The Role of Data Science and Machine Learning in Military Aircraft Threat Detection Systems

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Abstract

Data science (DS) and machine learning (ML) have become increasingly relevant in the advancement of military aviation threat detection systems (TDS). As enemy threats aimed at destroying aircraft and their aircrew have become more advanced and undetectable, the need for constant improvements to threat detection systems (TDSes) to protect aircraft and aircrew grows. This paper investigates the evolution of threat detection systems from the World War II era to today's fifth-generation fighters. It examines the implementation of DS and ML in various TDS sensors, including ultraviolet (UV), infrared (IR), radar, and laser detection systems. We also explore the types of threats that TDSes face. These threats include air-to-air and surface-to-air missiles fired from adversarial aircraft and ground-based weapons systems. Lastly, we investigate future applications in TDS with improved technologies, including upgraded sensors for improved differentiation of threats from background clutter and deep reinforcement learning (DRL) for autonomous decision-making in combat scenarios.

Introduction

Military pilots and their fighter aircraft are threatened by constantly evolving aerial threats from adversarial aircraft such as air-to-air missiles or sea-based and ground-based weapons systems such as surface-to-air missiles fired from ships, submarines, and land-based sites. The never-ending advancements in stealth technology, missile guidance, and electronic warfare present a critical challenge to maintaining air superiority; timely detection of threats and a response by the pilot and the aircraft are difficult. However, threat detection systems (TDS) are implemented into military aircraft, encompassing advanced sensors and technologies to identify airborne threats across various environments to ensure the safety of the pilot and the aircraft [1].

German physicist Christian Hulsmeyer first introduced the idea of detecting objects via radio waves in 1904, hoping to help avoid collisions between ships. Shortly after, in 1935, British meteorologist Robert Watson Watt pioneered radar, which consists of electromagnetic waves, to detect the distance to aircraft. On June 17 of that year, the first use of radio detection was officially recorded [2].

By the end of World War II, military aircraft were equipped with radars, the TDS at the time, capable of detecting other aircraft. These radars worked by sending signals to the target and measuring the time each signal took to return to the radar, which allowed the determination of the target's range. However, these radars suffered in accuracy when detecting aircraft flying at low altitudes; ground clutter, such as buildings and trees, would disrupt radar signals on their return to the aircraft, interfering with the detection accuracy. During the Korean conflict in the 1950s, aircraft radars were improved with airborne moving target indicators (AMTI) to mitigate the effects of ground clutter on detection accuracy. The AMTI used the Doppler frequency shift, a physical phenomenon caused by the reflection of waves on moving objects, to discriminate between moving targets, such as planes, from stationary clutter on the ground [3].
The frequency of the Doppler effect created by an object moving in the direction of the radar was higher than that of an object moving in the direction opposite of the radar [4].

In the 1970s, the first modern surveillance radar was developed, called the airborne warning and control system (AWACS), part of the Boeing E-3 Sentry. The AWACS was developed to give pilots comprehensive information about the location of friendly and enemy aircraft, with 360-degree radar coverage and a range of more than 215 nautical miles. AWACS was crucial in maintaining control of airspace to achieve air superiority in remote locations, as it could cover a surveillance area of more than 120,000 square miles when flying at 30,000 feet [5].

The field of military aerospace defense has made significant advancements in TDS and its threat-tracking abilities. With the implementation of machine learning (ML) in threat detection, TDSes have identified enemy aircraft and airborne threats by learning from prior data that describes aircraft threats. AI and ML can analyze vast amounts of data in real time, improving the efficiency and accuracy of data-driven TDSes.

While ML in military aircraft TDSes allowed the system to easily categorize what was and was not a threat, it still lacked the capability to detect state-of-the-art threats from enemies. Such state-of-the-art threats include stealth technologies and missiles, which continue to advance each year. Therefore, ML-based TDSes must acquire new data to learn about the new threats and perceive them as threats.

The shortcoming of having to train a TDS on a new threat every time was that false negatives of threats would occur. This meant that the TDS would categorize a threat as benign while it was actually deadly. Today, however, the rapid evolution of AI and ML allows TDS to detect, identify, and classify new and unknown threats in real-time, adapting to the evolving spectrum environment without requiring extensive reprogramming.

While the ability of TDSes to recognize unfamiliar threats represents a significant leap in aerial threat detection, false positives may occur as a result of the uncertain/incorrect categorization of friendly aircraft or projectiles. In response, pilots may take unnecessary countermeasures, such as shooting flares or chaffs, or performing dangerous and evasive aerial maneuvers.

Background

We provide the knowledge to better comprehend the components of threat detection systems. We start by explaining the different sensors TDS comprises, such as ultraviolet (UV) and infrared (IR) sensors. Such information is essential for understanding how airborne threats are detected and how data science and artificial intelligence fit in. We then talk about the brief history of the TDS implementation and the flaws with each development. The field of defense has introduced new TDS to actively develop new tracking solutions.

Ultraviolet Sensor. A UV sensor is a device that detects UV radiation. UV rays have shorter wavelengths and higher energy than visible light, and are invisible to the human eye. UV rays are mainly emitted by the sun [6]. UV light spans a range of wavelengths between about 10 and 400 nanometers (nm). The near UV region lies closest to visible light, including wavelengths between 200 and 400 nm. Extreme UV radiation has the shortest wavelength range, spanning the 10 to 30 nm wavelength range [7].

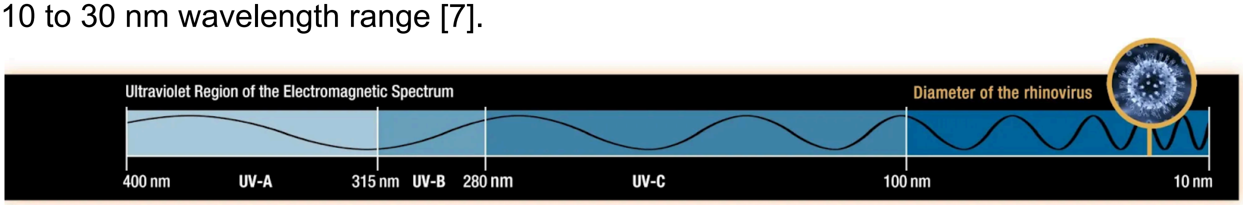

Fig. 1: A diagram of the ultraviolet region of the electromagnetic spectrum. The near UV region lies within the UV-A, UV-B, and UV-C spectral bands. The extreme UV lies within the border of the X-ray region, which is 10 nm.

In threat detection, UV sensors detect when a missile's rocket motor fires by looking at their smoke plumes, or emitted light, tracking incoming missile threats. Moreover, the extreme heat from missile exhaust produces significant radiation in the UV spectral region [8].

UV sensors provide passive, stealthy detection while not emitting signals of their own. They operate within the UV-A and UV-C spectral bands, or within 315 nm to 400 nm and 100 nm to 280 nm, as shown in Figure 1. The UV-A spectrum tracks reflective signatures, which is useful in identifying visually camouflaged adversarial aircraft or missiles. The UV-C spectrum detects missile plumes without the interference of the sun's UV radiation, meaning that it is solar-blind [9]. In TDS, the UV-C sensor can clearly distinguish UV signatures emitted by missile plumes from background environmental UV radiation.

The Hensoldt AN/AAR-60 missile launch detection system (MILDS) is an example of a modern TDS with sophisticated UV sensors. MILDS detects incoming missile threats, precisely indicating the direction of origin with maximum warning time, and automatically deploys countermeasures. Unlike radar systems, this system does not emit any signals of its own; it only collects UV radiation [10].

Infrared Sensor. An IR sensor is a device that detects IR radiation. IR rays have longer wavelengths than visible light, spanning between 760 nm and 100,000 nm [11]. The higher the wavelength, the higher the radiation of the IR rays. While humans are unable to see infrared waves, they can detect these waves as heat, as heat emits IR waves. An example of an IR sensor is thermal imaging, which allows us to see the IR waves emitting from warm objects, such as humans. Objects that are extremely hot, such as fire, also emit visible light [12].

In the air, objects which emit heat can include aircraft and missiles. Aircraft are typically hotter than the sky or the cloud background against which they are seen and appear as a bright point of IR light. When recognizing missile launches, and similar to the way UV sensors detect these, the launch is signaled with a very hot flash that can be detected. In this case, the background is likely to be the ground rather than the sky for infrared search and track systems [13]. However, IR sensors lack accuracy when detecting hot objects with high-temperature backgrounds.

IR sensors operate across multiple infrared spectrums, such as the long-wave (LWIR), medium-wave (MWIR), and short-wave (SWIR) infrared [14]. LWIR is effective at thermal imaging, which detects the naturally emitted heat from objects. MWIR is effective at detecting heat differences, making it useful for missile detection through a cluttered background. SWIR does not detect heat, but visible light, like that perceivable to the human eye [15]. SWIR complements LWIR and MWIR by improving visibility under low-light conditions [16].

These three spectrums are used on heat-seeking missiles to detect heat sources. An example of a modern IR sensor is the F-35's Electro-Optical Targeting System (EOTS). EOTS is a high-resolution, forward-looking, infrared search and track (IRST). Infrared search and track (IRST) technology allows the EOTS to detect and track heat-emitting targets without radar emissions [17].

Radar. A radar sensor is a device that emits radio waves and analyzes the reflected signals to detect and track objects in its environment. Radars operate by sending out electromagnetic waves in the microwave or radio frequency range, and then measuring the time delay of the returning signal. The timing of the returning signals allows complex algorithms to determine information about the distance, speed, size, and direction of objects.

Radar sensors in TDS include advancements such as active electronically scanned array (AESA) radars, which use the Doppler effect. AESA radars are implemented into fifth-generation fighters like the F-22 and F-35 and employ multiple transmit/receive modules to emit and receive signals concurrently, allowing for significant detection capabilities. These radars can perform rapid beam scans, which enable precise accuracy of tracking. Prior to AESA, there were passive electronically scanned array radars (PESA), which only operated on a single frequency at a time, leading to limitations in tracking multiple targets at once [18].

The Doppler effect detracts moving objects and differentiates them from stationary objects. These radars also analyze the frequency shift of reflected signals. The Doppler effect created by an object moving in the direction of the radar has a higher frequency than that of an object moving in the direction opposite of the radar [19]. The equation of the Doppler effect is

$$f_0 = f_s \frac{(v \pm v_0)}{(v \mp v_s)}$$

where f_0 is the observed frequency of sound, f_s is the source frequency, v is the velocity of sound waves, v_0 is the velocity of the observer, and v_s is the velocity of the source [53].

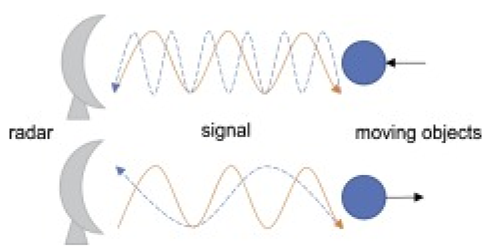

Fig. 2: Depicts the Doppler effect being created by a moving object. The waves reflected by the object moving toward the radar have a higher frequency, while the waves reflected by the object moving in the opposing direction have a lower frequency.

Laser Detection. Laser warning systems (LWS) detect and analyze laser emissions from laser-guided threats like rangefinders and target designators to provide an early warning to the pilot. When an enemy uses a laser to target an aircraft, the LWS identifies the source of the laser, its type, and the direction and elevation it is coming from. For instance, the different types of threats include laser range finders (LRF) for distance measurement, laser target designators (LTD) for target designation, and laser beam riders (LBR) for missile guidance.

A LWS usually consists of three subsystems: optical, detection, and processing. The optical subsystem is composed of mirrors and lenses to focus the optical signal on the laser detector. It could also be equipped with filters to reduce background noise, aiming to reduce false alarms. The detection subsystem includes different photosensors, such as a charge-coupled device (CCD), a complementary metal-oxide-semiconductor (CMOS), and a fast photodetector to cover the entire spectral band of the laser. The processor subsystem is the core of the LWS, consisting of digital signal processors that compare measured laser beams with prior pre-stored data to recognize the type of laser threat [20].

An example of the LWS can be seen in the AN/AAR-47B(V)2, an upgraded electronic warfare system of the AN/AAR-47, designed to protect against IR-guided and laser-guided missiles while reducing false alarms. The system includes a dynamic blanking sensor, which ignores benign, high levels of in-band irradiance energy that could overwhelm the system. As a result, false alarms are reduced. The dynamic blanking sensor also incorporates an adjunct detector to provide quick recovery whenever the system is overwhelmed [21].

Artificial Intelligence in TDSes

Artificial intelligence and machine learning have become crucial technologies in the evolution of threat detection systems, including their integration with infrared sensors, UV detection, and radar. These technologies allow for real-time analysis of large datasets, making systems more efficient in identifying and responding to threats.

Some AI-based systems excel in analyzing large volumes of data quickly, which is crucial in detecting fast-moving airborne threats such as missiles or enemy aircraft. AI can continuously improve its decision-making processes by leveraging past data and sensor inputs. Machine learning (ML), in particular, plays a critical role by enabling systems to "learn" from previous encounters and predict new threats. For example, AI can predict missile trajectories and help determine the best countermeasures before the missile gets too close [22].

Machine learning is a subset of AI that enables a machine to autonomously learn and improve using neural networks and deep learning, without being explicitly programmed, by feeding it a large amount of data [23]. TDS makes use of both supervised and unsupervised machine learning techniques. Supervised learning means that machines can recognize patterns within predetermined input-output options. In the case of TDS, this would be training the system with past encounters of threats. For instance, the Advanced Radar Threat System Variant 1 (ARTS-V1) is a training system currently used by the US Air Force to train TDS radars to detect different frequencies and waveforms. ARTS-V1 simulates the behavior of enemy radar systems, which includes specific waveform modes that are hard to detect. The aircraft crew has to decide how to react to the ARTS-V1 signals. Based on the aircrews' defensive or neutral reactions to the different signals of the training system, TDS can likely learn which signals should and should not be categorized as a threat [24]. As a result, TDS would be able to identify familiar threats accurately.

While it is not widely disclosed whether current TDSes use unsupervised learning, this type of learning is likely useful when certain threats are unknown, such as a missile or aircraft with new stealth technologies. Unsupervised learning includes analyzing and categorizing unlabeled data sets, and discovering data groupings independently without any on-the-fly guidance or instruction [25]. This type of machine learning uses self-learning algorithms without labels or prior training. There are three primary types of unsupervised learning tasks: clustering, association rules, and dimensionality reduction. Clustering is a technique for exploring raw and unlabeled data and breaking it down into clusters for similarities or differences, which is important in uncovering threat detection patterns. Association rules identify relationships within the data and the different connections between data objects. For instance, this could associate an infrared signature with a particular missile threat. Dimensionality reduction reduces the number of features in a dataset, making it easier to visualize the data. [26] In TDS, dimensionality reduction would include filtering out unnecessary information, such as weak radar signals from civilian aircraft.

AI and ML allow continuous adaptation to the threat environment. Unlike earlier TDS systems that required manual updates to recognize new types of threats, modern AI-driven systems can update their threat models in real-time. This is done through anomaly detection, like recognizing differences from previously known threats. For instance, this could include flagging enemy missiles with significantly different UV/IR radiation levels as a threat [22][27].

To minimize the occurrence of false positives in TDS, contrastive learning must be applied. Contrastive learning is a self-supervised learning technique that allows models to learn useful patterns from unlabeled data, which helps categorize data [28]. For instance, you are teaching a child how to recognize what a cat looks like. With exposure to pictures of different cats, the child learns to recognize common features of cats, such as claws, long tails, and whiskers. For TDS to reduce false positives, their sensors must learn the low-rank structure, or common characteristics, of normal data, such as allied aircraft and friendly missiles, for categorization. This way, only deviations from normal data will TDS correctly classify a threat. The absence of false positives ensures pilots can take appropriate actions without wasting valuable resources or endangering themselves by misidentifying threats.

Data Science in TDSes

Data science (DS) is used in countless fields, such as healthcare, finance, and autonomous vehicles. For instance, the healthcare field utilizes DS in medical imaging systems to detect anomalies in patients [29]. In finance, data science is used to improve the risk management of an investment or portfolio [30]. As for autonomous vehicles, data is processed to enable them to navigate complex environments safely [31]. In recent years, data science has also been applied to TDSes.

Data science combines math, statistics, programming, analytics, AI, and machine learning to study data in four main ways: descriptive, diagnostic, predictive, and prescriptive analysis. Descriptive analysis examines data to gain insights into past and present occurrences in the data environment. In TDS, descriptive analytics visualizes data to detect threats. Diagnostic analysis is a detailed data examination to uncover why a certain event happened. This type of analysis is used to investigate why TDS flagged a certain aircraft or aerial object as a threat. Predictive analysis uses past and present data to predict data patterns that may occur in the future. Threat detection systems can use predictive analysis to forecast the trajectories of hostile aircraft. Prescriptive analysis, like predictive analysis, predicts what is likely to occur in the future, but in addition, it suggests an optimum response to that outcome. In TDS, this type of analysis prompts the pilot to take countermeasures in response to detected threats.

A data scientist designs data modeling processes, creates algorithms and predictive models to extract the needed data, and analyzes data to share meaningful insights [32]. In TDS, data scientists collect and process data from TDS's different sensors. With the collected data, they design experiments to measure the effectiveness of the sensors' ability to detect threats. Moreover, they use the data to improve existing threat detection capabilities, such as distinguishing between benign and dangerous objects [33].

TDS uses data science; the system incorporates sensor fusion to integrate data from multiple sensors, allowing TDS to categorize potential threats more accurately [34].

For instance, in the F-35, advanced sensor fusion analyzes data from sensors throughout the jet and merges it into relevant information for the pilot, increasing battlespace space awareness [35]. The sensors include the Active Electronically Scanned Arrays (AESA) radar, Distributed Aperture System (DAS), Electro Optical Targeting System (EOTS), and Helmet Mounted Display System. As seen in Fig. 3, the fusion server creates a single, integrated picture of the battlefield from the various sensors. The fusion server is responsible for integrating and managing the performance of the sensors.

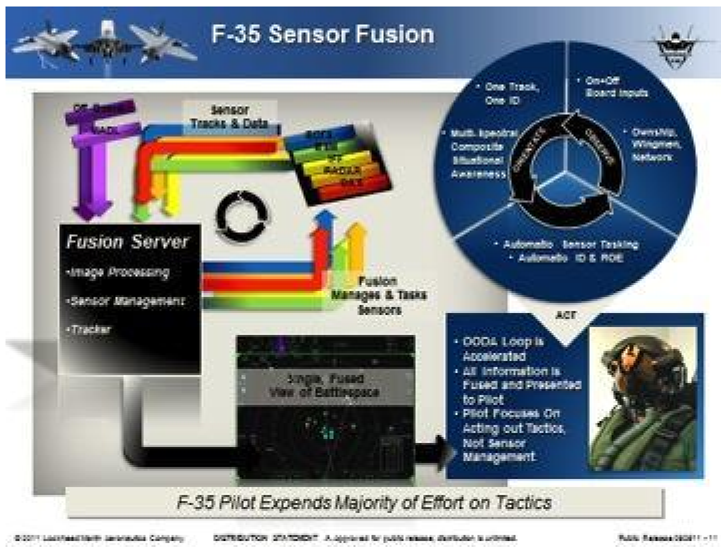

Fig. 3: A diagram of the 5th generation advanced sensor fusion suite in the F-35.

Application of AI and Data Science in Related Technologies

Data science also plays a crucial role within technologies in commercial aviation. For instance, data analytics is crucial within Traffic Alert and Collision Avoidance Systems (TCAS). TCAS monitors the airspace around an aircraft with transponders to help prevent mid-air collisions with other aircraft [36]. The system relies on a combination of various surveillance sensors to collect data on other aircraft within a threatening aerial proximity, such as range, speed, and heading [37]. TCAS sends a traffic advisory (TA) when an intruder aircraft is between 600–800 feet in altitude [38], 20–48 seconds away from colliding, and a resolution advisory (RA) within 15–35 seconds for specific maneuvers to avoid a collision. TCAS can only suggest altitude changes, not turns, to avoid traffic, as changing altitude is an effective way to avoid a midair collision. TCAS provides enough advance notice that the pilot's RA maneuver does not need to be abrupt. When done properly, passengers should not realize the maneuver occurred [39].

For instance, the Federal Aviation Administration's Airborne Collision Avoidance System X (ACAS X), meant to replace TCAS, represents a major revolution in how collision-avoiding advisories are represented. ACAS X uses a numeric table, which generates advisories based on data of real-time flight data and predictions, enhancing collision avoidance effectiveness [40]. ACAS X can use data analytics to predict future trajectories in flight paths and help prevent potential collisions. On the other hand, TCAS relies on a fixed approach to create advisories, lacking interpretation of real-time data in its decision-making process for advisories, which also means that it is unable to predict future trajectories.

For instance, ACAS X incorporates the Partially Observable Markov Decision Processes (POMDP), a mathematical framework for formulating sequential decision problems where outcomes are controlled by the pilot [37]. An MDP comprises a set of states that completely define the aircraft's position, heading, and speed, a set of actions that may be taken, such as ascending or descending, and a transition model that specifies the probability of moving from one state to another given an action. ACAS X does not make deterministic decisions, but relies on MDPs to evaluate probabilistically possible outcomes to generate advisories for a pilot to follow to avoid midair collisions. The benefits of not making deterministic actions are that ACAS X can plan a multi-step collision avoidance strategy instead of choosing the immediate best action, considering a series of actions, and optimizing advisories accordingly [41].

Future Applications in TDSes

Improved Threat Detection System (ISTDS). Current TDSes are equipped with two-color infrared sensors, which offer a broader detection spectrum and help improve accuracy compared to single-color IR sensors in older TDSes. Two-color IR sensors allow for accurate detection even though a sensor's field of vision is obstructed by smoke or dust [42]. The US Army's Improved Threat Detection System (ITDS) is a next-generation missile warning and TDS with a two-color IR sensor. The ITDS consists of IR sensors, a processor, and a memory module. The system can also differentiate between different types of threats, such as small arms fire and missile threats [43]. ITDS also includes high-resolution video and wide-band detection, allowing the system to quickly geolocate incoming threats [44].

Hyperspectral sensors. Hyperspectral sensors use hyperspectral imaging, a technique that collects and processes information across the electromagnetic spectrum to obtain the spectrum for each pixel in an image. They analyze a spectral response to detect and classify features or objects in images based on their unique spectra.

By combining the benefits of digital imaging and a spectrometer, hyperspectral imaging provides both spatial and spectral information about the object's physical and chemical properties. The spectral information allows for the identification and classification of materials, and the spatial data on the material's distribution and areal separation is provided. Hyperspectral imaging provides answers to questions concerning “what” (based on the spectrum), “where” (based on location), and “when” [45].

Unlike current TDS that rely on multispectral sensors, hyperspectral sensors can identify the chemical composition of missile plumes, improving accuracy in cluttered environments. Hyperspectral imaging also enhances target recognition by revealing camouflaged objects through surface reflectance.

Unmanned Aerial Vehicles (UAVs). Unmanned aerial vehicles are military aircraft that are remotely controlled by human operators and used for destroying enemy targets or surveillance. Unencumbered by manned aircraft's crew and design safety requirements, UAVs can be extremely efficient by offering greater range and endurance [46].

In the near future, UAVs will be capable of operating independently using AI. Machine learning algorithms will enhance UAVs' ability to detect and respond to threats without human intervention.

Deep Reinforcement Learning (DRL). Deep reinforcement learning is a subfield of machine learning that combines reinforcement learning and deep learning. Reinforcement learning is an ML technique that trains a model to achieve the most optimal results through trial and error, utilizing a learning policy to decide the best course of action and a reward function to provide feedback on those actions [47]. Deep learning is a subset of ML that uses multilayered neural networks, called deep neural networks, to simulate the complex decision-making power of the human brain [48].

Deep reinforcement learning in future TDS will allow UAVs to be capable of performing within-visual-range (WVR) air-to-air combat and performing in beyond-visual-range (BVR) air combat environments through fully autonomous decision-making. DRL will allow for the generation of new air combat tactics never seen before and will enhance UAVs' fighting capabilities over time [49]. With DRL, maneuver planning in air combat does not only apply to UAVs. Manned military aircraft can use RL to help calculate the best tactical maneuvers [50].

Conclusion

In this paper, we investigated the evolution of military aircraft threat detection systems from the radars of the World War II era to the data and AI-driven multi-sensor systems of the modern day, which have come a long way. This progression has been accelerated with the integration of data science and machine learning, transforming simple radar-driven TDSes into intelligent systems that can adapt to real-time aerial threats and gather information to refine future detection. As aerial threats continue to evolve in both complexity and lethality, future TDSes must have the capabilities to detect emerging threats with extreme accuracy and in greater scopes than current sensors. Ultimately, DS and ML play an imperative role in the continued advancement of TDSes, as they help to protect the lives of aircrew.

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