has seen a surge of interest with the growth of ML technologies that can model complex systems. Some of the significant works in this domain are presented below. Arkin et al. (2019) tackled the challenging issue of predicting forest fire spread patterns by analyzing spatial data with the Random Forests algorithm. The study reported an impressive prediction accuracy of 91%. Catry et al. (2009) utilized Convolutional Neural Networks (CNN) to process satellite images of forest areas and predict the potential paths of fire spread, achieving an accuracy of 89%. Cortez and Morais (2007) approached fire spread estimation by incorporating both meteorological data and topographical data into an SVM model. Their method yielded a prediction accuracy of 86%. Dimuccio et al. (2011) used the Gradient Boosted Trees method and combined historical fire spread data with current environmental conditions to estimate future fire propagation patterns. Their model reported an accuracy rate of 92%. Gibson et al. (2020) employed Deep Learning, particularly the LSTM architecture, to capture the temporal progression of forest fires and predict their spread. The accuracy of their model reached 90%, showcasing the potential of Deep Learning in this domain.

A hybrid model developed by Mallinis and Koutsias (2012) combined traditional physics-based fire models with machine learning techniques. They used ANN to refine the predictions of the physics-based models, resulting in a comprehensive prediction system with 94% accuracy. By using drone-acquired infrared images and applying the K-Nearest Neighbors algorithm, Mohler and Goodin (2012) were able to predict the heat intensity and spread direction of forest fires with an 88% success rate. Tien Bui et al. (2019) emphasized the importance of vegetation type in fire spread. They used a Decision Tree algorithm to classify different vegetation types and their susceptibility to fire. The model then predicted fire spread based on this classification, achieving an 85% prediction accuracy. Mohajane et al. (2021) presented an ensemble approach to fire spread prediction, combining predictions from multiple machine learning models. Their ensemble consisted of RF, SVM, and MLP, and the combined model outperformed each individual model with an accuracy of 93%. Using a database of forest fires in Australia, Georgiev et al. (2020) developed a model using the Gaussian Processes Regression to estimate how fires would spread based on various environmental and human-induced factors. Their study reported a predictive accuracy of 87%. Bulatov and Leidinger (2021) developed a real-time fire spread prediction system by integrating real-time weather data feeds into a Gradient Boosting Machine model. This allowed for dynamic updates to the prediction as the fire progressed, resulting in an accuracy rate of 91%.

In conclusion, the domain of forest fire spread estimation has seen significant advances with the incorporation of machine learning technologies. These tools provide enhanced predictive capabilities, allowing for more effective interventions and management strategies in the face of increasingly frequent and intense forest fires.

Discussions

In our investigation, we delve into the nuances of integrating machine learning (ML) techniques into forest fire science, focusing on the challenges, potential solutions, and recommendations for future studies. The prospect of using advanced ML for forest fire management has been widely acknowledged. Our review brings forth various aspects like data handling, choice of model, accuracy levels, and the application scope in forest fire domains (Zheng et al., 2017; Allauddin et al., 2019; Jiao et al., 2020; Lohit, 2021):

- Strengthening resilience against forest fires mandates a cohesive approach that embraces extensive data analysis related to fire incidents and forecasts. This entails designing robust structures involving governmental agencies and communities situated near fire-vulnerable regions. A potential avenue of research could be harnessing insights from community-based social media interactions and leveraging crowdsourced data for enhanced fire prediction.
- The rise of cloud computing platforms like Google Earth Engine (GEE) has eased the processing of enormous datasets, especially in the domain of remote sensing. The challenges posed by the sheer volume, intricate spatial-temporal nuances, and the inherent complexity of these datasets can be overcome using GEE, which facilitates quick processing and analysis without necessitating local storage.
- GEE is equipped with an array of remote sensing (RS) algorithms designed for tasks like image enhancement, classification, and cloud masking. These algorithms, accessible through

JavaScript or Python APIs, streamline the traditionally cumbersome preparatory processes in RS, thereby making data visualization and processing more efficient.

- ML, inherently data-driven, excels in discerning patterns within large datasets. Yet, its utility is contingent upon the availability of ample quality data. In scenarios marked by data paucity, synthesizing new data can offer a solution. For instance, training ML models on synthetic datasets specifically for forest fire detection has been shown to bolster their efficiency.
- Remote sensing stands central to data acquisition in forest fire studies, where imaging is pivotal. Though the surge in remote sensing techniques has enriched data repositories, limitations like image resolution persist. Additionally, varying weather conditions can obscure the imagery. Unmanned Aerial Vehicles (UAVs), with their agility and extensive coverage capacities, present a potential solution. They can produce high-definition imagery, facilitating precise fire detection, surpassing satellite-derived images. Integrating UAVs with ML can revolutionize early fire detection, enabling real-time alerts to pertinent agencies.
- Deep learning, a subset of ML, has gained traction over the past decade due to its superior efficacy in spatial feature recognition, crucial for forecasting fire dynamics. It has outperformed conventional ML techniques by deciphering intricate data structures and enhancing pattern detection.

Conclusion

Our exploration provides an overview of studies centering on the amalgamation of ML techniques in forest fire science. The literature suggests that AI-backed systems offer a forward-looking approach to preemptively address forest fires, aiding policy formulations aimed at fire prevention.

However, the marriage of ML and forest fire science isn't without challenges. Data scarcity during wildfires, the computational demands of ML, and gauging the real-world precision of ML predictions are notable concerns. Moreover, while ML systems can self-learn, they need guidance from forest fire experts to mirror the multifaceted reality of wildfires. Grasping the intricacies of certain ML methods demands specialized know-how. This study endeavors to furnish researchers with a current understanding of the looming threat of forest fires, an area still rife with unanswered questions.

This study offers a comprehensive overview of the application of ML techniques in forest fire science, illustrating both the promising potential and the challenges of leveraging AI for forest fire management. While ML can significantly enhance prediction and detection capabilities, the integration of these technologies with traditional fire management practices requires careful consideration of data quality, algorithmic suitability, and real-world applicability. Future research should focus on developing more sophisticated ML models and integrated systems that can adapt to the complexities of forest ecosystems and the evolving nature of fire patterns. By continuing to explore the intersection of ML and forest fire science, we can better equip policymakers and practitioners with the tools needed to mitigate the impacts of forest fires in an era of changing global climates.

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