International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 15, No.1 (Feb-24)

http://dx.doi.org/10.12785/ijcds/150157

Exploring Progress in Forest Fire Detection, Prediction, and Behavior: An In-Depth Survey

Ahmad Alkhatib[1], Khalid Mohammad Jaber[2], Hassan Alzo'by[3], Mohammad Abdallah[4] and Mousa Salah[5]

[1]*Department of Cyber Security, Al-Zaytoonah University of Jordan, Amman, Jordan*
[2,4]*Department of Computer Science, Al-Zaytoonah University of Jordan, Amman, Jordan*
[3]*Department of Mathematics, Al-Zaytoonah University of Jordan, Amman, Jordan*
[5]*Department of Multimedia Technology, Al-Zaytoonah University of Jordan, Amman, Jordan*

Received 24 Oct. 2023, Revised 30 Dec. 2023, Accepted 23 Jan. 2024, Published 1 Feb. 2024

Abstract: Forest fires present a substantial environmental challenge, constituting a dual menace to human life and ecological well-being. The imperative for forest fire prevention and management underscores the indispensability of robust detection, prediction, and behavior analysis systems. This scholarly paper offers a thorough exploration of diverse methodologies and techniques employed in the realms of forest fire detection, prediction, and behavior analysis.

Encompassing both ground-based and aerial surveillance systems, as well as remote sensing technologies, machine learning-based approaches, and social media-driven systems, the survey provides a comprehensive overview of the multifaceted landscape of forest fire monitoring. In addition to delineating the current state of the art, the paper critically examines the challenges and limitations inherent in existing systems. Furthermore, it imparts valuable insights into prospective avenues for research and development within this domain. In essence, this paper underscores the significance of amalgamating data from various sources and employing diverse analytical methods to enhance our comprehension of forest fire behavior. The overarching goal is to foster the formulation of efficacious strategies for mitigating the impact of this environmental menace.

Keywords: Forest Fire, Fire Detection, Fire Prediction, Fire Behavior Analysis, Early Warning.

1. INTRODUCTION

The causes of forest fires can be categorized as either natural or human-induced, with the 2020 World-Wide Fund (WWF) report indicating that human activities directly contribute to 75% of forest fires. This contribution stems from activities like road construction, land conversion for agriculture, urban expansion, and grazing by domestic livestock (Figure 1) [1].

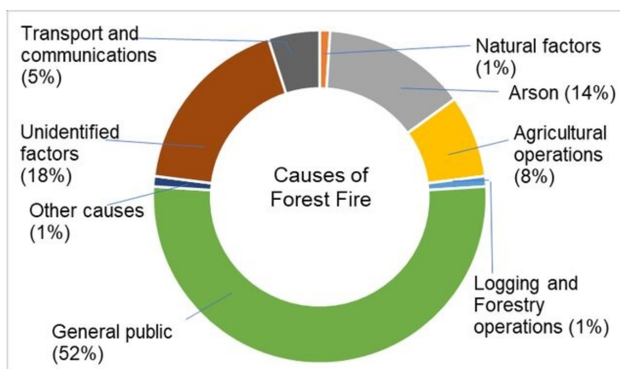


Figure 1. Causes of forest fire [1]

Forest fires pose a significant threat to the global environment, wildlife, and human lives. The imperative for early detection, precise prediction, and effective management of forest fires is paramount in minimizing their far-reaching impact. Recent years have witnessed notable progress in technology and machine learning, presenting novel avenues for enhancing forest fire detection, prediction, and behavior analysis. The administration of forest fires constitutes a critical aspect of forest oversight. Fire, being a vital element within forests, necessitates careful control and oversight. Fire management refers to the strategic approach of organizing, averting, and combating fires to protect both individuals and assets, as well as the invaluable resources within the forest. The management of forest fires encompasses a series of stages: fire prevention, detection, suppression, and post-fire handling, forming a continuous cycle in forest fire management (Figure 2).

Various methodologies and technologies play a pivotal role in forest fire managment, encompassing ground-based systems, aerial surveillance, and remote sensing techniques.

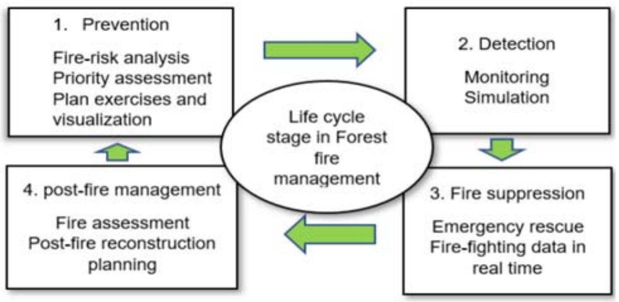


Figure 2. Life cycle stage in forest fire management

A noteworthy innovation in this domain involves the integration of machine learning algorithms and satellite data, offering a discerning approach to identify and monitor potential wildfires. Through the analysis of shifts in vegetation and thermal anomalies in satellite imagery, machine learning algorithms exhibit a commendable ability to detect and classify potential fires with a high degree of accuracy [2].

In addition to this advancement, the utilization of drones equipped with thermal cameras and sensors represents a further asset in the detection of forest fires. These drones possess the capability to rapidly and efficiently survey expansive forested areas, identifying regions characterized by heightened heat or smoke [3]. This dual integration of machine learning algorithms with satellite data and drone technology enhances the overall efficacy of forest fire detection and underscores the dynamic role that technological innovation plays in addressing this critical environmental challenge.

Beyond technological innovations, active community participation is indispensable in the endeavor to detect forest fires. Citizen reporting and monitoring systems, exemplified by the Firewatch app [4], empower individuals to promptly report potential fires and receive real-time alerts about nearby incidents.

In a comprehensive approach, the amalgamation of machine learning algorithms, satellite data, drones, Wireless Sensor Networks (WSN), the Internet of Things (IoT), and community engagement holds immense potential to markedly enhance the speed and precision of forest fire detection. This synergy of diverse technologies and active involvement from the community forms a robust framework for identifying and preventing forest fires. The following provides a concise summary of some of the current methods for achieving this objective:

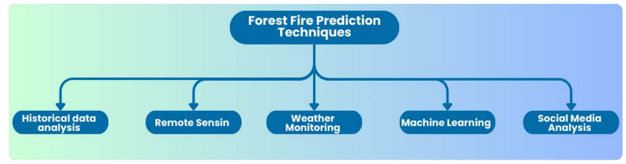


Figure 3. Forest Fire Detection Techniques

1) Forest Fire Detection Techniques

Over the years, a myriad of techniques has been developed to effectively detect forest fires, spanning from ground-based systems to sophisticated aerial surveillance methods. The subsequent delineation outlines the various methods employed for forest fire detection, as illustrated in Figure 3:

- Ground-Based Systems: Ground-based systems encompass both fixed and mobile sensors designed to identify crucial indicators such as smoke, heat, and other manifestations of fire. Notable examples of these systems include infrared cameras, flame detectors, and thermal sensors. While ground-based systems offer the advantage of being relatively cost-effective and capable of providing real-time data, their efficacy is constrained by their limited range. To cover expansive areas, a network of sensors is essential [5][6].
- Aerial Surveillance: Aerial surveillance entails the utilization of drones or aircraft for monitoring forests and identifying potential signs of fire. This method boasts a larger coverage area compared to ground-based systems and offers high-resolution imagery. However, its implementation necessitates specialized equipment and trained personnel for operation. Additionally, real-time analysis of captured imagery is imperative for effective utilization [7][8].
- Remote Sensing: Remote sensing leverages satellites and other remote sensors to detect heat and smoke emanating from forest fires. This technique proves especially valuable for surveying expansive areas, particularly in remote or inaccessible regions. Despite its efficacy, remote sensing can be cost-prohibitive and is subject to limitations imposed by cloud cover and other environmental factors [9][10].
- Machine Learning-Based Approaches: Machine learning-based approaches involve the training of algorithms to discern forest fires utilizing data from sensors or satellite imagery. These innovative methods contribute to heightened accuracy and speed of detection and are applicable to diverse types of data. However, their efficacy is contingent upon access to substantial training datasets and may be influenced by the quality of input data [11][12].
- Social Media-Based Approaches: Social

media-based approaches harness platforms to detect and monitor forest fires, relying on crowdsourced data for real-time insights into the location and severity of fires. While offering valuable information, these approaches are contingent upon the availability and reliability of social media data [13].

2) Forest Fire Prediction Techniques
Forest fire prediction techniques are designed to ascertain the likelihood of a fire occurrence in a specific area and estimate its potential size and behavior. The subsequent enumeration outlines common techniques employed for predicting forest fires, as depicted in Figure 4 (refer to Fig. 4. Forest Fire Prediction Techniques):

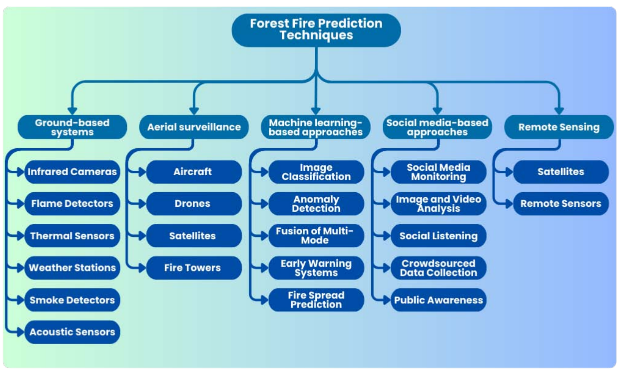


Figure 4. Forest Fire Prediction Techniques

- Historical Data Analysis: Entails the examination of past forest fire data to discern patterns and trends, aiding in the prediction of future fires. Statistical models are applied to analyze data encompassing fire frequency, location, size, and behavior. These models leverage environmental factors such as temperature, humidity, and precipitation to predict the likelihood of future fires [14][15].
- Remote Sensing: Remote sensing harnesses satellite imagery and other remote sensing technologies to detect changes in vegetation moisture and other environmental factors influencing the risk of forest fires. By identifying such alterations, this technique enables the prediction of the likelihood of a fire occurrence in a specific area, as well as estimation of its potential size and behavior [16].
- Weather Monitoring: Weather monitoring involves the tracking of weather conditions, including temperature, humidity, wind direction and speed, and precipitation. This information is pivotal for predicting the likelihood of a fire occurrence and estimating its potential behavior [17][18].
- Machine Learning: Machine learning techniques involve training algorithms to recognize patterns and trends in data, facilitating the prediction of future forest fires. Data related to weather conditions, vegetation moisture, and other environmental factors are scrutinized by machine learning algorithms to develop models predicting the likelihood of a fire in a specific area [19].
- Social Media Analysis:Social media platforms serve as valuable tools for identifying trends and patterns indicative of potential forest fires. An increase in posts discussing smoke or flames in a specific area, for instance, may signify the initiation of a fire. Leveraging machine learning algorithms to analyze this social media data enables the generation of early warning alerts, facilitating prompt responses from emergency responders [20].

In summary, forest fire prediction techniques draw upon a combination of diverse data sources and analysis methods to establish a comprehensive understanding of the risk of forest fires. Through the amalgamation of these techniques, fire managers can formulate effective strategies for both the prevention and management of forest fires.

3) Forest Fire Behaviour Analysis Techniques
Forest fire behavior analysis techniques play a crucial role in comprehending and predicting the behavior of a forest fire, encompassing factors such as its rate of spread, direction, intensity, and likelihood of ignition. The ensuing enumeration outlines common techniques employed for forest fire behavior analysis, as illustrated in Figure 5 (refer to Figure 5):

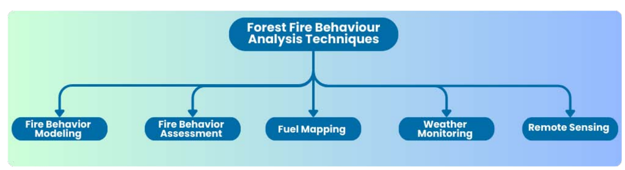


Figure 5. Forest Fire Behaviour Analysis Techniques

- Fire Behavior Modeling: This technique employs mathematical models to simulate the spread and behavior of a fire. Factors such as topography, fuel characteristics, and weather conditions are considered in these models to predict the behavior of the fire [21][22].
- Fire Behavior Assessment: Direct observation and analysis of a fire characterize this technique. Firefighters and fire behavior analysts utilize visual cues such as flame length, smoke color, and wind direction to assess the fire's behavior and predict its potential spread [23].
- Fuel Mapping: Detailed maps of the types and distribution of fuels in an area are created to predict the potential behavior of a fire. Understanding the types and densities of fuels enables analysts to anticipate the speed and

intensity of fire spread [24][25].

- Weather Monitoring: Weather conditions, including temperature, wind speed, and humidity, significantly impact fire behavior. Real-time monitoring of weather conditions allows fire behavior analysts to adjust predictions and provide more accurate information to firefighters and other emergency responders [26][18].
- Remote Sensing: Utilizing satellites or other remote sensing technologies, this technique gathers data on forest fires, including information on location, size, and behavior. This data contributes to the creation of more accurate fire behavior models and predictions [18].

In conclusion, comprehending the behavior of a forest fire is pivotal for effective firefighting and emergency response efforts. The combination of techniques, such as those listed above, enables analysts to furnish valuable information to firefighters and emergency responders, aiding in the rapid and safe containment and control of fires.

2. Ground-Based Techniques Used for Forest Fire Detection

Ground-based systems represent a key methodology for forest fire detection, utilizing networks of sensors, cameras, or instruments placed on the ground to identify indicators such as smoke, heat, or other cues associated with a forest fire. The ensuing discussion outlines some prevalent types of ground-based systems employed for forest fire detection:

- Infrared cameras, designed to detect infrared radiation emitted by objects based on their temperature, play a crucial role in detecting heat signatures from wildfires. Particularly effective during nighttime when visibility is limited, these cameras contribute significantly to fire monitoring [5].
  Examples of ground-based systems utilizing infrared cameras:
  - FireWatch: FireWatch is a ground-based system equipped with infrared cameras, offering a 360-degree view of the surroundings. Utilizing algorithms to analyze thermal images captured by infrared cameras, it identifies potential fire hotspots [27].
  - FLIR Aerial Firefighting System: This ground-based system utilizes infrared cameras to detect forest fires from a distance. Equipped with a thermal imaging camera mounted on a telescoping mast, it can detect temperature differences as small as 0.1 degrees Celsius, enabling early fire detection before becoming visible to the naked eye [28].
  - DRS Technologies Tamarisk: The DRS Technologies Tamarisk system is a portable ground-based solution employing infrared cameras for forest fire detection. Comprising a thermal imaging camera mounted on a tripod, it offers ease of transport and setup in the field. The camera's capability to detect hotspots as small as 0.5 square meters ensures swift detection and location of fires [29].

- Flame Detectors: Flame detectors utilize optical sensors to identify the light emitted by flames, enabling the detection of fires in their early stages when flames may be small and not visible to the naked eye [30].
  Examples of ground-based systems incorporating flame detectors:
  - Wasp Wildfire Detection System: The Wasp Wildfire Detection System is a ground-based solution utilizing a combination of flame detectors and infrared sensors for forest fire detection. Mounted on a telescoping mast, this system is suitable for monitoring expansive areas. Flame detectors within the system can identify the distinct signature of a forest fire, providing timely alerts to firefighters [31].
  - Fire Sentry FS24X Flame Detector: The Fire Sentry FS24X Flame Detector is a portable ground-based system employing a sophisticated infrared sensor for forest fire detection. Capable of detecting fires from up to 200 feet away, this system is easily transportable and deployable in the field. The flame detector exhibits the ability to differentiate between genuine fires and false alarms triggered by sources like sunlight, headlights, and other heat-emitting objects [32].
  - Viper Perimeter Protection System: The Viper Perimeter Protection System is a ground-based solution integrating flame detectors, infrared sensors, and video cameras for forest fire detection. Designed to monitor extensive areas, this system can be seamlessly integrated with other sensors and alarms, providing comprehensive wildfire detection and protection [33].

- Thermal Sensors: Thermal sensors, designed to detect changes in temperature, play a crucial role in identifying heat signatures from wildfires. These sensors can be strategically installed on towers or structures, connected to a central monitoring system.
  Examples of ground-based systems incorporating thermal sensors:
  - AlertWildfire: AlertWildfire is a ground-based system utilizing thermal sensors for forest fire detection. Comprising a network of cameras equipped with thermal sensors strategically placed in wildfire-prone areas, the system can detect heat signatures associated with forest fires. These cameras are connected to a central monitoring system, providing real-time alerts to firefighters and emergency responders [34].
  - ThermEye: ThermEye is a portable ground-based system leveraging thermal sensors for forest fire detection. Designed for rapid de-

ployment in the field, the system, mounted on a tripod, can monitor large areas. With the capability to detect temperature differences as small as 0.1 degrees Celsius, ThermEye can identify fires before they become visible to the naked eye [35].

- Weather Stations: Weather stations contribute to monitoring environmental conditions influencing wildfire spread. They measure variables such as temperature, humidity, wind speed, and other factors affecting fire behavior.
  Examples of ground-based systems incorporating weather stations:
  - The Campbell Scientific Weather Station is a ground-based system incorporating a weather station for forest fire detection. Equipped with sensors measuring temperature, humidity, wind speed, and other weather variables, the system's data informs fire management decisions and aids in predicting fire behavior [36].
  - Wildfire Watcher: Wildfire Watcher is a ground-based system utilizing a network of weather stations to monitor conditions conducive to forest fires. Collecting data on temperature, humidity, wind speed, and other variables, the system predicts the likelihood of a forest fire, supporting fire management decisions and prevention efforts [37].
  - Fire Weather Intelligence Portal: The Fire Weather Intelligence Portal is a ground-based system integrating a weather station for forest fire detection. Collecting data on temperature, humidity, wind speed, and other variables, the system generates fire weather forecasts, providing advance warning of conditions that could lead to a forest fire and informing fire management decisions [38].

- Smoke Detectors: Smoke detectors, equipped with sensors capable of detecting the presence of smoke and particulate matter in the air, play a pivotal role in forest fire detection by monitoring smoke concentration.
  Examples of ground-based systems incorporating smoke detectors:
  - FireOne Smoke Detection System: The FireOne Smoke Detection System utilizes multiple smoke detectors strategically placed in forested areas. These detectors can identify the unique smoke signature of a forest fire, triggering real-time alerts to firefighters and first responders upon detection [39].
  - FireGuard Smoke Detection System: The FireGuard Smoke Detection System is a portable ground-based solution employing smoke detectors for forest fire detection. Easily transportable and deployable in the field, the system is designed to monitor large areas. Smoke detectors are connected to a central monitoring system, providing real-time alerts to emergency responders [40].
  - VESDA Smoke Detection System: The VESDA Smoke Detection System incorporates advanced smoke detection technology to identify forest fires. Equipped with sensitive smoke detectors capable of detecting particles in the air even before a fire becomes visible, the system can be integrated with other sensors and alarms for comprehensive wildfire detection and protection [41].

- Acoustic Sensors: Acoustic sensors, capable of detecting the sounds of wildfires, contribute to locating fires in dense forest areas. These sensors identify characteristic sounds such as crackling and popping. Examples of ground-based systems incorporating acoustic sensors:
  - RASS: RASS utilizes acoustic sensors to detect the distinct sounds of a forest fire, including crackling flames and falling debris. Connected to a central monitoring system, the system provides real-time alerts to firefighters and first responders [42].
  - FireWatch: FireWatch integrates a combination of thermal and acoustic sensors for forest fire detection. Acoustic sensors detect the sound of a forest fire, while thermal sensors identify the heat signature. Advanced algorithms analyze the collected data to identify potential fire hotspots [43].
  - DASH (Detection and Alert System for High Risk Wildfires): DASH utilizes acoustic sensors to detect forest fires, equipped with sensors that can distinguish between the sound of a forest fire and other sources of noise. The system, designed for rapid deployment, can monitor large areas in the field [44].

Ground-based systems prove effective for detecting and monitoring forest fires in localized areas, such as campgrounds or residential neighborhoods. However, their limited range may not be practical for large-scale monitoring of remote forest areas. Combining ground-based systems with aerial surveillance and remote sensing offers a comprehensive solution for forest fire detection and prevention [45][46][47][48].

Forest Fire Prevention Ground-based systems are not only instrumental in detection but also play a crucial role in forest fire prevention through various methods:

- Firebreaks: Strips of land cleared of flammable materials, created using ground-based equipment such as bulldozers and excavators, act as barriers to slow or stop the spread of fires.

- Prescribed Burning: Ground-based equipment like drip torches or flamethrowers is used to intentionally set controlled fires, reducing the fuel load in forested areas and mitigating the risk of uncontrolled wildfires.

- Fuel Management: Ground-based equipment, including mowers, chainsaws, and chippers, is employed to remove dead and dry vegetation, reducing the risk of wildfires and creating fuel breaks.

- Fire Suppression: Ground-based equipment such as fire engines and water tenders, along with firefighting tools, are utilized to suppress fires and prevent their spread once detected.

- Education and Outreach: Ground-based systems contribute to education and outreach efforts for wildfire prevention. Public education campaigns and signage inform people about the causes of wildfires, fire danger levels, and restrictions, promoting awareness and prevention [45][46][47][48].

3. Aerial Surveillance Techniques used for forest fire detection

Aerial surveillance is a critical method for detecting forest fires, particularly in remote or challenging-to-reach areas. This technique involves using aircraft, drones, or other airborne platforms to scan large forested areas for signs of smoke or fire. Various technologies are employed for aerial surveillance, enhancing the ability to detect and monitor forest fires effectively [49].

- Aircraft: Fixed-wing aircraft and helicopters equipped with cameras, infrared sensors, and other instruments are employed for aerial surveillance to detect smoke and other indicators of forest fires. High-resolution cameras and infrared sensors can identify smoke plumes and fire hotspots. Pilots fly over remote areas to monitor and detect potential fires.

- Drones: Drones are utilized for forest fire detection and monitoring, equipped with cameras, thermal sensors, and other instruments. Drones can detect smoke and heat signatures, map fire locations, and monitor fire progression. They are particularly valuable for covering large areas quickly and providing real-time data.
  Examples of drones used for forest fire detection:
  - DJI Mavic 2 Enterprise Dual: Equipped with visual and thermal cameras, this drone can quickly cover large areas, providing real-time information about forest fires [50].
  - Lockheed Martin Indago: Featuring an electro-optical and infrared (EO/IR) camera, this rugged drone is designed for challenging environments, offering early warning of potential fires [51].
  - Insitu ScanEagle: A larger drone with a thermal camera for monitoring extensive areas. It can stay aloft for up to 24 hours, providing real-time video and data [52].

- Satellites: Satellites equipped with sensors that detect changes in temperature, reflectance, and other indicators are employed for forest fire detection. They can identify heat emitted by fires, smoke plumes, and changes in vegetation, providing valuable data for monitoring and managing wildfires [53].
  Examples of satellites used for forest fire detection:
  - MODIS (Moderate Resolution Imaging Spectroradiometer): Detects active fires and hot spots globally, providing near-real-time data to firefighters and first responders [53].
  - Landsat: Provides multispectral data for monitoring natural resources, detecting changes in vegetation that indicate potential fire risk [54].
  - Sentinel-2: Offers high-resolution multispectral imagery, detecting changes in vegetation and identifying areas at high risk of wildfire [54].

- Fire Towers: Fire towers, tall structures typically located on hilltops, are used for fire detection and monitoring. Fire spotters use optical instruments to scan for smoke or fire. Fire towers can be connected to central monitoring systems for efficient communication with emergency responders [53].

Aerial Surveillance for Forest Fire Prediction: Aerial surveillance is not only crucial for detection but also aids in predicting forest fires[54][55]. It involves:

- Mapping Vegetation and Fuel Types: Aerial imagery helps map vegetation and fuel types, predicting the likelihood and speed of fire spread.

- Monitoring Weather Conditions: Aerial surveillance tracks weather conditions like temperature, humidity, wind speed, and direction, predicting their impact on fire behavior.

- Early Warning Systems: Detecting early signs of fire, such as smoke plumes or hot spots, triggers early warning systems for timely alerts.

- Real-Time Monitoring: Aerial surveillance provides real-time monitoring of fires, aiding in predicting fire behavior and determining effective control strategies.

By combining ground-based systems, aerial surveillance, and remote sensing, forest managers can create a comprehensive strategy for both detecting and predicting forest fires, enabling more effective prevention and response.

4. Machine Learning-Based Approaches used for forest fire detection

Machine learning-based approaches have become integral in forest fire detection, leveraging their ability to analyze extensive data from diverse sources efficiently.

These approaches contribute significantly to automation and accuracy in identifying and alerting about forest fires. Here are several applications of machine learning in forest fire detection[56][57]:

- Image Classification: Machine learning algorithms, particularly those utilizing deep neural networks, are trained to classify images from ground-based systems, aerial surveillance, and remote sensing into fire and non-fire categories. These algorithms can discern subtle patterns and features of fire, even identifying small smoke plumes that may not be visible to the naked eye.
- Anomaly Detection: Machine learning algorithms excel at detecting anomalies in data, which can indicate the presence of a forest fire. Sudden changes in environmental factors like temperature, humidity, or wind direction can be identified as anomalies, triggering alerts.
- Fusion of Multi-Modal Data: Machine learning algorithms are employed to fuse data from various sources such as satellite imagery, drone footage, and ground-based cameras. This integration enhances the comprehensiveness and accuracy of forest fire detection, providing a holistic view of the situation.
- Early Warning Systems: Development of early warning systems is facilitated by machine learning algorithms. These systems utilize historical data, weather data, and other environmental data to predict the likelihood of a forest fire in a specific area. Timely alerts are then generated for fire departments and emergency responders.
- Fire Spread Prediction: Machine learning algorithms predict the spread of a forest fire by analyzing data such as topography, vegetation type, wind direction, and humidity levels. This predictive capability aids decision-making regarding fire management strategies.

Machine Learning for Forest Fire Prediction: Machine learning is also applied to predict forest fires before they occur, estimating their likelihood and severity [58]:

- Fire Risk Assessment: Machine learning algorithms predict the likelihood of a forest fire by considering factors like weather patterns, fuel moisture content, and historical fire data. Learning from past incidents, these algorithms identify areas at high risk and recommend preventative measures.
- Fuel Moisture Content Prediction: Predicting fuel moisture content is crucial for assessing fire severity. Machine learning algorithms use weather data, vegetation type, and other environmental factors to predict moisture content, providing early warnings of potential fires.
- Fire Spread Prediction: Machine learning algorithms simulate the behavior of a forest fire under different conditions, predicting its spread and intensity accurately. These simulations aid in planning and managing fire response strategies.
- Real-time Monitoring: Machine learning algorithms analyze real-time data from sensors and cameras, continuously adapting predictions based on the evolving situation. This capability ensures emergency responders receive accurate and up-to-date information.
- Smoke Prediction: Machine learning algorithms predict the trajectory and dispersion of smoke from forest fires. This information assists emergency responders in planning their response and protecting vulnerable populations.

By incorporating machine learning into forest fire detection and prediction strategies, forest managers can enhance their ability to respond effectively and mitigate the impact of wildfires. The combination of machine learning with other detection methods results in a comprehensive approach to managing forest fires.

5. Social Media-Based Approaches for Forest Fire Detection

Social media-based approaches have emerged as powerful tools for detecting and monitoring forest fires, leveraging the widespread use of platforms such as Twitter, Facebook, and Instagram. These approaches utilize social media data for both real-time detection and potential prediction of forest fires. Here are several examples of how social media is employed in forest fire detection [59][60][61][62][63]:

- Social Media Monitoring: Emergency responders actively monitor social media platforms for posts related to forest fires. Machine learning algorithms analyze posts to identify those most relevant to the fire, allowing for quick and targeted response efforts.
- Image and Video Analysis: Users on social media platforms share real-time images and videos of forest fires, providing crucial information about location, severity, and spread. Machine learning algorithms analyze these visual data to identify signs of smoke or flames, facilitating prompt alerts to emergency responders.
- Social Listening: Social listening tools are employed to track conversations on social media platforms regarding the fire. This enables emergency responders to identify trends and patterns, gaining insights into the location, size, and direction of the fire.
- Crowdsourced Data Collection: Social media platforms serve as a means to crowdsource data about the

fire, including information about its location and size. Emergency responders leverage this data to enhance their understanding of the fire and improve response strategies.

- Public Awareness: Social media is utilized to raise public awareness about the dangers of forest fires and encourage preventive measures. Educational content about fire safety is shared, and real-time updates on the current fire situation in specific areas are provided.

Social Media-Based Approaches for Forest Fire Prediction: While social media-based approaches for forest fire prediction are still evolving, several potential applications show promise [59][60][61]:

- Early Warning Systems: Social media data can be analyzed to identify trends indicative of a forest fire's onset. An increase in posts related to smoke or flames in a specific area may signal the beginning of a fire, prompting early warning alerts through machine learning algorithms.
- Crowdsourced Data Collection: Social media serves as a platform for crowdsourcing data related to environmental conditions relevant to forest fire prediction. Users share information about factors like the presence of dry or dead vegetation, contributing to a better understanding of fire risk.
- Public Awareness: Social media platforms are utilized to raise public awareness about the importance of preventing forest fires. Educational content about fire prevention is shared, and updates on the current fire situation help individuals reduce their risk.

While social media-based approaches hold significant potential, challenges such as developing effective algorithms, addressing privacy concerns, and ensuring data reliability need further research and consideration before widespread adoption. As technology and methodologies advance, social media can play a crucial role in enhancing forest fire detection and prediction capabilities.

6. QUALITY MATTER

The increasing frequency and severity of forest fires underscore the critical need for robust and efficient fire detection techniques. As technology advances, the integration of sophisticated algorithms and machine learning techniques has become pivotal in enhancing our ability to detect, predict, and comprehend the behavior of forest fires. This comprehensive survey delves into the multifaceted realm of forest fire detection, offering a nuanced examination of the quality factors that define the effectiveness of detection techniques. These quality factors play a pivotal role in evaluating the reliability, accuracy, and applicability of detection techniques in diverse environmental conditions. By scrutinizing factors such as accuracy, sensitivity, specificity, precision, and computational efficiency, this survey aims to provide a holistic understanding of the key attributes that contribute to the success of forest fire detection techniques. Beyond statistical metrics, considerations such as robustness to environmental factors, adaptability across diverse settings, and scalability become crucial in assessing the practicality and versatility of these techniques. Moreover, the survey delves into the importance of interpretability, reliability in data-scarce environments, and integration capabilities with existing systems. The exploration of user-friendly interfaces and the meticulous analysis of false alarms contribute to a comprehensive evaluation of these techniques. In essence, this survey serves as a guide to unravel the intricate landscape of forest fire detection, setting the stage for advancements that hold the promise of more effective and reliable fire management strategies.

Here are some suggested quality factors for evaluating fire detection techniques that help to define which one is to use in every different case:

- Accuracy: Measure of how well the technique correctly identifies the presence or absence of a fire.
- Sensitivity (True Positive Rate): Ability of the technique to correctly detect positive instances, i.e., actual fires.
- Specificity (True Negative Rate): Ability of the technique to correctly identify negative instances, i.e., non-fire scenarios.
- Precision (Positive Predictive Value): Proportion of instances predicted as fire that are actually fires, helping to assess the technique's reliability.
- False Positive Rate: Frequency of non-fire instances incorrectly classified as fire, which is crucial for minimizing false alarms.
- False Negative Rate: Frequency of fire instances missed by the technique, highlighting the importance of avoiding undetected fires.
- Area Under the Receiver Operating Characteristic (ROC) Curve (AUC-ROC): Overall measure of a technique's ability to discriminate between fire and non-fire instances.
- F1 Score: Harmonic mean of precision and sensitivity, providing a balanced measure that considers both false positives and false negatives.
- Computational Efficiency: Evaluation of how quickly the technique can process data and make predictions, crucial for real-time applications.
- Robustness to Environmental Factors: Assessment of the technique's performance under various environmental conditions, such as different weather patterns, times of day, or seasons.

- Adaptability: Ability of the technique to adapt and perform well in diverse geographical and ecological settings.
- Interpretability: Ease with which the technique's decisions and predictions can be understood, contributing to trust and transparency.
- Scalability: Evaluation of how well the technique performs as the size of the dataset or the complexity of the environment increases.
- Reliability in Data Scarce Environments: Capability of the technique to provide accurate predictions even when there is limited data available.
- Integration with Other Systems: How well the technique can be integrated with existing fire management and emergency response systems.
- False Alarm Analysis: In-depth examination of instances where the technique raises a false alarm to understand the underlying reasons and improve technique performance.
- User-Friendly Interface: Design and usability of the technique interface for end-users, ensuring effective interaction and decision-making.

Evaluating a fire detection techniques based on these factors can provide a comprehensive understanding of its performance, reliability, and applicability in real-world scenarios.

7. Conclusions

In conclusion, this survey paper has explored various techniques for forest fire detection, prediction, and behavior analysis, recognizing the complexity and challenges associated with addressing this critical issue. Forest fires pose significant threats to natural resources, wildlife, and human communities. The integration of ground-based systems, aerial surveillance technologies, and machine learning-based approaches offers a comprehensive strategy to detect, predict, and understand forest fires in real-time.

Ground-Based Systems: Ground-based systems, including infrared cameras, flame detectors, thermal sensors, weather stations, smoke detectors, and acoustic sensors, play a vital role in real-time fire detection. These systems provide critical data to firefighters and first responders, enabling rapid and effective responses. Techniques such as firebreaks, prescribed burning, fuel management, and fire suppression, coupled with education and outreach efforts, contribute to both fire detection and prevention.

Aerial Surveillance Systems: Aerial surveillance through drones, satellites, and aircraft provides a broader perspective of forested areas, especially in remote or challenging terrains. These systems offer early warning capabilities, allowing for swift responses to detected fires. The integration of drones equipped with visual and thermal cameras enhances monitoring efficiency, contributing to timely detection and control of forest fires.

Machine Learning-Based Approaches: Machine learning-based approaches, such as image classification, anomaly detection, and fusion of multi-modal data, offer automated and efficient methods for fire detection. These approaches enable near-real-time identification of fires, providing early warnings to first responders. Additionally, machine learning algorithms aid in predicting fire spread and understanding fire behavior, facilitating targeted firefighting efforts.

Future Considerations: Continued research into the causes of forest fires, including climate change and human activities, is essential. Effective prevention and management strategies require collaboration among scientists, policymakers, stakeholders, local communities, and indigenous peoples who possess valuable knowledge in forest fire management. Ongoing efforts should focus on developing sustainable practices, leveraging advanced technologies, and fostering a holistic approach to mitigate the devastating impacts of forest fires on ecosystems and communities.

In addressing the multifaceted challenges of forest fires, a collective and interdisciplinary approach is crucial for building resilient and adaptive strategies to protect our natural environments and the well-being of present and future generations.

Acknowledgment

Thank you for providing the continuation of the acknowledgment section. It appears to express gratitude to the Civil Defense Directorate, the Ministry of Agriculture, and Al-Zaytoonah University of Jordan for their invaluable support, assistance, guidance, expertise, and funding during the research process.

References

[1] A. A., A. Ashraf, and A. Ks, "Impact of forest fire on forest ecosystem," pp. 18–29, 10 2022.

[2] P. Jain, S. C. P. Coogan, S. G. Subramanian, M. Crowley, S. Taylor, and M. D. Flannigan, "A review of machine learning applications in wildfire science and management," *Environmental Reviews*, vol. 28, no. 4, pp. 478–505, 2020. [Online]. Available: https://doi.org/10.1139/er-2020-0019

[3] N. Guimarães, L. Pádua, P. Marques, N. Silva, E. Peres, and S. JJ., "Forestry remote sensing from unmanned aerial vehicles: A review focusing on the data, processing and potentialities," *Remote Sensing*, vol. 12, p. 6, 2020. [Online]. Available: https://doi.org/10.3390/rs12061046

[4] [Online]. Available: bit.ly/3vWm9be

[5] V. Ambrosia and S. Wegener, *Unmanned Airborne Platforms For Disaster Remote Sensing Support*. Geoscience and Remote Sensing. InTech, 2009.

[6] J. Ryu and D. Kwak, "Study on a complex flame and smoke detection method using computer vision detection and convolutional

neural network," *Fire*, vol. 5, p. 4, 2022. [Online]. Available: https://doi.org/10.3390/fire5040108

[7] S. M. S. M. Daud, M. Y. P. M. Yusof, C. C. Heo, L. S. Khoo, M. K. C. Singh, M. S. Mahmood, and H. Nawawi, "Applications of drone in disaster management: A scoping review," *Science Justice*, vol. 62, no. 1, pp. 30–42, 2022. [Online]. Available: https://doi.org/10.1016/j.scijus.2021.11.002

[8] M. Mehmood, Shahzad, A., B. Zafar, A. Shabbir, and N. Ali, "Remote sensing image classification: A comprehensive review and applications," *Mathematical Problems in Engineering*, vol. 2022, pp. 1–24, 2022. [Online]. Available: https://doi.org/10.1155/2022/5880959

[9] S. SMBd, A. Bento-Gonçalves, and A. Vieira, "Research on wildfires and remote sensing in the last three decades: A bibliometric analysis," *Forests*, vol. 12, p. 5, 2021. [Online]. Available: https://doi.org/10.3390/f12050604

[10] P. E. Dennison, S. C. Brewer, J. D. Arnold, and M. A. Moritz, "Large wildfire trends in the western united states, 1984-2011," *Geophysical Research Letters*, vol. 41, no. 8, pp. 2928–2933, 2014. [Online]. Available: https://doi.org/10.1002/2014GL059576

[11] V. E. Sathishkumar, J. Cho, M. Subramanian *et al.*, "Forest fire and smoke detection using deep learning-based learning without forgetting. fire ecol 19," vol. 9, 2023. [Online]. Available: https://doi.org/10.1186/s42408-022-00165-0

[12] Q. Zhang, J. Xu, L. Xu, and H. Guo. Deep Convolutional Neural Networks for Forest Fire Detection. [online] www.atlantis-press.com, 2016.

[13] V. Slavkovikj, S. Verstockt, S. Van Hoecke, and R. Van de Walle, "Review of wildfire detection using social media," *Fire Safety Journal*, vol. 68, pp. 109–118, 2014.

[14] A. A. Alkhatib and Q. Abed-Al, "Multivariate outlier detection for forest fire data aggregation accuracy," *Intelligent Automation and Soft Computing*, vol. 31, p. 2, 2022. [Online]. Available: https://doi.org/10.32604/iasc.2022.020461

[15] J. San-Miguel-Ayanz, T. Durrant, R. Boca, G. Libertà, A. Branco, and F. Sedano, "Forest fires in europe, middle east and north africa 2018," *EUR,7 EN. Publications Office of the European Union, Luxembourg*, vol. 2962, 2019.

[16] E. Chuvieco, I. Aguado, M. Yebra, H. Nieto, J. Salas, and M. P. Martín, "Development of a framework for fire risk assessment using remote sensing and geographic information system technologies," *Ecological Modelling*, vol. 221, no. 1, pp. 46–58.

[17] J. D. Cohen, "Preventing disaster: Home ignitability in the wildland-urban interface," *Journal of Forestry*, vol. 98, no. 3, pp. 15–21, Apr. 2000. [Online]. Available: https://www.fs.usda.gov/research/treesearch/4688

[18] P. R. al., "Prediction of forest fire using machine learning algorithms: The search for the better algorithm," in *2021 6th International Conference on Innovative Technology in Intelligent System and Industrial Applications (CITISIA)*, A. Sydney, Ed., 2021, pp. 1–6.

[19] C. Boulton, H. Shotton, and H. Williams, "Using social media to detect and locate wildfires," in *Proceedings of the International AAAI Conference on Web and Social Media*. 10(2, 2021, pp. 178–186.

[20] O. Kucuk and V. Sevinc, "Fire behavior prediction with artificial intelligence in thinned black pine (pinus nigra arnold) stand," *Forest Ecology and Management*, vol. 529, p. 120707, 2023.

[21] A. Alkhatib, "Smart and low cost technique for forest fire detection using wireless sensor network," *International Journal of Computer Applications*, vol. 81, p. 11, 2013.

[22] P. Andrews, "United states department of agriculture behave: Fire behavior prediction and fuel modeling system- burn subsystem," *Part*, vol. 29, p. 2023, Apr. 1986. [Online]. Available: https://www.fs.usda.gov/rm/pubs_int/int_gtr194.pdf

[23] J. Scott and R. Burgan, *Standard Fire Behavior Fuel Models: A Comprehensive Set for Use with Rothermel's Surface Fire Spread Model*, vol. 29, p. 2023, Apr. 2005. [Online]. Available: https://www.fs.usda.gov/rm/pubs_series/rmrs/gtr/rmrs_gtr153.pdf

[24] J. Heisig, E. Olson, and E. Pebesma, "Predicting wildfire fuels and hazard in a central european temperate forest using active and passive remote sensing," *Fire*, vol. 5, p. 1, 2022. [Online]. Available: https://doi.org/10.3390/fire5010029

[25] K. Miyanishi, *Forest fires: behavior and ecological effects*. Elsevier, 2001.

[26] "www.iq-firewatch.com. (n.d.)," *Home: IQ FireWatch*, vol. 29, p. 2023, Apr. [Online]. Available: https://www.iq-firewatch.com/

[27] G. Georgiades, X. Papageorgiou, and S. Loizou, *Integrated Forest Monitoring System for Early Fire Detection and Assessment*, vol. 29, p. 2023, Apr. [Online]. Available: http://users.ntua.gr/xpapag/Papers/CODIT19.pdf

[28] J. S. and K. W.Georgiades, "Thermal imaging fire detection algorithm with minimal false detection," *KSII Transactions on Internet and Information Systems, Korean Society for Internet Information (KSII)*, 2020.

[29] D. Parida, *IoT Based Forest Fire Detection System using Arduino and GSM Module*, 2021.

[30] W. W. D. System, *(n.d.)*. Rugged Monitoring.

[31] "Fs24x flame detector," *Fire Sentry Corporation*. [Online]. Available: www.firesentry.com/products/fs24x-flame-detector/

[32] "Viper perimeter protection system," February 22, 2023. [Online]. Available: https://www.viperwildfire.com/perimeter-protection-system

[33] *AlertWildfire. (n.d.)*. About AlertWildfire.

[34] *ThermEye. (n.d.)*. Portable Thermal Imaging Camera for Fire Detection.

[35] C. Scientific, *(n.d.)*. Forest Fire Monitoring with Weather Stations.

[36] *www.preventionweb.net. (n.d.)*. Wildfire monitoring and prevention: science, innovation and cross-border cooperation towards informed decisions for firefighting.

[37] "climate.ncsu.edu. (n.d.). fire weather intelligence portal." *products*,

vol. 29, p. 2023, Apr. [Online]. Available: https://products.climate.ncsu.edu/fwip/

[38] F. W. D. Inc, *FireOne Smoke Detection System*, 2021.

[39] W. Krüll, R. Tobera, I. Willms, H. Essen, and N. von Wahl, "Early forest fire detection and verification using optical smoke, gas and microwave sensors," *Procedia Engineering*, vol. 45, p. 584–594, 2012. [Online]. Available: https://doi.org/10.1016/j.proeng.2012.08.208

[40] *VESDA THE WORLD'S LEADING BRAND OF ASPIRATING SMOKE DETECTION*.

[41] Y. G. Sahin and T. Ince, "Early forest fire detection using radio-acoustic sounding system," *Sensors*, vol. 9, no. 3, pp. 1485–1498, 2009. [Online]. Available: https://doi.org/10.3390/s90301485

[42] E. B. S. D. T. sys, "Firewatch australia." [Online]. Available: https://firewatchaustralia.com/

[43] W. D. S. sys, *DASH Detection and Alert System for High-Risk Wildfire*, 2021.

[44] N. P. S. sys, *Fire management*, 2018.

[45] U. F. S. sys, *Fire management*, 2019.

[46] N. I. F. C. sys, *(n.d.)*. Fire education and prevention.

[47] U. S. D. o. t. I. sys, *Fire prevention and fuels management*, 2018.

[48] C. Yuan, Z. Liu, and Y. Zhang, "Aerial images-based forest fire detection for firefighting using optical remote sensing techniques and unmanned aerial vehicles," *J Intell Robot Syst*, vol. 88, p. 635, 2017. [Online]. Available: https://doi.org/10.1007/s10846-016-0464-7

[49] "Dji. (n.d.). mavic 2 enterprise dual." [Online]. Available: https://www.dji.com/mavic-2-enterprise-dual

[50] L. Martin. Indago.

[51] *Insitu. (n.d.)*. ScanEagle.

[52] A. Alkhatib, "A review on forest fire detection techniques," *International Journal of Distributed Sensor Networks*, vol. 10, p. 3, 2014.

[53] N. I. F. Center, *Detection and Monitoring*, 2021.

[54] S. Partheepan, F. Sanati, and J. Hassan, "Autonomous unmanned aerial vehicles in bushfire management: Challenges and opportunities," *Drones*, vol. 7, p. 1, 2023. [Online]. Available: https://doi.org/10.3390/drones7010047

[55] M. Z. Masoud, Y. Jaradat, I. Jannoud, and M. A. A. Sibahee, "A hybrid clustering routing protocol based on machine learning and graph theory for energy conservation and hole detection in wireless sensor network," *International Journal of Distributed Sensor Networks*, vol. 15, p. 6, 2019.

[56] M. Grari, M. Yandouzi, I. Idrissi, M. Boukabous, O. Moussaoui, M. Azizi, and M. Moussaoui, "Using iot and ml for forest fire detection, monitoring, and prediction: A literature review. [online] 100(19)," vol. 3, p. 2023, Apr. 2022. [Online]. Available: http://www.jatit.org/volumes/Vol100No19/4Vol100No19.pdf

[57] K. Bot and A. Borges JG., "Systematic review of applications of machine learning techniques for wildfire management decision support," *Inventions*, vol. 7, no. 15, p. 1, 2022. [Online]. Available: https://doi.org/10.3390/inventions7010015

[58] K. Wu, J. Wu, and M. Ye, "A review on the application of social media data in natural disaster emergency management," *Progress in Geography*, vol. 39, p. 1412–1422, 2020. [Online]. Available: https://doi.org/10.18306/dlkxjz.2020.08.014

[59] T. Sakaki, M. Okazaki, and Y. Matsuo, "Earthquake shakes twitter users: Real-time event detection by social sensors," in *Proceedings of the 19th international conference on World Wide Web*, 2010, pp. 851–860.

[60] A. M. Mukkamala. Social Media Analytics for Disaster Management, 2018.

[61] K. M. Jaber, O. M. Alia, and M. M. Shuaib, "P-hs-sfm: a parallel harmony search algorithm for the reproduction of experimental data in the continuous microscopic crowd dynamic models," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 30, no. 2, pp. 235–255, 2018. [Online]. Available: https://doi.org/10.1080/0952813X.2017.1421267

[62] K. M. Jaber, R. Abdullah, and N. A. Abdul Rashid, "Hdt-hs: A hybrid decision tree/harmony search algorithm for biological datasets," in *2012 International Conference on Computer Information Science (ICCIS)*, vol. 1, 2012, pp. 341–345.

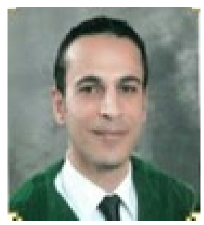
[63] K. Jaber, R. Abdullah, and N. A. Rashid, "A framework for decision tree-based method to index data from large protein sequence databases," in *2010 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, 2010, pp. 120–125.

Ahmad AA Alkhatib is an Associate Professor at the Faculty of Science and Information Technology at the Al-Zaytoonah University of Jordan, The Head of the Cyber Security Department, and an IEEE member. He has published more than 40 papers in journals and conference proceedings. Moreover, Dr Alkhatib has led four research grants, and supervised and examined Master and PhD students.

Khalid Mohammad Jaber is an Associate Professor of Computer Science at the Faculty of Science and Information Technology at the Al-Zaytoonah University of Jordan, director of the E-learning and Open Educational Resource Center, and IEEE Senior member. He has published more than 20 papers in journals and conference proceedings. Moreover, Dr Jaber has led four research grants, supervised Master students, and received a fellowship award.

Hassan Al-Zoubi received his Ph.D. in pure Mathematics (Geometry) from Aristotle University of Thessaloniki (Greece), in 2001. Since then, he is working at the Al-Zaytoonah University of Jordan as an Associate Professor in the department of mathematics. He acquired his Bachelor's and Master's degrees from Aristotle University of Thessaloniki, Greece in mathematics in 1994. His research focuses on Surfaces of finite type with respect to the first, second, or third fundamental form in the Euclidean 3-space and in Lorentz- Minkowski space. He is working on applications that are mainly based on the pure concepts of mathematics. He enjoys tourism, traveling, and landscaping.

Mohammad Abdallah Received the Ph.D. degree in Software Engineering from Durham University, UK in 2012. The M.Sc. degree in Software Engineering from Bradford University, UK in 2008. BSc in Computer Science from Al-Zaytoonah University of Jordan in 2007. Currently, he is the Director of Technology Transfer Office and an Assistant Professor of Software Engineering Department in Al-Zaytoonah University. His research interests in Software Engineering field, such as, Big Data and Quality Engineering. Dr. Mohammad is very active, he is an ACM Professional member–SIGCHI and SIGSOFT Member, Board Member in Jordan Computer Society (JCS), Jordan Country Officer - International Federation of Global and Green ICT (IFGICT), and Member of the International Association of Engineers.



Mosa I. Salah had finished his Master degree from The Arab Academy for Banking and Financial Sciences in computer information systems in 2006. He has been an Instructor and Researcher at Al-Zaytoonah University of Jordan in the Department of Computer Science and Multimedia Technology. His research interests, mainly in information retrieval, image processing and multimedia technology.