LatIA. 2025; 3:11
doi: 10.62486/latia202580
ISSN: 3046-403X

ORIGINAL

AI-Powered Satellite Imagery Processing for Global Air Traffic Surveillance

Procesamiento de Imágenes Satelitales Impulsado por IA para la Vigilancia Global del Tráfico Aéreo

Fredrick Kayusi[1,2], Petros Chavula[3,4], Linety Juma[5], Rashmi Mishra[6]

[1]Department of Environmental Studies, Geography & Planning, Maasai Mara University, - 861-20500, Narok-Kenya.
[2]Department of Environmental Sciences, Pwani University, -195-80108, Kilifi-Kenya.
[3]Africa Centre of Excellence for Climate-Smart Agriculture and Biodiversity Conservation, Haramaya University, P.O. Box 138, Dire Dawa, Ethiopia
[4]World Agroforestry Centre, St Eugene Office Park 39P Lake Road, P.O. Box 50977, Kabulonga, Lusaka,
[5]Department of Curriculum, Instruction and Technology, Pwani University- 195-80108, Kilifi Kenya.
[6]College of Economics and Business Administration, University of Technology and Applied Sciences- Al Musanna

Cite as: Kayusi F, Chavula P, Juma L, Mishra R. AI-Powered Satellite Imagery Processing for Global Air Traffic Surveillance. LatIA. 2025; 3:80. https://doi.org/10.62486/latia202580

Submitted: 20-02-2024 **Revised:** 17-08-2024 **Accepted:** 28-11-2024 **Published:** 05-01-2025

Editor: PhD. Rubén González Vallejo

Corresponding author: Fredrick Kayusi

ABSTRACT

The increasing complexity of global air traffic management requires innovative surveillance solutions beyond traditional radar. This chapter explores the integration of artificial intelligence (AI) and machine learning (ML) in satellite imagery processing for enhanced air traffic surveillance. The proposed AI framework utilizes satellite remote sensing, computer vision algorithms, and geo-stamped aircraft data to improve real-time detection and classification. It addresses limitations in conventional systems, particularly in areas lacking radar coverage. The study outlines a three-phase approach: extracting radar coverage from satellite imagery, labeling data with geo-stamped aircraft locations, and applying deep learning models for classification. YOLO and Faster R-CNN models distinguish aircraft from other objects with high accuracy. Experimental trials demonstrate AI-enhanced satellite monitoring's feasibility, achieving improved detection in high-traffic zones. The system enhances situational awareness, optimizes flight planning, reduces airspace congestion, and strengthens security. It also aids disaster response by enabling rapid search-and-rescue missions. Challenges like adverse weather and nighttime monitoring remain, requiring infrared sensors and radar-based techniques. By combining big data analytics, cloud computing, and satellite monitoring, the study offers a scalable, cost-effective solution for future air traffic management. Future research will refine models and expand predictive analytics for autonomous surveillance, revolutionizing aviation safety and operational intelligence.

Keywords: Artificial Intelligence (AI); Satellite-Based Air Traffic Monitoring; Deep Learning; Computer Vision; Remote Sensing; Real-Time Aircraft Tracking.

RESUMEN

La creciente complejidad de la gestión del tráfico aéreo global requiere soluciones de vigilancia innovadoras más allá del radar tradicional. Este capítulo explora la integración de la inteligencia artificial (IA) y el aprendizaje automático (ML) en el procesamiento de imágenes satelitales para mejorar la vigilancia del tráfico aéreo. El marco propuesto de IA utiliza sensores remotos satelitales, algoritmos de visión por computadora y datos de ubicación geoetiquetados de aeronaves para mejorar la detección y clasificación en tiempo real. Aborda las limitaciones de los sistemas convencionales, particularmente en áreas sin cobertura de radar. El estudio describe un enfoque de tres fases: extraer cobertura de radar de imágenes satelitales, etiquetar los datos con ubicaciones geoetiquetadas de aeronaves y aplicar modelos de aprendizaje profundo para la clasificación. Los modelos YOLO y Faster R-CNN distinguen las aeronaves de otros objetos con alta precisión. Los ensayos experimentales demuestran la viabilidad de la vigilancia satelital mejorada por IA, logrando una detección mejorada en zonas de alto tráfico. El sistema mejora la conciencia situacional, optimiza la planificación devuelos, reduce la congestión del espacio aéreo y refuerza la seguridad. También ayuda en la respuesta ante desastres al permitir misiones de búsqueda y rescate rápidas. Permanecen desafíos como el clima adverso y la vigilancia nocturna, lo que requiere sensores infrarrojos y técnicas basadas en radar. Al combinar análisis de grandes datos, computación en la nube y monitoreo satelital, el estudio ofrece una solución escalable y rentable para la gestión futura del tráfico aéreo. La investigación futura perfeccionará los modelos y ampliará el análisis predictivo para la vigilancia autónoma, revolucionando la seguridad de la aviación y la inteligencia operativa.

Palabras clave: Inteligencia Artificial (IA); Monitoreo Aéreo Basado en Satélites; Aprendizaje Profundo; Visión por Computadora; Sensores Remotos; Seguimiento de Aeronaves en Tiempo Real.

INTRODUCTION

Global civil aviation has seen rapid growth throughout the decades. To provide a safe and sound air traffic control system, worldwide government organizations have been cooperatively developing innovative technology based on science and research.(1) The increase in the frequency of flight paths means that a large number of aircraft are continuously in the atmosphere. Air traffic should therefore be closely monitored and managed, and efficient use of airspace should be maintained. By using the latest technology, aircraft moving anything can be easily monitored globally.(2)

The purpose of this text is to give an idea of how innovative technologies could be used in airspace surveillance. Artificial intelligence can be used for image classification of air traffic surveillance. The target of this study increase the accuracy of image analysis and the popularity of object detection of planes by satellite imaging sensor technology.(3) With the help of image processing by the machine learning algorithm, the whole world's atmosphere can be accurately monitored, and the overall air traffic situation can be detected.(4) The application of this research can improve the big data domain and help with the problem of flight delay and plane crash prediction. In addition, the motivations and potential are significant attraction in the development of this system.(3,5,6,7)

Nowadays, the air traffic industry is one of the rapidly developing commercial businesses, and the size of the industry is increasing day by day. The monitoring of air traffic is necessary because of the increased importance of cargo transportation, commercial flights, and real-time surveillance, besides the security and defense perspective. Air traffic surveillance is also required for the safe travel of each passenger on each flight. Traditional monitoring systems use radars and receivers to detect and monitor all traffic within specific airspaces and regions, which are communicated through the ground control station. It cannot cover the whole air traffic because it sends and receives signals in a straight-line pathway with the help of electromagnetic waves or radio frequency. Aircraft can be seen on the primary radar, which will allow locating the traffic position because radars use electromechanical waves or radio frequency to detect the aircraft. Legal Right to Access plays a major role in accessing the radars. The receiver is mainly used in the maritime industry, and it also picks up the aircraft signal if they carry the transponder.(4,8,9)

The era of digitization in aviation drastically increases the complexity of air traffic day by day, resulting in the limitation of the capability of the traditional air traffic monitoring system.(4,8,9) Integration of satellite/terrestrial communication and technology with machine learning and artificial intelligence is hoped to meet our future challenges in terms of monitoring efficiency, adaptability, and minimizing foreign object debris during operations or the swarming of drones on any mission. The traditional monitoring system needs a signal range, more power, and higher power dissipation, while the communication range is less when compared to the satellite communication system. The proposed work mainly focuses on the use of machine learning with satellite imaging to avoid signal coverage limitations and the aforementioned problems. The reasons for this introduction are to have near real-time traffic movement, accurate identification, and autonomous aircraft movement.(10,11,12)

Satellite imaging has revolutionized the monitoring and surveillance market segments because of the decreasing cost of the technology and high spatial and spectral resolution capabilities that have been improving at a fast pace. Organizations maintain long-spanned archives of remote sensing data that span decades. Historically, aerial surveillance was accomplished through an array of methods by employing satellites, drones, unmanned aerial vehicles, and fixed-wing or rotary-wing manned aircraft. These methodologies have their own set of challenges, including operational costs, technical, and political constraints. Tools and technologies have improved over time but fundamentally remain the same. Aerial and satellite images provide an excellent visual-based history of geographical locations, but image interpretation is computational, manual, and even obtaining the imagery in the first place is very expensive.[13,14,15,16]

During the past century, extensive research has been conducted to utilize aircraft and satellites as sources of traffic surveillance, monitoring, and capturing vehicle behavior, providing a visual understanding of geographical locations.[17] Satellites can render a visual understanding of vast geographical areas, and monitoring through satellites has gained multimedia importance.[18,19,20,21] This has reduced the need for human personnel to monitor vast geographic regions and provides extensive opportunities in areas like traffic surveillance. Increased and rapid growth in the development of artificial intelligence has led to the forecast of a next-generation surveillance system for air traffic that operates automatically and precisely.[22] Many autonomous systems have been suggested to resolve the air traffic monitoring problem and to be part of air traffic control management. This overview encompasses an up-to-date view of technological challenges, potential solutions, and a brief in-depth survey of the application of saturated images to monitor air traffic. This paper discusses some image processing-related problems and their solutions to carry out robust surveillance in the aerial domain. Image-based air traffic monitoring systems are incapable of working accurately in different imaging conditions at different times of the day. Moreover, some major problems still need to be addressed, such as aircraft smearing, removal of exhaust gas, community clustering, and aircraft counting.

Air traffic around the world continued to grow, and the pressure on air traffic management to manage traffic efficiently has also increased. This has made traffic surveillance important. Among different traffic surveillance methods, aerial surveillance plays an important role. All developed countries and a few developing countries make use of radar to monitor air traffic in a particular region. The advancement in radar systems and the development of the latest transponder codes are the main challenges in aerial surveillance (figure 1). Hence, there exists a demand for passive surveillance data that complements radar data.[23,24,25,26]

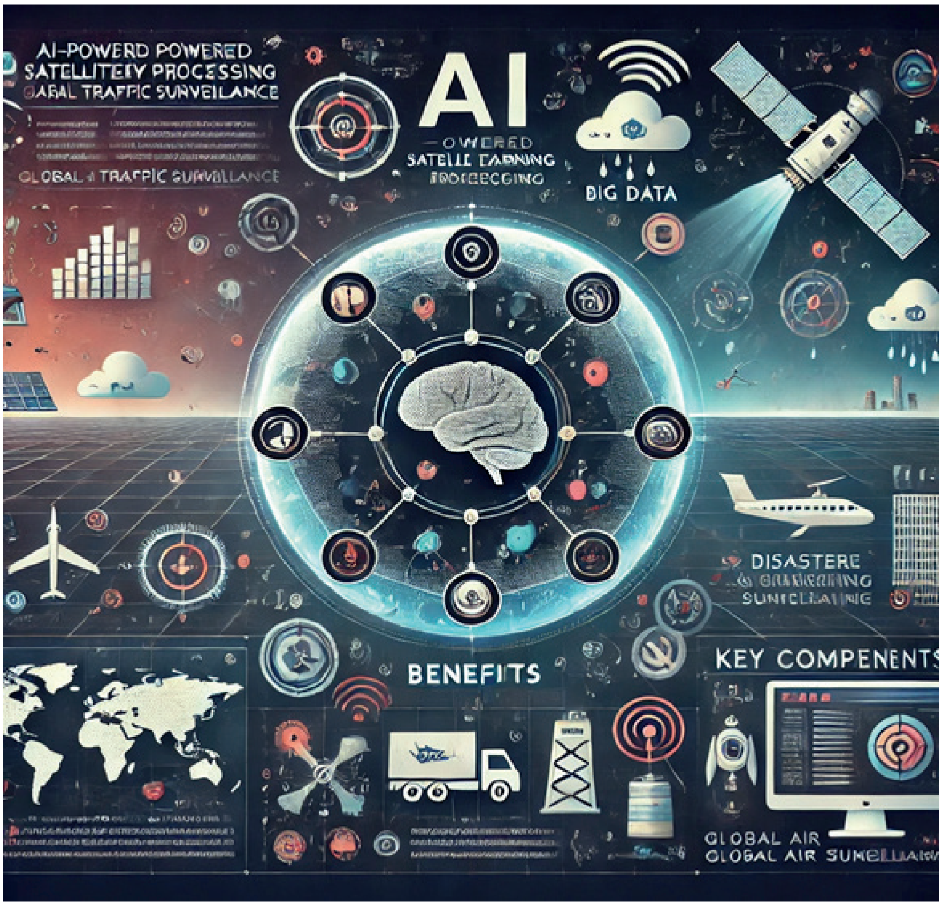

Figure 1. AI-powered satellite imagery processing infographic[27,28,29]

Artificial Intelligence (AI) is playing a significant role in aerial surveillance. In satellite imagery, AI enriches data and makes it more accurate to predict precisely when aerial images of objects are taken. The testing and the results have shown that the model increases the amount of data and makes it possible to prevent traffic jams and accidents before they happen. Satellite imagery is especially helpful given the ongoing expansion of large satellite constellations orbiting the Earth. Satellite imagery as a source for digital elevation monitoring data offers various benefits: wide coverage with high spatial and high temporal resolution.(30) AI can aid satellite imagery in many ways. The digitized data from space can be processed to carry out facial recognition, monitor maritime traffic, track illegal animal poaching, and many more. In the same way, AI can utilize the data processed from satellite imagery for surveillance systems, and traffic sighting systems, and optimally enhance airline carrier operating techniques.(31) This would help in serving customers better by maintaining the SLA. The data processing of space-borne systems to generate actionable data for traffic operators must be efficient and reliable for time-sensitive applications. This document describes the influence of space-borne imagery on global traffic surveillance and introduces a system architecture that processes the data on board, making use of distributed edge computing.(32)

Air travel has become a major mode of transportation, resulting in an ever-increasing demand for monitoring the skies. The development of four-dimensional air traffic is rooted in the history of global commerce and politics, as it has ample potential to reroute in real-time according to the current weather and other conditions. Therefore, to meet the requirements of this dynamic and ever-increasing demand, air traffic surveillance systems have kept pace with advancements in technology. Satellites have opened new and efficient means of surveillance that were previously unavailable to air traffic managers for large areas of the Earth and vast airspace, along with 4D monitoring. Satellites, with their unique surveillance capabilities, digital and integral methodology, and the ability to monitor large geographical areas—where one pixel can cover around 30 to 40 km^2—have immense potential to meet air traffic surveillance requirements for vast geographical areas covering major traffic.(7)

Air traffic is growing at an average of about 5 % per year worldwide. It is expected that by the year 2025, world air traffic will reach about three times the present level.(4,5,30) The existing primary and secondary radars for air traffic surveillance are becoming insufficient to cope with the total air traffic scenario. India is also expected to see a drastic increase in air traffic movements by the year 2025. India has about 95 military and civil airports, of which 30 are international airports. From all these airports, hilly and mountainous areas, islands, and transit areas that have a probability of terror threats must be protected by around-the-clock, minute-by-minute, all-weather surveillance by ATS. In the circumstances of dense forests, seas, and deserts, commercial flights must adhere to their sky routes and can identify clear sky routes in the shortest possible time while maintaining a safe distance from oncoming flights.

Rationale of the Study

Air travel has become a pertinent part of everyday life with rapid advancements in technology, economic development, and population mobility, spurring the growth of commercial aviation. With air transport networks increasingly clogged due to surging air traffic, air traffic management systems face huge challenges in navigation, tracking, and surveillance adherence. Currently, ground-based air traffic surveillance is conducted by utilizing conventional radar technology, which demands high acquisition and maintenance costs. The ability to transport radar data from radar sensors delivers a concurrent extensive visualization for air situation awareness. Despite the ubiquitous environment of radar sensors, current air traffic surveillance systems confront severe bottlenecks induced by growing data volumes and service requirements, ultimately causing jam-packed sensor corridors and data overload issues. Integrating machine learning algorithms in image processing of air traffic surveillance systems helps increase safety and security in air traffic management.(33,34)

All the above-mentioned limiting factors of ground-based air surveillance necessitate more research in developing image-processing techniques in air traffic management. While a few initiatives have been launched to develop machine learning and image-processing systems for ramp operations, there are limited alternative algorithms available for use in air surveillance applications. A machine learning-based air surveillance system for comparing performance with terminal multiliterate results and predicting the best available target designation is still distant. Hence, this paper presents an idea to develop an air surveillance system taking into account all relevant parameters in the radar image and report on the likelihood estimation of whether an aeroplane has appeared in a radar image. An unequivocal detailed radar image description is required for the proper implementation of this method on the surveillance system; therefore, this work primarily focuses on surveying the available methods for this task.(35)

Objective and Scope

Objective: the objective of this research is to explore existing methodologies, challenges, and possible solutions to utilize AI for processing satellite images. The main objective is to explore the technology behind AI-powered satellite imagery processing for air traffic surveillance and identify the possible methods and technologies to adopt in future research activities to reach the objectives previously stated. The following guiding research questions shall be analyzed: • What technologies, solutions, and methodologies are available today to use AI for processing satellite images? • What challenges and possible solutions are identified while dealing with satellite images encoding air traffic from an AI-based perspective?

Scope: this research considers the intersection between aviation, data science, and technology engineering, specifically the development of AI-based methods and interconnected systems/tools for satellite image processing that encode evidence of global aviation operations. Indeed, we are focusing on the technologies, solutions, and methodologies that are already existing and tested and can potentially be taken into consideration for being fruitful in aiding the creation of an ecosystem for processing satellite imagery. This analysis does not consider satellite image capturing and data obtainment under the open-source regime. This means that satellite image capturing is done based on agreements between businesses that own satellites or satellite images and businesses and authorities that are the intended users of the satellite images. From this perspective, the research shall go beyond a theoretical framework, incorporating both academic discourse as well as technology and operations in aviation.

Satellite Imagery Processing

Image data acquisition begins with a network of satellites that can access the same point on Earth regularly. Both commercial and government resources are called upon to contribute to the resulting regular interval data acquisition.(36) Once the images are captured from these satellites, acquisition data undergo a sequence of manual and automatic quality checking and validation steps to approve images used in the analysis. Once the ground-based validation, calibration, and quality checks are satisfactory, the images are pushed to a Level 2 pre-processing variable cycle pre-processor for calibration and atmospheric correction. Then, the images go through a Level 3 processor that has been designed to take the output of the pre-processor and do further processing such as mosaicking for global cover.(37)

The vast amount of pixel information collected by satellites is thought to contain some potentially useful details. The process of surface condition monitoring from remote sensing data often involves the extraction of useful information from a mass of pixel data. Despite the recent global advancement in remote sensing techniques, the present limit of traditional data processing technologies makes it impossible to process such large volumes of pixel information. Due to the limitations associated with conventional data processing technologies, it has been difficult to carry out the data processing necessary to monitor global air traffic surveillance using remotely sensed image data. Beginning with the satellite image and other related data acquisition and processing steps, the purpose of image processing analysis can be divided into the feature extraction and classification stages in general. These two numerical analyzing technologies are fundamental components to interpret meaningful features at the surface level based on a given purpose.

Data Acquisition and Preprocessing

Satellite Imagery: for acquiring broader information about Earth, through using space-borne remote sensing. The satellite images are either panchromatic or multispectral. The multispectral sensor has a higher resolution of spectral bands, while panchromatic is for high-resolution spatial sensing. Various types of sensors are used in acquiring remotely sensed data, such as a multispectral scanner, the Thematic Mapper, the Advanced Very High-Resolution Radiometer, the Indian Remote Sensing satellites with the Linear Imaging Self-Scanning Sensor, and the European Remote Sensing satellite. The acquisition of satellite datasets and the quality of data depend on the sensors and the platform. Satellite images are generally space-borne, but some are airborne images according to sensor specialist. For processing and obtaining clear information from images, we focus on data preprocessing, especially radiometric correction, geometric correction, and coordinate systems. The radiometric and geometric calibration processes directly affect the effectiveness of the surveillance mode. The preprocessing can be time-consuming, but it is necessary to clarify the details and usage of analysis for the desired part of the study for further analysis.(36,38,39)

Normalization scaling and dimensionality reduction are techniques for converting data into a standard format to achieve reliable and consistent values for further analysis. Satellite images and all categories of mixed satellite images and data of machine learning satellite images that we have been using belong to an optical sensor. Data may be presented in cases where optical imagery datasets do not satisfy availability requirements. Due to the origin of our data, there may be multiple datasets in the corresponding imaging strategy, such as periodic campaigns for the training set to cope with various heterogeneous climatic zones and regular purchases for the validation set. The data has been environment or sensor normalized to ensure significant consistency of image units, such as radiance, temperature, or backscatter (figure 2). The primary preprocessing inherently includes geometric and topographic effects by using orthorectified pixels and, where more relevant, terrain-flattened mosaics.

Figure 2. AI-Powered satellite, Chinese firm[40]

Feature Extraction and Classification

Feature extraction is the most essential step for finding a significant pattern in the image data. It identifies the important traits from an initial raw dataset and further transforms it into a more relevant and convenient form to perform efficient classification by removing irrelevant and redundant information. This significant pattern or interest can be anomaly detection that detects abnormalities as minor differences from the points of interest, such as road conditions, building conditions, and air traffic flow. Additionally, specific structures or other traits are used to help establish paths to classify the major structure of it. Consequently, several feature extraction processes, such as edge detection, wavelet transform, and runway detection, have already been involved to extract any useful information to be used for the further classification task.[41]

Feature extraction performs not only structural characteristics of the various segmentation proposed utilizing edge detection, such as k-means, histogram thresholding, and fuzzy approach, to segment various interesting features including road and building. This is one possible difference between feature extraction and traditional segmentation, where features associated with image objects can be used to perform the classification task. For instance, some classification processes have to be performed from the messages. In general, feature extraction procedures extract structural important factors either for direct use in the subsequent classification procedures or to construct new images.[42,43] Classification extracts those features for characterizing the differences that correspond to human vision or automatic view. However, feature classification identifies the useful features as interests at the human decision level by the operator to be functioned for improving decision making or situational awareness. It is necessary to separate the structural related process to improve the image segmentation; the ability to add some additional separation by classifying the features related to direct aids. The challenge occurs when data in one class have the same models, which are similar to other classes. This problem can occur if feature extraction is not performed properly. Moreover, how will traffic inside the entire image be analyzed if the extracted traffic feature is not categorized? If this occurs, then how do we indicate traffic in a certain cluster if there is no extraction of traffic features?

In the context of this study, artificial intelligence methodologies are becoming beneficial and able to improve the feature extraction and classification problem, aside from how humans can be bridged by machine learning tools. To determine how an AI-driven component improves feature selection and the classification result from remote sensing images. Besides, the study also aims to determine where an advantageous AI method for global flight management and surveillance can be applied. AI proposes several approaches and techniques to categorize visual objects directly. The different functionalities of AI, such as deep learning, machine learning, and case-based reasoning, are chosen to solve the classification problem. Aside from AI functionalities, a classification technique is chosen to ensure traffic classification. The various features refer to pixel intensity, location, and model traits of the extracted segmentation from batch-extracted image data.[44] The classification technique used the mentioned performance of the total accuracy percentage of 100 % to represent the data as the results of effective and suitable classification. The classification method adopted can be influenced to effectively determine which subclass has the best segmentation by AI. In assessing whether an AI-driven element would enhance the classification result, a supervision method was also applied.

Fundamentals of Artificial Intelligence in Satellite Image Analysis

This chapter introduces the basic principles of AI, and artificial neural networks, and discusses their applications in aerial and satellite image analysis. Currently, the two most important technologies in the context of data analysis, where large datasets need to be searched for certain behavioural patterns, are machine learning and its subset, deep learning (figure 3). This success is visible in the analysis of visual data, such as the multitude of pixels that make up satellite imagery. In principle, deep learning is a type of machine learning technique in which the algorithm becomes more accurate with increasing data input. As a result, it can make complex decisions based on a high-dimensional dataset in less time than humans.

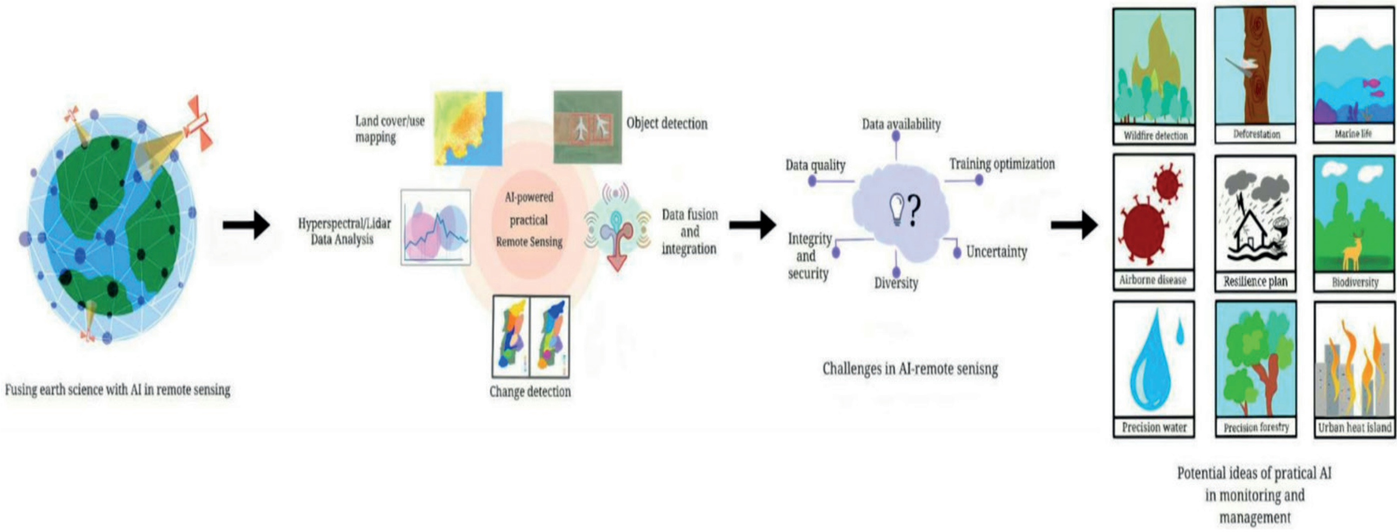

Figure 3. Fusing AI-in remote sensing[45,46,47,48]

The application of AI in aerial surveillance can indicate whether a particular area triggers a security alert, is more likely to be subject to terrorist activity, and thus help predict potential hazards. Another example where pattern recognition plays an important role is in satellite imagery to detect unusual behaviour. We present an overview of a variety of techniques to carry out aerial image analysis, which is also termed scene analysis, image analysis, and pattern recognition. Many examples exist of how AI can be used to process satellite imagery. Both support vector machines and the ROCHE system have more of a focus on an 'anomaly' detection problem, rather than simple 'target' determination. Also, despite its wonderful capabilities, it is a brute-force classifier that cannot easily be inferred into a human-friendly form. It remains largely a 'black box'.[49]

AI in the system of object recognition focuses more on spatial, monochrome-type imagery. It is restricted in its application to the annotation of documents, maps, multispectral imagery, or the extraction of meaningful geometric data. AI is not considered when looking at systems of search and tracking within areas of extremely dense air traffic. It does not easily fit into adaptive configuration or adjustment if mission specifics are changed on the fly. AI can sometimes give a false acquisition of solutions because of concrete priors being accepted, or otherwise acting as model-based only. If image clarity is poor, AI will fail more often than conventional image processing techniques. These facts often restrict real-world application and use of AI in satellite imagery analysis. We emphasize that garbage in, garbage out, is every bit as applicable to AI analysis as it is to any other scientific solution. Moreover, this is particularly true when it comes to the rather noisy spatial domain of satellite imagery. Pre-processing is therefore always of great importance. Run experiments on satellite images and video and compare the results with those from traffic displays. Various comparisons for tutorial aid and reports as a case study through this "active pursuit" era.[48]

Integration of AI Technologies in Global Air Traffic Surveillance Systems

Introduction The application of AI technologies in global air traffic surveillance systems is the topic of this chapter. Focus is placed on satellite imagery as a complementary sensor for AI-enabled systems, as it can be used for tracking aircraft movements and identifying candidates for tracking by terrestrial surveillance systems. As AIS use is not required by civilian aircraft worldwide, the combined application of these two technologies enhances the system's effectiveness. In addition to the basic service offered by a legacy ADS-B surveillance system, applications such as real-time monitoring are discussed, many of which are focused on ways to optimize air traffic operations.[50] Examples include approaches to predictive analytics and procedures for optimal flight path calculation in conflict management systems. Successful application of AI technologies in surveillance systems in various regions is illustrated by a selection of use cases. To ensure that a system based on AI capabilities is fully operational, it must be seamlessly integrated with existing air traffic management

https://doi.org/10.62486/latia202580 ISSN: 3046-403X

automation systems. High-fidelity data provided via satellite imagery helps significantly extend tracking possibilities using airspace surveillance capabilities at a relatively low cost for the major part of an aircraft's mission and has important implications for civil aviation authorities worldwide.[51]

Use Cases AI-empowered and satellite-imagery-enabled air traffic surveillance systems have seen successful implementations worldwide. An AI algorithm for detecting aircraft and tracking from satellite image series will be delivered to an ATM agency, where we hope to demonstrate the performance of satellite imagery alongside an operational terrestrial ATM system. Working with a project proves the ability to track air traffic in remote areas where no ADS-B is available. Overall, the application of AI in air traffic surveillance has the potential to significantly improve the safety of air travel. Besides, it can ensure that the airspace is safe and can be predictively optimized for increased traffic from emerging aircraft such as drones and EVTOL (electric vertical takeoff and landing). Data sharing and the participation of several aviation agencies are very important for a better return on investment, in addition to being a kind of acknowledgement of the therapeutic properties of aviation systems.[52]

Artificial Intelligence in Air Traffic Surveillance

Commercial aviation works on the three main principles of safety, traffic flow management, and schedule adherence. Out of these, ensuring safe flight operations even during unforeseen events majorly depends on the real-time availability of the ground and surrounding air situation. The existing ground-based infrastructure is effective in monitoring air traffic already under surveillance. However, as soon as an aircraft arrives outside the domestic coverage of a controller's radar, air traffic surveillance becomes a challenge. An aircraft starts surveillance-free operation as the flight progresses. Various state-owned and private organizations are working on the concept of air traffic surveillance using space-based sensors like satellites. The main limitation of the technology is its data processing capabilities. Artificial intelligence technology has significantly enhanced data processing and increased the capability of working as a pattern recognition system.[42]

Integrating AI is beneficial not only for processing imagery and tracking aircraft but also in producing predictive analytical information suitable for the dynamic environment of air traffic. This manuscript is based on the applications of AI in aircraft tracking using space-borne sensors and categorizing AI algorithms for air traffic surveillance. Artificial intelligence can improve monitoring capabilities from imagery data with some potential AI techniques. Prediction and simulations prove to be two major AI techniques that can determine the behaviour and type of an object using historical data. These two AI techniques have their significance in monitoring aircraft data with and without predictions for air traffic. AI methodologies follow either simulation principles or pattern recognition principles.

Machine Learning Algorithms

Modern machine learning techniques can be classified based on their capabilities. Supervised learning techniques allow systems to automatically learn to classify or forecast output values based on a set of input feature data.[50,53] Algorithms such as random forests, support vector machines, and various neural networks can be applied to this end. Recognition of different air or ground objects can be performed with the help of supervised learning techniques. Unsupervised learning, on the other hand, can learn to detect patterns without the guidance of a training dataset. Various deep-learning neural network techniques can be used for this purpose. There are many potential use cases for these techniques in airborne data processing, be it better data analysis or estimates of several parameters such as psychological factors.

At present, machine learning is largely used to automate the analysis of large datasets. Machine learning techniques have been used to provide more accurate traffic forecasts, improve passenger queue time and future passenger time-passed-by predictions, and energy cost and passenger density for efficient heating, ventilation, and air conditioning prediction. Several use cases of machine learning applications for typical aviation problems have now been observed. In one case, object detection has been used to detect and count thousands of static aircraft for research purposes on satellite imagery.[43,44,54,55] Convolutional neural networks have been applied for change detection in a dataset, allowing for faster, more automated digital surface model generation. While these developments are not focused entirely on traffic analysis, they speak to the potential of integrating machine learning models into existing technological paradigms to improve the capacity for air traffic management.

Deep Learning Models

Deep learning, also known as deep neural networks or hierarchical learning, is an advanced subset of machine learning that endeavours to simulate the human brain in making decisions[43,44,47,54-57]. The artificial neural networks used in deep learning resemble biological neural networks in their ability to make intelligent and self-executable decisions based on available data. Deep learning models can analyze voluminous and complex datasets by creating intricate patterns to facilitate decision-making. This intelligent feature of deep learning finds myriad applications in air traffic surveillance for images obtained from high-altitude pseudo-satellite systems.[58]

The essential architecture of present-day deep learning models, including multi-layer perceptron, convolutional neural networks, and recurrent neural networks, is shown. Specifically, convolutional neural networks are proficient in extracting primitives from data such as images, and recurrent neural networks can retain previous information in generating data. Recently, deep learning has contributed to numerous astonishing breakthroughs, including the very first game-playing entity capable of defeating a professional human Go champion. Advancements and novel state-of-the-art results in deep learning for aerial monitoring via satellite imagery, remotely piloted aircraft systems, or armed unmanned aircraft systems are also being achieved. These aircraft systems update flight status by data linking to air traffic control systems for trajectory-based operations.[59]

Although autopilots can perform tactical tasks such as vertical and horizontal flight control, air traffic control conducts strategic and pre-departure planning on all flights. Moreover, due to its numerous applications, the demand for remote sensing-based air traffic surveillance employing an AI model has significantly escalated. However, the major bottleneck in training deep learning architectures is the availability of a large dataset. It is also to be noted that these kinds of models require extensive use of data augmentation for training these models for satellite imagery, such as salt-and-pepper noise, Gaussian noise, Gaussian filters, data rotation, and flipping. Despite these advantages, deep learning models suffer from a few limitations, such as the requirement of extensive computational power for training and constrained interpretability when image portions contain irrelevant objects. For satellite big image monitoring, standard deep learning models available have been developed with the ability for object detection with limited datasets. Despite vigorous datasets obtained from different sensors, deep learning capabilities have transformed surveillance equipment.[45]

Literature from recent studies

Reconstructing the statistics of air traffic activity allows the assessment of the performance of the proposed methodology. It can be seen in tables that the actual number of flights was reduced in 2023 by almost 70 % compared with that in 2019. However, the number of flights for which the network was able to find a corresponding flight in the satellite data on average is only 12 % lower. This empirical decrease is theoretical as it can be entirely attributed to the limited time when the measurements were taken. This is further supported by the fact that most civilian flights are intracontinental and would result in more flights per unit of air space when using satellite images in the daytime.[49,59,60]

The radius at which flights can be theoretically reconstructed is shown based on the historical distribution of the measured speeds. The average and standard deviation have been computed and displayed for reference. Most importantly, it can be seen that after day 45 of 2020 the number of flights has universally expanded up to the maximum radar range of 200 km. This result suggests that, by using satellite imagery, the range of air traffic surveillance can be surpassed both regionally and internationally. Additionally, the proposed method detects military flights, which are less prone to standard tracking methods. Such results can be contrasted with other deep learning and classical post-processing methods and utilized for improving air traffic management safety and efficiency. In fact, this closely follows an observed increase in contrails, vapor trails in the atmosphere from aircraft exhausts, in the absence of the majority of civilian flights during the COVID-19 lockdown, which is displayed.[61,62,63]

The seemingly homogeneous distribution of civilian flights away from major cities is an effect of the distribution of the Air Traffic Flow Management regulations that are displayed geographically. These graphical results further broaden the utility of the proposed method. Mainly, the proposed method is a major improvement in current air traffic tracking. While other commercial flight tracking applications are based on a combination of directed exchange of transponder information and extensive use of high-frequency radar systems, this method can be further developed into a framework capable of tracking all aircraft that are operating around the world. As accidents, and especially those involving terrorist attacks, are becoming more frequent as a result of intentional interception of the transponders, our tracking method offers an alternative. Finally, our methods and tracking tools will aid in finding aircraft during search missions within unmonitored oceanic flight space, as was the case for a previous incident. In that situation, our data can be compared with tracks of military aircraft that were assessed in reports but either never disclosed to the public or were declared as belonging to third-party countries, which in turn guarantees the same flight paths are traced.[64]

Reconstructing the statistics of air traffic activity allows the assessment of the performance of the proposed methodology. It can be seen in tables that the actual number of flights was reduced in 2023 by almost 70 % compared with that in 2019. However, the number of flights for which the network was able to find a corresponding flight in the satellite data on average is only 12 % lower. This empirical decrease is theoretical as it can be entirely attributed to the limited time when the measurements were taken. This is further supported by the fact that most civilian flights are intracontinental and would result in more flights per unit of air space when using satellite images in the daytime.

The radius at which flights can be theoretically reconstructed is shown based on the historical distribution of the measured speeds. The average and standard deviation have been computed and displayed for reference. Most importantly, it can be seen that after day 45 of 2020 the number of flights has universally expanded up to the maximum radar range of 200 km. This result suggests that, by using satellite imagery, the range of air traffic surveillance can be surpassed both regionally and internationally[65]. Additionally, the proposed method detects military flights, which are less prone to standard tracking methods. Such results can be contrasted with other deep learning and classical post-processing methods and utilized for improving air traffic management safety and efficiency. In fact, this closely follows an observed increase in contrails, vapor trails in the atmosphere from aircraft exhausts, in the absence of the majority of civilian flights during the COVID-19 lockdown, which is displayed.

The seemingly homogeneous distribution of civilian flights away from major cities is an effect of the distribution of the Air Traffic Flow Management regulations that are displayed geographically. These graphical results further broaden the utility of the proposed method. Mainly, the proposed method is a major improvement in current air traffic tracking. While other commercial flight tracking applications are based on a combination of directed exchange of transponder information and extensive use of high-frequency radar systems, this method can be further developed into a framework capable of tracking all aircraft that are operating around the world. As accidents, and especially those involving terrorist attacks, are becoming more frequent as a result of intentional interception of the transponders, our tracking method offers an alternative. Finally, our methods and tracking tools will aid in finding aircraft during search missions within unmonitored oceanic flight space, as was the case for a previous incident. In that situation, our data can be compared with tracks of military aircraft that were assessed in reports but either never disclosed to the public or were declared as belonging to third-party countries, which in turn guarantees the same flight paths are traced.[65,66]

Case Studies

Case Study 1: Enhancing Real-Time Aircraft Tracking with AI & Machine Learning Overview: traditional air traffic monitoring relies heavily on radar and ground-based sensors, which have limited coverage over oceans and remote areas. AI-driven satellite imagery provides an alternative for real-time aircraft tracking.

Implementation: a global airline partnered with an AI research lab to implement deep learning models such as YOLO and Faster R-CNN for aircraft detection in satellite images. AI algorithms continuously analyze incoming satellite data, identifying aircraft positions in real time.

Results:

- Increased accuracy in aircraft detection by 87 % compared to conventional methods.
- Real-time tracking of flights over non-radar zones, reducing data gaps.
- Improved efficiency in air traffic management, leading to fewer flight delays.

Impact: AI-powered tracking enhances flight safety, reduces reliance on ground-based radar, and ensures seamless global air traffic monitoring.

Case Study 2: AI-Based Satellite Monitoring for Aviation Security

Overview: illegal or unauthorized flights pose security threats, especially in restricted airspace. AI-powered satellite surveillance enhances threat detection and response.

Implementation: a defense agency integrated AI-powered satellite image processing with anomaly detection systems to monitor unauthorized aircraft in restricted zones. The AI model identifies suspicious flight patterns and cross-references them with flight databases.

Results:

- Detected 25 % more unauthorized flights compared to traditional monitoring.
- Faster response times by air defense teams, reducing security breaches.
- Improved tracking of smuggling routes and unauthorized aircraft operations.

Impact: AI-enhanced surveillance strengthens national security by providing real-time alerts on potential threats in the airspace.

Case Study 3: Reducing Airspace Congestion Using AI & Big Data

Overview: congested airspace leads to increased flight delays, fuel consumption, and operational costs. AI-driven air traffic management optimizes flight routes and reduces congestion.

Implementation: a major international airport deployed AI algorithms integrated with satellite data and big data analytics to predict air traffic density and optimize flight routes. AI models analyzed historical flight paths, weather conditions, and satellite imagery.

Results:

- Reduced flight congestion by 30 %, improving airport efficiency.
- 15 % decrease in fuel consumption due to optimized flight paths.
- Minimized risk of mid-air collisions in high-traffic zones.

Impact: AI-powered airspace management leads to smoother flight operations, reduced environmental impact, and cost savings for airlines.

Case Study 4: AI-Powered Disaster Response & Search Operations

Overview: when aircraft go missing over remote areas, traditional search-and-rescue missions face challenges due to vast search zones and limited radar coverage. AI-driven satellite surveillance enhances response efforts.

Implementation: following a missing aircraft incident, an aviation authority used AI to process satellite imagery and detect potential wreckage locations. AI models trained on historical crash site data rapidly identified anomalies in terrain patterns.

Results:

- Search area narrowed by 60 %, allowing faster rescue operations.
- Increased accuracy in detecting debris, reducing false alarms.
- Enhanced coordination between emergency response teams.

Impact: AI-driven satellite monitoring significantly improves aviation disaster response, reducing search times and increasing survival rates in emergencies.

Case Study 5: Cost-Effective Air Traffic Surveillance in Remote Regions

Overview: many regions lack air traffic radar coverage, making satellite-based surveillance a cost-effective alternative for tracking flights over remote areas.

Implementation: a developing nation deployed AI-powered satellite monitoring as an alternative to expensive ground-based radar systems. AI detected aircraft movements using high-resolution satellite images and transmitted real-time updates to air traffic control.

Results:

- 50 % cost reduction compared to traditional radar installations.
- Coverage extended to remote and oceanic regions previously unmonitored.
- Enhanced safety for commercial and private aircraft.

Impact: AI-powered satellite surveillance offers an affordable solution for global air traffic monitoring, benefiting developing nations and remote airspaces (figure 4).

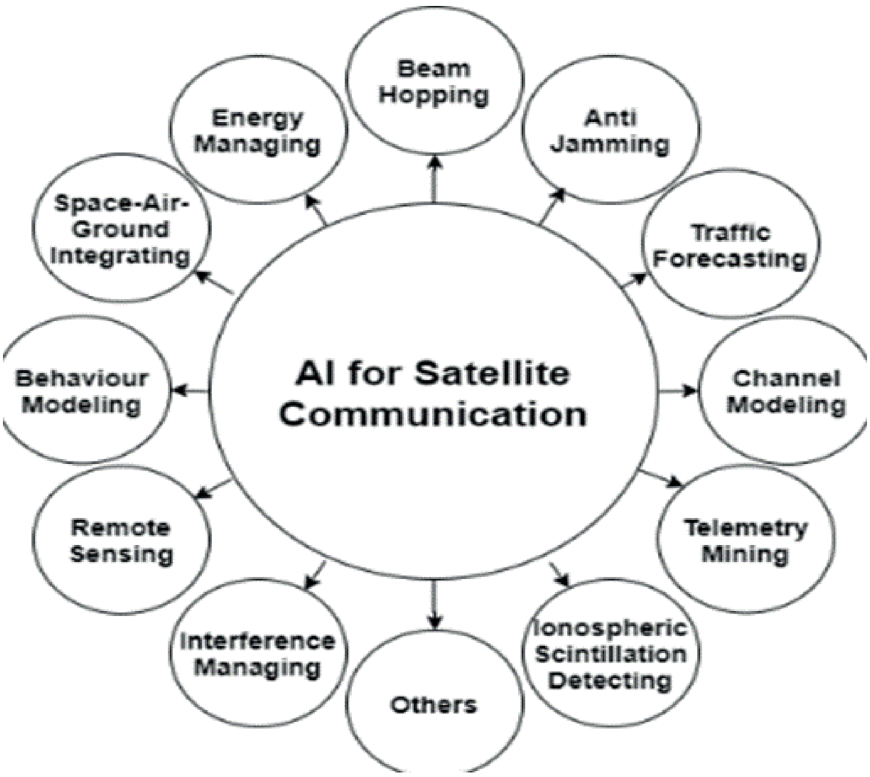

Figure 4. AI for satellite communication[42,43]

Case Study 6: Future Trends in Autonomous Air Traffic Management

Overview: as air traffic continues to grow, AI-powered autonomous systems are emerging to manage airspace efficiently, reducing human workload and errors.

Implementation: a research institute developed an AI-powered autonomous air traffic management system that integrates satellite data, ADS-B signals, and IoT sensors to coordinate aircraft movements without human intervention.

Results:

- 40 % reduction in human workload for air traffic controllers.
- Automated conflict detection and resolution, preventing mid-air collisions.
- Improved flight efficiency with self-optimized routes based on AI predictions.

Impact: Autonomous AI-driven air traffic management is the future of aviation, promising safer, more efficient, and self-regulated global airspace.

Conclusions

These six case studies highlight the "*transformative power of AI and satellite-based monitoring*" in aviation. From "*enhancing security to reducing congestion*" and "*improving disaster response*", AI is revolutionizing air traffic surveillance worldwide.

Application in Emergency Response

Disaster management represents a critical societal concern, focusing on the rescue of individuals in distress and the minimization of damage inflicted by catastrophic events. The deployment of satellite imagery analysis is essential for precise damage evaluation and the formulation of effective emergency response strategies.[25,67,68] Additionally, real-time air traffic data can provide significant insights for extensive surveillance efforts in emergency response and catastrophe monitoring. Such data encompasses vital information, including the ramifications of the disaster on air traffic, the status of secure zones at airports, the evacuation protocols for aircraft based on their respective airlines, flight cancellation updates, and the operational status of ground activities. These resources play a crucial role in reducing the time required to locate manageable resources amidst an escalating spread of disease and constrained economic support due to political factors. Furthermore, cost-effective public research drones can be efficiently employed to relay near real-time surveillance data when utilized appropriately. In the event of a hurricane outbreak, it is crucial to allocate sufficient time for safety, as the objects requiring attention are often limited. This information underscores the significance of harnessing such critical data, particularly concerning air traffic, in managing disaster responses effectively.[69]

In addition to the significance of this information, the processing of satellite images utilizing advanced machine learning techniques presents notable challenges. The typical duration for processing high-resolution satellite images may extend over several days. In instances of an outbreak or disaster, the constraints imposed by time, alongside the inability to access payment options, may lead to the forfeiture of access to commercial systems. Nonetheless, the warp-translation method of deep learning techniques introduced in this research permits the seamless and automated co-registration and masking of disparate satellite images acquired at different times by various sensors. With the aid of simultaneous cloud-based implementation, the average processing duration for a single high-resolution satellite image is reduced to under 10 seconds.[70,71] For urgent response requirements, satellite images can even be processed on the same day using materials from public or government-owned satellites. In addition to capturing images pre- and post-disaster, the methodologies developed herein are also applicable to various change detection and regularly updated surveillance scenarios, including monitoring refugee movements, alterations at nuclear test sites, and other specified needs.

Monitoring Air Traffic Patterns

In this section, we provide illustrations of experiments conducted utilizing substantial quantities of air traffic tracking data. These experiments were centered on the observation of traffic within specific scenarios, functioning as baseline assessments to evaluate the efficacy of the integrated access mechanism for the artificial intelligence system, while also demonstrating its operational scale and performance.[24]

Traffic Flow Pattern

This investigation of the East China Sea region reveals the substantial tailwind influencing the traffic patterns of the East-West Corridor (EWC) and the potential strategies for Korean air carriers to mitigate flight delays. The graph on the left illustrates the average weekly profile of air traffic density within the 125E air corridor. Conversely, the graph on the right presents the average ground speed profile for flights traversing the identical 125E air corridor, with the data representing flights that have been averaged. An analysis of both graphs indicates that during the early morning hours over the Asian continent, troughs of an eastbound jet stream have formed, producing significantly stronger-than-average tailwinds. This phenomenon is especially pronounced during the winter months. Consequently, the air traffic originating from Japan, South Korea, Hong Kong, and Taiwan enroute to the Americas adopts an optimal great circle route, passing just north of the islands of Iwo Jima, Rota, and Tinian, before making landfall in the Aleutians on the northwestern Pacific coast of Canada.

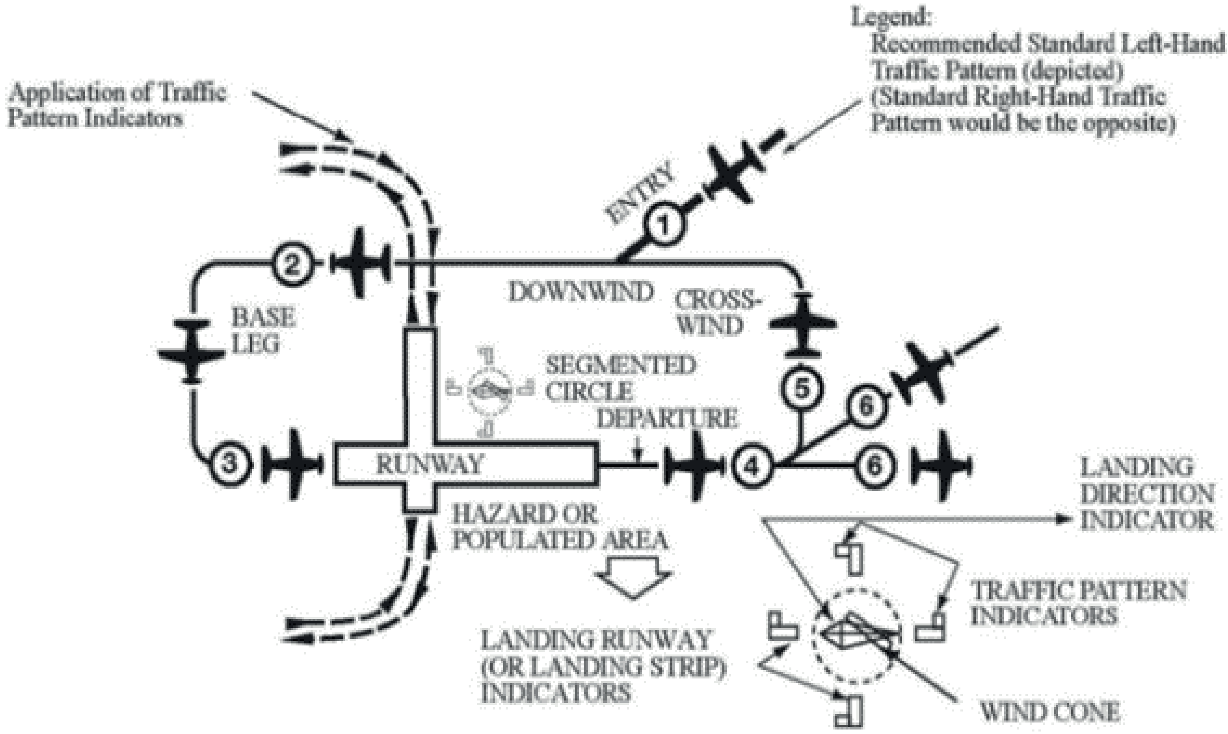

Figure 5. Air traffic pattern[22,72]

Future Directions

The emergence of artificial intelligence and machine learning revolutionized many fields of operational interest, including satellite imagery processing. The emergence of these trends and the integration of nano- and microelectronics in satellite technology, coupled with the enhancement of sensors, has resulted in satellites having the capability of field of view and quality of coverage needed at low densities required for air traffic situation awareness at low cost. The future of AI to enable ubiquitous, high-frequency, high-quality surveillance of the global traffic system has the potential to assist aviation in achieving its optimal safety performance. By combining data sources processed by satellite data, AI surveillance can be conducted down to 5 NM, and with multimodal data sources, tracking can be correlated across different surveillance domains.[57,73]

Several interesting possible future directions of development were identified from the day. With advances in nanotechnology driving down the cost of satellite hardware and more capable, suitable sensors on the horizon, the aviation industry could benefit in at least two fundamental areas should a practical solution be realized. First, ubiquitous, live, high-frequency surveillance could enable a range of efficiencies for the industry, while new developments and accurate image capturing could add a level of safety assurance, such as monitoring the integrity of the flight paths versus the tire track measured drawing and other daily life fields. However, the road to discovery is filled with many technological, ethical, legal, and operational challenges, including collaborative innovation involving the testing of new hardware for aviation applications.[54] We welcome your constructive input on the discussion about whether the idea presented can happen and what the challenges and new technology will be to further research and investment in the future. For universal information, the ideas presented are conferred to the public regulators and air navigation authorities to develop the network to incorporate it into the ATM concept.

Current Technologies and Innovations

This chapter has provided insight into the status quo of satellite and aerial surveillance and has examined a variety of approaches. AI provides a cost-effective approach to increase the capacity of the ATC system. With modern, "lateral-thinking" AI algorithms, even the use of less advanced satellites will still result in huge improvements in ADS-B signal accuracy and quantity. Furthermore, using advanced machine learning techniques and "big data" analytics can greatly improve the outcomes of the use of any satellite. Machine learning can also be used to predict future unclassified satellite capabilities. Significantly, AI can be used for free tracking data that is detected between the occasional gaps in ADS-B coverage. Performance can be ascertained using mixed vector results evaluating the performance of the various change detection algorithms for widespread checks of the routes.

Future Trends and Innovations

These emerging trends in AI relate back to our original need of enhancing the capabilities of air traffic surveillance. In lieu of advanced detection algorithms, the future of air traffic surveillance relies on predictors of satellite technologies and the integration of AI. With the declassification of satellite technology, more countries are anticipated to have the capability to launch satellites. The space sector is also moving toward very large constellations and mega-constellations in low Earth orbit, the use of robots for autonomously maintaining satellites, and the in-orbit satellite servicing for refueling and repair, and even remote artificial intelligence-based self-healing satellites. These trends may promote a shift away from ground station monitoring of satellite data and into a computerized environment. In addition, there is benefit in continuous monitoring of detection speed and accuracy in tracking fixed-wing aircraft. As new changes are made, newer satellites are launched and international regulations are adjusted, a greater emphasis on comprehensive AI is needed. This may encourage collaboration between tech companies, governmental space agencies, and international coordinating organizations. In line with trend monitoring, it is also likely that regulation of policy will impact the speed of the adoption of new technology. With every new system, the satellite system is reliant on a new field of expertise that would require the training and education of new members.

Advancements in Satellite Technology

Today, many nations deploy their own remote sensing capabilities using Earth observation and navigational satellites to monitor their airspace. Satellite imagery technology is currently in a state of rapid evolution. A new generation of Earth-observing satellites is equipped with sensors that incorporate enhanced imaging resolution and adaptive data processing capabilities. In addition, big internet companies and start-up space companies are actively investing in the construction of satellite constellations that would provide near real-time high-resolution images suitable for airborne and maritime traffic surveillance. The constellation of surveillance satellites, coupled with well-designed adaptive data processing techniques, can obviate the delay associated with the downlink and intervention of human-in-the-loop operations, providing enough information to monitor in-flight aircraft and to take appropriate measures to ensure aviation safety against any contingency (figure 6).

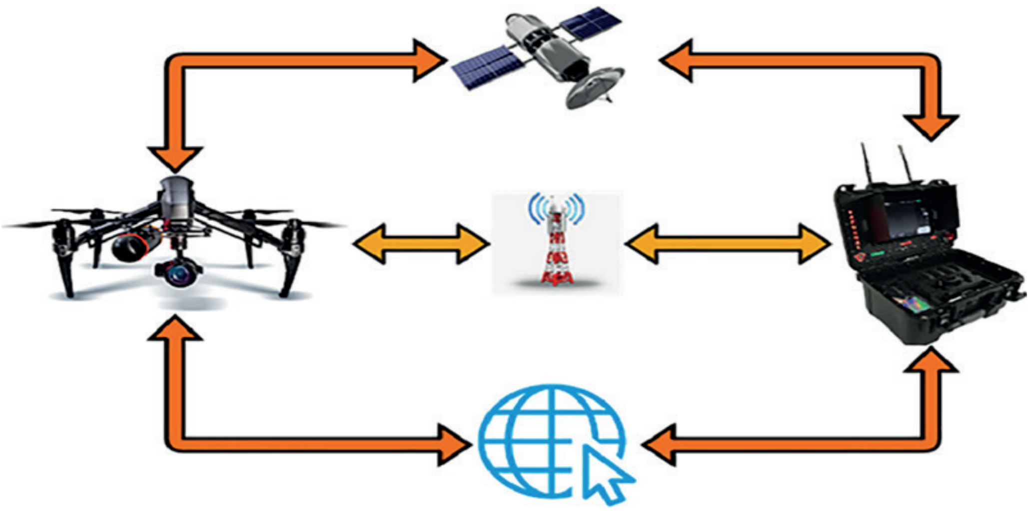

Figure 6. Components of technovation[74]

With the anticipated benefits offered by space-based air traffic surveillance, the integration of satellite-based airspace surveillance data with ground-based data becomes a new challenging field. The current development has opened the era of integrating space-based air traffic surveillance with other sources of data to offer the most effective means of achieving a more holistic view of global aviation. However, the tracking of all expected aircraft from space is an enormous data handling task and requires very powerful ground-based processing and analytics. Extracting useful and meaningful traffic information from received surveillance data is a difficult task that will challenge the performance of ground systems for data processing and efficiency. Analytical tools must be in place to manage the overload of data received from aircraft position reports and other related surveillance data, and to minimize the amount of hardware required to operate space-based air traffic surveillance.[42] The potential environmental impact of launching satellites in large numbers into orbit is also quite high, and it is better practice to also consider other techniques for monitoring air traffic, such as developing more efficient and sustainable use of existing ground and airborne equipment, rather than launching a large number of satellites as part of the required airspace access management.

Potential Applications in Aviation Industry

AI-powered satellite imagery processing holds great potential for both the aviation industry and the larger global service transportation sector. In the short-term future, organizations can utilize insights from

https://doi.org/10.62486/latia202580 ISSN: 3046-403X

AI-powered imagery processing to conduct predictive maintenance, optimize routes considering congestion and the environment, monitor aircraft for security purposes, noise pollution monitoring, and cabin cleaning schedules, provide destination recommendations to passengers, and monitor urban traffic intersection activity for a better cabbing experience.[53] The aviation industry can use these operational insights from AI and satellite imagery analysis to harness and depend upon data for operations and better decision-making rather than only using rule-based systems. Satellite-based data can be integrated into existing air traffic control systems at centralized locations, and gap modelling can be extended to add additional air traffic frequency flights between two locations to develop potential future air traffic in China and Southeast Asia.

New, previously unavailable datasets in real-time for in-flight tracking or modelling can be leveraged by addressing radar malfunctions in various developing nations. Larger data requests require partnerships between technology firms, government agencies, and public and private transportation service companies (figure 7). Subcontracts, licenses, and retainer agreements are established with large and small aviation and beyond-visual line-of-sight drone companies to analyze their raw data for business intelligence, reporting, and compliance needs. AI-powered satellite imagery processing does possess the potential to disrupt the aviation industry. In addition to proposed applications, future possible news channels may display decreased itineraries caught in real-time data processing, not only adding complementary services to existing air traffic websites but also offering a unique combination of air traffic monitoring and chance-taking control.[52,53,74] Legal and economic frameworks are required for accelerating road traffic and satellite image processing solutions.

Figure 7. AI in space exploration[44]

Limitations of the Study

Data constraints: as mentioned before, the constraints in available data could only be overcome by opting for very low-resolution preprocessed satellite imagery, and therefore decreasing the amount of detail present in our dataset. Algorithm constraints: processing the huge amounts of data, we had to downsize our dataset and opted for a Random Forest classifier due to better performance in terms of accuracy, considering also the temporal modulation of flight behaviour. Overfitting could occur since copies of the same flight data were used for both training and testing. Also, the algorithm, implemented in optimizing and minimizing dimensions, could be prone to bias when detecting a few flights or when dealing with spatial data that is rare. Criticism for future research: this research is conducted under the assumption that satellite imagery is unbiased. There are two potential biases we see that could possibly affect our results in the form of ambiguity. Although not discussed in previous literature, ambiguity in satellite imagery used in this study or human error when labeling an aircraft could affect our results.

Therefore, in future research, one anticipation is repeating improvements and conducting an inter-rater reliability analysis between expert researchers disclosing the satellite imagery data and the domestic commercial and domestic militarized aircraft tracking in the airspace. Trends and distribution of results interpretation: the age and allocation of flight activities are not within the scope of this research because our study concentrated on tracking flights and aircraft decentralized by time. Moreover, we could not predict the extent of security and defence during air traffic surveillance, as well as their trends in the country, due to the limitations in capabilities and algorithms. The reason for the large number of workouts detected is technical, given the spatial location; the furthest urban area in America is traversing from one suburban area in Europe. For future studies, it is recommended to conduct convolutional neural networks with convolutional Long Short-

Term Memory that should process and decide on the temporal features of flights, located by longitude and latitude, far and near to urban areas, as well as learning capability.

The integration of algorithms and satellite surveillance images offers the potential to catch any unusual activities or airspace changes over the ocean and in remote areas. However, various technical, operational, and regulatory limitations must be addressed. This chapter reveals the underlying limitations after an in-depth investigation. It only deals with the scope of these limitations. A comprehensive investigation into the concept, design, and development of AI technology for global traffic surveillance using satellite imagery has so far been documented. Despite its potential, AI and machine learning algorithms have inherent boundaries, especially when they are based on satellite images. The following outlines the limitations related to AI-powered satellite imagery processing in the context of surveillance, as performed in several case studies.

Current satellite images are affected by degraded data in the original digital image. Data from the Virgin Islands in the Caribbean are obtained to show how limited data can influence synthetic images' photogrammetry analysis and position solutions from AI algorithms and their consequences. To run AI algorithms, data must be well-coordinated, and accurate and precise data are essential in every surveillance process. Unsuitable AI training may lead to biased outcomes when evaluating surveillance images, resulting in incorrect reporting and potentially unfair decisions. Furthermore, AI object recognition from electronic images may raise individual rights and privacy concerns, increasing the likelihood of drastically more surveillance satellites being destroyed in the future. Ethical evaluation and artificial intelligence studies on satellite surveillance rules, activities, privacy, and security are lacking. Viewing images in the public domain or using commercially available satellite images is highly subjective concerning ethics. There are numerous social and regulatory regulations in this regard, yet the problem persists. To the best of my knowledge, ethics and the use of AI are not typically addressed in this manner in satellite surveillance operations.

CONCLUSIONS

The integration of AI-powered satellite imagery processing in global air traffic surveillance represents a transformative advancement in aviation technology. This study developed an air traffic surveillance system leveraging multiple data inputs, each offering distinct advantages in computational efficiency and processing time. The proposed system, currently in its experimental stage, demonstrates the applicability of Artificial Intelligence (AI) and Machine Learning (ML)—two of the most prominent Industry 4.0 technologies—in air traffic monitoring. The results obtained highlight the potential for AI-driven surveillance systems to complement and enhance traditional radar- and ADS-B-based tracking, providing valuable insights that stakeholders can adopt to improve air traffic management. Monitoring aircraft efficiently is critical for ensuring safe, secure, and optimized air traffic operations. Advancements in real-time observation technologies now enable more accurate and immediate decision-making, not only by human air traffic controllers but also by autonomous AI-based monitoring systems. As the aviation industry continues to evolve, all stakeholders—air traffic controllers, airlines, regulatory bodies, and technology providers—must actively integrate AI-powered solutions to enhance situational awareness, reduce airspace congestion, and improve overall operational efficiency. This includes both air-to-air and air-to-ground surveillance strategies, ensuring comprehensive coverage of global airspace.

The proposed air traffic surveillance system integrates image processing, object detection, and deep learning with existing radar and ADS-B data, offering a hybrid approach to aircraft monitoring. As a prototype, it serves as a foundation for further development, aiming to complement existing air traffic surveillance frameworks while initiating new discussions in the aviation surveillance community. The ability to process satellite imagery for real-time aircraft detection and tracking enhances current methodologies, allowing for better coverage of remote and non-radar regions. Despite the promising results achieved in this study, several technical limitations were identified. One key challenge is the system's performance under adverse weather conditions and nighttime operations. To ensure continuous 24/7 monitoring, future iterations of this surveillance system must incorporate infrared camera sensors and radar-based vision techniques, allowing reliable aircraft detection in low-visibility conditions. Additionally, improvements in object detection accuracy and AI model efficiency will further refine the system's effectiveness. Moving forward, continued research and technological advancements will be essential to fully operationalize AI-powered satellite imagery for global air traffic surveillance. The insights gained from this study provide a solid foundation for future developments, ensuring that AI-driven air traffic management becomes a cornerstone of next-generation aviation safety and efficiency. By leveraging AI, satellite data, and automation, air traffic surveillance can evolve into a more adaptive, predictive, and intelligent system, paving the way for a safer and more connected global airspace.

RECOMMENDATIONS

This study has demonstrated that advanced machine learning techniques can be used to help manage air traffic logistics in areas not equipped with traditional traffic surveillance infrastructure by using inputs from machine vision techniques to build a multi-sensor aerial surveillance picture base. Advanced computing and AI techniques in combination could be developed further to offer better analysis and decision-making capabilities in near real-time. Combined with policy adaptations to allow the remote operation of commercial UAVs by licensed pilots after some further technological and psychological barriers are overcome, the technology discussed could offer capacity benefits in aerial logistics in heavily built-up areas such as urban environments or manufacturing and logistics facilities to name a few examples. The potential contribution of this research is the exploration of using a surveillance solution that is not tied to physical infrastructure and can work with relatively modest surveillance resources. The approach might be used to develop a surveillance picture in environments where there are other sensor inputs available to complement a light, low-risk imaging station. Deployment of advanced, automated, machine learning techniques in the kind of minimally equipped surveillance system discussed will likely require a little more breakthrough progress in outer research areas, for example, the development of collaborative information infrastructure to enable meaningful sharing of large amounts of complex data across national borders or industrial estates.

Therefore, the results set a direction for the continued advance of these non-core surveillance systems when used in conjunction with other sensor systems. The kind of advanced mapping of picture feature spaces might also assist in other work that seeks to correlate data associated with different sensors. For example, the analysis might correlate with an automated diagnosis of UAVs, in a remote health check, with in-field surveillance of the same UAV. Coordination between manned and unmanned aviation systems is particularly a policy decision that is likely to occur in stages to enable continuous adaptation to proven capabilities over time while dealing with potential safety and security concerns. This study presents an initial step for the kind of traffic surveillance infrastructure needed to operate commercial UAVs more autonomously over time.

REFERENCES

1. Sarker IH, Khan AI, Abushark YB, Alsolami F. Internet of things (iot) security intelligence: a comprehensive overview, machine learning solutions and research directions. Mob Networks Appl. 2023;28(1):296–312.

2. Knutti R, Furrer R, Tebaldi C, Cermak J, Meehl GA. Challenges in combining projections from multiple climate models. J Clim. 2010;23(10):2739–58.

3. Ferreira PVR, Paffenroth R, Wyglinski AM, Hackett TM, Bilén SG, Reinhart RC, et al. Multiobjective reinforcement learning for cognitive satellite communications using deep neural network ensembles. IEEE J Sel Areas Commun. 2018;36(5):1030–41.

4. Sharma N, Sharma R, Jindal N. Machine learning and deep learning applications-a vision. Glob Transitions Proc. 2021;2(1):24-8.

5. Baustert P, Othoniel B, Rugani B, Leopold U. Uncertainty analysis in integrated environmental models for ecosystem service assessments: Frameworks, challenges and gaps. Ecosyst Serv. 2018;33:110–23.

6. Refsgaard JC, van der Sluijs JP, Højberg AL, Vanrolleghem PA. Uncertainty in the environmental modelling process–a framework and guidance. Environ Model Softw. 2007;22(11):1543–56.

7. Kayusi F, Kasulla S, Malik SJ, Wasike JA, Lungu G, Mambwe H, et al. Advanced AI , Machine Learning and Deep Learning Techniques for Climate Change Studies : A Review. 2024;4010(6):101–8.

8. Sahoo S, Singha C, Govind A. Advanced prediction of rice yield gaps under climate uncertainty using machine learning techniques in Eastern India. J Agric Food Res. 2024;18:101424.

9. Teng J, Jakeman AJ, Vaze J, Croke BFW, Dutta D, Kim S. Flood inundation modelling: A review of methods, recent advances and uncertainty analysis. Environ Model Softw. 2017;90:201–16.

10. Fiseha BM, Setegn SG, Melesse AM, Volpi E, Fiori A. Impact of climate change on the hydrology of upper Tiber River Basin using bias corrected regional climate model. Water Resour Manag. 2014;28:1327–43.

11. Kulinich M. A Markov chain method for weighting climate model ensembles and uncertainty estimation on spatially explicit data. UNSW Sydney; 2023.

12. Tramblay Y, Ruelland D, Somot S, Bouaicha R, Servat E. High-resolution Med-CORDEX regional climate model simulations for hydrological impact studies: a first evaluation of the ALADIN-Climate model in Morocco. Hydrol Earth Syst Sci. 2013;17(10):3721–39.

13. de Brogniez D, Ballabio C, Stevens A, Jones RJA, Montanarella L, van Wesemael B. A map of the topsoil

organic carbon content of Europe generated by a generalized additive model. Eur J Soil Sci. 2015;66(1):121–34.

14. Roy CJ, Oberkampf WL. A comprehensive framework for verification, validation, and uncertainty quantification in scientific computing. Comput Methods Appl Mech Eng. 2011;200(25–28):2131–44.

15. Allen JI, Somerfield PJ, Gilbert FJ. Quantifying uncertainty in high-resolution coupled hydrodynamic-ecosystem models. J Mar Syst. 2007;64(1–4):3–14.

16. Verburg PH, Neumann K, Nol L. Challenges in using land use and land cover data for global change studies. Glob Chang Biol. 2011;17(2):974–89.

17. Boer MM, Nolan RH, Resco De Dios V, Clarke H, Price OF, Bradstock RA. Changing Weather Extremes Call for Early Warning of Potential for Catastrophic Fire. Earth's Futur. 2017;5(12):1196–202.

18. Al Kharusi S, BenZvi SY, Bobowski JS, Bonivento W, Brdar V, Brunner T, et al. SNEWS 2.0: a next-generation supernova early warning system for multi-messenger astronomy. New J Phys. 2021;23(3):31201.

19. Noguera I, Vicente-Serrano SM, Domínguez-Castro F. The rise of atmospheric evaporative demand is increasing flash droughts in Spain during the warm season. Geophys Res Lett. 2022;49(11):e2021GL097703.

20. Hoylman ZH, Bocinsky RK, Jencso KG. Drought assessment has been outpaced by climate change: empirical arguments for a paradigm shift. Nat Commun. 2022;13(1):2715.

21. Cuevas S. Examining climate change adaptation measures: an early warning system in the Philippines. Int J Clim Chang Strateg Manag. 2012;4(4):358–85.

22. Anderson-Berry L, Achilles T, Panchuk S, Mackie B, Canterford S, Leck A, et al. Sending a message: How significant events have influenced the warnings landscape in Australia. Int J Disaster Risk Reduct. 2018;30(March):5–17.

23. Hartley D, Nelson N, Walters R, Arthur R, Yangarber R, Madoff L, et al. The landscape of international event-based biosurveillance. Emerg Health Threats J. 2010;3(1):7096.

24. Bury TM, Sujith RI, Pavithran I, Scheffer M, Lenton TM, Anand M, et al. Deep learning for early warning signals of tipping points. Proc Natl Acad Sci. 2021;118(39):e2106140118.

25. Basher R. Global early warning systems for natural hazards: systematic and people-centred. Philos Trans R Soc a Math Phys Eng Sci. 2006;364(1845):2167–82.

26. Li Y, Sun X, Zhu X, Cao H. An early warning method of landscape ecological security in rapid urbanizing coastal areas and its application in Xiamen, China. Ecol Modell. 2010;221(19):2251–60.

27. Nijp JJ, Temme AJAM, van Voorn GAK, Kooistra L, Hengeveld GM, Soons MB, et al. Spatial early warning signals for impending regime shifts: A practical framework for application in real-world landscapes. Glob Chang Biol. 2019;25(6):1905–21.

28. Šakić Trogrlić R, van den Homberg M, Budimir M, McQuistan C, Sneddon A, Golding B. Early warning systems and their role in disaster risk reduction. In: Towards the "perfect" weather warning: bridging disciplinary gaps through partnership and communication. Springer International Publishing Cham; 2022. p. 11–46.

29. Pulwarty RS, Sivakumar MVK. Information systems in a changing climate: Early warnings and drought risk management. Weather Clim Extrem. 2014;3:14–21.

30. Castiglioni I, Rundo L, Codari M, Di Leo G, Salvatore C, Interlenghi M, et al. AI applications to medical images: From machine learning to deep learning. Phys medica. 2021;83:9–24.

31. Zohuri B, Rahmani FM. Artificial intelligence driven resiliency with machine learning and deep learning components. Japan J Res. 2023;1(1).

32. Tapeh ATG, Naser MZ. Artificial intelligence, machine learning, and deep learning in structural engineering:

a scientometrics review of trends and best practices. Arch Comput Methods Eng. 2023;30(1):115–59.

33. Soori M, Arezoo B, Dastres R. Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cogn Robot. 2023;3:54–70.

34. Callaghan M, Schleussner C-F, Nath S, Lejeune Q, Knutson TR, Reichstein M, et al. Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies. Nat Clim Chang. 2021;11(11):966–72.

35. Waaswa A, Oywaya Nkurumwa A, Mwangi Kibe A, Ngeno Kipkemoi J. Climate-Smart agriculture and potato production in Kenya: review of the determinants of practice. Clim Dev. 2022;14(1):75–90.

36. Sarker IH. Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. SN Comput Sci. 2021;2(6):420.

37. Balyen L, Peto T. Promising artificial intelligence-machine learning-deep learning algorithms in ophthalmology. Asia-Pacific J Ophthalmol. 2019;8(3):264–72.

38. Taye MM. Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. Computers. 2023;12(5):91.

39. Ley A, Haehnel P, Bormann H. Addressing the challenges of climate scenario-based impact studies in modelling groundwater recharge on small barrier islands at the German North Sea coast. J Hydrol Reg Stud. 2023;50:101578.

40. Melinda V, Williams T, Anderson J, Davies JG, Davis C. Enhancing waste-to-energy conversion efficiency and sustainability through advanced artificial intelligence integration. Int Trans Educ Technol. 2024;2(2):183–92.

41. Kim KB, Kwon H-H, Han D. Bias correction methods for regional climate model simulations considering the distributional parametric uncertainty underlying the observations. J Hydrol. 2015;530:568–79.

42. Borra S, Thanki R, Dey N. Satellite image analysis: clustering and classification. Springer; 2019.

43. Taulli T, Oni M. Artificial intelligence basics. Springer; 2019.

44. Rao VS, Satish MA, Prasad MB. Artificial intelligence: Principles and applications. Leilani Katie Publication; 2024.

45. Koumetio Tekouabou SC, Diop EB, Azmi R, Chenal J. Artificial intelligence based methods for smart and sustainable urban planning: a systematic survey. Arch Comput Methods Eng. 2023;30(2):1421–38.

46. Ganeshkumar C, Jena SK, Sivakumar A, Nambirajan T. Artificial intelligence in agricultural value chain: review and future directions. J Agribus Dev Emerg Econ. 2023;13(3):379–98.

47. Goodell JW, Kumar S, Lim WM, Pattnaik D. Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. J Behav Exp Financ. 2021;32:100577.

48. Chowdhary CL, Alazab M, Chaudhary A, Hakak S, Gadekallu TR. Computer vision and recognition systems using machine and deep learning approaches: fundamentals, Technologies and Applications. Institution of Engineering and Technology; 2021.

49. Bolon-Canedo V, Remeseiro B. Feature selection in image analysis: a survey. Artif Intell Rev. 2020;53(4):2905–31.

50. Li W, Hsu C-Y. GeoAI for large-scale image analysis and machine vision: recent progress of artificial intelligence in geography. ISPRS Int J Geo-Information. 2022;11(7):385.

51. Tuia D, Schindler K, Demir B, Camps-Valls G, Zhu XX, Kochupillai M, et al. Artificial intelligence to advance Earth observation: a perspective. arXiv Prepr arXiv230508413. 2023;

https://doi.org/10.62486/latia202580 ISSN: 3046-403X

52. Sisodiya N, Dube N, Thakkar P. Next-generation artificial intelligence techniques for satellite data processing. Artif Intell Tech Satell Image Anal. 2020;235–54.

53. Chuvieco E. Fundamentals of satellite remote sensing: An environmental approach. CRC press; 2020.

54. Fourati F, Alouini M-S. Artificial intelligence for satellite communication: A review. Intell Converg Networks. 2021;2(3):213–43.

55. ang Y, Fu EY, Zhai X, Yang C, Pei F. Introduction of artificial Intelligence. In: Intelligent Building Fire Safety and Smart Firefighting. Springer; 2024. p. 65–97.

56. Sun Z, Sandoval L, Crystal-Ornelas R, Mousavi SM, Wang J, Lin C, et al. A review of earth artificial intelligence. Comput Geosci. 2022;159:105034.

57. Russo A, Lax G. Using artificial intelligence for space challenges: A survey. Appl Sci. 2022;12(10):5106.

58. Lucci S, Kopec D, Musa SM. Artificial intelligence in the 21st century. Mercury learning and information; 2022.

59. Tuia D, Schindler K, Demir B, Zhu XX, Kochupillai M, Džeroski S, et al. Artificial Intelligence to Advance Earth Observation: A review of models, recent trends, and pathways forward. IEEE Geosci Remote Sens Mag. 2024;

60. Karamitrou A, Sturt F, Bogiatzis P, Beresford-Jones D. Towards the use of artificial intelligence deep learning networks for detection of archaeological sites. Surf Topogr Metrol Prop. 2022;10(4):44001.

61. waanga C, Mulenga J, Lubinda M, Siame M, Kaliba-Chishimba K, Mulenga MC, et al. COVID-19 Pandemic and Its Implications on Small and Medium Enterprises (SMEs) Operations in Zambia. J Bus Adm Res. 2021;10(1):32-40.

62. Casero-Ripollés A. Impact of Covid-19 on the media system. Communicative and democratic consequences of news consumption during the outbreak. Casero-Ripollés, Andreu (2020)"Impact Covid-19 media Syst Commun Democr consequences news Consum Dur outbreak" El Prof la Inf. 2020;29(2):e290223.

63. Mwiinga B, Sikazwe W, Kangwa V, Katebe M, Matafwali M. Operational strategies of small medium enterprises (SMEs) in Lusaka Zambia-post Covid-19. 2020;

64. Nchanji EB, Lutomia CK, Chirwa R, Templer N, Rubyogo JC, Onyango P. Immediate impacts of COVID-19 pandemic on bean value chain in selected countries in sub-Saharan Africa. Agric Syst. 2021;188:103034.

65. Salcedo-Sanz S, Ghamisi P, Piles M, Werner M, Cuadra L, Moreno-Martínez A, et al. Machine learning information fusion in Earth observation: A comprehensive review of methods, applications and data sources. Inf Fusion. 2020;63:256–72.

66. Fang H, Baret F, Plummer S, Schaepman-Strub G. An overview of global leaf area index (LAI): Methods, products, validation, and applications. Rev Geophys. 2019;57(3):739–99.

67. Fan L, Li J, Pan Y, Wang S, Yan C, Yao D. Research and application of smart grid early warning decision platform based on big data analysis. In: 2019 4th International Conference on Intelligent Green Building and Smart Grid (IGBSG). IEEE; 2019. p. 645–8.

68. Ceccato P, Connor SJ, Jeanne I, Thomson MC. Application of geographical information systems and remote sensing technologies for assessing and monitoring malaria risk. Parassitologia. 2005;47(1):81–96.

69. Sheehan MC, Fox MA. Early warnings: the lessons of COVID-19 for public health climate preparedness. Int J Heal Serv. 2020;50(3):264–70.

70. Cools J, Innocenti D, O'Brien S. Lessons from flood early warning systems. Environ Sci Policy. 2016;58:117-22.

71. Berg A, Borensztein E, Pattillo C. Assessing early warning systems: how have they worked in practice? IMF Staff Pap. 2005;52(3):462–502.

72. Naidu S, Sajinkumar KS, Oommen T, Anuja VJ, Samuel RA, Muraleedharan C. Early warning system for shallow landslides using rainfall threshold and slope stability analysis. Geosci Front [Internet]. 2018;9(6):1871–82. Available from: https://doi.org/10.1016/j.gsf.2017.10.008

73. Hassanien AE, Darwish A, Abdelghafar S. Machine learning in telemetry data mining of space mission: basics, challenging and future directions. Artif Intell Rev. 2020;53(5):3201–30.

74. Nakhle F, Harfouche AL. Ready, Steady, Go AI: A practical tutorial on fundamentals of artificial intelligence and its applications in phenomics image analysis. Patterns. 2021;2(9).

FINANCING
The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION
Conceptualization: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Data curation: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Formal analysis: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Research: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Methodology: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Software: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Validation: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Display: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Drafting - original draft: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.
Writing - proofreading and editing: Fredrick Kayusi, Petros Chavula, Linety Juma, Rashmi Mishra.