Volume 9, Issue 2, pp. 90-101, 2025.

International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

A Comprehensive Review of Smoke Detection in Wheat Fields from UAV Images using Machine Learning Techniques

Ahmed Alsalem[1], Mohamed Zohdy[2]
[1]Department of Industrial and Systems Engineering, Oakland University, Rochester, USA,MI 48309
[2]Department of Electrical & Computer Engineering, Oakland University, Rochester, Michigan, USA,MI 48309
*Corresponding author email: aalsalem@oakland.edu

Abstract— *Recent technological advancements in Unmanned Aerial Vehicles (UAVs) have significantly revolutionized agricultural monitoring, particularly in detecting smoke in wheat fields, thus aiding in precision agriculture. This comprehensive review delves into various UAV technologies and machine- learning techniques that have been developed to enhance smoke detection. It scrutinizes existing methods, highlights innovative technologies, and discusses the challenges and obstacles that hinder effective implementation. Also, the review evaluates different studies, comparing the efficacy of machine-learning approaches in detecting smoke. Key shortcomings in the current state of technology are identified, emphasizing the need for technological advancements to bridge these gaps. By collating insights from various studies, this review not only presents the current landscape but also points toward future directions for research and technological development. The aim is to foster advancements that could ultimately lead to more effective smoke detection systems, thereby improving response times and reducing economic losses in agriculture due to fires.*

Keywords— *UAV, Smoke Detection, Wheat Field Fires, Agriculture, Machine Learning Environmental monitoring.*

I. INTRODUCTION

Wheat is an important, food crop across the world, feeding billions of people [1]. Wheat is known among the big three main crops of the world, vital for the delivery of essential phytochemicals that are crucial to human health, such as vitamins, starch, protein, and dietary fiber [2]. During the growth period from the heading stage to maturity, the development and condition of wheat heads play a critical role in determining both the yield and quality of the wheat crop [3] [4]. Currently, various technologies are employed in the agriculture field, from cultivation and storage to transportation and marketing. In the case of wheat cultivation, some situations need to be taken attention, such as the plague of insects [2] and fire [2] in wheat fields can be caused by natural factors like storms [4], human activities like the burning of residues [5], or mechanical heat emanating from farming equipment. Early monitoring of wheat fields as a means of early detection of smoke has great potential to prevent small incidents and their further development into large fires, which among other things can devastate crops and cause economic losses [6].

Agricultural cultivation is extremely important for global food sufficiency and is one of the main sources of the diet of billions of people all over the world [7]. Out of the many types of plants, wheat is the basic dietary constitution of people of different cultures and that is why, it can be considered as one of the most important food crops [8]. However, the agricultural sector challenges many difficulties that cause crop productivity and sustainability threats. The occurrence of different environmental disasters is one of the most significant threats to wheat farming, which can be the cause of large-scale fires that can quickly engulf vast areas of farmland. These fires are not only responsible for the direct loss of food but also impact the long-term adverse conditions on the soil quality, the level of biodiversity, and the local economy [9].

Fire effects on the economy can devastate farmers [10]. Serious outdoor fires can result in the transfer of people and health problems since air quality is poor because smoke and particulates are a source of severe respiratory hazards. When a fire occurs in the wheat fields, farmers suffer direct losses, including the cost of the crop that was destroyed and the energy fees for planting and cultivating. Such losses in these farms are particularly devastating as they mostly have very low profit margins. A reduction of wheat supply in other areas results in increased market volatility, which consequently raises prices for consumers and could lead to food insecurity in vulnerable areas. Crop residue burning renders soil unfit for growth by abolishing organic matter and emitting an excess of greenhouse gases including carbon dioxide and methane along with creating an artificial environment for unintentional fires that might be quite hazardous at times [11]. Furthermore, fire-induced soil erosion results in a shift in the fertility of the land affecting not only the water quality of rivers and streams nearby through runoff but also the agricultural output in subsequent cycles on the land.

One of the recent technological advances is the creation of innovative tools for the solution of agricultural problems with the most common one being the use of Unmanned Aerial Vehicles. Named drones, UAVs, have many benefits and advantages in various industries, for instance, they offer a new position for remote observation and operation. In the farming sector, UAVs are increasingly becoming the primary equipment for crop monitoring, pest control, and irrigation management. Particularly in the fire protection and management area, UAVs are equipped with modern sensors and image technologies that are a new invention giving hope for an early smoke alert system.

Remote sensing technology can be classified as space, air, or ground. The satellite imaging methods of remote sensing

International Journal of Scientific Engineering and Science
Volume 9, Issue 2, pp. 90-101, 2025. ISSN (Online): 2456-7361

based in space have some weaknesses because they are affected by the weather, have longer observation intervals, and have a low spatial resolution compared to air-based methods such as UAVs. The ground-based remote sensing technologies which include fixed monitoring stations, on the contrary, are constrained due to high costs, limited coverage, and the difficulties of deployment in extensive areas [12-14]. Indeed, the predominant challenges of remote sensing are multi-sector effects. Interestingly, in recent times, the pace of industrial transformation worldwide, particularly in the field of UAV formations, and sensors that detect data changes has been remarkable [15],[16],[17],[18]. Unmanned Aerial Vehicles (UAVs) have completely changed the agricultural monitoring area by providing solutions for early detection of smoke, which are the main factors preventing massive destruction in wheat fields.

Fig.1 shows that the economic impact of the application of UAV technology in the early detection of smoke is quite significant since it significantly brings down the losses suffered owing to traditional detection methods. As a rule, delays in pinpointing and extinguishing fires are common in the conventional firefighting approach and this usually causes higher financial losses to the farmers. The surveillance of the use of UAV enables real-time surveillance and detection of fire at the stage of its ignition, which means that the fire will not be able to spread and the wheat fields will not be destroyed on a large scale. The fact that resources are efficiently deployed, UAV-based detection plays a crucial role in the tackling of fires before they become massive. This technical development moreover not only brings about agricultural sustainability but also secures financial solidarity for the actors in the agricultural sector.

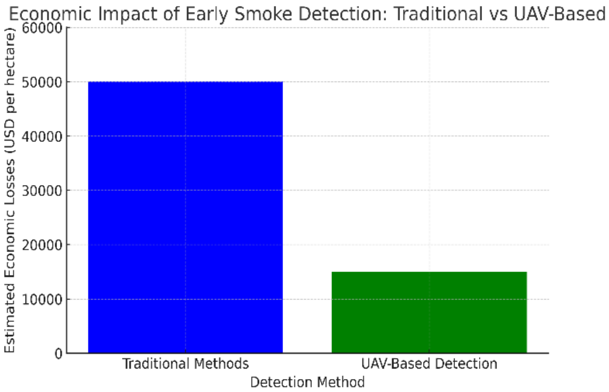

Fig. 1. Economic Impact of early detection

Following are the contributions of the study on the use of UAV technology for early smoke detection in wheat fields:

The study demonstrates an innovative integration of UAV technology with advanced machine learning algorithms, such as CNNs and LSTMs, to detect smoke in wheat fields more accurately and rapidly than traditional methods. This integration highlights the study's contribution to enhancing precision agriculture tools.

By implementing UAVs equipped with multispectral and thermal imaging sensors, the study contributes to the development of more sensitive and precise early detection systems. These systems can identify potential fire threats before they escalate, thereby enabling quicker response times and reducing potential damage.

The research provides new insights into the effectiveness of various machine-learning techniques in processing complex datasets collected by UAVs. This not only advances our understanding of smoke detection dynamics but also improves the data analysis framework used in agricultural monitoring.

The study's findings underscore the scalability of UAV technology across different agricultural settings and geographic regions. It offers a roadmap for other researchers and practitioners to adapt the technology to local conditions, enhancing its utility and applicability in global agriculture practices.

By facilitating early detection and efficient response to field fires, the study contributes to more sustainable agricultural practices. It helps in preserving the ecosystem, minimizing crop losses, and reducing the carbon footprint associated with large-scale agricultural fires.

1.1. Wheat Fields

Wheat is one of the grains that are essential in every country of the world, not only as the staple food but also as the most significant one in the international trade [19]. Wheat is grown in different climatic zones worldwide, with the countries contributing to different parts of the wheat supply in the world [20]. Some of the factors that cause inequality in wheat cultivation areas among countries include geographical, climatic, economic, and technological. Countries such as China, India, and Russia are the top wheat producers [21], which is in line with their fertile land and usage of advanced agricultural technology shown in Fig. 2.

In these countries, large populations are mainly focused on agriculture to provide food security and to develop rural economies. The endless Russian land and favorable steppe areas are the ideal conditions for the wheat fields on a large scale. Also, the U.S. and Canada, along with their infrastructure for agricultural development [22], are the major players in both local and worldwide wheat markets. France is leading in wheat production numbers among European countries [23], thanks to its fertile soil and good weather conditions, thus it is a main exporter within the European Union. On the other hand, Turkey and Ukraine are also the leading countries in the global trade of wheat due to their strategic geographical positions and rich agricultural heritage [24].

The study discusses the Physical Structure of Wheat in particular the fuel characteristics, e.g., load, height, and compactness of the grain analyzed using different crop conditions: Cropped, Harvest, and Pressed. In summary, the first clear indication of the uniformity of the BASS PMG01 initial observations in time was demonstrated. Exact studies involved using a 1.0 m² quadrat in both Harvested and Baled conditions to measure fuel bed height and carry out the load assessments. Computations from squares were first performed by cutting the standing materials to the ground and thus collecting them.

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International Journal of Scientific Engineering and Science
Volume 9, Issue 2, pp. 90-101, 2025. ISSN (Online): 2456-7361

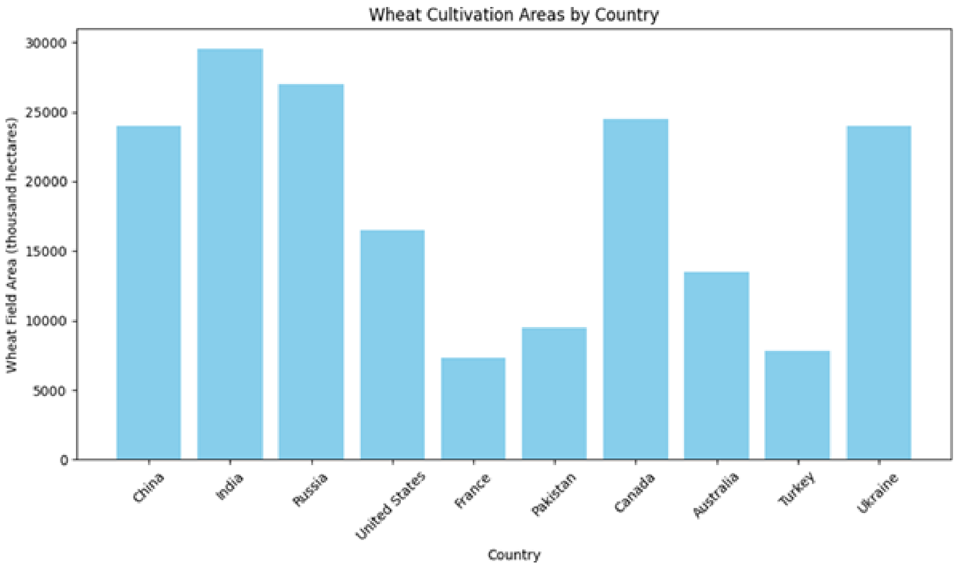

Fig. 2. Wheat cultivation by countries

Matted materials were picked from the earth and bagged individually. Ground fuels, in the first scenario, were taken over a length of 1.0 m in the planting line area, where minimal soil was matted. Such a physical parting of kernels from stalks played an essential role in explaining their different combustion potential. At the first stage, the measurement of the weight was conducted using an oven-drying machine at 105°C for 24 hours to remove the moisture from these samples, which was a necessary process to further augment the use of the smoke detection algorithm [25].

1.2 Need for early detection

Through the early detection of fires Shown in Table 1, it is done to limit their effects thus it is the most successful way for fire management. One of the earlier warning systems that can be implemented in this way through the use of UAVs as the fire control system for environmental monitoring and risk prevention of part of the damage [26]. UAVs can keep track of the crops while local communities and the land owners can also be informed about the situation these new power devices are providing. So, UAVs can do the monitoring in a little 45 minutes rather than in around 8 hours with that kind of crawler [27]. The UAV- based detection system of smoke lets the UAVs tell when the smoke is present even when it is an illegal system in the mines [28]. The UAVs now are integrated with thermal and multispectral imaging methods that can measure temperature variation and specific spectral bands that allow for the detection of a fire's early stage.

The information that has been gathered is supposed to allow firefighters to be better prepared and to be in an area with the least risky firefighting capability by doing this more effectively and thus the large area of crops will be saved and the chance of spreading the fire to populated areas will be reduced. Owing to recent climate change, more and more instances of nature behaving unpredictably are seen. This situation has compelled the scientists dealing with fire safety technocrats to evolve their research methodologies. One of the most important things for fire prevention in wheat fields is the detection of the smoke that might cause the devastating effect of the fire over large areas of fields. Wheat fields are vulnerable to fires, which can cause significant damage to crops and properties [29]. Detecting smoke early in such areas is crucial for preventing larger fires.

TABLE 1: Summary of previous studies that discuss the different types of UAV

Benefits of Early Detection	**Challenges Addressed**	**Potential Impacts on Agriculture**
Rapid Response Activation	Delay in fire detection	Reduces the extent of fire damage by enabling quicker firefighting responses
Preventative Measures	Uncontrolled fire spread	Allows for the implementation of fire breaks and other containment strategies before the fire escalates
Resource Allocation	Resource wastage	Optimizes the use of firefighting resources by targeting areas at high risk of fire development
Data Collection for Analysis	Lack of real-time data	Provides valuable data for analyzing fire patterns and improving future prevention techniques
Reduction in Economic Loss	High damage costs	Minimizes financial losses related to crop damage, thereby protecting farmers' income
Environmental Protection	Ecological damage	Helps preserve the local ecosystem by preventing large-scale fires and reducing smoke emissions

1.3 UAV Technology

Drones or Unmanned Aerial Vehicles have become a popular technique in the field of agriculture [30]. This is because these technologies are used in the bounds where the ground may not be reached. More and more farmers today are employing drones on their farms to ensure that their crops are monitored and datasets are collected shown in Table 2. Two main kinds of unmanned aerial vehicles can be conventionally divided into UAVs so called based on their design and machinery which are as follows shown in Fig. 3.

The Artificial Intelligence (AI) revolution in agriculture is imminent, thanks to the enormous progress made in the integration of unmanned aerial vehicles (UAVs) with artificial intelligence. These high-tech drones will soon be able to make much more accurate forecasts and will analyze them more accurately. Due to the improvements in sensors and data processing HAVs (hyper agile vehicles) would be able to quickly give drivers back informed decisions. Even very delicate changes that occur in the landscape can be understood by machines and not by the people or the robots until now. For example, the newly incorporated hyperspectral imaging feature in UAVs will help the drone to catch the chemical signature of a fire before the smoke is even visible, thus fire-related problems can be tackled early. Also, scientists and technologists of the future are likely to start discovering UAV groups they are a bunch of drones that are able to instantly communicate with one another and thus can cover a big area all at once so that a data overload will not be the problem.

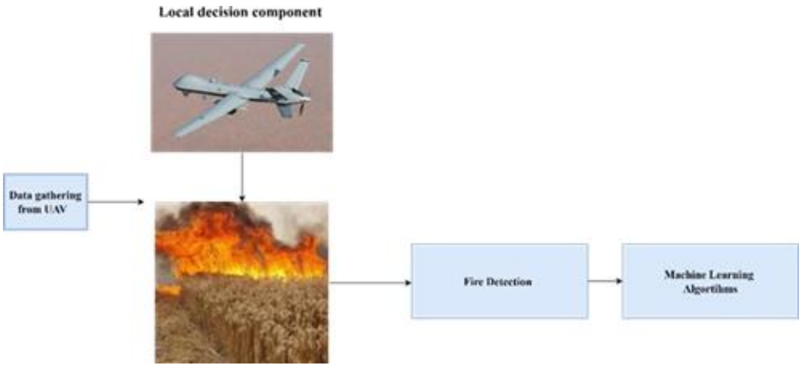

Fig. 3. Fire detection system utilizing UAVs for data gathering and machine learning algorithms for rapid and accurate analysis

TABLE 2: Summary of previous studies that discuss the different types of UAV

Author	Year	UAV type	Summary
[40]	2025	Fixed-Wing	Improve the computation efficiency and reliability of trajectory generation
[41]	2024	Fixed-Wing	Analyzing A2G wireless links from aircraft like fixed-wing UAVs, it is clear that the fading characteristic channels have a significant dependence on their altitudes.
[42]	2024	Rotary-wing	Energy-consumption model of rotary-wing drones, sufficiently predicts the power usage in the various flight phases, pours the significance of horizontal flight into the battery's capacity, and unveils the impact of total mass on the aircraft.
[43]	2020	Fixed-Wing	Compare different aerodynamic coefficient estimation methods
[44]	2019	Rotary-wing	Minimize the total UAV energy consumption.
[45]	2019	Rotary-wing	Effective solution; one has to rely on alternating optimization and successive convex approximation methods.
[46]	2018	Rotary-wing	Advance the development and application of such systems in agricultural production.
[47]	2017	Fixed-Wing	Emphasizing that recent breakthroughs in both fuel cell technology and hydrogen storage have resulted in remarkable advancements in battery capacity.
[38]	2016	Rotary-wing	Achieves a power transfer efficiency of greater than 50% on average
[48]	2014	Fixed-Wing	Three-dimensional airplane model when applied to small fixed-wing UAVs and using a vector field steering technique can effectively navigate altitude variations and complicated motions, as exemplified by simulations that give evidence of the model's match with the fixed-wing aircraft's motion laws.

Several studies highlight fixed-wing UAV design [31], [32],[33], [34],[35]. Fixed-Wing UAVs [36] main specialty of these drones is to cover expansive areas in a short time shown in Table 1. They are designed like regular aircraft and are supposed to have a launch or a runway for take-off. One advantage of a fixed-wing multicopter is its capability to stay airborne for longer than a rotorcraft can and its capability to endure stronger winds shown in Fig.4. The drones are primarily different types of aerial vehicles with various configurations and specifications, such as, but not limited to, shape, dimensions, propulsion systems, etc. However, not much effort is put into optimizing the aerodynamic efficiency and performance of these designs. Furthermore, when such studies do occur, they are usually quite restricted and solely dependent on the case, like those that are based on winglets [34].

Rotary-wing UAVs [37] might consist of quadcopters as well as other multirotor configurations that can be flown like a helicopter, i.e., vertical take-off and landing (VTOL). They are perfect for locations with obstacles, where high accuracy is required, for instance, targeted observation of small sections of a field. Besides this, rotary-wing UAVs are very well suited for close-up image capturing and spot-checks of sites, which are necessitated by the necessity of moving and hovering over the area. The vertical take-off and landing processes of multi-rotor UAVs are based on the balancing of the forces acting on the rotors [38]. In the modern UAV market, they continue to be the most popular choice because they can fly in a specified path, lift off and land vertically, and maintain a hover. Accordingly, these characteristics are the reason why rotary-wing UAVs are considered one of the most significant advancements in the field of aerial robotics. The smart people at research centers and universities seem to be mad about the benefit of using said

UAVs for their projects. Also, these aircraft do not take up runways or other wide facilities, which increases their value. They are classified according to the number of engines possessed. This is one of the reasons that tricopters, quadcopters, pentacopters, hexacopters, and octocopters are included as types [39].

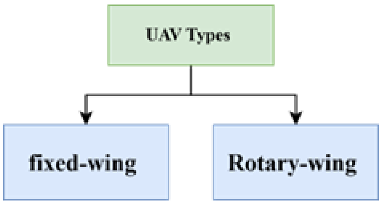

Fig. 4. Types of UAV

Nowadays, UAVs are continuously appreciated for their immense advantages in the field of agricultural monitoring, with a continuous study of their remarkable potential. With the help of high-tech cameras and sensors, UAVs can collect images of the highest possible resolution as they are the most important factor for the prompt detection of different kinds of agricultural problems [49] like pest infestations, nutrient deficiencies, or water stress. By doing so, farmers are given more time to interfere, saving the crop and reducing losses. Besides, UAVs can quickly stay in a vast area, so the regular and effective monitoring of crop field health is facilitated. This is the most important part of modern technology, especially in contrast with the use of traditional methods like satellite imaging or manned aircraft surveys, which can be very expensive and less frequent due to their high operational expenses. For several aspects, UAVs are, therefore, an alternative that is more cost-effective for frequent field assessments. Also, using UAVs helps to improve the precision in data collection by the principles of precision agriculture following this, the farmers can precisely use the resources like water, fertilizers, and pesticides just in the amount that is needed. This not only reduces the costs but also minimizes the environmental impacts, thus demonstrating the key role of UAVs in promoting sustainable agricultural practices.

Fig.5 shown above depicts a drastic decrease in the median response time to the implementation of unmanned aerial vehicle (UAV) technology in the event of a wheat field fire when compared to the conventional methods. In the traditional methods, the response time was averaged at 30 minutes, but the inclusion of UAVs to agricultural practices has progressively reduced this to only 10 minutes. The major improvement is a consequence of UAVs being able to rapidly scan big areas from the sky, thus providing on-the-spot information that results in quick decision-making and intervention. Such a decrease in response time is of utmost importance to limit fire spread and reduce damage as well as to improve agricultural management.

The introduction of UAV technology in wheat field firefighting operations has helped to save some money because of resource allocation efficiency shown in Fig.6. Unmanned aerial vehicles are the only way we could detect smoke some minutes earlier than we did and then we could send resources, and everything to the right place, intensifying the overall efforts of the fire brigade. Most of the current methods are the human operators and the equipment hire which is always cost and time consuming as well as ineffective working. But when the use of drones or UAVs becomes an option, the fire risks can be identified at an early stage and the solutions provided therefore would only require targeted interventions and will not demand the manpower necessary for the large-scale firefighting efforts. This will not only enable managers to better prepare for fires but also will lead to the reduction of operating expenses and the waste of resources, hence sustainable agriculture becomes a reality.

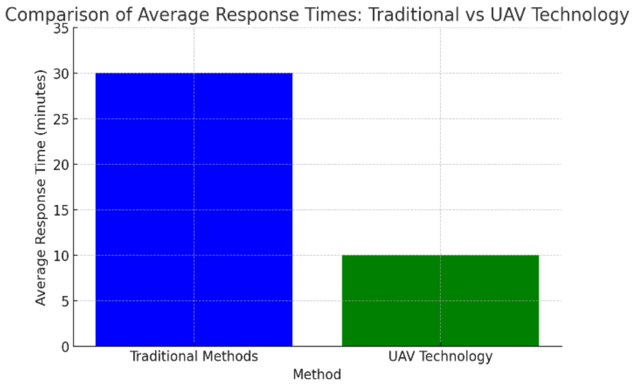

Fig.5. Comparison of average response time

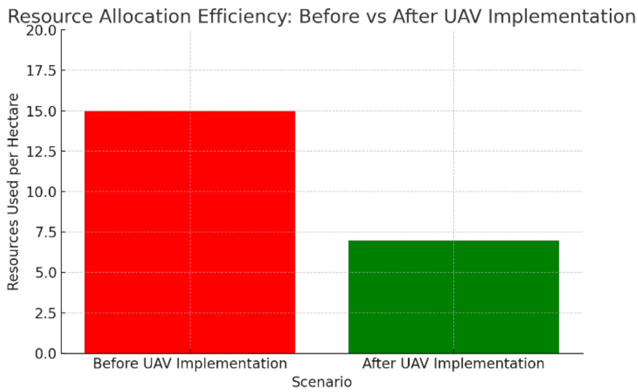

Fig. 6. Machine learning techniques

1.4 Wheat fire datasets

The utilization of UAV technology in the agricultural sector has brought the management and containment of fires in wheat fields to an entirely new level shown in Table 3. By providing high-resolution imagery and a wide range of data, drones have significantly extended the range of early fire detection. Not only do these advances enable rapid response and prevention of fires but also, in some cases, they can be fired off deliberately leading to acting on the situation effectively.

Complete and thorough databases are crucial for the progress and assessment of the machine learning models that are uploaded for wheat field fire detection and analysis. Generally, these datasets are a mix of multiple image types such as RGB, multispectral, and thermal imagery and are critical for the training of the algorithms to identify the characteristic images of smoke and fire.

At first, using unmanned aerial vehicles (UAVs) to collect agricultural data facilitated new capabilities for monitoring crop health and the early detection of distress, such as fire. The earlier data sets mainly consisted of RGB images, which provided basic visual insights into wheat fields' conditions. In the article [50], it is stated that the original datasets were very significant in creating baseline models of agricultural UAV applications.

With UAV technology improvements, the multispectral and thermal sensors inclusion turned out to be possible, which in turn resulted in the creation of sophisticated datasets. These sensors can find infrared and heat sources, which are the first signs of fires. The paper [51] is about how the combination of these imaging techniques can enhance the accuracy of fire identification in wheat fields.

Because fires in natural settings are so rare and unpredictable, synthetic datasets have become a goldmine. These datasets, which are created through simulations, can help us overcome the fact that there are very few real events that can happen in the real world. The study [52] illuminates how synthetic data can be used to complement actual data, which allows a more robust training framework for smoke detection models.

However, even with the advancements made, the datasets still face several obstacles. Due to the variability in fire behavior, which is caused by weather conditions and crop maturity, the data may not be as consistent and reliable as expected. Additionally, the moral aspects of data collection from a fire emergency which is discussed in the publication [53] give rise to some additional constraints.

The gradual enhancement of the algorithms in fire event identification, along with the strong datasets like the one in Table 2, emphasizes the essential role of UAVs in the safety of wheat crops being damaged by fire. One published in the Remote Sensing Journal in 2023, is the dataset which includes high-resolution RGB and thermal images that are ideal for the early detection of fires and providing crucial data for developing effective early warning systems. As well, the IEEE's multispectral UAV image dataset from 2022 is annotated specifically for smoke and fire symptoms within agricultural settings, hence, it delivers a very valuable tool for the machine learning models for identifying stages of fire development.

TABLE 3: Examples of some used datasets from previous studies

Study/Publisher	Dataset	Year
[2], Remote Sensing Journal	High-resolution RGB and thermal images for detecting early signs of fire in wheat fields.	2023
[54], IEEE	Multispectral UAV images annotated for smoke and fire symptoms in agricultural settings.	2022
[55],Elsevier	Open-access dataset featuring a variety of crop fire images, including wheat, collected from multiple countries.	2021

Besides, the University of Agriculture Studies first introduced a synthetic dataset in 2024, which was put together by simulating fire scenarios in wheat fields, testing and improving the fire detection algorithms under controlled conditions are made possible this way, and the synthetic dataset given is to their aid in this task. These datasets as a group are the main factors as they enable the UAV systems to have more predictive capability and that of sending quick response to fire publications thus reducing damage to the crops and consequently the economic loss.

1.5 Defining the Grounds for Conducting a Review

The introductory discussion not only presents pertinent questions but also highlights the essential reasons for undertaking a detailed examination of the advancements and ongoing challenges in the domain of smoke detection in wheat fields using UAV-based imagery. This need is especially pronounced in the context of the technological advancements that have characterized the twenty-first century, marked by rapid developments in drone technology, artificial intelligence, and machine learning. The primary aim of this study is to conduct a comprehensive review of existing literature on the use of UAVs and machine learning techniques for smoke detection in agricultural settings over the past five years. This comprehensive analysis seeks to explore the complex landscape of UAV-based smoke detection, considering technological progress, evolving detection methodologies, and the broader implications for agricultural management and safety.

UAV-based smoke detection technologies should be reviewed systematically, given the increasingly complex and dynamic shifts that are the result of climatic and economic changes in agriculture. It is necessary to develop detection methods to reduce the effects of wildfires that are becoming more and more frequent and severe as a result of the different weather patterns and agricultural practices. The UAV technology, in its ability to immediately acquire data in high resolution, is the main vehicle of this endeavor. Nevertheless, the multiplicity of the UAV models to choose from, together with analytical algorithms that show different capabilities, result in diverse research findings.

This technology has the potential to link all the knowledge that currently exists, as well as find the gaps in the present methodologies, hence, cooperation will be the basis for the development of novel and scalable solutions. This review is meant to be the first step in creating a new understanding of the past and presenting a future in which the technology developments will have a real impact on the field of global agricultural sustainability. In this way, by testing the possible strategies developed up to now and applying the appropriate theoretical framework, this review will be able to set future research and application as the main goal and not only a bonus.

This review is intended to ensure that technological advancements are realized as real-world efficiencies in global agriculture sustainability. By evaluating past and current strategies through a rigorous academic lens, this review aims to set a benchmark for future research and application, ensuring that technological advancements translate into tangible benefits for global agricultural sustainability.

Over the decades, technological progress helped corporations to increase the ability to detect fires quite remarkably with the help of UAVs and machine learning systems. As depicted on the chart for fire detection rate analysis, the detection rate has been significantly growing since 2015 to the current figure of 95% in 2025, which indicates the efficiency of modern detection systems shown in Fig.7. The foremost traditional methods of detection were based on the fact

International Journal of Scientific Engineering and Science
Volume 9, Issue 2, pp. 90-101, 2025.
ISSN (Online): 2456-7361

that the ground was the primary medium for surveillance. However, it was always time-consuming, and it was often ineffective. Nevertheless, after the use of drones with the most inventive technology such as thermal imaging and AI algorithms, it is now quick and error-free to detect fires. These advancements have enabled live monitoring which in turn has lessened the number of false alarms and also it has led to a proactive response to possible fire outbreaks. The introduction of AI, sensor technology, and the automation of UAVs are likely to be responsible to a great extent for an improvement in the accuracy of fire detection that will, in turn, make fire management in the agricultural and environmental sectors a greater success.

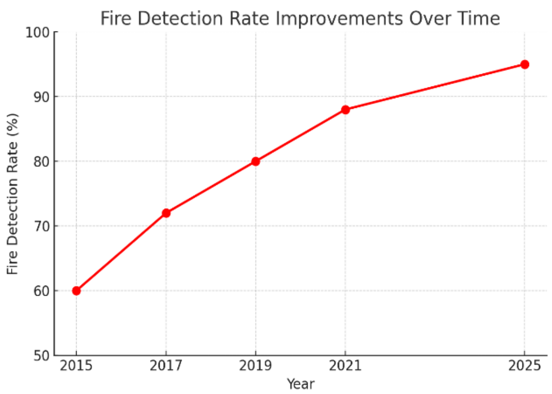

Fig. 7. Machine learning techniques

II. RESEARCH QUESTION

This survey is centered on the area of agricultural monitoring, primarily the area of detecting smoke in wheat fields using UAV-based imaging within the scope of machine learning. To structure the review, the following fundamental research questions have been established: The following are the research questions: Q1: Which machine learning algorithms are most effective for detecting smoke in UAV images of wheat fields? Q2: What challenges arise in using machine learning for smoke detection in UAV images of wheat fields, and how can these be overcome? What are the future trends and emerging technologies in machine learning that could further enhance smoke detection in wheat fields using UAVs?

III. MACHINE LEARNING TECHNIQUES FOR SMOKE DETECTION

Detecting smoke or fire as the first sign of it is pivotal for fast and appropriate intervention to stop excessive damage. Several techniques and devices have been developed to categorize fire or smoke in environments [56]. The application of machine-learning algorithms for detecting smoke in wheat fields via UAV images is a critical area of research that integrates computational methodology to boost the performance of fire detection and response systems [57]. The methods of these facts are numerous, and all range from old-school machine learning to deep learning networks which are the most recently developed ones that have each its advantages such as speed to environmental conditions [56].

However, in the field of agricultural monitoring, more precisely, in smoke recognition in wheat fields via the use of UAV images, the efficiency of machine learning algorithms [58] varies significantly with the complexity of the task. In Fig.8 we can see an illustration of Support Vector Machines (SVM), Random Forests, and other models which are traditional machine learning algorithms [55]. These techniques are the most useful in coping with the non-linearity which is the common element in machine learning tasks, and they are also respected because of their overfitting resistance. To distinguish between smoke, fire, and normal conditions the models are trained with the help of the various colors, texture patterns, and differences in thermal signatures among UAV-captured images. On top of that, the algorithms' performance is a direct consequence of the quality and representativeness of the feature engineering process; thus, they are most effective when optimized for specific scenarios only. A different approach entails making use of deep learning algorithms where the unique aspects of coloring and smoky materials in images and videos are recognized and elucidated shown in Table 3. The performance levels of deep learning, more specifically convolutional neural networks (CNN), on visual recognition tasks have been remarkable [59], but there are not many research undertakings that have taken advantage of these new methods in the detection of smoke or fire.

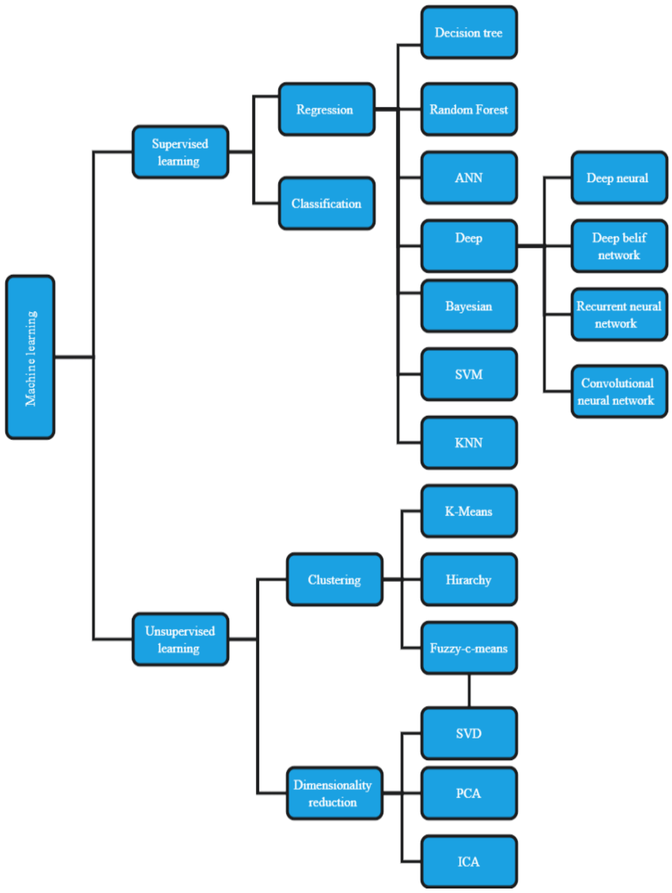

Fig. 8. Machine learning techniques

It is the CNNs, that analyze the images, in this case, to find the pattern between the detected smoke and a possible timeline

International Journal of Scientific Engineering and Science
Volume 9, Issue 2, pp. 90-101, 2025. ISSN (Online): 2456-7361

or event, on the one hand, while happening on the other [60]. But the most important thing is to know that Convolutional Neural Networks can drill down the whole hierarchy of spatial discontinuity in high-resolution images and recognize the ability of smoke patterns and a variety of complex lighting and weather conditions as well [61]. Some recent studies incorporate temporal data into the models and employ Long Short-Term Memory (LSTM) networks to click a series of images to see if the smoke would turn into a real fire. Hence, predictive capabilities become strengthened and interventions could be made earlier [62] The use of multispectral as well as current imaging systems with deep learning models has emerged as quite fruitful [63]. These models use the distinctive spectral signs of smoke and fire to increase the accuracy of detection by distinguishing it from fog or dust among other weather-related conditions. The issue is how to effectively collect the data and have such a big and different database (as labeled one is) on which one of the most advanced models can be trained which is crucial when solving real-world problems.

In the agriculture sector, if UAV images are used to gauge smoke, then different machine-learning algorithms can be utilized. Each one of these algorithms will have its strengths and weaknesses according to the specific conditions and the data characteristics. Below is a comprehensive explanation of some machine learning methods shown in Table 4.

Support vector machine (SVM) are particularly effective in high-dimensional spaces, which is typical for image data from UAVs [64]. They can easily separate the classes when there is a separating hyperplane with a large margin. However, they can be quite slow and difficult to handle if the data set is quite large and there is a large amount of noise or overlapping between the classes. The best places for their utilization are in places where the difference between the presence of smoke particles and their absence is tall and non-challenging.

This ensemble learning method has a strong and accurate performance both in the presence of noise and large datasets. One of the ways that Random Forests work is through the course of setting up several decision tree (DT) training processes and then providing output where class is the mode of the classes of the individual trees [65]. RFs are less prone to overfitting than other algorithms but they can be slower than others if trained with big datasets. RF will do the best in a place where illumination and weather conditions are dynamic as they can adapt to great changes in luminance and weather.

Whereas CNNs are a special kind of neural network used for image data, what they are good at is finding some spatial representation of the image [66]. This is usually carried out entirely through an automatic implementation promoting the significant capture of images by machines, hence it is mostly used for UAV images to detect smoke. Consistently, conjointly, they are limited and have such restrictions as large training datasets that need to be present for them to perform with maximum accuracy and a high computation requirement. CNNs are for the most part suited for more complex formations where smoke may be less visible covered in small translucent water droplets or other forms of environmental pollution like fog or dust.

LSTM is a type of recurrent neural network (RNN) suitable for classification, processing, and prediction of time series data [67]. The LSTMs can be used to analyze video data with the detection of UAV smoke, where there is temporal continuity between frames is important. They can deal with data where the smoke looks differently over time. Although it is hard to teach LSTMs, they can be in the case of smaller or more diverse datasets overfit.

YOLO (You Only Look Once this is a state-of-the-art, real-time object detection system that has been applied to smoke detection in some studies [68]. YOLO is very fast. It is made for the tasks of real-time detection and could, therefore, be less accurate when compared to CNNs. It is used in situations when time is of the essence than the exactness of the detection of the fire.

Though YOLO is fast, and have a faster time of detection. This trade-off will be particularly palpable in complicated farm and wildfire scenarios where smoke are not clearly visible. The AI's need for the swiftness of the data flow over the precision level may produce that higher number of false alarms and missed detections as compared to detailed but slow CNNs.

Nonetheless, the presence of YOLO on an unmanned aerial vehicle (UAV) is a tremendous opportunity to detect smoke, which in combination with other systems can capture all the advantages of the aerial platform. For instance, it can be fused with thermal-based imaging sensors which will give more evidence of fire-related heat sources alongside the visual smokes' appearance. This approach uses different probes to breathe new life into the accuracy when the UAV is still using all its quick functionalities.

TABLE 4: Comparisons of different machine learning techniques used in state-of-the-art studies

Reference	Dataset	Method	Result
[69]	1916 sample data	• Random Forest (RF) • Support Vector Regression (SVR) • K-Nearest Neighbours (KNN) • Decision Tree (DT)	Accuracy • DT= 94% • RF= 93% • SVR= 90% • KNN= 92%
[56]	Fire and smoke images	Deep convolutional neural network (DCNN)	Achieves high accuracy and a high detection rate
[57]	UAV based dataset	CNN	Accuracy = 96.67% in
[70]	UAV-based dataset Straw burning dataset	YOLOv5	Recall = mAP@0.5 and mAP@0.5:0.95
[71]	Sentinel-2	YOLOv5	Accuracy = 75.63%
[72]	Fire And Smoke dataset 9k images	YOLOv8	Precision = 1.39 % Recall = 1.48 % F1-score = 1.44 %
[73]	Smoke contamination	Two model ANN 1. Leaf spectra (Model 1) 2. Grape spectra(Model 2)	Model 1: 98.00%; Model 2: 97.40%

Besides, new methods like YOLOv4 and YOLOv5 have been found in the construction of YOLO algorithms which lead

International Journal of Scientific Engineering and Science
Volume 9, Issue 2, pp. 90-101, 2025. ISSN (Online): 2456-7361

to this increase in both speed and detection accuracy. These improved versions come with advanced techniques, for example, data augmentation, better anchor box calculation, and cross-mini-batch normalization, that increase the model's capacity not to fail and work well under a variety of conditions.

The full potential of YOLO in smoke detection is achieved only when the research establishes approaches where YOLO is used alongside machine learning to converge on the findings. By the same token, the swift but accurate systems could be obtained that detect the incendiary smoke clouds quickly yet do not compromise on the reliability aspect of not-detecting.

To begin, while the implementation of the YOLO smoke detection system in or wheat field presents some problems, its real-time detection capability is unbeatable. By continuously refining the technology and combining it with other cutting-edge solutions, YOLO can be the driving force behind the next generation of UAV-based monitoring systems that would deliver quick and precise smoke detection, thus greatly improving fire management strategies and agricultural safety.

A. Challenges Using Machine Learning

Using machine learning for smoke detection in UAV images of wheat fields presents several challenges shown in Table 5, primarily due to the variability in environmental conditions such as lighting, weather changes, and seasonal variations, which can lead to false positives or missed detections. To overcome these challenges, it is crucial to train the detection algorithms on diverse datasets encompassing images captured under various conditions. Also, integrating multispectral and hyperspectral imaging can enhance the detection accuracy by providing more detailed information on smoke signatures. Employing advanced deep learning models that adapt to new scenarios without extensive retraining and using ensemble techniques to combine the strengths of multiple models can also help mitigate these issues, ensuring more reliable and robust smoke detection in agricultural settings.

B. Overcoming Challenges in Machine Learning

The use of machine learning, for smoke detection in UAV images of a wheat field is challenging and happens mostly due to the environmental conditions which always are dynamic and usually not predictable in outdoor agriculture locations. Here's a more detailed analysis of these challenges and the strategies to overcome them

1) Change in Environmental Conditions

Smoke detection algorithms should be immune to changes in light, weather, and seasonal impacts which have the power to drastically modify the appearance of the smoke plume and the landscape in the image. Hence, for instance, low illumination conditions such as in the early morning and at night can be the reason for the bad quality of images, as a result, the detectors may ignore the smoke plume. Furthermore, incorrect detections can be the result of such weather conditions as fog or rain as it may block smoke or its visual signatures.

2) Ways of Fighting variability

A fundamental step toward a machine learning model which is robust is simulating the exposure of the model to different images corresponding to the times of day, weather, and seasons. The diversity in the training helps the model to comprehend the differences between smoke and other visually similar phenomena in various environments.

TABLE 5: Machine learning techniques challenges and solution

ML Technique	Suitability for UAV Data	Common Challenges	Potential Solutions
CNN (Convolutional Neural Networks)	High	Requires large datasets; Computationally intensive	Use of transfer learning; Data augmentation; Advanced hardware
SVM (Support Vector Machines)	Moderate	Sensitive to scale; Overfitting in high-dimensional space	Feature scaling; Kernel tricks; Regularization techniques
Random Forests	High	High complexity and memory usage in large datasets	Feature selection; Ensemble methods to reduce variance
LSTM (Long Short-Term Memory)	Moderate	Difficulty with long sequences; Overfitting	Regularization; Dropout techniques; Using stateful LSTMs
YOLO (You Only Look Once)	Suitable for real-time applications	Less accurate for small or overlapping objects	Improving architecture; Integrating with other models for precision
AdaBoost	Moderate	Sensitive to noisy data and outliers	Combine with robust algorithms; Adjust weights on misclassified instances
Gradient Boosting Machines (GBM)	High	Prone to overfitting with complex data	Subsampling; Regularization; Optimal number of trees
K-Nearest Neighbors (KNN)	Low	Computationally intensive with large datasets; Sensitive to irrelevant features	Dimensionality reduction; Weighted distances
Decision Trees	Moderate	Prone to overfitting; Not very robust	Pruning; Combining with ensemble methods like Random Forests
Deep Reinforcement Learning ((DRL))	Emerging	Requires substantial amounts of data for training; Complex to implement	Simulation environments; Reward system tuning

Deployment of augmentation techniques in the form of brightness adjustment, noise addition, and artificial weather conditions during the training stage is the strategy to get the model to evolve by being more capable of going from the training data to the real world.

The combination of the information from the red-green-blue sensor, multispectral sensor, and hyperspectral sensor can make the detection possible on the machines exposing the semi-

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International Journal of Scientific Engineering and Science

Volume 9, Issue 2, pp. 90-101, 2025. ISSN (Online): 2456-7361

autonomous or autonomous vehicles by delivering the better feature set for the machine learning algorithms to do the final analysis and techniques like spectral unmixing and anomaly detection can be used on the raw data collected by the microsatellites in the hyperspectral band to create a separate signal of the signatures of the smoke.

Transfer learning using pre-trained models and adapting for the smoke detection task is a good alternative to manual training and also shorter training times can be made. Instead of a large number of definitive cases to train this model, with transductive clustering, we could automatically classify unlabeled batches of instances and then design new categories to further cross-verify our annotation as no dataset is perfect. This detects the inconsistencies between those elements and the dataset and results in the steps that may Continuous Model Evaluation and

Over time, machine learning models can change due to the development of both artificial conditions and farming methods. Regular checks of the model's performance and frequent retraining with new information are the best ways to maintain the correctness of the model. To deal with these challenges and improve the efficacy and reliability of smoke detection systems in the agricultural sector by using advanced machine learning technologies not only programmatically but also through robust data handling strategies, leading to improved prevention and management of fires in wheat fields.

IV. Limitations

This review, while comprehensive, encounters several limitations that must be acknowledged:

- The datasets reviewed predominantly feature specific scenarios or types of fires, which might not comprehensively represent all possible conditions in wheat fields globally. The absence of universally applicable datasets limits the generalizability of the detection models developed based on this data.
- The efficacy of UAV-based smoke detection heavily relies on the sophistication of the UAVs and sensors employed. This reliance could limit deployment in regions where access to advanced technologies is restricted due to economic constraints.
- UAV operations are significantly influenced by weather conditions. Adverse weather, such as high winds or heavy rains, can impair the UAVs' ability to collect data and the accuracy of smoke detection algorithms, which predominantly depend on visual and thermal sensors.
- The use of UAVs for surveillance and data collection raises legal and privacy issues, particularly in jurisdictions with stringent air space regulations. These factors could hinder the operational scope of UAV-based smoke detection systems.
- Although UAVs offer a cost-effective alternative to manned aircraft for monitoring large agricultural areas, the initial setup, maintenance, and operational costs could still be prohibitive for small to medium-sized farms.
- While machine learning models are proficient at identifying patterns, their performance can degrade when confronted with smoke plumes that deviate from the trained scenarios. Furthermore, the training of these models requires large, labeled datasets, which are expensive and time-consuming to produce.

V. Conclusion Future Direction

This comprehensive review has highlighted the significant advancements and potential of UAV-based smoke detection in wheat fields, driven by the integration of sophisticated machine-learning techniques. By harnessing high-resolution imagery and advanced detection algorithms, UAVs offer a promising solution to early smoke detection, which is crucial for mitigating fire-related damages in agriculture. The analysis of diverse datasets, coupled with the application of both traditional machine learning and deep learning approaches, has demonstrated improved accuracy and efficiency in detecting and responding to fire events. Despite facing technological, environmental, and regulatory challenges, the continued evolution of UAV technology and machine learning models promises to enhance the capabilities and accessibility of smoke detection systems. Looking forward, the field stands to benefit significantly from the development of more generalized models that can operate under varied conditions and the formulation of frameworks that address privacy and regulatory concerns, thereby ensuring the widespread adoption of this technology in safeguarding vital agricultural resources.

A close analysis of the scope of Unmanned Aerial Vehicles (UAVs) merged with advanced machine learning techniques used in the reformation of the agricultural monitoring sector aims to catch the development of smoke in wheat fields something of the past. It has been widely found that the utilization of such kind of imaging instrument with flight certainly helped to realize the accuracy and timeliness of alerts in a case of smoke turning into fire, which is the first and main step of any detection and prevention mechanism including the one for a large-scale, smoke-producing fire.

The research has put forward an example of how UAVs with compost multispectral and thermal sensors can identify signs of smoke that are light and before which is still unknown to the traditional systems that encounter sooner the emergency triggered alarms. This way how the tool works without getting hit by the crop by the fire, which is another cause of the farmer's income lack. In addition, the flexibility of UAV technology in different types of agricultural settings shines a light on the field as a great instrument in the world of precision agriculture.

On the downside, the review indeed points out several hurdles that will have to be overcome in realizing the promise of UAV-aided smoke detection systems. These issues shall require new and better algorithms for machine learning that can withstand all the different conditions of the atmosphere as well as the use of datasets that properly represent the various situations encountered in a given area.

Future research in UAV-based smoke detection in wheat fields should focus on enhancing the robustness and applicability of detection algorithms across diverse environmental conditions and fire scenarios. There is a critical need to develop datasets that encapsulate a broader range of fire characteristics, including those influenced by varying climatic conditions, to train more adaptive machine learning models.

Also, efforts should be directed towards integrating multispectral and hyperspectral imaging technologies, which can provide more detailed data on smoke and fire signatures, potentially increasing the accuracy of early detection systems. Finally, the economic aspect of UAV technology in agriculture should be examined more closely, developing cost-effective solutions that enable small to medium-sized farms to adopt this potentially lifesaving technology.

ABBREVIATIONS

UAVs Unmanned Aerial Vehicles
CNN Convolutional Neural Networks
SVM Support Vector Machines
LSTM Long Short-Term Memory
VTOL Vertical Take-off and Landing
SVM Support Vector Machine
RNN Recurrent Neural Network
YOLO You Only Look Once
DL Deep Learning
KNN K-Nearest Neighbors
GBM Gradient Boosting Machines
AI Artificial Intelligence
ML Machine Learning
DRL Deep Reinforcement Learning
DT Decision Tree
HAV Hyper Agile Vehicles

ACKNOWLEDGMENTS

Not applicable.

AUTHORS' CONTRIBUTIONS

All authors participated in the writing. Writing a review, language correction & editing were done

FUNDING

Not applicable.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

CONSENT FOR PUBLICATION

All authors have read and approved the final version of the manuscript. Competing interests

REFERENCES

[1] L. B. Hansen *et al.*, "A low-gluten diet induces changes in the intestinal microbiome of healthy Danish adults," *Nature communications,* vol. 9, no. 1, p. 4630, 2018.
[2] K. Zhang *et al.*, "Efficient wheat lodging detection using uav remote sensing images and an innovative multi-branch classification framework," *Remote Sensing,* vol. 15, no. 18, p. 4572, 2023.
[3] A. Watson *et al.*, "Speed breeding is a powerful tool to accelerate crop research and breeding," *Nature plants,* vol. 4, no. 1, pp. 23-29, 2018.
[4] A. Alsalem and M. Zohdy, "Wheat Field Fire Smoke Detection from UAV Images using CNN-CBAM," in *2024 2nd International Conference on Artificial Intelligence, Blockchain, and Internet of Things (AIBThings)*, 2024: IEEE, pp. 1-8.
[5] T. Shi, Y. Liu, L. Zhang, L. Hao, and Z. Gao, "Burning in agricultural landscapes: an emerging natural and human issue in China," *Landscape Ecology,* vol. 29, pp. 1785-1798, 2014.
[6] M. Iqbal *et al.*, "Effect of plant derived smoke on germination and post germination expression of wheat (Triticum aestivum L.)," *American Journal of Plant Sciences,* vol. 7, no. 06, p. 806, 2016.
[7] D. Fróna, J. Szenderák, and M. Harangi-Rákos, "The challenge of feeding the world," *Sustainability,* vol. 11, no. 20, p. 5816, 2019.
[8] P. R. Shewry and S. J. Hey, "The contribution of wheat to human diet and health," *Food and energy security,* vol. 4, no. 3, pp. 178-202, 2015.
[9] S. Kalogiannidis, F. Chatzitheodoridis, D. Kalfas, C. Patitsa, and A. Papagrigoriou, "Socio-psychological, economic and environmental effects of forest fires," *Fire,* vol. 6, no. 7, p. 280, 2023.
[10] G. V. Nkomo and M. Sassi, "Impact of veld fires on land on smallholder farmers in Cashel Valley in Zimbabwe," *Natural Resources and Agricultural Development and Food Security, International Research Network, International working paper series,* no. 09/02, pp. 1-17, 2009.
[11] S. Bhuvaneshwari, H. Hettiarachchi, and J. N. Meegoda, "Crop residue burning in India: policy challenges and potential solutions," *International journal of environmental research and public health,* vol. 16, no. 5, p. 832, 2019.
[12] H. Yao, R. Qin, and X. Chen, "Unmanned aerial vehicle for remote sensing applications—A review," *Remote sensing,* vol. 11, no. 12, p. 1443, 2019.
[13] X. Jin *et al.*, "High-throughput estimation of crop traits: A review of ground and aerial phenotyping platforms," *IEEE Geoscience and Remote Sensing Magazine,* vol. 9, no. 1, pp. 200-231, 2020.
[14] B. Zhang *et al.*, "Progress and challenges in intelligent remote sensing satellite systems," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 15, pp. 1814-1822, 2022.
[15] M. Maimaitijiang, V. Sagan, P. Sidike, S. Hartling, F. Esposito, and F. B. Fritschi, "Soybean yield prediction from UAV using multimodal data fusion and deep learning," *Remote sensing of environment,* vol. 237, p. 111599, 2020.
[16] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, "A compilation of UAV applications for precision agriculture," *Computer Networks,* vol. 172, p. 107148, 2020.
[17] D. R. A. De Almeida *et al.*, "Monitoring restored tropical forest diversity and structure through UAV-borne hyperspectral and lidar fusion," *Remote Sensing of Environment,* vol. 264, p. 112582, 2021.
[18] P. K. R. Maddikunta *et al.*, "Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges," *IEEE sensors journal,* vol. 21, no. 16, pp. 17608-17619, 2021.
[19] I. Sharma, B. Tyagi, G. Singh, K. Venkatesh, and O. Gupta, "Enhancing wheat production-A global perspective," *The Indian Journal of Agricultural Sciences,* vol. 85, no. 1, pp. 03-13, 2015.
[20] G. Mills *et al.*, "Ozone pollution will compromise efforts to increase global wheat production," *Global change biology,* vol. 24, no. 8, pp. 3560-3574, 2018.
[21] O. Erenstein, M. Jaleta, K. A. Mottaleb, K. Sonder, J. Donovan, and H.-J. Braun, "Global trends in wheat production, consumption and trade," in *Wheat improvement: food security in a changing climate*: Springer International Publishing Cham, 2022, pp. 47-66.
[22] S. A. Wengle, *Black earth, white bread: a technopolitical history of Russian agriculture and food*. University of Wisconsin Pres, 2022.
[23] V. C. Tudor *et al.*, "The use of fertilizers and pesticides in wheat production in the main European Countries," *Sustainability,* vol. 15, no. 4, p. 3038, 2023.
[24] B. F. Ballatore, "The importance of Russia's agricultural sector in the MENA geopolitics," 2021.
[25] K. Anupam, A. K. Sharma, P. S. Lal, S. Dutta, and S. Maity, "Preparation, characterization and optimization for upgrading Leucaena leucocephala bark to biochar fuel with high energy yielding," *Energy,* vol. 106, pp. 743-756, 2016.
[26] C. Yuan, Y. Zhang, and Z. Liu, "A survey on technologies for automatic forest fire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques," *Canadian journal of forest research,* vol. 45, no. 7, pp. 783-792, 2015.
[27] R. Watson, "Unmanned aerial vehicles for contact-based inspection," 2023.
[28] M. Ronkainen, "Designing a drone based measurement system for outdoor material fields in industrial environment," M. Ronkainen, 2016.
[29] M. Grosse-Heilmann, E. Cristiano, R. Deidda, and F. Viola, "Durum wheat productivity today and tomorrow: A review of influencing factors and climate change effects," *Resources, Environment and Sustainability,* p. 100170, 2024.

[30] J. Del Cerro, C. Cruz Ulloa, A. Barrientos, and J. de León Rivas, "Unmanned aerial vehicles in agriculture: A survey," *Agronomy,* vol. 11, no. 2, p. 203, 2021.
[31] P. Panagiotou, P. Kaparos, C. Salpingidou, and K. Yakinthos, "Aerodynamic design of a MALE UAV," *Aerospace Science and Technology,* vol. 50, pp. 127-138, 2016.
[32] A. Sóbester, A. Keane, J. Scanlan, and N. Bressloff, "Conceptual design of UAV airframes using a generic geometry service," in *Infotech@ Aerospace*, 2005, p. 7079.
[33] T. Goetzendorf-Grabowski, A. Frydrychewicz, Z. Goraj, and S. Suchodolski, "MALE UAV design of an increased reliability level," *Aircraft Engineering and Aerospace Technology,* vol. 78, no. 3, pp. 226-235, 2006.
[34] S. G. Kontogiannis and J. A. Ekaterinaris, "Design, performance evaluation and optimization of a UAV," *Aerospace science and technology,* vol. 29, no. 1, pp. 339-350, 2013.
[35] P. Panagiotou, S. Fotiadis-Karras, and K. Yakinthos, "Conceptual design of a blended wing body MALE UAV," *Aerospace Science and Technology,* vol. 73, pp. 32-47, 2018.
[36] G. Cai, K.-Y. Lum, B. M. Chen, and T. H. Lee, "A brief overview on miniature fixed-wing unmanned aerial vehicles," *IEEE ICCA 2010,* pp. 285-290, 2010.
[37] S. Darvishpoor, J. Roshanian, A. Raissi, and M. Hassanalian, "Configurations, flight mechanisms, and applications of unmanned aerial systems: A review," *Progress in Aerospace Sciences,* vol. 121, p. 100694, 2020.
[38] A. B. Junaid, Y. Lee, and Y. Kim, "Design and implementation of autonomous wireless charging station for rotary-wing UAVs," *Aerospace science and technology,* vol. 54, pp. 253-266, 2016.
[39] M. Gatti, F. Giulietti, and M. Turci, "Maximum endurance for battery-powered rotary-wing aircraft," *Aerospace Science and Technology,* vol. 45, pp. 174-179, 2015.
[40] S. Jing, X. Guangtong, W. Zhu, L. Teng, and S. Jingliang, "Safe flight corridor constrained sequential convex programming for efficient trajectory generation of fixed-wing UAVs," *Chinese Journal of Aeronautics,* vol. 38, no. 1, p. 103174, 2025.
[41] Y. Lyu, W. Wang, and P. Chen, "Fixed-wing uav based air-to-ground channel measurement and modeling at 2.7 ghz in rural environment," *IEEE Transactions on Antennas and Propagation,* 2024.
[42] H. Li, Z. Zhan, and Z. Wang, "Energy-consumption model for rotary-wing drones," *Journal of Field Robotics,* vol. 41, no. 6, pp. 1940-1959, 2024.
[43] P. Panagiotou and K. Yakinthos, "Aerodynamic efficiency and performance enhancement of fixed-wing UAVs," *Aerospace Science and Technology,* vol. 99, p. 105575, 2020.
[44] Y. Zeng, J. Xu, and R. Zhang, "Energy minimization for wireless communication with rotary-wing UAV," *IEEE transactions on wireless communications,* vol. 18, no. 4, pp. 2329-2345, 2019.
[45] C. Zhan and H. Lai, "Energy minimization in Internet-of-Things system based on rotary-wing UAV," *IEEE Wireless Communications Letters,* vol. 8, no. 5, pp. 1341-1344, 2019.
[46] L. J. Li JiYu, L. Y. Lan YuBin, and S. Y. Shi YeYin, "Research progress on airflow characteristics and field pesticide application system of rotary-wing UAV," 2018.
[47] A. Gong and D. Verstraete, "Fuel cell propulsion in small fixed-wing unmanned aerial vehicles: Current status and research needs," *International journal of hydrogen energy,* vol. 42, no. 33, pp. 21311-21333, 2017.
[48] T. McLain, R. W. Beard, and M. Owen, "Implementing dubins airplane paths on fixed-wing uavs," 2014.
[49] N. Delavarpour, C. Koparan, J. Nowatzki, S. Bajwa, and X. Sun, "A technical study on UAV characteristics for precision agriculture applications and associated practical challenges," *Remote Sensing,* vol. 13, no. 6, p. 1204, 2021.
[50] I. D. Lawrence, J. Agnishwar, and R. Vijayakumar, "Drone technology in agriculture for surveillance and inspection," *Eur. Chem. Bull,* vol. 12, no. Special Issue 12, pp. 1253-1263, 2023.
[51] M. V. Deshpande, D. Pillai, and M. Jain, "Agricultural burned area detection using an integrated approach utilizing multi spectral instrument based fire and vegetation indices from Sentinel-2 satellite," *MethodsX,* vol. 9, p. 101741, 2022.
[52] Y. O. Sayad, H. Mousannif, and H. Al Moatassime, "Predictive modeling of wildfires: A new dataset and machine learning approach," *Fire safety journal,* vol. 104, pp. 130-146, 2019.
[53] R. Hoek Spaans *et al.*, "Ethical considerations related to drone use for environment and health research: A scoping review protocol," *Plos one,* vol. 19, no. 1, p. e0287270, 2024.
[54] A. K. Dwivedi, A. K. Singh, and D. Singh, "An object based image analysis of multispectral satellite and drone images for precision agriculture monitoring," in *IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium*, 2022: IEEE, pp. 4899-4902.
[55] A. Sharma *et al.*, "IoT and deep learning-inspired multi-model framework for monitoring Active Fire Locations in Agricultural Activities," *Computers & Electrical Engineering,* vol. 93, p. 107216, 2021.
[56] A. Namozov and Y. Im Cho, "An efficient deep learning algorithm for fire and smoke detection with limited data," *Advances in Electrical and Computer Engineering,* vol. 18, no. 4, pp. 121-128, 2018.
[57] A. Sharma and P. K. Singh, "Applicability of UAVs in detecting and monitoring burning residue of paddy crops with IoT Integration: A step towards greener environment," *Computers & Industrial Engineering,* vol. 184, p. 109524, 2023.
[58] S. Chitram, S. Kumar, and S. Thenmalar, "Enhancing Fire and Smoke Detection Using Deep Learning Techniques," *Engineering Proceedings,* vol. 62, no. 1, p. 7, 2024.
[59] P. Li and W. Zhao, "Image fire detection algorithms based on convolutional neural networks," *Case Studies in Thermal Engineering,* vol. 19, p. 100625, 2020.
[60] S. Khan *et al.*, "Deepsmoke: Deep learning model for smoke detection and segmentation in outdoor environments," *Expert Systems with Applications,* vol. 182, p. 115125, 2021.
[61] D. Dubey *et al.*, "Fire Smoke Detection System using Machine Learning Models," in *2024 6th International Conference on Computational Intelligence and Networks (CINE)*, 2024: IEEE, pp. 1-6.
[62] Y. Peng and Y. Wang, "Real-time forest smoke detection using hand-designed features and deep learning," *Computers and Electronics in Agriculture,* vol. 167, p. 105029, 2019.
[63] M. Sultan Mahmud, M. S. Islam, and M. A. Rahman, "Smart fire detection system with early notifications using machine learning," *International Journal of Computational Intelligence and Applications,* vol. 16, no. 02, p. 1750009, 2017.
[64] M. Al-Naeem, M. Hafizur Rahman, A. Banerjee, and A. Sufian, "Support vector machine-based energy efficient management of UAV locations for aerial monitoring of crops over large agriculture lands," *Sustainability,* vol. 15, no. 8, p. 6421, 2023.
[65] D. J. Wu, T. Feng, M. Naehrig, and K. Lauter, "Privately evaluating decision trees and random forests," *Cryptology ePrint Archive,* 2015.
[66] B. B. Traore, B. Kamsu-Foguem, and F. Tangara, "Deep convolution neural network for image recognition," *Ecological informatics,* vol. 48, pp. 257-268, 2018.
[67] P. S. Muhuri, P. Chatterjee, X. Yuan, K. Roy, and A. Esterline, "Using a long short-term memory recurrent neural network (LSTM-RNN) to classify network attacks," *Information,* vol. 11, no. 5, p. 243, 2020.
[68] C. Bahhar *et al.*, "Wildfire and smoke detection using staged YOLO model and ensemble CNN," *Electronics,* vol. 12, no. 1, p. 228, 2023.
[69] T. Maity, A. N. Bhawani, J. Samanta, P. Saha, S. Majumdar, and G. Srivastava, "MLSFDD: Machine Learning-Based Smart Fire Detection Device for Precision Agriculture," *IEEE Sensors Journal,* 2025.
[70] H. Wen, X. Hu, and P. Zhong, "Detecting rice straw burning based on infrared and visible information fusion with UAV remote sensing," *Computers and Electronics in Agriculture,* vol. 222, p. 109078, 2024.
[71] J. Li *et al.*, "Detection of smoke from straw burning using sentinel-2 satellite data and an improved YOLOv5s algorithm," *Remote Sensing,* vol. 15, no. 10, p. 2641, 2023.
[72] L. Ramos, E. Casas, E. Bendek, C. Romero, and F. Rivas-Echeverría, "Hyperparameter optimization of YOLOv8 for smoke and wildfire detection: Implications for agricultural and environmental safety," *Artificial Intelligence in Agriculture,* vol. 12, pp. 109-126, 2024.
[73] V. Summerson *et al.*, "Classification of smoke contaminated Cabernet Sauvignon berries and leaves based on chemical fingerprinting and machine learning algorithms," *Sensors,* vol. 20, no. 18, p. 5099, 2020.