Overview of State-of-the-Art Applications of UAVs Integrated with Image Processing Techniques

Lin Wang and Jun Xiao

***Abstract*—Unmanned aerial vehicles (UAVs) with sensors are cost-effective and powerful image-capture tools. Government, industrialists, workers, and researchers extensively deploy UAVs for monitoring, mapping, and management tasks in various domains to automate operations, optimize production, and reduce cost. However, the captured images may have blur and noisy effects owing to handling issues, platform limitations, camera geometry, and weather effects, requiring image processing and analysis. To leverage the significance of UAVs integrated with image processing techniques, artificial intelligence (AI) techniques are applied, enhancing their capabilities. This work endeavors to conduct a comprehensive review of recent applications of UAVs with an emphasis on image processing techniques, advanced machine learning (ML) algorithms, and deep learning (DL) models. From this perspective, elemental limitations with recent innovations of UAVs are presented. Fundamental procedures of data collection, preprocessing and processing steps, and taxonomy of ML algorithms are delineated. Applications of image processing-based UAVs are explored for agricultural, environmental, remote sensing and mapping, and surveillance and law enforcement applications. Potential avenues and certain limitations of the implemented methodologies are also evaluated. Findings validate implementations of image processing techniques using ML and DL models, which result in reliable and quick results, efficiency, and automation, ultimately promoting UAV applications. These results contribute to the existing literature and significantly impact the scientific community.**

***Index Terms*—Unmanned Aerial Vehicles (UAVs); Monitoring; Image Processing; Artificial Intelligence (AI); Machine Learning (ML); Deep Learning (DL); Agriculture; Environment; Remote Sensing; Surveillance**

I. INTRODUCTION

UNMANNED aerial vehicles (UAVs), often acknowledged as drones, were recognized as potential armed tools with explosive air balloons in 1849 [1]. Gradually, UAVs gained popularity with innovations and rapid advancements, owing to their availability, cost-effectiveness, easy deployment, and high flexibility and mobility. Researchers propose using UAVs is more significant than traditional manual methods, aircraft, and advanced line robots for inspecting transmission lines and ensuring stable and safe power lines [2]. They observe manual methods are relatively less efficient because of negligence and personnel fatigue; however, line robots enhance automation but may have some technical issues like climbing, whereas aircraft allow speedy and comprehensive detection but are incapable of patrolling at different positions and angles.

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Some characteristics of humans, satellites, manned aircraft, and UAVs are displayed in Table I, indicating UAVs are more advantageous than other methods for imagery in various domains. Moreover, UAVs are budget-friendly and environmentally friendly, with no or less emissions [3]. Due to all these supremacies, a significant increase is noticed in their military applications such as aerial surveillance, coastal and border protection, search and rescue operations, etc., as well as in civilian domains covering forestry and precision agriculture, infrastructure inspection and surveillance, environmental monitoring, remote sensing and mapping, mining, disaster management, parcel delivery, and many others.

TABLE I
COMPARATIVE ANALYSIS OF EMPLOYING HUMAN, SATELLITE, MANNED AIRCRAFT, AND UAVS FOR CAPTURING IMAGES

Specifications	Human Labor	Satellite	Manned Aircraft	UAVs
Cost	High	Too High	High	Low
Operating mode	Manual	Autonomous	Pilot	Remote control or autonomous
Availability	High	Poor	Moderate	High
Accessibility in unreachable areas	Very Low	High	High	High
Resolution	Up to meters	Up to 1kilometer	Up to 100meters	Up to meters
Flexibility	Less	Poor	Poor	High

UAVs are classified into fixed-wing, rotary-wing, flapping-wing, and hybrid UAVs equipped with imaging and ranging sensors. The introduction of low-cost and miniature imaging sensors magnified the applications of UAVs. The extensively used imaging sensors are red-green-blue (RGB), multispectral, hyperspectral, thermal, fluorescence imaging, light detection, and ranging (LiDAR) [4]. However, payload limitations, handling issues, capturing images from a distance, camera geometry, lighting and weather effects, and other challenges may impact UAVs-captured images. These images may contain low quality, noise, blur effects, and other obstructions. Therefore, image processing techniques have paved the way for applications.

Image processing techniques convert images into digital formats and conduct specific procedures to extract appropriate information [5]. However, the proliferation and diverse applications of UAVs cause some challenges. They collect enormous amounts of data, especially high-resolution imagery, and require efficient processing and analyzing techniques and massive storage capacities. Data with high accuracy, reliability, and consistency is essential for various applications, such as precision agriculture, infrastructure inspection, and environmental monitoring. Real-time data analysis requires advanced computational and specialized algorithms. Implementations of image processing techniques for UAV imagery may be complex and require expertise [6].

We propose a multifaceted approach to address the mentioned challenges and leverage the potential of UAVs integrated with image processing techniques. The solution is comprised of user-friendly UAV platforms integrated with optimized image processing algorithms, artificial intelligence (AI) techniques, machine learning (ML), and deep learning (DL) models. User-friendly UAV platforms are designed to seamlessly integrate their control and image processing strengths [7]. Adopting a data collection standard procedure before deploying UAVs based on pre-flight preparation, efficient mission planning, and appropriate choice of UAV platform and sensor allows secure and thriving surveys. In addition, preprocessing procedures rectify the effects of atmosphere, lens distortion, terrain or platform, low contrast, noise, etc., and make them useful for further processing. Image preprocessing implements various steps of radiometric correction, geometric calibration, geo-referencing and orthorectification, image enhancement, and restoration. Finally, optimized image processing algorithms are applied to handle enormous datasets efficiently and enable real-time data analysis. Applications of AI techniques (ML and DL algorithms) automate data analysis and recognize patterns complementing decision-making processes [8].

Comprehensive research has been carried out to develop these improved techniques and algorithms for contributing valuable insights into various phases, such as image enhancement, image generation, image segmentation, object detection and recognition, and image classification [9]. Several studies validate the applications of k-nearest neighbor (KNN), support machine vector (SVM), and random forest (RF) for classifying UAV-captured images of different areas [10]. Alkhatib *et al.* [11] analyze DL, neural network (NN), and reinforcement learning (RL) for detecting, mapping, and forecasting forest fires. This brief review validates the integration of UAV-based aerial images, image preprocessing and processing techniques, and ML algorithms as potential tools.

A. Related Work

Numerous studies have explored remarkable results of deploying UAVs with image processing techniques for modern agriculture [12], agro-environmental monitoring [13], urban traffic [14], disaster management [15], different domains [16], and plant disease detection [17]. Olson and Anderson [12] comprehensively review classifications of UAV and remote sensors, image processing techniques, and their integration in modern agriculture. This review shows that image-processing-based UAVs are significant for phenotyping, assessments of yield, and biotic and abiotic stress. Eskandari *et al.* [13] conducted a meta-analysis of UAV-obtained images for monitoring the agro-environmental domain. They validate the implementation of ML and statistical models for producing fast and reliable results in forestry, agriculture, and grassland mapping.

Butilă *et al.* [14] executed a review of applications of UAVs to monitor and analyze urban traffic. The conclusions drawn after analysis state that advanced image processing techniques integrated into UAVs will boost their applications and social benefits, such as unpleasant collisions and congestion reduction in major urban centers. Nikhil *et al.* [15] analyze the contributions of UAVs furnished with cameras in disaster management. This review demonstrates that UAVs, image processing, and communication technologies allow emergency communication between rescue teams, victims, and survivors. Osco *et al.* [16] explore the integration of UAV remote sensing and DL techniques in diverse sub-fields of agriculture, environment, and urban areas. This study discusses the promising results and the potential of deep neural network (DNN) algorithms for processing images captured by UAVs. Ali *et al.* [17] extensively reviewed studies that employed image-processing techniques to analyze UAV-captured data. The main focus was on disease detection in Rosaceae fruits. It discussed diverse classifications of imaging sensors and UAVs, ML-based models, and recent technologies that address the challenges related to disease detection and UAV imagery.

Analysis of these review articles illustrates most of them have discussed traditional models and algorithms, focusing on single domains, such as agriculture, urban planning, and disaster management, except a few. The novelty of this review lies in the UAV applications endowed with the advantages of ML and DL approaches for diverse fields.

B. Motivation and Contributions

Government, organizations, researchers, and academia are embracing advanced technology and systems for timely and efficient operations and enhanced production. The motivation for this review paper is to promote applications of UAVs integrated with the latest image processing techniques as potential tools and provide comprehensive knowledge into a single platform that will assist researchers, organizations, and the government. The leading contributions of this review paper are as follows,

a. Presenting a comprehensive overview of the technical limitations, regularity issues, and ethical concerns of UAVs along with recent advancements encountering these challenges.
b. Delineating comprehensive knowledge on the workflow of processing UAV imagery from data collection to processing with advanced AI models and recent versions of algorithms.
c. Exploring the applications of image processing based UAVs for agricultural, environmental, remote sensing and mapping, and surveillance and law enforcement applications.
d. Outlining the opportunities of the implemented methodologies from reputed research papers.
e. Evaluating challenges that require future considerations.

C. Paper Organization

This review paper is structured into nine sections, as indicated in Fig. 1. Section II outlines the adopted methodology, and Section III provides insights into challenges and recent advances in UAV technology. Section IV explains the fundamental procedures of data collection and preprocessing steps for UAV imagery. Section V expounds on various image processing techniques, and Section VI details AI algorithms and software required for processing UAV-generated images. Section VII delineates applications of image processing-based UAVs in agriculture, environmental monitoring, remote sensing and mapping, and surveillance and law enforcement applications. Section VIII compares and discusses the opportunities and limitations of the analyzed methodologies. Section IX finally summarizes the key points, concludes the paper, and defines research implications and future research directions.

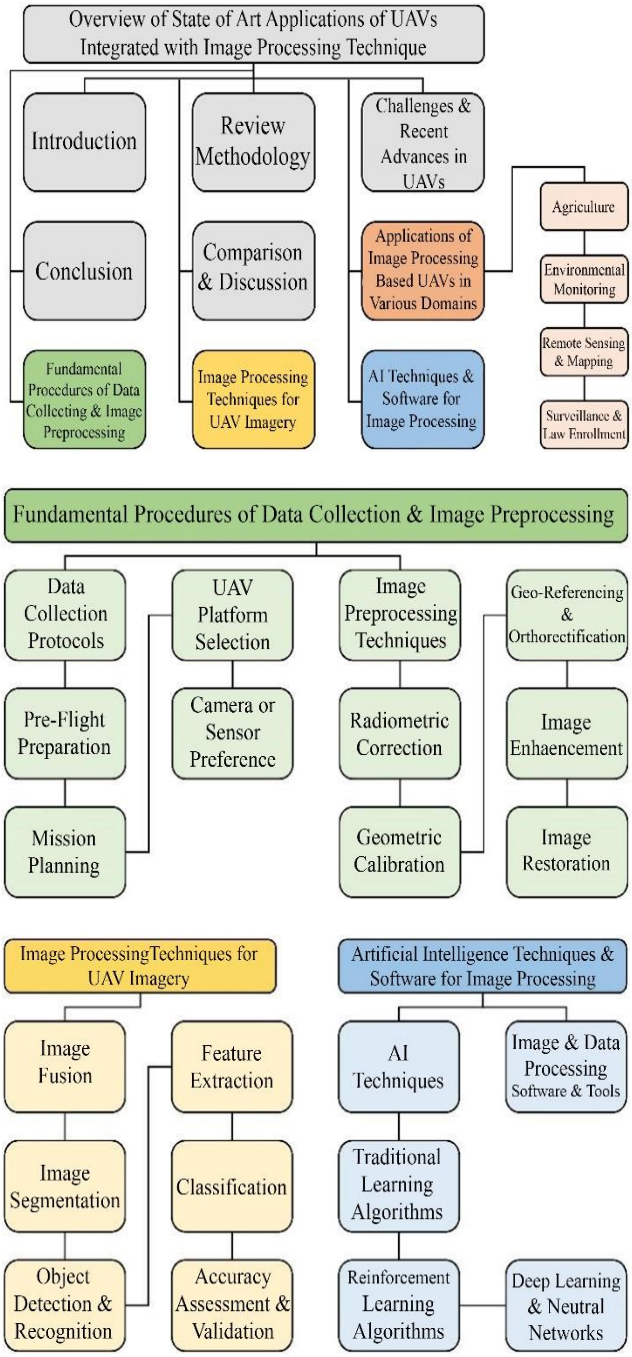

Fig. 1. Paper structure.

II. Review Methodology

A four-step methodology was developed similar to Ali *et al.* [17], which integrated UAV swarms, ML approaches, and image processing techniques for reviewing studies on monitoring and disease detection in Brassica plants. Initially, the objectives were planned. Then, a conceptual framework was developed by taking inspiration from Azoulay *et al.* [18], which fused UAVs, ML approaches, and swarms or flocks as variables of a conceptual framework to survey ML methods for UAV flock management. The developed framework for this review illustrates the relationship among the selected variables (UAVs, image processing techniques, AI techniques), maps out how integrating these variables results in various applications and draws coherent conclusions. Fig. 2 presents the conceptual framework.

In the next phase, we searched relevant and recent research published in the last six years to collect data. The articles were retrieved from ScienceDirect, IEEE, IAENG, and Google Scholar. Three classified keyword groups were used representing the sub-domains to extract relevant research articles. The first group contained keywords: "UAV, unmanned aerial vehicle, and drones." The second group is comprised of terms: "image processing, segmentation, classification." The third group had the terms: "artificial intelligence, machine learning, and deep learning." The Boolean operators "AND" and "OR" were used to create combinations of all the groups. Then, relevant articles screening was performed, curtailing the selection criteria by screening for duplicates and non-English articles, articles published before 2019, non-peer review journals, PhD dissertations, and books.

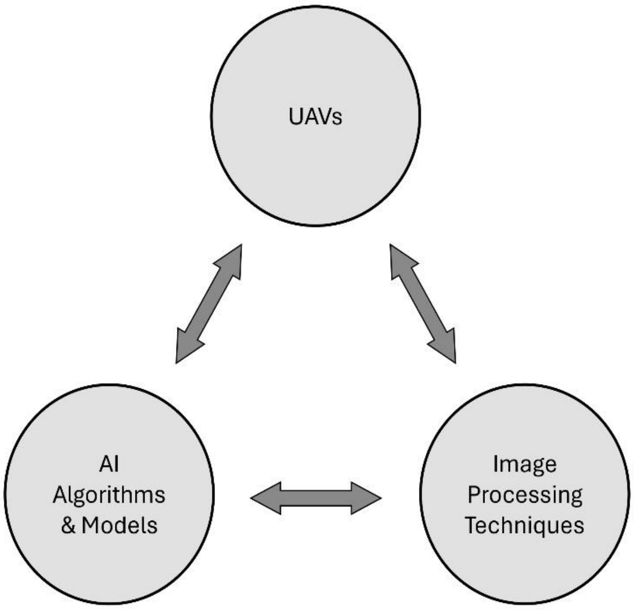

Fig. 2. Conceptual framework.

Grey literature based on reports, website blogs, and newspaper articles, was also searched and included to increase the scope. In the fourth phase, the common topics were extracted, analyzed, and summarized from the accumulated data, and finally, synthesized and concluded this review in manuscript form. The step-wise methodology for conducting this review is illustrated in Fig. 3. All the authors of this review article searched and participated equally in the paper selection process. Disagreements were resolved by consensus.

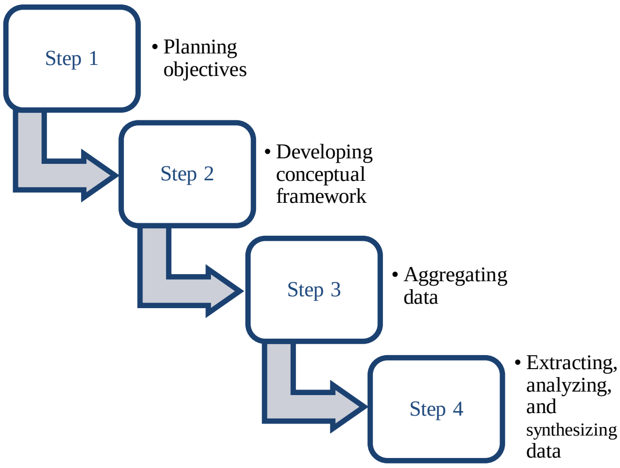

Fig. 3. Stepwise review methodology.

III. Challenges and Recent Advances In UAVs

UAVs are controlled aerial vehicles capable of performing various missions without human intervention, even in hazardous areas. Electronic gadgets like sensors and microprocessors can remotely operate them. They use communication links to establish connectivity with ground control systems (GCS) or satellites. They are categorized depending on characteristics of their size, payload, battery life, coverage range, altitude, and flying principle into fixed, rotary-wing, flapping-wing, and hybrid UAVs [4], [19].

Limitations of certain technical aspects, regularity issues, and ethical concerns hinder the applications of UAVs. Enhanced battery, proper navigation, obstacle avoidance, and low-cost sensors and image processors are challenging technical requirements of UAVs. Researchers have addressed these limitations to enhance the capabilities and applications of UAVs. They are adopting new battery chemistries, for instance, Li-ion and lithium-sulfur batteries, and have explained their higher energy density [20]. Moreover, Panasonic announced that its solid-state batteries will charge the batteries in a couple of minutes. These advancements will empower UAVs in lighter packages to extend their flight times and operational ranges [21].

Navigation technologies such as satellites, Doppler, etc., strongly affect flight controls. According to Mohsan *et al.* [22], advanced navigation systems employ intelligent systems, new inertial systems, and data fusion technology. Among these, intelligent navigation systems elevate the UAV technology and update their navigation system using information technology. On the other hand, a new inertial navigation system consumes less energy, modifying the flight pliability. Alternatively, navigation systems based on data fusion technology ensure expected flight by determining flight status.

Sensors are also prerequisites of UAVs for obstacle avoidance, tracking, and localization. Some advanced sensors include radar, infrared, and ultrasonic sensors, allowing UAVs to avoid obstacles, prevent collisions, and enhance maneuverability [23]. Moreover, the global positioning system (GPS) is an extensively used onboard sensor for navigation, mapping, tracking, localization, and timing. Furthermore, researchers also focus on advanced LiDAR sensors for monitoring and accumulating altitude data and maintaining precise height above ground.

Another issue is the generation of high-quality data, which is highly affected by technical limitations, sensor accuracy and resolution, and data processing capabilities [24]. Many sensors are expensive and have low resolution. Low-quality data acquired from these sensors results in inaccurate assessments, impacting decision-making and task outcomes. Imaging sensors are continuously advancing in affordability, reliability, ease of deployment, resolution, and accuracy. Maguire *et al.* [25] integrate UAV with FLIR Duo Pro R (FDPR), a thermzsnal camera, for capturing images of a soybean and maize field. This study demonstrates that the stability and accuracy of FDPR measurements are enhanced by increasing the warm-up, validating its usage for better decision-making and management of agricultural systems. Besides monitoring altitude, LiDAR accurately and precisely captures detailed features of the vegetable fields, enabling accurate fertilizer and pesticide applications [26].

Table II
Contributions of Advancements in UAV Technology- Summary

Advancements	Contributions
Li-ion battery	Provides the highest power, energy density, and charge rate, enhancing the battery
Lithium-Sulphur battery	Provides higher energy density, extending the battery
Solid-state battery	Extends flight times and operational ranges
Intelligent navigation system	Enhances the UAV technology and updates the navigation system
New inertial navigation system	Simplifies the weight and volume and consumes less energy for flight flexibility modification
Navigation system with data fusion	Determines the flight status and ensures a regular flight
Radar, infrared, and ultrasonic sensors	Avoid obstacles, prevent collisions, and enhance maneuverability
GPS sensor	Small-sized, budget-friendly, consumes less power, and is effective for navigation, mapping, tracking, localization, and time
LiDAR sensor	Has high spatial resolution plus accuracy and performs well for near-field obstacle tracking and precise altitude maintenance
Thermal infrared camera	Smaller-sized, easy to deploy, consumes less power, and works in the dark condition
Fluorescence imaging sensor	Has optimum sensitivity with accuracy and responds rapidly
Software-based data analysis	Processes without limitations, highly customizable, and bears on a one-time cost
Cloud computing-based data processing	Bears low initial cost, enables in-field processing, quickly processes data, and does not require a high-performance computer or additional software
DL model-based image processing	Reduces training time and accelerates processing speed and accuracy
CAAC	Restricts flying in densely populated and sensitive areas
Anti-GPS-spoofing methods, data attestation approaches, ML-based intrusion detection systems, firewall implementations, etc.	Handles vulnerabilities, attacks, and threats to security and privacy

UAVs generate large datasets while capturing high-resolution data such as images and videos that require processing and analysis [27]. Researchers evaluate that data processing and analysis is complex and time-consuming, affecting the accuracy of the generated data and the efficiency of the monitoring and detection processes. They implement ML and DL models to process captured images. *Li et al.* [28]

propose and provide evidence of the efficacy of the Ric-You Only Look Once (Ric-YOLOv5) algorithm to process remote sensing images. Another research reduces training time and enhances detection speed and accuracy by incorporating transfer learning (TL) in Yolov6 [29].

Subsequently, regularity issues and ethical concerns also jeopardize UAV operations. Deploying UAVs is subject to laws and regulations in every country. Registration, certification, restrictions in certain areas, as well as data security and privacy, are the main requirements of regularity bodies. In this context, the Civil Aviation Administration of China (CAAC) restricts drones from flying in densely populated and sensitive areas like airports, police checkpoints, no-fly zones, etc. [30]. For storing data, off-the-shelf software and onsite personal computers are used. However, researchers are focusing on infield processing with cloud computing. Privacy and security issues of vulnerabilities, attacks, and threats for UAVs are extensively surveyed in [31]. Anti-GPS-spoofing methods, collaborative and software-based data attestation approaches, ML-based intrusion detection systems, firewall implementations, etc., are the discussed innovative mitigation techniques and countermeasures. Table II summarizes the contributions of recent advancements in UAV technology, addressing challenges.

IV. Fundamental Procedures of Data Collection and Image Preprocessing

A. Data Collection Protocol

Data collection with UAVs necessitates extensive planning before the flight. Therefore, a data collection protocol with two components of UAV operation and data capture is a fundamental procedure for carrying out research on UAV applications. According to this protocol, specific steps must be followed to capture images with safe flights and surveys. Eskandari *et al.* [13] described these essential phases as pre-flight preparation, mission planning, and selection of UAV platforms and sensors. After these, UAVs are deployed to collect data.

1) Pre-Flight Preparation

Pre-flight preparation includes undertaking the regulations set by the government related to UAV operations. Such as obtaining a remote pilot license and acquiring the landowner's permission. Data collection concerning study area features and weather conditions is also a prerequisite. Data collection must meet privacy and ethical concerns [32]. Relatively constant environmental conditions of wind speed, sun radiance, and angle must be monitored for deploying the UAV to the field site. UAVs fly smoothly and create less impact on the captured data, usually in the morning and afternoon, as the wind speed is minimal during these intervals. Moreover, the clear and cloudless conditions are considered ideal weather. This step ensures data collection without mistakes.

2) Mission Planning

The next step is to plan the mission for safe flight operations by considering flight altitude, range, direction, path, camera's interior orientation, etc. Agurob *et al.* [26] and Ahmad *et al.* [33] operated a mission planner software for planning navigation waypoints of a UAV and a personal remote sensing system (PRSS) comprised of a quadrotor, laptop, and smartphone. In addition, flying at low altitudes reduces the field of view, enhances spatial resolution, and causes no feature delineation. However, many flight missions are essential to cover the entire study area if UAVs fly at low heights. Besides flight height, focal length, and sensor pixel size are to be regarded in camera settings, as their combination influences the ground sampling distance. Moreover, firmware on UAVs must be updated, embedded equipment must be prepared, adequate battery levels must be charged, and controls must be verified to operate correctly. Amraoui *et al.* [34] used DroneDeploy software to initially set up mission parameters of flight altitude, number of batteries, camera angle, etc., for optimal mission control.

3) UAV Platform Selection

The third step is to select the most suitable UAV platform according to the mission requirement. UAVs are selected on different criteria for diverse applications. Large UAVs are extensively deployed for surveillance, and nano or small platforms are significant for commercial applications. For example, Munawar *et al.* [35] selected River-map, a small UAV, for flood detection. Fixed-wing UAVs are high-altitude and wide-range drones capable of covering a larger field of view. Conversely, rotary-wing UAVs are low-altitude and low-medium-range UAVs, competent for capturing multi-angular data. Park *et al.* [36] deployed DJI Mavic Pro, a rotary-wing UAV, for acquiring multi-angular data on highways. Rotary-wing UAVs can be either single-rotor UAVs or multi-rotors, such as tri-copters, quadcopters, hexacopters, and octa-copters. Agurob *et al.* [26] utilized a hexacopter for spraying fields. Amraoui *et al.* [34] and Zhou *et al.* [37] used DJI Phantom 4 Pro for capturing agricultural images, and Dabetwao *et al.* [38] employed DJI Matrice 200 V2 for clicking building images. Reedha *et al.* [39] sent Starfury, a Pilgrim UAV, for the survey fields. On the other hand, Flapping-wing UAVs adopt bird-flying mechanics, providing excellent flight efficiency and wind tolerance. Hybrid UAVs, commonly referred to as vertical take-off and landing (VTOL), possess the energy-saving flying capability of fixed-wing UAVs and easy control of rotary-wing UAVs for take-off and landing.

4) Camera or Sensor Preference

UAV-equipped cameras encompass maximum sampling points, capture images with high spatial and temporal resolution, and generate images in digital number form. Imaging sensors involve ordinary calibrations and can be selected on their characteristics, benefiting specific applications. For instance, low-cost RGB is extensively used in remote sensing to capture visible light and collect multiple valuable data. On the other hand, spectral cameras capture visible, color infrared (CIR), near-infrared (NIR), red edge (RE), as well as short-wave infrared segments of the electromagnetic spectrum, which are invisible to the naked eye. CIR renders the dominant reflection wavelength in false colors. Fluorescence imaging sensors possess a laser light source, identifying changes in any activities. Thermal cameras capture the infrared segment of the electromagnetic spectrum. Some studies have deployed single sensors like RGB [34], [37], [40], [41], IR [38], and multispectral [42]. Others have employed combined sensors for high-quality images, such as multispectral with thermal [43] and RGB with multispectral [44]. Fig. 4 displays different UAV platforms and their carried imaging sensors, including RGB, multispectral, hyperspectral, fluorescence imaging, thermal infrared, and LiDAR.

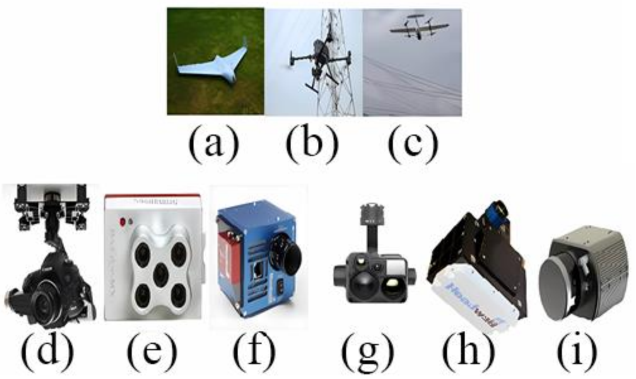

Fig. 4. Different UAV platforms and imaging sensors/ cameras: (a) Fixed-wing UAV, (b) rotary-wing UAV, (c) VTOL, (d) RGB camera, (e) Multispectral camera, (f) Hyperspectral camera, (g) Thermal camera, (h) Fluorescence imaging sensor, (i) LiDAR.

After these four crucial steps, UAVs proceed to the image acquisition mission.

B. Image Preprocessing Techniques

Images captured using UAVs are vulnerable to corruption, noise, inconsistency, and missing data. Poor raw data may lead to false predictions. Therefore, pre-processing activities are required to improve the dataset's quality by removing distortions, noise, and other effects and assuring expediency for further processing. This section delves into preprocessing procedures of radiometric correction, geometric corrections, geo-referencing and orthorectification, image enhancement, and restoration.

1) Radiometric Correction

Earth's surface reflects electromagnetic energy, which interferes with atmospheric surface activities. Low-altitude UAVs capture images with significant radiometric error. Moreover, optical sensor-induced distortions and lighting variation add more error. Radiometric calibration refers to standardizing the affinity between incoming radiation and output generated by sensors at different locations and times. Radiometric calibration is employed by utilizing spectral targets of comprehended reflectance in the field to adjust color, eliminate noise, and remove blur. If radiometric issues of tangential and radial distortions or vignetting effects are not addressed, then errors will result in feature extraction and classification. Bartalan *et al.* [43] involve radiometric calibration to derive absolute reflectance values from the raw multispectral bands. Jiang *et al.* [45] applied a concurrent satellite imagery-based correction method to overcome the radiometric inconsistency in multiflight UAV images. This method followed cross-sensor spectral fitting with fine-resolution spectral calibration to correct images, yielding better consistency, predicting results with the highest accuracy, and reducing spectral mismatch across multiple sensors.

2) Geometric calibration

Geometric calibration corrects and compensates various intrinsic parameters, for example focal length, and lens distortions (such as barrel or pincushion) of internal optical sensors or cameras. These distortions are influenced by the sensor position, shooting angle, camera lens, or motion and may alter the geometry of the captured object. Liebold *et al.* [46] introduce a bi-radial model to address unusual lens distortion patterns of the DJI Mavic Pro camera, providing exceptionally adequate precision values with no systematic effects and evident improvement at the center of the image. Furthermore, by applying geometric calibrations, UAV images represent accurate angles, shapes, and distances corresponding to the real world. Banerjee *et al.* [47] first apply radiometric calibration addressing illumination issues then, geometric correction on hyperspectral images of swamp vegetation, improving reflectance spectral quality and accuracy.

3) Geo-referencing and Orthorectification

Geo-referencing and orthorectification align UAV images. Geo-referencing uses ground control points (GCPs) and establishes a relationship between UAV images and Earth's coordinate system, aligning with known geographic coordinates. On the other hand, orthorectification utilizes camera geometry and digital elevation models (DEMs) to remove terrain relief and camera perspective distortions, ensuring uniform scale and spatial measurements. Islam *et al.* [10] geo-registered the UAV images using GCPs, measured by differential GPS [DGPS], geometrically adjusted, and converted them into orthoimage, accurately representing the earth's surface. Brunier *et al.* [44] first corrected the UAV images through radiometric calibration and then employed a similar procedure integrating DGPS with continuous real-time kinematic (RTK). Other research [40] and [43] adopted RTK with a global navigation satellite system (GNSS) for generating the spatial coordinates of GCPs. However, RTK-GNSS increases positional accuracy but enhances the UAV cost. On the other hand, orthorectification is used to remove the distortion caused by tilts and terrain effects, creating a planimetrically correct image [35]. However, the corrected image fails to specify the floodwater depth and requires DEM or LiDAR application. The classification accuracy was much higher after geo-referencing and orthorectification than the standard ones.

4) Image Enhancement

The acquired image is manipulated, improving its quality in the preprocessing step called image enhancement. It highlights significant or hidden details by automatically adjusting the brightness and contrast of an image using image editing software. Enhancing the brightness or contrast makes the images easier to see. This phase has crucial applications in remote sensing, vision-based tasks, and surveillance. Wang *et al.* [48] applied an image enhancement approach to improve the low illumination quality of images generated for reliable pedestrian detection. In this research, a hyperbolic tangent curve maps the brightness of the block matching using (1), and three-dimensional (3D) filtering approaches are used for denoising and sharpening images that enhance detection accuracies up to 0.907 and validate it more suitable. Fig.5 presents low-illumination images, and the results obtained after applying the suggested method. Visualizing images is difficult in Fig. 5 (a), whereas Fig. 5 (b) provides smoother and sufficient enhancement with less noise.

$$Tanh\ (\theta) = \frac{1-\exp(-2\theta)}{1+\exp(-2\theta)} \tag{1}$$

Here, the pixel values I (i, j) of the RGB image are assumed to be [R(i, j), G(i, j), B(i, j)]. θ=kI (i,j) with a scalar factor, k, and its value is defined according to the image brightness.

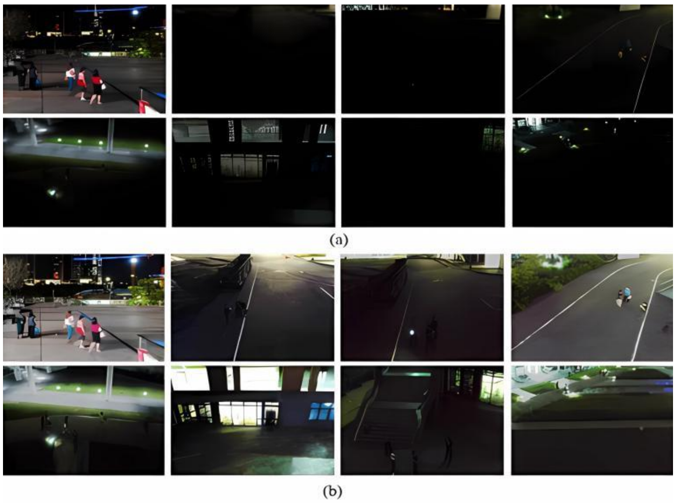

Fig. 5. Images captured under different illumination conditions and results after enhanced illumination: (a) Input images, (b) Results obtained by the proposed method.

5) *Image Restoration*

The step that improves the appearance of an image is image restoration. It is a crucial step to prevent the degraded image from being assigned to a probabilistic or mathematical model. Researchers put forward diverse algorithms for image restoration based on median filtering, histogram equalization, Retinex methods, DL, and hybrid approaches. Ahmad *et al.* [33] applied variable sizing median filtering to restore UAV remote sensing images by removing noise effects. Li *et al.* [49] used histogram equalization to repair the low brightness and motion deblurring technology for jitter interference. The restored images increased the training accuracy and reduced time but affected the region extraction, positioning, and recognition accuracy. Conversely, DL methods possess pattern recognition capabilities and are most suitable for revealing massive chunks of missing information and removing noise or blur from images. Qiao *et al.* [50] designed a U-Net architecture with a feature loss-enhanced generative adversarial network (GAN) for restoring smoke or wildfire images. The obtained results are sharper, as illustrated in Fig. 6. Moreover, the proposed model entirely removes the number. This results in getting the prime features in human concepts showing good performance.

Fig. 6. Results of a loss U-net enhanced GAN. Crapped, predicted, and targeted images.

V. Image Processing Techniques for UAV Imagery

Image processing is a method to analyze, improve the quality, and remove undesired objects and backgrounds from an image. Sometimes, it constructs new images from scratch, incorporating various phases, from image acquisition to image classification [51]. This sub-section presents insights into various image processing steps, including image fusion, image segmentation, object detection and recognition, feature extraction, image classification, and accuracy assessment and validation.

A. *Image Fusion*

Image fusion is an optional step in pre-processing but is nevertheless crucial in image processing. In certain cases, radiometric correction is inadequate for geology and topography research or soil analysis, and then, auxiliary, ancillary, or multi-source data is incorporated in the UAV-captured images, supplying additional attribute information and enhancing the image quality. Coupling UAV-spectral data with ancillary or auxiliary data reduces UAV sampling intensity. Efficient sampling strategies increase further details in ancillary or auxiliary datasets under restricted field measurements, creating a balance between data acquisition and costs. Liu *et al.* [52] use UAV-LiDAR samples and multispectral GF-6 satellite images to conduct extrapolation assessment for structural parameters (height, stem density, etc.) in Chinese forests. Coupling UAV-captured images with auxiliary datasets improves the prediction performance. Biney *et al.* [53] estimate and map soil organic content in erosion-prone fields, integrating UAV images with auxiliary datasets (indices and terrain attributes). Findings reveal that all the datasets detect high and low soil estimation. However, merging these three datasets estimates organic content with high accuracy and the least prediction error. Li *et al.* [54] fuse infrared and visible light images to improve visibility, ultimately improving target detection ability for surveillance missions.

B. *Image Segmentation*

This step partitions an image into multiple regions and changes its representation into a more simple, meaningful, and easily acceptable form. Segmentation allows focusing on significant parts, resulting in improved automatic system performance. The extensively used approach for image segmentation is thresholding, which transforms an image into a binary image by representing objects with distinct white and black regions. Park *et al.* [36] implement a mask region-based convolutional neural network (Mask R-CNN) to segment vehicles and mask those areas for generating vehicle-free ortho mosaic of highways. It effectively eliminates unwanted vehicles from UAV-captured images. According to Tetila *et al.* [55], the simple linear iterative clustering algorithm (SLIC) superpixel algorithm efficiently identifies and segments individual pests in soybean leaves, as shown in Fig. 7.

Fig. 7. SLIC-based image segmentation of soybean leaves.

C. Object Detection and Recognition

After the image segmentation, this step assigns a label to each object. These labels assist users in understanding what object has been identified. This step is widely used to process images acquired for security and surveillance purposes. CNN outputs are bounding boxes depicting the locations and class labels for objects. Mittal *et al.* [56] conducted a survey evaluating one-stage and two-stage DL-based algorithms contributions for object detection in images captured by low-altitude UAVs. This review identifies that two-stage detectors achieve significant results at a slower speed, having advantages over one-stage detectors. Liu *et al.* [57] utilize three models-linear regression (LR) detection model, the Harris corner detection (HCD) model, and the DL model (faster R-CNN) for maize seedling detection and recognition. These methods identify the maize seedlings rapidly with an accuracy of 99.9%, 99.78%, and 98.45%. Results indicate the supremacy of the LR algorithm and its specific form, Ic, is given in (2),

$$I_n = a + b \cdot I_c + c \cdot I_s + d \cdot I_e \tag{2}$$

Fig. 8. Tea bud detection by original YOLO and ST-YOLO.

Here, Ic, Is, and Ie denote the percentage of three morphological parameters-the coverage image feature percentage, skeleton image feature, and edge image feature. Similarly, Wen *et al.* [58] implement an original YOLO model and a Swin transformer-integrated YOLO (ST-YOLO) model for identifying tea buds in complex natural environments. The original YOLO unnotices two target tea buds and imprecisely detects shadow as a target, whereas the ST-YOLO detects significantly identifies all the buds flawlessly, as displayed in Fig. 8.

D. Feature Extraction

The step that extracts features based on color, shape, and texture from an area of interest in an image is feature extraction. The extracted features are valuable for the interpretations of the sample image. Histogram-based methods, local binary pattern (LBP), color co-occurrence method, gray-level co-occurrence matrix (GLCM), scale-invariant feature transform (SIFT), and spatial grey-level dependence matrix are commonly used methods. CNN architectures and ML techniques also give optimal feature extraction outcomes. Tetila *et al.* [55] propose Resnet-50, Xception, VGG-16, VGG-19, and Inception-v3 for feature extraction in soybean images. Results show that the applied DL models outperform traditional methods, using random forest (SURF) with the bag-of-visual words approach and SIFT. Li *et al.* [49] implement an edge-grabbing point positioning method for extracting disease contour, leaf contour, and distribution classification features. The centroid extraction formula, given in (3) and (4), is adopted to obtain blade edge contour. Fig. 9 shows an original image and feature recognition image, depicting the leaf profile with a green edge, the first disease edge with a red edge, the second disease outline with an orange edge, and the yellow part with a pink edge.

$$x_o = \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x \cdot f(x,y)\,dx\,dy}{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\,dx\,dy} \tag{3}$$

$$y_o = \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} y \cdot f(x,y)\,dx\,dy}{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\,dx\,dy} \tag{4}$$

Here, f(x,y) is the outermost contour image, (x_o, y_o) denotes the center of mass coordinates. First, a coordinate system is established using the center of mass, and then, the original coordinates are mapped to it.

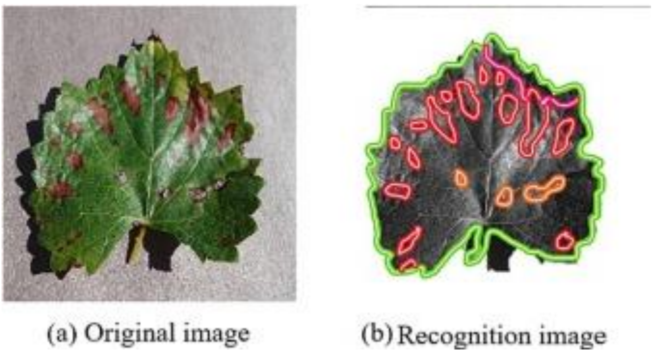

Fig. 9. Image of diseased grape before and after feature extraction.

E. Image Classification

In this step, the class of an object to which it belongs is identified. The images are classified into different categories that supply efficient information to the researchers that they can use to enhance their decision-making abilities. ML and DL algorithms are mostly employed for remarkable results. Reedha *et al.* [39] apply the visual transformers (ViT) B-16 model to classify and identify weeds in parsley, beet, and spinach images. Findings show that ViT B-16 has more potential than ResNet and EfficientNet. Munawar *et al.* [35] employ a Haar cascade classifier for identifying buildings and roads and a CNN-based DNN for predicting flooded and non-flooded areas with 91% overall accuracy (OA). Researchers view a 2D function $x_{a,b}$ of an image and implement a 2D convolution function, $y_{a,b}$, using (5) to determine the output image $c_{a,b}$. Furthermore, the convolutional layer output O_c is yielded with a feature map using (6).

$$c_{a,b} = x_{a,b} * y_{a,b} \quad (5)$$

$$O_c = \sum_{i=1}^{n} w_{ij} * y_i + v_j \quad (6)$$

Here, y_i is the sum of all neurons' input values, w_{ij} is their weights, whereas v_j denotes a bias value. Fig. 10 presents the classification results, detecting and mapping all the significant flooded regions with red highlights.

Fig. 10. Classification output of flooded regions.

F. Accuracy Assessment and Validation

This step utilizes ground truth, reference, or validation datasets to compare the accuracy of various image processing phases, such as classification, object detection, etc. From this perspective, samples are collected for training and testing data through various sample selection procedures or cross-validation tuning methods. Bartalan *et al.* [43] split the dataset into 70% training dataset for model building and used cross-validation for accuracy control and 30% testing dataset for predictions on reference data. Reference [5] split the dataset into training 80% and validating/testing 20%, ensuring the output reliability and validating the YOLO algorithms.

For evaluating the classification accuracy of models, various assessment indices are exploited from a confusion matrix (NxN), where N is the number of predicted classes or categories. A confusion matrix holds the counts of a true negative (TN), true positive (TP), false negative (FN), and false positive (FP) [59]. Besides evaluation, these metrics are applied to compare and assess the model performance and quality. Some classification indices are recall (R), precision (P), average precision (AP), mean average precision (mAP), F1-score, and overall accuracy (OA). R and P are also called producer's and user's accuracy, respectively. All these indices are for discrete dependent variables representing the category or class. Devarajan *et al.* [60] evaluates that the proposed two-stage deep RL model outperforms traditional deep Q-networks-based intensive learning methods owing to their obtained P, R, OA, and F-measure. Conversely, for accuracy assessment of regression tasks and measuring error in their predicting outputs, mean absolute error (MAE), mean bias error (MBE), mean square error (MSE), coefficient of determination (R^2), and root mean square error (RMSE) are used [61]. All these indices are for discrete dependent variables representing the category or class. Equation and interpretation of the extensively used evaluation indices both for classification and regression tasks are listed in Table III.

TABLE III
DESCRIPTION OF EVALUATION METRICS

Performance Metrics	Formulae	Interpretation
Recall (R)	$\frac{TP}{TP+FN}$	R is the algorithm's ability to calculate true positive cases
Precision (P)	$\frac{TP}{TP+FP}$	P determines the positive predicted rate
Average precision (AP)	$\sum_{n} \frac{P}{n}$	AP sums up the P-R curve into one value denoting the average of all precisions
Mean average precision (mAP)	$\sum_{i=1}^{N} \frac{AP}{N}$	mAP is the mean of all AP values for all categories
F_1-score	$\frac{2 \times R \times P}{R+P}$	F1-score gives the harmonic mean of recall and precision
Overall accuracy (OA)	$\frac{TN+TP}{TN+TP+FN+FP}$	OA is the ratio of correct positive and negative predictions to the total sample
Root mean square error (RMSE)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}$	RMSE sheds knowledge on the prediction model's short-term performance
Coefficient of determination (R^2)	$1 - \frac{\sum(x_i - y_i)^2}{\sum(x_i - \bar{x}_i)^2}$	R2 examines the suitability of a model with the predicted values
Mean absolute error (MAE)	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - x_i\rvert$	MAE determines the mean absolute difference between the predicted and measured values
Mean bias error (MBE)	$\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)$	MBE gives details of the prediction model's long-term performance
Mean square error (MSE)	$\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2$	MSE is the mean squared difference of the predicted and measured values

Here, n denotes the total data number or observations, N represents the number of categories, TP is the true positive instances, TN denotes true negative cases, FN stands for negative detections, and FP symbolizes false positive instances. y_i, x_i, and $\bar{x}_i$ represent predicted, measured, and mean of measured values at ith observation.

VI. ARTIFICIAL INTELLIGENCE TECHNIQUES AND SOFTWARE FOR IMAGE PROCESSING

A. Artificial Intelligence Techniques

AI algorithms instruct computers how to learn to operate unattended and mimic human intelligence [62]. ML is a subset of AI that designates a turning point in AI development and allows machines to learn independently through ingesting enormous data and identifying patterns. Thus, these algorithms enable the processes to be fully visible and address many complex scenarios. These algorithms are classified into traditional learning, RL, DL, and NN [63]. Fig. 11 displays the taxonomy of ML algorithms.

1) Traditional Learning Algorithms

Traditional learning algorithms are categorized into clustering and association algorithms, classification and regression algorithms, and dimensionality reduction [64]. Clustering and association algorithms constitute k-means, fuzzy c-means, frequent pattern (FP) growth, apriori, etc. Classification and regression algorithms are linear regression, logistic regression, SVMs, decision trees (DT), RF, NN, KNN, Naive Bayes, etc. Eskandari *et al.* [13] explore the advantages of using regression and classification algorithms for UAV imagery. This study evaluates that 62% of the studies used regression algorithms, whereas 38% applied classification algorithms. On the other hand, dimensionality reduction algorithms include principal component analysis (PCA) and linear discriminant analysis (LDA).

2) Reinforcement Learning Algorithms

RL algorithms include Q-learning, deep Q-network (DQN), Monte Carlo tree search, and state–action–reward–state–action (SARSA) [65]. Devarajan *et al.* [60] implement two-stage deep RL models for smart agricultural systems. ACO is integrated with DQN to offload various tasks to fog, edge, or cloud networking devices in the first stage. Then, a deep RL-based DQN model is implemented in the second stage for agricultural activity prediction and monitoring. The proposed model outperforms in terms of planning success rate, path accuracy, and convergence speed. Nguyen *et al.* [66] optimize environmental monitoring using a UAV group and exploiting RL with a deep deterministic policy gradient (DDPG) algorithm. Findings validate the proposed algorithm is effective in sensing data and monitoring.

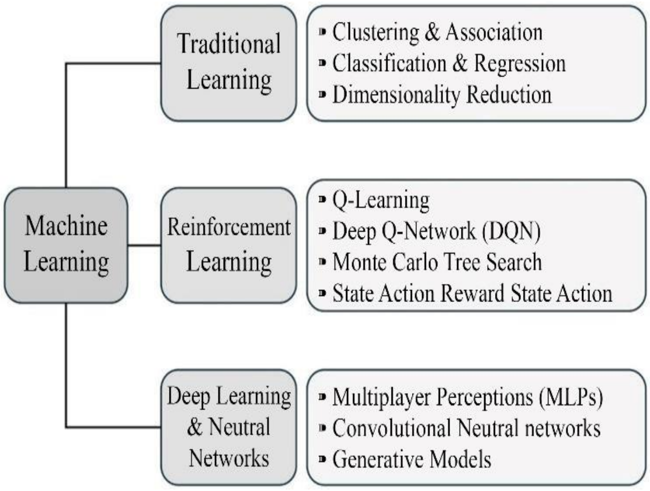

Fig. 11. Taxonomy of machine learning algorithms.

3) Deep Learning and Neural Networks

DL is a subset of ML and labels a milestone in the evolution of AI techniques. It involves neural networks and employs layers of information processing to realize massive, unstructured, and interconnected data. It produces better results than ML, especially in prediction, object detection, and classification tasks [67]. Zualkernan *et al.* [68] evaluate the potential applications of ML and DL approaches in image processing for precision agriculture. Findings reveal traditional ML and recent DL techniques are optimal choices for simple classification, segmentation, and detection

The group of DL and NN are composed of multilayer perceptrons (MLPs), convolutional neural networks (CNNs), and generative models like recurrent neural networks (RNNs). Other models include YOLO, U-Net, autoencoders, ViT, and GANs [69]. Ding and Wang [70] analyze that increasing the depth of CNNs affects their performance efficiency and suggest the integration of triplet attention models for improving mAP in object detection and accuracy in image classification. Wen *et al.* [58] examine incorporating a Swin transformer into the YOLO (ST-YOLO) model for tea bud detection, significantly surpassing original YOLO models with the highest AP value and F1 score.

B. Image and Data Processing Software and Tools

Many vendors provide high-cost software and low-cost, easy tools over the cloud for image processing. The cloud services have limited upload and download bandwidth, storage capacity, and output. The UAV-captured images are downloaded to computers for further processing. Reference [12] delineates the pros and cons of software for on-site processing and cloud computing for in-field processing of UAV imagery. According to this study, Agisoft Metashape, Pix4D Mapper is highly customizable and performs processing with no limitations but assumes more time and requires a high-performance PC and additional software for analysis. Conversely, cloud computing, Drone Deploy, UAV-IQ, has a simplified user interface, consumes less time, and requires no high-performance PC or additional software, but has limited processing options, other limitations, and recurs monthly or yearly charges. Reference [8] suggests DJI Terra, Pix4D, DroneDeploy, Agisoft Metashape, etc., as off-the-shelf software, whereas OpenDroneMap is open-access software for pre-processing UAV images. Similarly, Islam *et al.* [10] prefer Pix4D Mapping software for offline image processing. However, focusing only on inputs and software results may give rise to uncertain resulting datasets. Thus, users must be aware of any change in data collecting method or processing parameter affecting the data accuracy.

AI algorithms can be applied using commercial software or open-source software. Reference [8] prefer commercial software, like ENVI and eCognition, for object-based image analysis and Python, MATLAB, and Caret Package in RStudio software for regression algorithms. Python and R are open-source, freely available, and may be modified and redistributed. Alkhatib *et al.* [11] propose Python or JavaSript Application Program Interfaces (APIs) for enabling data processing and visualization. SAS and MATLAB are created and maintained by companies. Researchers use MATLAB to simulate ML algorithms in [10] and deep transfer learning models in [51]. Another reference [5] uses Ultralytics Hubto, a groundbreaking platform to deploy YOLOv5, whereas [40] implements YOLOv5 using PyTorch. According to reference [8], an unprecedented volume, velocity, and variety of data can be analyzed by AI algorithms with cloud computing, parallel computing, and edge intelligence. Graphics Processing Units (GPU), Central Processing Unit (CPU), Application-specific integrated circuits (ASICs), and Field-programmable gate array (FPGA) are some popular edge intelligence processors. Bouguettaya *et al.* [6] analyze various studies implementing YOLOv4 and YOLOv5 on Tesla V100 GPU, Tesla P100 GPU, and GitHub (open source) for object-based crop classification.

VII. APPLICATIONS OF IMAGE PROCESSING BASED-UAVS IN VARIOUS DOMAINS

A. Agriculture

UAVs are widely employed for various agricultural tasks, such as weed detection, fertilizer spraying, soil water content predictions, growth status monitoring, and yield estimation, to enhance precision and ensure food security. Detecting maturity stages is a crucial task. Zhou *et al.* [37] suggest YOLOv3 to classify strawberry RGB images obtained by UAV into immature fruit, flower, and mature fruit classes and digital images captured by near-ground camera into seven classes. The images are obtained quickly by UAV, and YOLOv3 detects and classifies the images three times faster for the dataset obtained at 2m height. Weed causes yield damage, affecting the nation's economy. Ajayi *et al.* [40] apply YOLOv5 for weed and crop classification in UAV–captured RGB images of farmland in Minna, Nigeria. YOLOv5 identifies weeds and classifies images into banana trees, sugarcane, pepper, spinach, and weeds. Li *et al.* [42] deploy multiple UAVs of DJI Phantom 4 and XAG P20s are deployed with multispectral sensors for spraying pesticides. A genetic algorithm (GA) is applied to find the appropriate segmentation points, fully consider different pesticide needs in each sub-area, and take 90.6% of operation time.

Bertalan *et al.* [43] obtain thermal and multispectral images for soil water content predictions. Four ML algorithms-elastic net (ENR), RF, robust linear model (RLM), and general linear model (GLM) are applied. Results indicate that the multispectral images give better input, and RF and ENR perform better for these images, whereas thermal data is acceptable with only RF. Merging the multiple survey data improves the model fitting. Estimating yield at ripening stages while monitoring the spatial variability encloses more significance. Peng *et al.* [71] propose mask R-CNN to segment ear instances and to extract ear phenotypic features such as ear size, ear count, and ear anomaly index of wheat. ML methods, random forest regression (RFR), support vector regression (SVR), and multiple linear regression (MLR) are employed for estimating wheat yield. RFR estimates the most accurately.

B. Environmental Monitoring

UAV imagery has the potential for environmental monitoring from the context of monitoring and managing forestry, wildlife, and natural disasters. Researchers have performed various challenging tasks in these domains while using ML and DL algorithms for image processing. For instance, forests have diverse kinds of trees, and monitoring and identifying tree species are crucial for commercial purposes. Amazonian palm trees are mapped at the individual tree crown (ITC) level and classified into three species-Attalea butyracea (AB), Europe precatoria (EP), Iriartea deltoidea (ID) [41]. Researchers incorporate ResNet-18 into the DeepLabv3+, identify more ITCs, and map the Euterpe precatoria species with the highest accuracy.

Wildlife monitoring requires effective management, regular detection, and population counting. Corcoran *et al.* [72] deploy UAVs assembled with IR sensors for automatic koala detection in Eucalypt forests. Thermal images distinguish animal heat signatures, although these signatures are partially covered with a canopy. Faster R-CNN and YOLO are applied for detection, reducing duplicate detections. The applied methods are less invasive and more reliable and yield more accuracy in detection than manual methods. Another reference [73] employs modified faster R-CNN to identify kiangs that further support wild animal conservation. Results reveal that the proposed model accelerates manual verification 25 times for the semiautomatic survey and yields a higher F1 score for an automatic survey.

UAV imagery is also reliable and practical for emergency responses in disaster. Munawar *et al.* [35] capture RGB images using UAVs for detecting floods. The Haar cascade classifier is used to identify landmarks (roads and buildings). CNN surpasses ML algorithms like SVM and RF and efficiently classifies the images of non-flooded and flooded regions. Hashemi-Beni and Gebrehiwot [74] also focus on mapping flood extent to support recovery activities. UAV-based and manned aerial-based RGB and LiDAR data are obtained in this study, where flooded areas are extracted using the fully convolutional network (FCN)-8s model. The extent of flooded regions, visible and covered by vegetation, is estimated using the region growing (RG) method. The applied strategies address the occlusion issue.

C. Remote Sensing and Mapping

UAV-based remote sensing is extensively used for topography, cartography, and urban planning. It assists in mapping land with its topography and cartography, mapping unreachable areas, identifying infrastructure damages, and managing and planning the fuel break. Mapping inaccessible regions like intertidal mudflats is possible with remote sensing. Brunier *et al.* [44] deploy UAVs equipped with RGB and multispectral cameras to address the similarity issues of geomorphic features. The proposed solution combines high spatial resolution with geomorphic mapping and RF classifier for mapping mudflats on the France Atlantic coast. RF classified images into eight classes based on an index and, after the segmentation phase, classified them into five geomorphic units. Results show the added value of combining topographic with radiometric data.

Mapping the land image with its topography is performed to produce cartographic documents. Klapa *et al.* [75] employ UAVs to acquire details to chart maps of rural regions. The Vector Support Machine (VSM) algorithm is used for pixel-based and object-based classification, enhancing the effectiveness of occurrence range and types of all the topographic objects and classifying the images into high, medium, low, and ground vegetation. Later, the cloud point is processed while generating class boundaries along with contours that enable the presentation of an appropriate thematic layer.

Identifying heat loss and structural damage in existing buildings improves urban planning. Dabetwar *et al.* [38] capture infrared (IR) images of real-world buildings in a lab environment using a UAV. Various DL algorithms, namely VGG16, CNN, transfer learning VGG16 (TL-VGG16), and transfer learning InceptionV3 (TL-InceptionV3), are applied to classify the heat loss damage. These applied algorithms identify heat loss, window seal damage, and wall damage with higher accuracies. Fuel break management and planning are integral for protecting infrastructure, forests, and human lives. Rodríguez-Puerta *et al.* [76] acquire UAV-based very high-density LiDAR and RGB data, satellite-based multispectral data, and airborne laser scanning (ALS)-based low-density LiDAR data to plan wildland-urban interface fuel break. The fractal net evolution approach (FNEA) is applied for multiresolution segmentation. Variable selection using random forest (VSURF) is used for feature selection. ML algorithms RF, linear and radial SVM (SVML) and (SVMR), and artificial neural network (ANN) are applied to classify five fuel-area types. SVML and SVMR achieve the highest accuracy, followed by ANN and RF integrating multispectral data with LiDAR, reducing the errors.

D. Surveillance and Law Enforcement

In recent years, law enforcement agencies operated UAVs for surveillance tasks, such as border patrol, dangerous object detection, crowd monitoring, vehicle tracking, and crime scene analysis. With insufficient staff and increased societal risks, UAVs are extensively deployed for monitoring and computerized image/video surveillance. However, individual or object identification is difficult in crowded areas videos. Therefore, most researchers focus on UAV imagery. Lie *et al.* [54] proposed the fusion of multiple sensors, infrared and visible light, Zedboard (ARM + FPGA) accelerator, and the application of thermal shot detector / CNN for UAV surveillance operations. The adopted methodology improved target detection ability and computing performance with reduced energy/frame. Matthew *et al.* [62] model a UAV system empowered with in infrared camera, modeled with CNN, and embedded with an IoT framework to detect humans within the Nigerian forest region. This work revolutionizes search and rescue missions, security surveillance, and extraditing terrorists by Nigerian security forces. Besides security surveillance, UAVs exploit law enforcement to detect prohibited activities, such as illegal fishing prevention. Prayudi *et al.* [77] present a UAV-based surveillance system to conserve the fishes and environment. MobileNetV2 and ResNet50 achieve higher accuracy, but ResNet50 glimpses much earlier in detecting and locating vessels carrying out fishing, making surveillance more effortless and the applied SIFT and KNN for hull plate classification. This study efficiently identifies illegal vessels, reducing unlawful fishing activities.

UAV imagery assists investigators in documenting and analyzing the crime scene. Srivastava *et al.* [78] suggest UAV imagery and implement different transfer learning models VGG16, VGG19, InceptionV3, DenseNet201, ResNet101V2, MobileNet, and NASNetLarge with LSTM architectures for detecting and identifying faces of individuals incriminated in violence. The proposed LSTM model outperforms and achieves the highest accuracy in feature extraction, whereas a CNN model with residual blocks gave the best accuracy in individual face identification. Another example of crowd monitoring is in the context of ensuring health measures during a pandemic situation. Masmoudi *et al.* [79] prefer using UAVs to observe crowd activities and generate alerts while detecting anomalies. In this regard, images are captured and analyzed using a scaled YOLOv4 approach, efficiently detecting and locating people. Then, a bounding box correction process is implemented to evaluate distances among them. Finally, a reliable and energy-efficient trajectory is provided using 2-Opt, genetic algorithm (GA), and ant colony optimization (ACO) algorithms to optimize path and inspect clusters violating restrictions, among which 2-Opt outperforms in terms of execution time and cost. This proposed framework requires improvement as it is prone to inaccuracies and errors.

VIII. Comparison and Discussion

This manuscript analyzes recent advancements in UAV technology and implementations of image processing and AI algorithms to improve the quality of images captured by UAVs. This study initially discusses UAVs contrary to human labor, satellite, and manned aircraft. Judging the differences demonstrates UAVs are cost-effective, highly flexible, and stable, give a higher degree of automation at various tasks, work autonomously at different speeds, positions, and angles, are accessible to unreachable areas, and capture high-resolution images. As UAVs overcome the shortcomings of these traditional methods, which entails the replacement of these methods with UAVs. Assessing current review studies on the state-of-the-art applications of UAVs reveals some similarities and correspondingly dissimilarities in purposes, data collection, image processing steps, and applied models. Significant research and reviews are conducted on agriculture, environmental monitoring, remote sensing and mapping, and surveillance.

Grasping the current technological UAV status, enhanced batteries, navigation systems with data fusion and intelligence, and modified obstacle avoidance sensors and imaging and ranging sensors are observed to improve maneuverability, flight timings, and flight safety, capture high-resolution images, and improve classification accuracy. Cloud-computing-based infield data storage and processing improve the acquired data quality without any high-performance computer or additional software. UAVs consolidated with such features are advanced technological devices with a bright future. Moreover, the potency of national and authority regulatory laws and data security systems boost UAV usage, making a breakthrough in the automation of detection, monitoring, mapping, and other tasks.

Researchers adopt proper protocols for safe operations and efficient data collection. From this context, initially, they make pre-flight preparations, such as observing rules and regulations, collecting weather, and studying area features. Most studies deploy UAVs in constant environmental conditions, usually daytime. Another step of this protocol is to plan the mission. Researchers plan flight parameters, plot paths using mission planner software, and update embedded equipment prior to the mission. Researchers deploy UAVs at high flight heights to cover large study areas and low flying heights to reduce atmospheric effects. The following steps are the appropriate platform and sensor selections according to the mission. For this, the authors focus on rotary-wing UAVs in most research, as they can capture multi-angular images for better analysis. Fixed-wing UAVs have been deployed in fewer studies, whereas hybrid and flapping-wing UAVs are not covered in this review. This observation aligns with the analysis conducted by [12] for agriculture applications. Most studies propose RGB sensors due to their cost-effectiveness and ability to collect comprehensive, valuable data. Some deploy combined sensors to obtain high-quality images.

After the fundamental data collection procedure, UAVs are deployed to acquire images of respective missions. However, flying at different altitudes, tilts, and terrains causes some distortion levels, and environmental factors of fog, smoke, or pollution may lead to noisy effects in the images. Hence, distortion and noise must be removed from images to infer meaningful insights through image preprocessing and processing techniques. For preprocessing images, researchers implement different steps. Radiometric correction is preferred for rectifying atmospheric interference and sensor-induced distortions and deriving absolute reflectance values. The following preprocessing step is geometric calibration, adjusting distortion caused by internal sensors or camera orientation. Researchers implement geometric calibrations to ensure accurate angles, shapes, and distance representation of captured objects in images.

Geo-referencing and orthorectification are other mosty discussed preprocessing phases. Researchers extensively perform geo-referencing to align images using GCPs and GPS data (especially RTK) and orthorectification to remove terrain-induced distortion using DEMs and LiDAR. This step ensures spatial accuracy and uniform scale in the images. The subsequent discussed steps are image enhancement and image restoration. The visual quality of images is enhanced by adjusting brightness, contrast, and sharpness and applying filters. Moreover, images are restored by abstracting blur effects and noise using filtering, histogram equalization, DL models, and hybrid approaches. In comparison, DL models show good performance and produce sharper images. All these steps improve the quality of UAV-captured images of canopies, disaster sites, etc.

High spatial and temporal resolution images generated by UAVs then undergo image processing measures- image fusing, various region segmenting, label assigning, feature extracting, classifying them into distinct groups, and finally, estimating the accuracy and validating the model. In the image fusion step, researchers are observed incorporating auxiliary datasets or ancillary data into UAV images or merging multiple datasets in certain cases to provide supplemental attribute data, improving accuracy and prediction performance. Subsequently, images are segmented into regions using thresholding and Mask-RCNN. Table IV summarizes the segmentation performance of analyzed AI techniques involved in various studies. According to this table, Mask R-CNN achieves a high AP for segmenting vehicles from single images and F1-score for segmenting images captured for estimating yield. Moreover, other methods do not employ the discussed metrics but efficiently perform semantic and intertidal mudflat segmentation, refining classification and mapping accuracy. Furthermore, comparing this table, this research realizes that all the techniques achieve outstanding metrics in segmentation tasks.

The ensuing image processing step is object detection and recognition, assigning bounding boxes to label and locate objects for better understanding. Table V summarizes the performance of AI-based object detection, revealing improved DCNN architectures of Mask R-CNN and YOLO, showing remarkable performance for fire blight detection in apples, seedling number estimation, tea bud identification, and wildlife monitoring. Mask R-CNN with ResNet-101 backbone gives the highest, whereas Retina Net renders the most nominal performance. Smaller-sized YOLO models have a faster detection time average than other models. However, the linear regression and Harris corner detection models deliver the highest accuracy. Scrutinizing Table V, both ML and DL models are noticed to be applied and yield outstanding results with less training time, speedy procedures, high-throughput, and more stable models.

Feature extraction is evaluated as a step to identify key characteristics based on color, shape, and texture for valuable analysis. Studies focused on CNN architectures and ML techniques extract features with optimal outcomes. Another evaluated step is classification, which organizes different image regions into their predefined classes. Table VI showcases the performance of AI techniques implemented for classification. This table demonstrates CNN, TL incorporated VGG16, and InceptionV3 significantly surpass. SVMR, SVML, ANN, RG, and FCN-8s with RG also achieve higher classification accuracy. Moreover, valuable observation evaluates that the CNN models outperform when TL is introduced, increasing training time raises classification accuracy, YOLO performs thrice faster, and ML algorithms also exhibit good performance.

The last step of image processing is accuracy assessment and evaluation. This step compares reference or ground data with classification results, examining the accuracy of image processing and analysis. Various evaluation metrics, such as P, R, OA, and F1-score, are widely used to assess the model performance and quality. Comparatively, R^2 and RMSE are less used for measuring errors in predicting outputs in some studies. After implementing different image processing techniques, the images become more meaningful, easy to visualize and understand, and supply efficient details, enhancing a user's decision-making abilities.

Analyzing AI techniques in the considered research papers, advanced DL algorithms are regarded as capable of classifying without employing image enhancement and restoration phases. ML techniques are observed to add value to image processing tasks, whereas DL tackles massive data and performs complex computations. RF is the most applied ML technique, whereas YOLO is commonly used as a DL technique. YOLO is capable of identifying the most undersized objects quickly. The highest accuracies are achieved by CNN backbones, especially when TL is incorporated. These works validate the better performance of DL models over ML techniques. UAVs are widely deployed for monitoring and managing complex tasks. Researchers mostly use off-the-shelf software, such as Pix4D, DroneDeploy, and Agisoft Metashape, to process UAV images. Moreover, MATLAB is an extensively adopted tool for AI-enabled data processing, followed by Python, GPU-based edge intelligence, and cloud computing.

TABLE IV
SEGMENTATION PERFORMANCE OF ANALYZED TECHNIQUES-SUMMARY

Purpose	Applied Methods	AP	F1-Score
Vehicle-free ortho mosaic [36]	Mask R-CNN	97.03	-
Tree detection and species classification [41]	SIFT and ResNet-18 with DeepLabv3+	-	-
Pesticide spraying [42]	GA	-	-
Intertidal mudflat mapping [44]	SIFT and RF	-	-
Yield estimation [71]	Mask R-CNN	-	0.87
Wildland-urban interface fuel break planning [76]	FNEA	-	-

TABLE V
SEGMENTATION PERFORMANCE OF ANALYZED TECHNIQUES-SUMMARY

Time	P	R	Remarks
2.1	-	-	Segments vehicles and masks the segmented regions from single images
-	-	-	Outperforms semantic segmentation, benefitting classification
4.83	-	-	GA gives more reasonable partition segmentation and performs well for practical operation in less operating time
-	-	-	Segments intertidal mudflat into geomorphic units, refining the mapping accuracy
-	0.86	0.89	Shows high performance, whereas combined ear features yield the most accurate results
-	-	-	Small segments have less spectral details, whereas larger segments give enough details

Here, AP denotes average precision, P denotes precision, and R denotes recall. Mask R-CNN is a mask region-based convolutional neural network, SIFT is a scale-invariant feature transform, GA is a genetic algorithm, RF is a random forest, and FNEA is a fractal net evolution approach.

TABLE VI
OBJECT DETECTION PERFORMANCE OF ARTIFICIAL INTELLIGENCE TECHNIQUES (SUMMARY)

Purpose	Applied Method	AP	Accuracy	F1-Score	R-Squared
High-density, small target object detection [29]	Improved YOLOv6	59.73	-	-	-
Fire blight detection [51]	Mask R-CNN with ResNet-50 and ResNet-101	-	-	ResNet-50: 91.63 ResNet-101: 91.96	-
Seedling number estimation [57]	HCD, LR, and faster R-CNN	-	CD: 99.78	Seedling number estimation [57]	HCD, LR, and faster R-CNN
Tea buds' identification [58]	ST-YOLO	86.2	-	88	-
Wildlife detection and monitoring [72]	DCNN	-	-	-	-
Wildlife detection [73]	Modified faster R-CNN	-	-	90	-

TABLE VII
OBJECT DETECTION PERFORMANCE OF ARTIFICIAL INTELLIGENCE TECHNIQUES (SUMMARY)

RMSE	Time	P	R	Remarks
-	-	-	-	Effectively detects objects with higher accuracy and less training time
-	-	ResNet-50: 91.23 ResNet-101: 92.79	ResNet-50: 92.04 ResNet-101: 91.15	Efficiently detects fire blight and segments infected apple canopies in a complex environment
HCD: RMSE-3.78 rRMSE-16.17 LR: RMSE-2.11 rRMSE-9.05 Faster R-CNN: RMSE-1.38 rRMSE-5.94	-	-	-	All methods are high-throughput and fast, but among them, the LR model and faster R-CNN are more stable
-	21.29	-	-	ST-YOLO outperforms with reduced size, whereas original YOLO misses targets because of lighting conditions
Testing data: 1.9272	136	North site: 60-71 South site: 43–58	-	Distinguishes animal heat signatures with more accuracy
-	26	0.85	0.96	Accelerates the manual verification and provides accurate and inexpensive surveys

Here, AP denotes average precision, R-squared denotes coefficient of determination, RMSE denotes root mean square error, P denotes precision, and R denotes recall. Mask R-CNN is a mask region-based convolutional neural network, HCD is Harris corner detection, LR is linear regression, ST-YOLO is a Swin transformer-you only look once, and DCNN is Faster RCNN and YOLO.

TABLE VIII
CLASSIFICATION PERFORMANCE OF STATE-OF-THE-ART MODELS-SUMMARY.

Applied Method	AP	mAP	Accuracy	F1-score
Haar cascade classifier and CNN [35]	-	-	91	0.93
YOLOv3 [37]	UAV: 0.93 Digital camera: 0.94	UAV: 0.88 Digital camera: 0.89	-	-
VGG16, CNN, TL-VGG16, and TL-InceptionV3 [38]	-	-	CNN: 100 VGG16: 32 TL-VGG16: 96 TL-InceptionV3: 100	-
YOLOv5 [40]	0.823	-	0.671	0.752
SIFT and ResNet-18 with DeepLabv3+ [41]	-	-	AB: 78.6 ± 5.5 EP: 98.6 ± 1.4 ID: 96.6 ± 3.4	-
SIFT and geomorphic-based RF [44]	-	-	93.12	-
RFR, SVR, and MLR [71]	-	-	-	-
FCN-8s with RG [74]	-	-	Scenario 1: 88.4 Scenario 2: 92.4	-
RF, SVML, SVMR, and ANN [76]	-	-	Training data SVMR: 94.04 SVML: 94.46	-

RF: 90.66 ANN: 91.35 Testing data SVMR: 91.18 SVML: 90.44 ANN: 91.91 RF: 91.80

TABLE IX
CLASSIFICATION PERFORMANCE OF STATE-OF-THE-ART MODELS-SUMMARY.

R-Squared	RMSE	P	R	Remarks
-	-	0.92	0.95	Shows high computational speed, extracts landmarks under varying scale, lighting, and color, and classifies quickly and accurately
-	-	-	-	YOLO performs three times faster and better
-	-	-	-	CNN and TL-InceptionV3 outperform smaller datasets, illustrating TL improves efficiency
-	-	-	-	Identifies even smaller objects, whereas an increase in training time increases classification accuracy till 600 epochs
-	-	-	-	Detects and classifies at less computational cost, successfully detects closer trees, and produces accurate maps
-	-	-	-	Proves to be a user-friendly method, maps soft-bottom intertidal regions with extra value, whereas geomorphic-based classification shows higher accuracy
RFR: 0.86 SVR: 0.85 MLR: 0.83	RFR: 17.53 SVR: 18.93 MLR: 22.78	-	-	RFR estimates the best yield estimation
-	-	-	-	This integrated approach efficiently identifies floods in both hidden and visible areas
-	-	-	-	Data integration reduces classification time, and most of the algorithms surpass 90%

Here, AP denotes average precision, mAP denotes mean average precision, R-squared denotes coefficient of determination, RMSE denotes root mean square error, P denotes precision, and R denotes recall. CNN is a convolutional neural network, YOLO is you only look once, UAV is an unmanned aerial vehicle, CNN is convolutional neural network, TL-VGG16 is transfer learning VGG16, TL-InceptionV3 is transfer learning InceptionV3, SIFT is scale-invariant feature transform, AB is Attalea butyracea, EP is Europe precatoria, ID is Iriartea deltoidea, RF is the random forest, RFR is random forest regression, SVR is support vector regression, and MLR is multiple linear regression, FCN is fully convolutional network, RG is region growing, SVML is linear support machine vector, SVMR is radial support machine vector, and ANN is artificial neural network.

From an application perspective, most of the analyzed research articles are based on agriculture studies, followed by environmental monitoring, remote sensing, and mapping. These observations are similar to the results of [13]. DL and neural networks are implemented for crop classification, plant maturity stages, weed detection, tree species identification, wildlife detection and conservation, flood detection and extent mapping, heat loss and structural damage identification, target detection, search and rescue missions, and crime scene analysis. On the other hand, classification and regression algorithms are applied for soil water content predictions, yield estimations, mudflats mapping, and map charting. A few studies implement both traditional learning and DL models. In the case of flood detection, ML yields less performance than CNN. Conversely, in the context of fuel break management and planning, ML outperforms the applied ANN model. Moreover, in some studies based on illegal fishing prevention and crowd monitoring, ML and DL are involved in different tasks. All the examined research demonstrates the efficiency and potential of AI techniques for processing UAV images for precision agriculture, environmental monitoring, remote sensing and mapping, and surveillance.

The above findings can be summarized as (1) UAVs-obtained data raises the recognition accuracy. (2) Researchers have extensively deployed rotary-wing UAVs and budget-friendly RGB cameras. The multispectral camera provides added value, whereas LiDAR analyzes the depth of flooded water. (3) Geo-referencing and orthorectification are widely implemented preprocessing steps. (4) Image segmentation and feature extraction steps are extensively considered in various studies to improve the classification accuracy. Moreover, image fusion and object detection are also employed to supplement additional attribute data and identify and classify different species and objects, respectively. (5) AI models take a reasonable time to process images from scratch and then to segment regions, extract features, and classify images. These processed images allow better analysis for instigating response plans for emergencies, enhancing accuracy and precision. Contrarily, other techniques consume more time (weeks or months) for planning an immediate response.

IX. CONCLUSION

UAVs have acquired remarkable attention from researchers. Innovations are modifying several aspects of UAVs, expanding their applications in various domains. The main objective of this paper is to promote their applications while integrating image processing techniques and AI algorithms. In this context, an overview of UAV technology is presented while conceptualizing its elementary concepts, modified components such as the battery, navigation system, proximity, optical avoidance sensors, imaging and ranging sensors, and image processors. A protocol for efficient data collection is presented. Image preprocessing phases of correcting images through radiometric and geometric calibration, geo-referencing and orthorectification, image enhancement, and restoration are elaborated. Image processing techniques, such as image fusion, feature extraction, segmentation, object detection, classification, and accuracy assessment and validation, are explained in detail. ML and DL models and image and data processing software and tools are discussed. Their applications are explored in agriculture, showing the aid of the proposed solution in precision agriculture and yield optimization. Their usage for environment monitoring illustrates their capabilities for forestry, wildlife, and natural disaster assessment and management. Similarly, UAV-based remote sensing and mapping contribute to topography, cartography, and urban planning. Moreover, UAV-enabled surveillance is significant for search and rescue missions, security surveillance, crowd monitoring, and crime scene analysis, benefiting law enforcement agencies. Besides many opportunities, certain constraints still hinder performance and applications. These challenges include technical limitations, regularity issues, data quality challenges, data processing issues, and training and expertise requirements, necessitating future considerations and development to refine their efficiency, safety, and accuracy. The proposed multifaceted approach promotes automation, sustainability, and effectiveness in various domains.

The limitations of this review include a lack of software application, methodology based on statistical techniques, and exploration of case studies from the real world. However, the developed conceptual design (integrating UAVs, image processing techniques, and AI) efficiently analyzes and interprets sources (research papers), interlinking and strengthening the theoretical framework (core theories are UAV, image processing, and AI) and creating a robust review paper. This review has substantial implications for researchers, scholars, and the scientific community. It enriches their knowledge by synthesizing recent research, providing valuable and comprehensive insights, and advancing theoretical understanding. Moreover, it addresses the societal and ethical implications of using UAVs and AI algorithms in a responsible manner. This work informs engineers, developers, and the government about the significance and limitations of UAV applications, which may lead to further development in UAV platforms, sensors, techniques, and effective policies.

For future research, we will consider other conceivable areas, such as applications in energy and utilities, cultural heritage, construction, and mining operations. Furthermore, LiDAR sensors and multiple UAVs offer potential avenues for future exploration.

References

[1] S. Manfreda and E. B. Dor, “Remote sensing of the environment using unmanned aerial systems,” *Unmanned Aerial Systems for Monitoring Soil, Vegetation, and Riverine Environments*, pp. 3–36, 2023.

[2] B. Xu, Y. Zhao, T. Wang, and Q. Chen, “Development of power transmission line detection technology based on unmanned aerial vehicle image vision,” *SN Appl. Sci.*, vol. 5, no. 3, p. 72, Mar. 2023, doi: 10.1007/s42452-023-05299-7.

[3] H. T. Kieu and A. W.-K. Law, “Remote sensing of coastal hydro-environment with portable unmanned aerial vehicles (pUAVs) a state-of-the-art review,” *Journal of Hydro-environment Research*, vol. 37, pp. 32–45, 2021.

[4] T. B. Shahi, C.-Y. Xu, A. Neupane, and W. Guo, “Recent advances in crop disease detection using UAV and deep learning techniques,” *Remote Sensing*, vol. 15, no. 9, p. 2450, 2023.

[5] V. Dewangan, A. Saxena, R. Thakur, and S. Tripathi, “Application of image processing techniques for uav detection using deep learning and distance-wise analysis,” *Drones*, vol. 7, no. 3, p. 174, 2023.

[6] A. Bouguettaya, H. Zarzour, A. Kechida, and A. M. Taberkit, “Deep learning techniques to classify agricultural crops through UAV imagery: a review,” *Neural Comput & Applic*, vol. 34, no. 12, pp. 9511–9536, Jun. 2022, doi: 10.1007/s00521-022-07104-9.

[7] Z. Zhang and L. Zhu, “A review on unmanned aerial vehicle remote sensing: Platforms, sensors, data processing methods, and applications,” *drones*, vol. 7, no. 6, p. 398, 2023.

[8] J. Su, X. Zhu, S. Li, and W.-H. Chen, “AI meets UAVs: A survey on AI empowered UAV perception systems for precision agriculture,” *Neurocomputing*, vol. 518, pp. 242–270, 2023.

[9] Z. A. Ali, D. Deng, M. K. Shaikh, R. Hasan, and M. A. Khan, “AI-Based UAV Swarms for Monitoring and Disease Identification of Brassica Plants Using Machine Learning: A Review.,” *Computer Systems Science & Engineering*, vol. 48, no. 1, 2024.

[10] N. Islam *et al.*, “Early weed detection using image processing and machine learning techniques in an Australian chilli farm,” *Agriculture*, vol. 11, no. 5, p. 387, 2021.

[11] R. Alkhatib, W. Sahwan, A. Alkhatieb, and B. Schütt, “A brief review of machine learning algorithms in forest fires science,” *Applied Sciences*, vol. 13, no. 14, p. 8275, 2023.

[12] D. Olson and J. Anderson, “Review on unmanned aerial vehicles, remote sensors, imagery processing, and their applications in agriculture,” *Agronomy Journal*, vol. 113, no. 2, pp. 971–992, Mar. 2021, doi: 10.1002/agj2.20595.

[13] R. Eskandari, M. Mahdianpari, F. Mohammadimanesh, B. Salehi, B. Brisco, and S. Homayouni, “Meta-analysis of unmanned aerial vehicle (UAV) imagery for agro-environmental monitoring using machine learning and statistical models,” *Remote Sensing*, vol. 12, no. 21, p. 3511, 2020.

[14] E. V. Butilă and R. G. Boboc, “Urban traffic monitoring and analysis using unmanned aerial vehicles (UAVs): A systematic literature review,” *Remote Sensing*, vol. 14, no. 3, p. 620, 2022.

[15] N. Nikhil, S. M. Shreyas, G. Vyshnavi, and S. Yadav, “Unmanned aerial vehicles (UAV) in disaster management applications,” in *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)*, IEEE, 2020, pp. 140–148.

[16] L. P. Osco *et al.*, “A review on deep learning in UAV remote sensing,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 102, p. 102456, 2021.

[17] Z. A. Ali, C. Yang, A. Israr, and Q. Zhu, “A comprehensive review of scab disease detection on Rosaceae family fruits via UAV imagery,” *Drones*, vol. 7, no. 2, p. 97, 2023.

[18] R. Azoulay, Y. Haddad, and S. Reches, “Machine learning methods for uav flocks management-a survey,” *IEEE Access*, vol. 9, pp. 139146–139175, 2021.

[19] F. Ahmed, J. C. Mohanta, A. Keshari, and P. S. Yadav, “Recent Advances in Unmanned Aerial Vehicles: A Review,” *Arab J Sci Eng*, vol. 47, no. 7, pp. 7963–7984, Jul. 2022, doi: 10.1007/s13369-022-06738-0.

[20] S. Jiao, G. Zhang, M. Zhou, and G. Li, “A Comprehensive Review of Research Hotspots on Battery Management Systems for UAVs,” *IEEE Access*, 2023.

[21] “Panasonic to produce solid-state battery for drones by 2029,” Nikkei Asia. Accessed: Dec. 16, 2024. [Online]. Available: https://asia.nikkei.com/Business/Technology/Panasonic-to-produce-solid-state-battery-for-drones-by-2029

[22] S. A. H. Mohsan, N. Q. H. Othman, Y. Li, M. H. Alsharif, and M. A. Khan, “Unmanned aerial vehicles (UAVs): practical aspects, applications, open challenges, security issues, and future trends,” *Intel Serv Robotics*, Jan. 2023, doi: 10.1007/s11370-022-00452-4.

[23] “How are Latest Developments in Drone Sensors Empowering Drone Functionality?,” Research Dive. Accessed: Dec. 16, 2024. [Online].

Available: https://www.researchdive.com/blog/drone-sensors-driving-innovation-in-drone-technology-through-sensor-excellence

[24] S. Guan, Z. Zhu, and G. Wang, "A review on UAV-based remote sensing technologies for construction and civil applications," *Drones*, vol. 6, no. 5, p. 117, 2022.

[25] M. S. Maguire, C. M. Neale, and W. E. Woldt, "Improving accuracy of unmanned aerial system thermal infrared remote sensing for use in energy balance models in agriculture applications," *Remote Sensing*, vol. 13, no. 9, p. 1635, 2021.

[26] Manuel Chad Agurob, Amiel Jhon Bano, Immanuel Paradela, Steve Clar, Earl Ryan Aleluya, and Carl John Salaan, "Autonomous Vision-based Unmanned Aerial Spray System with Variable Flow for Agricultural Application," IAENG International Journal of Computer Science, vol. 50, no.3, pp1058-1073, 2023

[27] H. S. Munawar, A. W. Hammad, S. T. Waller, M. J. Thaheem, and A. Shrestha, "An integrated approach for post-disaster flood management via the use of cutting-edge technologies and UAVs: A review," *Sustainability*, vol. 13, no. 14, p. 7925, 2021.

[28] Hongyan Li, Baoqing Xu, Ziyang Zhang, and Weifeng Wang, "Small Target Detection Method of Optical Remote Sensing Image Based on Multi-scale Information Fusion," IAENG International Journal of Computer Science, vol. 51, no. 6, pp681-687, 2024

[29] Yingwei Li, and Xiaoxia Zhang, "Object Detection for UAV Images Based on Improved YOLOv6," IAENG International Journal of Computer Science, vol. 50, no.2, pp759-768, 2023

[30] "Drone Laws in China | UAV Coach (2023)." Accessed: Dec. 16, 2024. [Online]. Available: https://uavcoach.com/drone-laws-in-china/

[31] Y. Mekdad *et al.*, "A survey on security and privacy issues of UAVs," *Computer Networks*, vol. 224, p. 109626, 2023.

[32] A. J. Mathews, K. K. Singh, A. R. Cummings, and S. R. Rogers, "Fundamental practices for drone remote sensing research across disciplines," *Drone Syst. Appl.*, vol. 11, pp. 1–22, Jan. 2023, doi: 10.1139/dsa-2023-0021.

[33] A. Ahmad, K. A. M. Fauzey, M. M. Abdullah, S. F. Sufahani, M. Y. A. Sari, and A. R. M. Amin, "Noise and restoration of UAV remote sensing images," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 12, 2020.

[34] K. E. Amraoui *et al.*, "Avo-AirDB: An avocado UAV Database for agricultural image segmentation and classification," *Data in Brief*, vol. 45, p. 108738, 2022.

[35] H. S. Munawar, F. Ullah, S. Qayyum, and A. Heravi, "Application of deep learning on uav-based aerial images for flood detection," *Smart Cities*, vol. 4, no. 3, pp. 1220–1242, 2021.

[36] J. Park, Y. K. Cho, and S. Kim, "Deep learning-based UAV image segmentation and inpainting for generating vehicle-free orthomosaic," *International Journal of Applied Earth Observation and Geoinformation*, vol. 115, p. 103111, 2022.

[37] Zhou, W. S. Lee, Y. Ampatzidis, Y. Chen, N. Peres, and C. Fraisse, "Strawberry maturity classification from UAV and near-ground imaging using deep learning," *Smart Agricultural Technology*, vol. 1, p. 100001, 2021.

[38] S. Dabetwar, R. Padhye, N. N. Kulkarni, C. Niezrecki, and A. Sabato, "Performance evaluation of deep learning algorithms for heat loss damage classification in buildings from UAV-borne infrared images," *Journal of Building Engineering*, vol. 75, p. 106948, 2023.

[39] R. Reedha, E. Dericquebourg, R. Canals, and A. Hafiane, "Transformer neural network for weed and crop classification of high resolution UAV images," *Remote Sensing*, vol. 14, no. 3, p. 592, 2022.

[40] O. G. Ajayi, J. Ashi, and B. Guda, "Performance evaluation of YOLO v5 model for automatic crop and weed classification on UAV images," *Smart Agricultural Technology*, vol. 5, p. 100231, 2023.

[41] M. P. Ferreira *et al.*, "Individual tree detection and species classification of Amazonian palms using UAV images and deep learning," *Forest Ecology and Management*, vol. 475, p. 118397, 2020.

[42] Y. Li, Y. Wu, X. Xue, X. Liu, Y. Xu, and X. Liu, "Efficiency-first spraying mission arrangement optimization with multiple UAVs in heterogeneous farmland with varying pesticide requirements," *Information Processing in Agriculture*, vol. 11, no. 2, pp. 237–248, 2024.

[43] L. Bertalan *et al.*, "UAV-based multispectral and thermal cameras to predict soil water content–A machine learning approach," *Computers and Electronics in Agriculture*, vol. 200, p. 107262, 2022.

[44] G. Brunier, S. Oiry, N. Lachaussée, L. Barillé, V. Le Fouest, and V. Méléder, "A machine-learning approach to intertidal mudflat mapping combining multispectral reflectance and geomorphology from UAV-based monitoring," *Remote Sensing*, vol. 14, no. 22, p. 5857, 2022.

[45] J. Jiang *et al.*, "MACA: A relative radiometric correction method for multiflight unmanned aerial vehicle images based on concurrent satellite imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–14, 2022.

[46] F. Liebold, D. Mader, H. Sardemann, A. Eltner, and H.-G. Maas, "A Bi-Radial Model for Lens Distortion Correction of Low-Cost UAV Cameras," *Remote Sensing*, vol. 15, no. 22, p. 5283, 2023.

[47] B. P. Banerjee, S. Raval, and P. J. Cullen, "UAV-hyperspectral imaging of spectrally complex environments," *International Journal of Remote Sensing*, vol. 41, no. 11, pp. 4136–4159, Jun. 2020, doi: 10.1080/01431161.2020.1714771.

[48] W. Wang, Y. Peng, G. Cao, X. Guo, and N. Kwok, "Low-illumination image enhancement for night-time UAV pedestrian detection," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 8, pp. 5208–5217, 2020.

[49] W. Li, X. Yu, C. Chen, and Q. Gong, "Identification and localization of grape diseased leaf images captured by UAV based on CNN," *Computers and Electronics in Agriculture*, vol. 214, p. 108277, 2023.

[50] L. Qiao, Y. Zhang, and Y. Qu, "Pre-processing for UAV based wildfire detection: a loss U-net enhanced GAN for image restoration," in *2020 2nd International Conference on Industrial Artificial Intelligence (IAI)*, IEEE, 2020, pp. 1–6.

[51] M. S. Mahmud *et al.*, "Detection and infected area segmentation of apple fire blight using image processing and deep transfer learning for site-specific management," *Computers and Electronics in Agriculture*, vol. 209, p. 107862, 2023.

[52] H. Liu, F. Cao, G. She, and L. Cao, "Extrapolation Assessment for Forest Structural Parameters in Planted Forests of Southern China by UAV-LiDAR Samples and Multispectral Satellite Imagery," *Remote Sensing*, vol. 14, no. 11, p. 2677, 2022.

[53] J. K. M. Biney, J. Houška, J. Volánek, D. K. Abebrese, and J. Cervenka, "Examining the influence of bare soil UAV imagery combined with auxiliary datasets to estimate and map soil organic carbon distribution in an erosion-prone agricultural field," *Science of the Total Environment*, vol. 870, p. 161973, 2023.

[54] J. Li, Y. Peng, and T. Jiang, "Embedded real-time infrared and visible image fusion for UAV surveillance," *J Real-Time Image Proc*, vol. 18, no. 6, pp. 2331–2345, Dec. 2021, doi: 10.1007/s11554-021-01111-0.

[55] E. C. Tetila *et al.*, "Detection and classification of soybean pests using deep learning with UAV images," *Computers and Electronics in Agriculture*, vol. 179, p. 105836, 2020.

[56] P. Mittal, R. Singh, and A. Sharma, "Deep learning-based object detection in low-altitude UAV datasets: A survey," *Image and Vision computing*, vol. 104, p. 104046, 2020.

[57] S. Liu *et al.*, "Estimating maize seedling number with UAV RGB images and advanced image processing methods," *Precision Agric*, vol. 23, no. 5, pp. 1604–1632, Oct. 2022, doi: 10.1007/s11119-022-09899-y.

[58] Xin Wen, Yi Yao, Ying Cai, Zixing Zhao, Tianjiao Chen, Ziyu Zeng, Zhen Tang, and Fangzheng Gao, "A Lightweight ST-YOLO Based Model for Detection of Tea Bud in Unstructured Natural Environments," IAENG International Journal of Applied Mathematics, vol. 54, no. 3, pp342-349, 2024

[59] O. Rainio, J. Teuho, and R. Klén, "Evaluation metrics and statistical tests for machine learning," *Scientific Reports*, vol. 14, no. 1, p. 6086, 2024.

[60] G. G. Devarajan, S. M. Nagarajan, T. V. Ramana, T. Vignesh, U. Ghosh, and W. Alnumay, "DDNSAS: Deep reinforcement learning based deep Q-learning network for smart agriculture system," *Sustainable Computing: Informatics and Systems*, vol. 39, p. 100890, 2023.

[61] C. Nguyen, V. Sagan, S. Bhadra, and S. Moose, "UAV multisensory data fusion and multi-task deep learning for high-throughput maize phenotyping," *Sensors*, vol. 23, no. 4, p. 1827, 2023.

[62] U. O. Matthew, J. S. Kazaure, A. Onyebuchi, O. O. Daniel, I. H. Muhammed, and N. U. Okafor, "Artificial intelligence autonomous unmanned aerial vehicle (UAV) system for remote sensing in security surveillance," in *2020 IEEE 2nd International Conference on Cyberspac (CYBER NIGERIA)*, IEEE, 2021, pp. 1–10.

[63] D. Yu *et al.*, "Deep convolutional neural networks for estimating maize above-ground biomass using multi-source UAV images: a comparison with traditional machine learning algorithms," *Precision Agric*, vol. 24, no. 1, pp. 92–113, Feb. 2023, doi: 10.1007/s11119-022-09932-0.

[64] S. Sai, A. Garg, K. Jhawar, V. Chamola, and B. Sikdar, "A comprehensive survey on artificial intelligence for unmanned aerial vehicles," *IEEE Open Journal of Vehicular Technology*, 2023.
[65] N. Cheng *et al.*, "AI for UAV-assisted IoT applications: A comprehensive review," *IEEE Internet of Things Journal*, vol. 10, no. 16, pp. 14438–14461, 2023.
[66] T. N. Nguyen, T. B. Nguyen, T. Van Chien, and T. H. Nguyen, "Utilizing Deep Reinforcement Learning to Control UAV Movement for Environmental Monitoring," *International Journal of Electrical and Electronic Engineering & Telecommunications*, vol. 12, no. 5, pp. 317–325, 2023.
[67] V. Chamola, V. Hassija, S. Gupta, A. Goyal, M. Guizani, and B. Sikdar, "Disaster and pandemic management using machine learning: a survey," *IEEE Internet of Things Journal*, vol. 8, no. 21, pp. 16047–16071, 2020.
[68] I. Zualkernan, D. A. Abuhani, M. H. Hussain, J. Khan, and M. ElMohandes, "Machine learning for precision agriculture using imagery from unmanned aerial vehicles (uavs): A survey," *Drones*, vol. 7, no. 6, p. 382, 2023.
[69] Y. Zhu, M. Wang, X. Yin, J. Zhang, E. Meijering, and J. Hu, "Deep learning in diverse intelligent sensor based systems," *Sensors*, vol. 23, no. 1, p. 62, 2022.
[70] Y. Y. Ding, and L. Wang, "Research on the Application of Improved Attention Mechanism in Image Classification and Object Detection," IAENG International Journal of Computer Science, vol. 50, no.4, pp1174-1182, 2023
[71] J. Peng *et al.*, "Combination of UAV and deep learning to estimate wheat yield at ripening stage: The potential of phenotypic features," *International Journal of Applied Earth Observation and Geoinformation*, vol. 124, p. 103494, 2023.
[72] E. Corcoran, S. Denman, J. Hanger, B. Wilson, and G. Hamilton, "Automated detection of koalas using low-level aerial surveillance and machine learning," *Scientific reports*, vol. 9, no. 1, p. 3208, 2019.
[73] J. Peng *et al.*, "Wild animal survey using UAS imagery and deep learning: modified Faster R-CNN for kiang detection in Tibetan Plateau," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 169, pp. 364–376, 2020.
[74] L. Hashemi-Beni and A. A. Gebrehiwot, "Flood extent mapping: An integrated method using deep learning and region growing using UAV optical data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 2127–2135, 2021.
[75] P. Klapa, P. Bożek, and I. Piech, "Charting topographic maps based on UAV data using the image classification method," *Geomatics, Landmanagement and Landscape*, 2019.
[76] F. Rodríguez-Puerta *et al.*, "Comparison of machine learning algorithms for wildland-urban interface fuelbreak planning integrating ALS and UAV-borne LiDAR data and multispectral images," *Drones*, vol. 4, no. 2, p. 21, 2020.
[77] A. Prayudi, I. A. Sulistijono, A. Risnumawan, and Z. Darojah, "Surveillance system for illegal fishing prevention on UAV imagery using computer vision," in *2020 International Electronics Symposium (IES)*, IEEE, 2020, pp. 385–391.
[78] A. Srivastava, T. Badal, P. Saxena, A. Vidyarthi, and R. Singh, "UAV surveillance for violence detection and individual identification," *Autom Softw Eng*, vol. 29, no. 1, p. 28, May 2022, doi: 10.1007/s10515-022-00323-3.
[79] N. Masmoudi, W. Jaafar, S. Cherif, J. B. Abderrazak, and H. Yanikomeroglu, "UAV-based crowd surveillance in post COVID-19 era," *Ieee Access*, vol. 9, pp. 162276–162290, 2021.

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