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UNLEASHING AUTONOMOUS FORCES: INTEGRATING AI-DRIVEN DRONES IN MODERN MILITARY STRATEGY

Abstract. The impact of Artificial Intelligence (AI) on international security is unmistakable, as machines are now capable of undertaking tasks traditionally reserved for human intelligence. This shift brings forth a myriad of challenges in international security, affecting both conventional military capabilities and hybrid threats. Simultaneously, AI presents new opportunities to address these challenges, influencing key aspects of collective defense, cooperative security systems and crisis management. Given its profound implications for prosperity and security, effective management of AI requires collaborative efforts. The scope of promise and peril associated with AI is vast, necessitating collective action to mitigate security risks and leverage its potential to restructure operational processes, support missions, and streamline operations. This paper primarily focuses on introducing drones equipped with artificial intelligence and autonomous learning capabilities, exploring their applications in military contexts. It examines the potential for the independent use of AI-driven drones in both combat and non-combat army operations. By leveraging GIS, C5IRS (Command, Control, Computers, Communications, Cyber-Defense, Intelligence, Surveillance, and Reconnaissance), and AI, these drones provide a significant battlefield advantage by operating autonomously and adapting to dynamic ground situations. In a battlespace where the amalgamation of human, information, and physical components is crucial for strategic advantage, interoperability emerges as a vital factor.

Keywords: UAV, YOLOv8, Drone, GIS, Artificial Intelligence (AI), Security, C5IRS.

Introduction

Contemporary combat operations require the deployment of sophisticated combat technologies to effectively carry out assigned missions. Over the years, there has been a substantial enhancement in combat activities, with the application of scientific and technological advancements significantly improving the efficiency and effectiveness of contemporary military units. The use of the most sophisticated combat means is essential for the successful execution of modern combat missions. To carry out these operations effectively, state-of-the-art command and information systems are required. The primary objective is to collect, analyse, and visualize real-time battlefield data, facilitating and expediting the decision-making process for commanders (decision-makers) [1].

The utilization of unmanned aerial vehicles (UAVs) or Unmanned Aircraft Systems (UAS) - with their supporting equipment (for instance drop-off mechanism, reflectors, speakers, thermal cameras, streaming devices) is an integral component of contemporary combat operations. Engagement in military operations demands the adoption of cutting-edge combat technologies to efficiently accomplish designated objectives. Given their adaptable applications and varied capabilities, such vehicles provide a wide array of benefits to units equipped with such combat gear. The integration of UAV into the C5IRS framework enables the acquisition of real-time imagery from the battlefield. This capability empowers decision-makers to command forces efficiently and promptly during operations. Various types of modern unmanned aerial vehicles, ranging from commercial to armed variants, are employed in present-day combat operations.

The utilization of drones equipped with artificial intelligence and streaming devices in military combat operations represents an advanced technological dimension that is transforming the way battles are led and tactical strategies are executed. The integration of artificial intelligence into drones enables them to operate autonomously and swiftly analyze large volumes of real-time data. This creates the capability to make precise decisions on the battlefield, often within seconds, significantly enhancing the reactivity and efficiency of military forces.

The advantages of this technology range from improved situational awareness and more precise reconnaissance to the rapid identification of potential threats and targets. The use of artificial intelligence enables drones to recognize behavioral patterns, differentiate between friendly and hostile units, and even predict the moves of adversaries. This paper will explore key aspects of integrating artificial intelligence into drones for military purposes, analyze current research, and consider the implications of this technology on the future of warfare.

The purpose of the work is to present drones with artificial intelligence, operating autonomously, used for military and civilian purposes. The following **tasks** are solved in the article:

1) definition and classification of unmanned aircraft and combat operations;

2) The YOLOv8 approach for enhancing military drone surveillance through AI software capabilities.

The following research **methods** are used: comparison, abstraction, axiomatic, analysis, synthesis, formalization and induction, modeling. The following **results** were obtained: This paper introduces a real-time vital detection system for Military Objects utilizing a Convolutional Neural Network within the YOLOv8 (You Only Look Once) framework.

Conclusions: This obtained value and prediction results there is compelling evidence to support the effective utilization of the YOLOv8 algorithm for real-time detection of Military Targets during drone surveillance. The model demonstrates consistently high confidence levels in recognizing Military Targets. Moreover, its lightweight design and swift processing capabilities make it highly deployable. Integrated seamlessly with onboard surveillance cameras on drones, this model ensures near-instantaneous recognition with minimal latency, enhancing the efficiency of military surveillance operations. Furthermore, its adaptability allows for potential integration with other defense systems, promising even greater operational effectiveness.

Literature review

In the paper Bayramov et al. consider the issues of detecting invisible enemy objects using GIS technologies [2]. Bares conducts interoperability modeling for the C4IRS system within a framework of collective security [3]. Petrovski and Toshevski demonstrate the utilization of GIS in geographic reconnaissance and its integration with C5IRS for military objectives [4]. Jović investigates the tactical deployment of drones in counter-terrorism operations [5]. Petrovski et al. investigate the application of GIS in conjunction with the C5IRS system for military geography [6]. Milić et al. examine the potential utilization of drones in urban operational environments [7]. Adamski assesses the efficacy of UCAVs in contemporary armed conflicts [8]. Žnidaršič et al. present various types of drones and counter-drone measures for integration into Serbian Army units [9]. Petrovski and Radovanović scrutinize the integration of drones with the C5IRS system for military purposes [10]. Hashimov and Huseynov provide a brief analysis of the combat application and capabilities of some unmanned aerial vehicles in the armies of developed countries and the Azerbaijani Army [11]. Radovanovic et al. examines the process of selecting UAVs for military and police tactical units through the fuzzy AHP - VIKOR model of multicriteria decision making [12]. Ilić and Tomašević analyze the ramifications of the Nagorno-Karabakh conflict on perceptions of combat drones [13]. Radovanovic et al. explore the feasibility of incorporating drones into mortar units to enhance fire support efficiency through collaborative integration with the C4IRS system [14]. Ciolponea analyzes the integration of unmanned aerial vehicle systems into current combat operations [15]. Szulc analyzes the possibility of using unmanned combat vehicles in tactical actions in mountainous terrain [16]. Zaher analyses drones and their role in the evolution of warfare generation [17]. Hashimov et al. devoted his research to the use of GIS and photogrammetric technologies in military affairs, determining the coordinates of the desired target, drawing up an orthophoto map of the area for operational decision-making and other actions, constructing a detailed 3-dimensional model of the area for organizing future operational actions [18]. Li et al. presents an algorithm for glove detection based on improved YOLOv8 [19]. Roy and Bahaduri shows DenseSPH-YOLOv5: An automated damage detection model based on DenseNet and Swin-Transformer prediction head-enabled YOLOv5 with attention mechanism [20]. In their study, Duan et al. aims to enhance the speed and accuracy of YOLOv8 algorithm detection by combining its lightweight features with ShuffleNetV2, proposing a simple closure detection method based on ShuffleNetV2 and YOLOv8 [21]. Wang et al. explore automatic crack identification on roads using an improved YOLOv8 approach [22]. Sun et al. apply an enhanced YOLOv8 model for pest detection in agriculture within a complex environment [23]. Wu et al. utilize an enhanced YOLOv8 model for overhead power line damage detection [24]. Wen et al. shows the improved YOLOv8 algorithm based on EMSPConv and SPE-head modules [25]. Niu et al. present an improved YOLOv8 model for application in agriculture [26]. Fazekas explores the potential use of artificial intelligence tools for application in military operations [27]. Kania explores Chinese military innovations in the artificial intelligence revolution [28]. Morgan et al. analyze the military application of artificial intelligence [29]. Walsh et al. showcase geospatial-temporal visualizations for military operations [30]. Bhagat examines the use of artificial intelligence in offensive and defensive military operations [31]. Castro et al. illustrate the use of artificial intelligence in military logistics support operations and its application in Logistics 4.0 [32]. Lee et al. investigates the shift towards intelligent drones with minimal human dependence, showcasing the necessary technological advancements [33]. Shah et al. examines the utilization of artificially intelligent drones in smart city environments [34]. Pomortseva et al. illustrate the specifics of attracting additional resources during the conduct of military operations in modern conditions using the latest technologies and geographic information systems [35].

1 Definition and classification of unmanned aerial vehicles

Until now, there hasn't been a universally accepted definition of unmanned aerial vehicles (UAVs), nor a standardized classification. The European Association of Unmanned Vehicle Systems (EUROUVS) has endeavored to tackle this issue by establishing classifications rooted in factors such as purpose, duration, flight altitude, dimensions, speed, signal range, Maximum Takeoff Weight (MTOW), and more [36].

In terms of control and management models, UAVs are categorized into autonomous systems, self-control systems, radar or radio beam control systems, telecommand control systems, and combined systems (autonomous and non-autonomous). The US Department of Defense has classified UAVs into five distinct categories, as illustrated in Table 1 [36].

Another classification system, originating from Europe, is presented in Table 2. This system appears to alternate its criteria between size categories (Nano, Micro, Mini), range (Close, Short, Medium), and altitude and endurance. A significant differentiation in the European system is observed at the threshold of 150kg (approximately 330 lbs.). Remarkably, the European agency overseeing aircraft certification exempts unmanned aircraft systems below this weight from their standard certification requirements, leaving airworthiness standards to be managed by individual nations [37-39].

Table 1 – **Categorization of unmanned aerial vehicles as outlined by the US Department of Defense [37]**

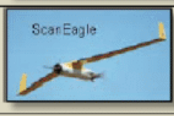
UAS Groups	Maximum Weight (lbs) (MGTOW)	Normal Operating Altitude (ft)	Speed (kts)	Representative UAS	
Group 1	0 – 20	<1200 AGL	100	Raven (RQ-11), WASP	 Raven
Group 2	21 – 55	<3500 AGL	< 250	ScanEagle	 ScanEagle
Group 3	< 1320	< FL 180		Shadow (RQ-7B), Tier II / STUAS	 Shadow
Group 4	>1320		Any Airspeed	Fire Scout (MQ-8B, RQ-8B), Predator (MQ-1A/B), Sky Warrior ERMP (MQ-1C)	 MQ-1/Predator
Group 5		> FL 180		Reaper (MQ-9A), Global Hawk (RQ-4), BAMS (RQ-4N)	 RQ-4/Global Hawk

Table 2 – **European UAS Classification System**

UAS Categories	Acronym	Range (km)	Flight Altitude (m)	Endurance (hours)	MTOW (kg)	Currently Flying
Tactical						
Nano	η	< 1	100	< 1	< 0,025	yes
Micro	μ (Micro)	< 10	250	1	< 5	yes
Mini	Mini	< 10	150 b to 300 a	< 2	< 30 (150 b)	yes
Close Range	CR	10 to 30	3.000	2 to 4	150	yes
Short Range	SR	30 to 70	3.000	3 to 6	200	yes
Medium Range	MR	70 to 200	5.000	6 to 10	1.250	yes
Medium Range Endurance	MRE	> 500	8.000	10 to 18	1.250	yes
Low Altitude Deep Penetration	LADP	> 250	50 to 9.000	0,5 to 1	350	yes
Low Altitude Long Endurance	LALE	> 500	3.000	> 24	< 30	yes
Medium Altitude Long Endurance	MALE	> 500	14.000	24 to 48	1.500	yes
Strategic						
High Altitude Long Endurance	HALE	> 2000	20.000	24 to 48	(4.500 c)12.000	yes
Special Purpose						
Unmanned Combat Aerial Vehicle	UCAV	approx. 1500	10.000	approx. 2	10.000	yes
Lethal	LETH	300	4.000	3 to 4	250	yes
Decoy	DEC	0 to 500	5.000	< 4	250	yes
Stratospheric	STRATO	> 2000	>20.000 & <30.000	> 48	TBD	no
Exo-stratospheric	EXO	TBD	> 30.000	TBD	TBD	no
Space	SPACE	TBD	TBD	TBD	TBD	no

TBD = To Be Defined   a = according to national legislation   b = in Japan   c = Predator B

According to the maximum take-off mass, ISO standard characterized even six classes [40]:

I (0 < mass ≤ 0,25),

II (0,25 < mass ≤ 0,9),

III (0,9 < mass ≤ 4),

IV (4 < mass ≤ 25),

V (25 < mass ≤ 150),

VI (150 < mass).

It is also worth mentioning that NATO adopted their own classification in which distinguishes 3 classes (Fig. 1) [41, 42]:

I (< 150 kg), II (150 kg - 600 kg), III (> 600 kg).

Class	Category	Normal Employment	Normal Operating Altitude	Normal Mission Radius	Primary Supported Commander	Example Platform
Class III (> 600 kg)	Strike/ Combat *	Strategic/ National	Up to 65,000 ft MSL	Unlimited (BLOS)	Theatre	Reaper
	HALE	Strategic/ National	Up to 65,000 ft MSL	Unlimited (BLOS)	Theatre	Global Hawk
	MALE	Operational/ Theatre	Up to 45,000 ft MSL	Unlimited (BLOS)	JTF	Heron
Class II (150 kg - 600 kg)	Tactical	Tactical Formation	Up to 18,000 ft AGL	200 km (LOS)	Division, Brigade	Watchkeeper
Class I (< 150 kg)	Small (>15 kg)	Tactical Unit	Up to 5,000 ft AGL	50 km (LOS)	Battalion, Regiment	Scan Eagle
	Mini (<15 kg)	Tactical Sub-unit (manual or hand launch)	Up to 3,000 ft AGL	Up to 25 km (LOS)	Company, Platoon, Squad	Skylark
	Micro ** (<66 J)	Tactical Sub-unit (manual or hand launch)	Up to 200 ft AGL	Up to 5 km (LOS)	Platoon, Squad	Black Widow

Fig. 1. NATO UAS classification

Petrovski and Radovanović offer a detailed exploration of the definitions and classification of "drone" and "UAV" (depicted in Fig. 2) [10].

UAV encompasses motorized devices controlled remotely or possessing varying degrees of autonomy. Control typically involves communication software, often integrating artificial intelligence and diverse sensors. UAVs serve diverse purposes, from carrying cargo and transmitting real-time data to functioning as WiFi stations. They vary in purpose, construction, environment of use, and energy source. UAV applications span numerous fields including defense, security, agriculture, construction, communication, science, and more.

The term "drone" is broader than "unmanned aerial vehicle," encompassing all UAVs but not vice versa [10].

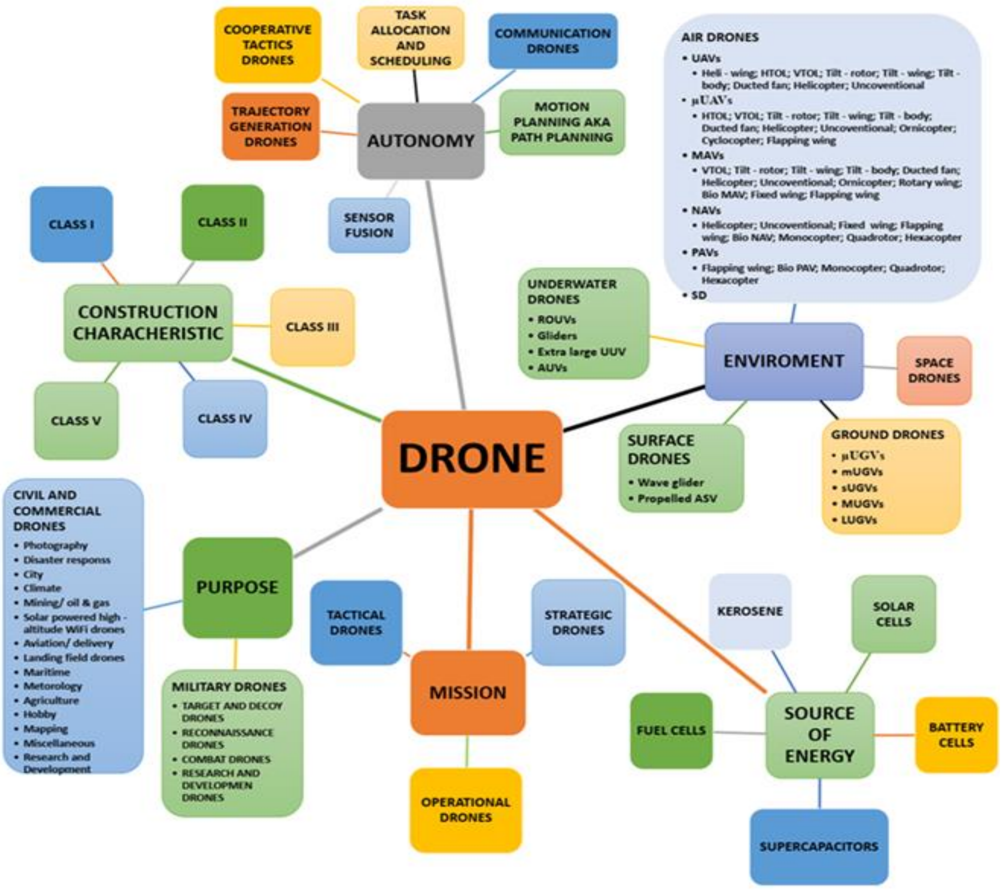


Fig. 2. NATO UAS classification

The categorization of unmanned aerial vehicles (UAVs) implies that their attributes are typically determined by their intended purpose. Analyzing the tactical and technical features of UAVs is essential to assess their suitability for deployment in modern combat operations.

Military utilization of UAVs can be classified into three primary categories: naval, land, and aerial deployment. On the civilian front, UAVs have diverse applications spanning numerous domains, such as geodesy (photogrammetry), agriculture, industrial production, civil protection, disaster management, surveillance of critical infrastructure, environmental protection, police surveillance, search and rescue operations, intelligence and security services, journalism, commercial activities, and recreational pursuits. Additionally, their versatility and adaptability continue to drive innovation and expand their utility in various fields [43].

2 Combat operations

Land-based military operations form is the bedrock of overall military endeavor, as almost all capabilities, regardless of their deployment in other domains, are fundamentally rooted in or overseen from land. While specific domains may take precedence in certain situations, resolutions to conflicts typically unfold on land because of its importance as a place where people live, where political decisions are made, and where national power is located. Military forces achieve their objectives through the execution of operations, defined as a series of tactical actions with a common purpose or central theme. Operations vary in several dimensions and encompass different physical environments such as urban, subterranean, desert, jungle, mountain, maritime, and arctic environments. There is also variability in the scale of forces deployed and the duration of operations. Operations bring about changes in the physical, informational, and human dimensions of the operational environment.

Also important are technologies and devices that increase situational awareness and support decision making by providing live images from the battlefield, such as the Mobile Command Centre (Fig. 3) or Tactical Command Case that enable video transmission from several drones to any location, two-way radio communication between commander and pilot, and the creation of a secure wireless WiFi network [43, 44]. Although designed for civilian use and emergency services, they can be successfully used for military purposes, just as civilian commercial-off-the-shelf drones (COTS) were use in the Ukrainian-Russian war [45].

Fig. 3. Example of Mobile Command Centre

The complexity of the operational environment requires leaders who understand both the scientific and artistic aspects of operations. A comprehension of the scientific facets, including combat power ratios, weapons ranges, and movement tables, aids leaders in enhancing synchronization and mitigate risk. However, uncertainty persists, and leaders must employ operational art to make decisions and embrace risk. Intangible elements like the influence of leadership on morale, leveraging shock effect against enemy forces, and gaining the support from populations are inherently human factors that can overcome physical challenges and frequently determine the outcomes of an operation. Army forces face a wide range of challenges, contributing to national objectives across various operational categories, such as large-scale combat operations, limited contingency operations, crisis response, and support to security cooperation.

Armed conflicts are typically characterized by major combat operations that demand intense combat activities and significant logistical resources. These major operations often involve large-scale maneuvers conducted by complex joint forces organized and commanded as functional components. The primary focus is on preserving freedom of action for one's own forces while denying the same to the adversary. Combat operations involve conventional force-on-force engagements of varying scale, frequency, and intensity between opposing armed forces. The armed forces of a state act to implement the state's national policy and assert dominance over other instruments of power. Combat operations comprise a series of battles and major engagements, leading to intense activity and high logistic consumption. The tempo of activities is usually rapid, requiring the prioritization of resources and the generation of additional combat power. These operations often involve large-scale manoeuvres by complex and multifaceted Joint Task Forces, organized and commanded as functional components [41].

Combat operations refer to military actions that involve direct engagement with enemy forces in a physical confrontation. These operations are a subset of military activities and focus on achieving specific tactical the use of force. Here are key elements related to combat operations:

Direct Engagement: Combat operations involve direct and deliberate engagement with enemy forces. This may include infantry clashes, armored warfare, artillery bombardment, and other forms of direct confrontation.

Tactical Objectives: The primary purpose of combat operations is to achieve immediate and specific tactical objectives on the battlefield. These objectives could include seizing key terrain, neutralizing enemy positions, or disrupting enemy movements.

Fire and Maneuver: Fire and maneuver tactics are fundamental to combat operations. This involves using firepower to suppress or destroy enemy positions while maneuvering troops to gain a positional advantage.

Close Combat: Combat operations often involve close combat, where opposing forces engage each other at close range. This may occur in urban environments, open terrain, or other battlefield conditions.

Strategic Context: While combat operations are tactical in nature, they are conducted within the broader context of a strategic plan. Tactical victories contribute to achieving overall strategic goals in a conflict.

Dynamic and Fluid: Combat situations are dynamic and fluid, requiring commanders to make rapid decisions based on real-time information. The ability to adapt to changing circumstances is critical for success.

Combined Arms: Successful combat operations often involve the coordinated use of combined arms, including infantry, armor, artillery, and air support. The synergy of these elements enhances the effectiveness of military forces.

Risk and Uncertainty: Combat operations inherently involve risk and uncertainty. Commanders must make decisions with incomplete information and navigate through fog of war.

Casualties and Medical Support: Combat operations can result in casualties, and medical support is a critical component. The evacuation and treatment of casualties contribute to the overall effectiveness of the force.

Conclusion and Follow-Up:

Combat operations conclude with an assessment of achieved objectives and may be followed by the consolidation of gains, preparation for subsequent operations, or other strategic actions.

In summary, combat operations are intense, direct engagements with enemy forces, focused on achieving specific tactical goals within the broader context of a military campaign.

3 Utilizing AI-Enhanced Drones in Military Combat Operations

Unmanned aerial vehicles (UAVs) have significantly bolstered global military capacities, catalysing revolutionary shifts in military tactics. The utilization of military drones has profound implications for land forces and legal considerations, in the area of command and control. Drones play a pivotal role in relaying vital information about by providing intelligence on enemy movements, positions, and key targets, commanders are enabled to operate with greater efficiency and make well-informed decisions in the field. While drone technology is relatively new in the military domain, rapid advancements have been made by integrating drones with artificial intelligence. Companies like Shield.AI, AeroVironment, and Lockheed Martin exemplify how defense contractors utilize computer vision technology and image recognition to tackle military challenges while maintaining... jeopardizing human lives. Shield AI's drone, for instance, boasts the capability to navigate unfamiliar terrain without relying on GNSS tracking. This class of UAV empowers military units with rapid data collection capabilities, elevating their agility and situational awareness in tactical reconnaissance, tracking, combat assessment, and cartographic missions. Furthermore, drones afford operators the liberty to make decisions autonomously, alleviating concerns regarding potential rear ambushes. With their versatile functionalities, UAVs play a pivotal role in modern warfare, ensuring swift and effective responses to dynamic battlefield scenarios.

The integration of AI into drones involves a combination of physical components, machine vision, and navigational instruments. Training the artificial intelligence behind the drone involves a supervised learning process, a task considered more challenging than it may seem. From my perspective, combat drone technology emerges as among the most potent and effective tools ever created for intermediate and close combat situations. Its precision strikes and real-time reconnaissance capabilities redefine battlefield strategies, granting military forces unparalleled tactical advantages. Additionally, the continuous advancements in drone technology promise further enhancements in combat effectiveness and mission success rates, cementing their position as indispensable assets in modern warfare.

Recognizing the strategic importance of countering small drones, the Army emphasizes machine learning and AI as pivotal technologies in neutralizing opposing systems. Swarms of drones, capable of simultaneous multi-directional attacks, pose the potential to overwhelm human defenders. Initially designed for anti-insurgency and defense, drones have demonstrated immense value in such contexts. The aerospace and defense industry is now actively integrating drone technology into various global military programs, offering diverse benefits and advantages across different roles.

Military drones have revolutionized warfare by operating on land, soaring through the skies, and navigating underwater. Evolving over more than fifty years, drones have become key artificial intelligence weapons seamlessly integrated into military forces worldwide. Consequently, armed forces increasingly turn to drones to enhance their capabilities in combat and surveillance.

The benefits of autonomous weapons systems serve as force multipliers, reducing the personnel required for a mission while amplifying the effectiveness of each individual. Advocates also attribute autonomous weapons systems with expanding the operational scope of the battlefield, facilitating engagement in remote or otherwise inaccessible regions. Moreover, these systems offer the potential to minimize casualties by eliminating the need for human intervention in hazardous missions. Additionally, the integration of artificial intelligence enables swift adaptation to dynamic combat scenarios, further enhancing operational efficiency and mission success rates.

4 Transforming Military Drone Surveillance: Harnessing YOLOv8 and AI Software Capabilities

This paper looks at the integration of real-world models into either drones or the AI software powering them (Fig. 4). The focus is on various military drones and UAVs equipped with AI capabilities. AI plays a crucial role in multiple use cases within drone technology, especially in the military context where it is often used to enable autonomous flight through machine vision. It should be noted that although COTS drones have object recognition capabilities (e.g. Active Track in Autels and in DJIs), the algorithms do not identify whether the visible objects are vehicles or people, nor whether they are military vehicles or soldiers.

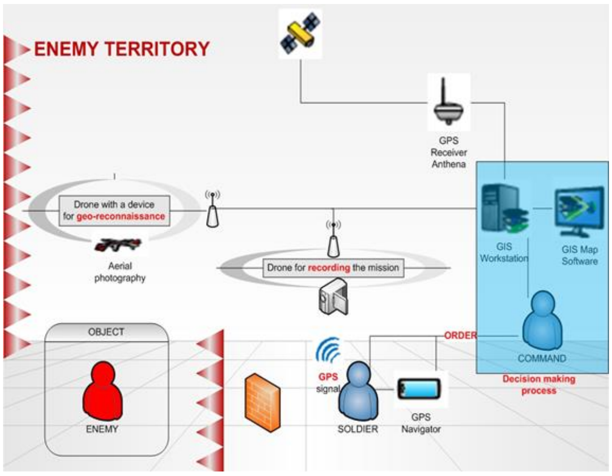


Fig. 4. Model of Geo-Reconnaissance and Command Information System (GRCIS) in UAVs Enhanced with C4IRS Systems and AI

4.1 Advanced Military Drone Surveillance Utilizing the YOLOv8 Method

The outlined framework is designed to identify objects of significant military relevance using images extracted from the live feed from military surveillance drones. Subsequent actions will be contingent upon the acquired outcome. Fig. 5 provides a concise overview of the proposed methodology in this article.

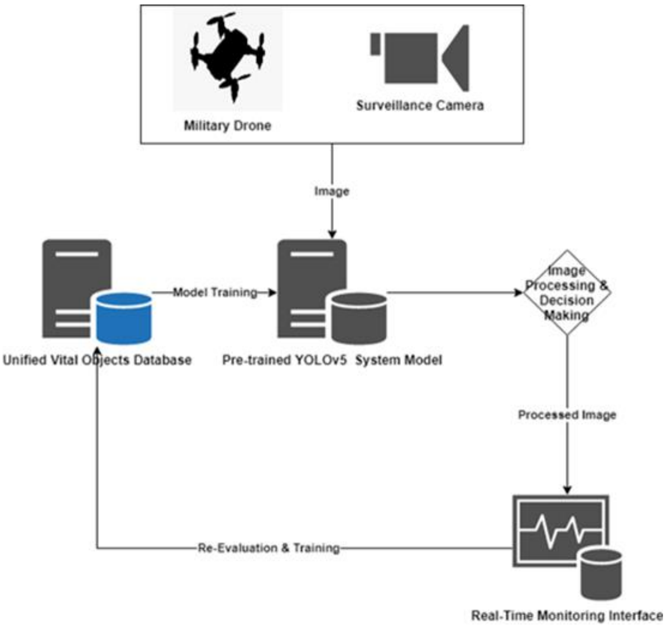


Fig. 5. Methodology Overview

Initially, a comprehensive Database of Vital Military Objects is established by aggregating verified images sourced from diverse online and local repositories. These images encompass crucial surveillance items such as weapons, bunkers, military structures, vehicles, tanks, and artillery pieces. Subsequently, the YOLOv8 model undergoes rigorous training and evaluation using this extensive dataset, ensuring robust performance in real-world scenarios.

To facilitate real-time surveillance, a Surveillance Camera is seamlessly integrated onto a military drone, forming a crucial component of the System Model. This camera transmits live video feeds through the system model, enabling instantaneous data processing. Moreover, sophisticated image filtering algorithms are applied to enhance image clarity and stability, ensuring reliable performance even in adverse weather conditions.

The processed video feed is then presented on the Real-Time Monitoring Interface, providing instant insights into detected vital military objects. Alarms are triggered to alert operators upon the identification of such objects, enhancing situational awareness and enabling prompt decision-making. Instances of false positives and undetected objects identified by human operators are meticulously logged and transmitted to the consolidated Vital Objects Database for further analysis and system refinement.

In essence, this paper introduces a cutting-edge real-time system for the detection of vital military objects, leveraging state-of-the-art Convolutional Neural Network technology within the YOLOv8 framework. Key contributions of this innovative approach include its seamless integration onto existing surveillance drones, high-precision detection capabilities over considerable distances, and utilization of open-source development software. Additionally, the establishment of a comprehensive dataset for vital military objects, along with its support for military decision-makers in tracking and identifying such objects, underscores its significance in modern warfare.

The development of a real-time system for detecting vital military objects represents a significant advancement in military surveillance technology. By leveraging the power of Convolutional Neural Networks within the YOLOv8 framework, this approach enables seamless integration onto existing surveillance drones and ensures high-precision detection capabilities over vast distances. The establishment of a comprehensive database of vital military objects, coupled with its support for decision-makers in tracking and identifying such objects, underscores its pivotal role in enhancing situational awareness and enabling prompt response in dynamic battlefield scenarios. Moreover, the utilization of open-source development software underscores its accessibility and potential for widespread adoption across military contexts. Moving forward, continued refinement and enhancement of this system hold the promise of further strengthening military capabilities and safeguarding national security interests.

4.2 Advancing Military Surveillance: YOLOv8-Based Detection of Vital Objects

YOLO is built on Convolutional Neural Network (CNN) and serves as a highly efficient end-to-end object detection algorithm **[46].** Continuous enhancements have positioned it as a top performer on two official object detection datasets: Pascal VOC (Visual Object Classes) **[47]** and Microsoft COCO (Common Objects in Context) **[48].**

The network architecture of Yolov8 is depicted in Fig. 6. Several factors contribute to the selection of Yolov8 as the primary method for training the system model. First and foremost, Yolov8 integrates Cross Stage Partial Network (CSPNet) **[49]** into Darknet, forming CSPDarknet as its backbone. CSPNet addresses issues related to repeated gradient information in large-scale backbones by incorporating gradient changes into the feature map. This leads to a reduction in model parameters and FLOPS (Floating-Point Operations Per Second), balancing inference speed and accuracy while also minimizing the model size. In military surveillance operations, the speed and accuracy of detection are paramount, and a compact model size significantly enhances inference efficiency on edge devices with limited resources. Additionally, the streamlined model architecture contributes to improved real-time processing capabilities, enabling swift and precise identification of vital military objects in dynamic environments.

Secondly, Yolov8 implements the Path Aggregation Network (PANet) **[50, 51]** as its neck to enhance information flow. PANet adopts a novel Feature Pyramid Network (FPN) structure with an improved bottom-up path, enhancing the propagation of low-level features. Simultaneously, adaptive feature pooling, linking the feature grid and all feature levels, facilitates the direct propagation of useful information in each feature level to the subsequent subnetwork. PANet improves the utilization of accurate localization signals in lower layers, significantly enhancing the location accuracy of detected objects.

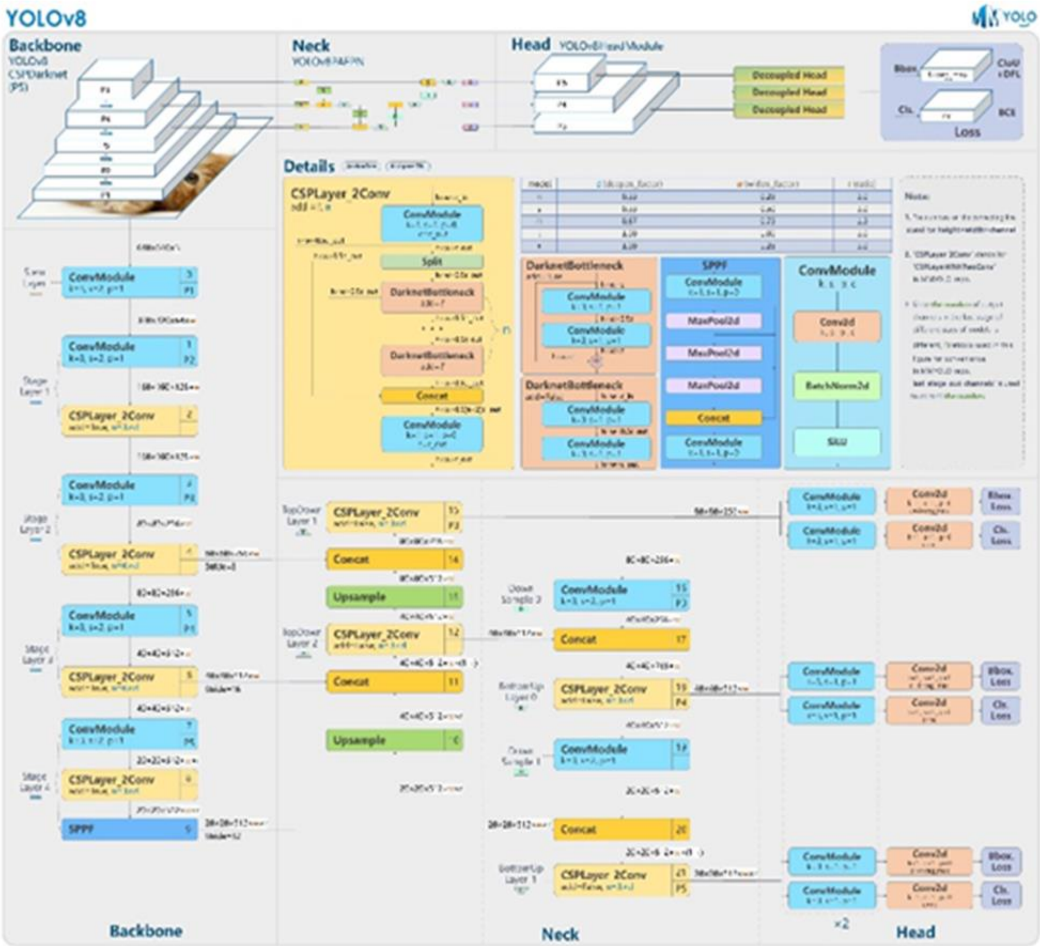


Fig. 6. Network Architecture of Yolov8: Backbone (CSPDarknet), Neck (PANet), and Head (Yolo Layer) [52]

Thirdly, the head of Yolov8, namely the Yolo layer, generates feature maps of three different sizes (18 × 18, 36 × 36, 72 × 72) to achieve multi-scale prediction [51]. This capability allows the model to efficiently detect objects of various sizes, ranging from small to large. Moreover, its adaptive nature ensures robust performance across diverse environmental conditions and operational scenarios, further enhancing its utility in military surveillance missions.

In the YOLO method, the input images undergo a single pass through the neural network, predicting the detected objects in the image (Fig. 7). The process involves dividing the input image into various grids based on a predefined grid size. Subsequently, the algorithm predicts the probability of the desired object in each grid. This approach enables the prediction of all classes and the bounding boxes of objects in the image in a single run of the algorithm [53].

The proposed solution, utilizing pre-trained YOLOv8, boasts exceptional lightweight design and rapidity in identifying vital military objects. Maintaining both high accuracy and a swift frame rate (fps) is imperative for effective real-time surveillance and data collection in military operations. Moreover, the adaptability of the YOLOv8 model ensures robust performance across diverse environmental conditions, further enhancing its suitability for critical military applications.

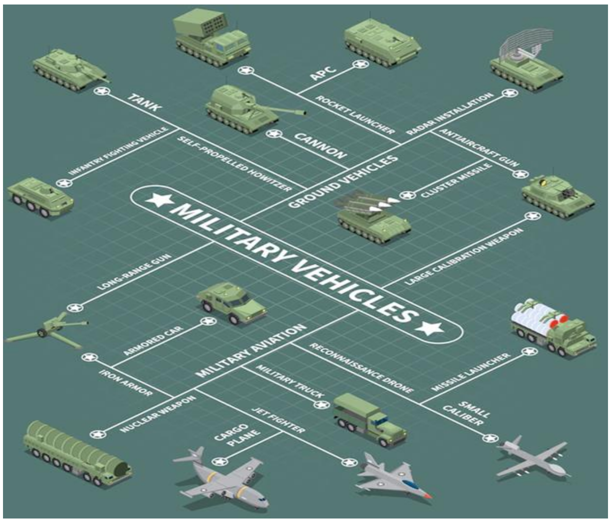


Fig. 7. Overview of Military Vehicles Recognizable with Pre-Input Images in Drone Databases

To better understand the process, we divide and analyses it step by step [54]:

Grid-Based Approach:

— YOLOv8 divides the input image into a grid of cells.

— Each cell is responsible for making predictions within its boundaries.

— This grid-based approach ensures efficient processing and simplifies object localization.

Predictions in Each Cell:

— For every cell, YOLOv8 predicts:

— Bounding Boxes: These represent the coordinates (x, y, width, height) of detected objects.

— Class Probabilities: The likelihood that an object belongs to a specific class (e.g., car, person, dog).

— These predictions are made independently for each cell, allowing parallel computation.

Anchor Boxes:

— YOLOv8 introduces anchor boxes to refine localization.

— Each anchor box corresponds to a specific aspect ratio and scale.

— The predicted bounding boxes are adjusted based on anchor box properties.

Feature Extraction Backbone:

— YOLOv8 employs a neural network backbone (often based on Darknet or CSPDarknet).

— This backbone extracts high-level features from the input image.

— These features are crucial for accurate predictions.

Loss Function: Guiding Training:

— During training, YOLOv8 optimizes a loss function.

— The loss considers both localization (bounding box accuracy) and classification (class probabilities).

— It guides the model to learn from mistakes and improve predictions.

Non-Maximum Suppression (NMS):

— After predictions, YOLOv8 applies NMS.

— NMS removes duplicate or overlapping bounding boxes.

— Only the most confident bounding box for each object remains.

Inference: Real-Time Detection (Fig. 8):

— During inference, YOLOv8 processes an image.

— The final output includes bounding boxes and associated class labels.

In summary, YOLOv8 is a highly efficient algorithm that incorporates image classification, Anchor-Free object detection, and instance segmentation. Its detection component incorporates numerous state-of-the-art YOLO algorithms to achieve new levels of performance.

4.3 Training Process and Dataset Overview for Model Development

For model training, validation, and evaluation purposes, a tailored dataset was meticulously curated. This finalized dataset includes around 10,000 images depicting military trucks and tanks, sourced from diverse repositories such as publicly available datasets, Google Images, and local archives, as detailed in Table 3.

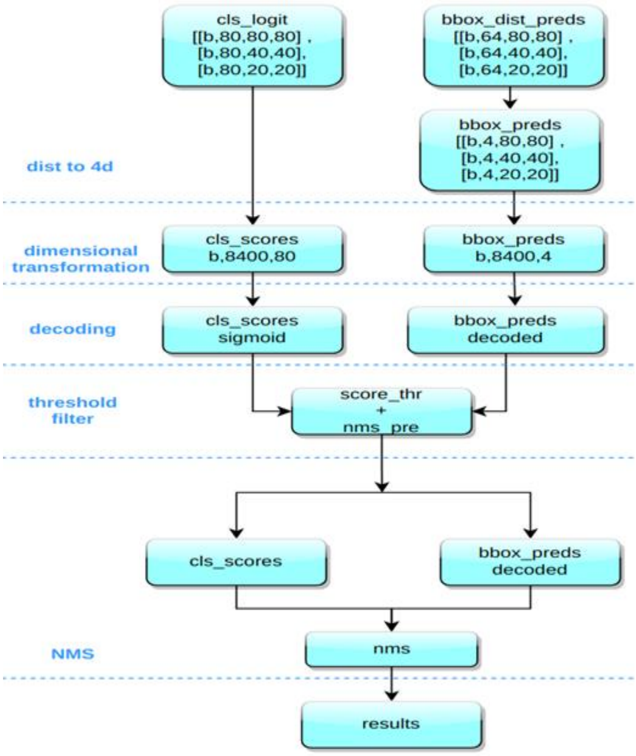


Fig. 8. Inference process implemented in MMYOLO

4.4 Training Process and Dataset Overview for Model Development

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Tabl. 3 – **Image Distribution in the Dataset**

Dataset type	Size & Type	Source
APC, Tanks, Military Trucks	6772 images	Military Vehicles - Mendeley Data Collection [55]
Military Tanks	1078 images	Military Tanks – Kaggle [56]
Military Artillery, Tanks, MRL Systems, Trucks	1000 images	Moving and Stationary Target Acquisition and Recognition (MSTAR) Dataset [57]
Command posts & fire stations, Artillery, Stationary Military Equipment	20 videos & 2000 images	Indigenous Sources

The images encompass a wide range of scenarios involving military targets across diverse terrains, including day and night settings, forests, deserts, and urban environments, as depicted in Fig. 9. Despite this diversity, the dataset exhibits limitations. To overcome these constraints, several videos featuring various military targets in different conditions, such as size, shape, and color, were incorporated.

Fig. 9. Unified Dataset Training Process: Annotating Military Targets by Class (Tanks, APCs, Artillery, MRL Systems)

To prepare the dataset for training with YOLOv8, labels and bounding boxes were meticulously assigned to each image, with the coordinates of annotating boxes normalized between 0 and 1. This annotation process was facilitated by Roboflow [58], ensuring efficient data labeling in the desired format. Additionally, the dataset was thoughtfully divided into training, validation, and testing sets, maintaining balance across categories to prevent model bias. During the model training phase, fine-tuning of the YOLOv8 model, initially pre-trained on the COCO dataset, was conducted using transfer learning on the unified dataset. To clarify further, the training process involved utilizing pre-trained weights from a model that was trained on a large and diverse dataset. Transfer learning helps leverage the knowledge gained from the initial training, which is beneficial when working with limited labeled data.

Various augmentation processes, such as HSV (Hue, Saturation, Value) augmentation adjusting the color space parameters to make the model invariant to changes in lighting conditions., color spacing including transforming images between different color spaces, which helps the model handle variations in how colors are represented., mosaic combining multiple images into a single mosaic image, providing the model with diverse contexts and increasing its ability to handle complex scenes, and image scaling including resizing images to different dimensions, allowing the model to learn from variations in object sizes., were applied. Hyperparameters that were fine-tuned, including SGD optimizer used for updating model parameters during training, 0.01 learning rate which is the step size which the model's weights are updated during training., 0.0005 weight decay as a regularization term that helps prevent overfitting by penalizing large weights, and finally, 600 epochs as the number of times the entire dataset was processed by the model during training, on batch size 32 as the number of training examples used in each iteration of a training epoch.

5 Results and Analysis

To evaluate the effectiveness of the proposed system, the trained model was tested across diverse environments, such as forests, mountains, and open fields. Results were obtained using a confidence threshold of 0.4, indicating that predictions with a confidence score below this threshold were excluded from consideration during model evaluation were likely filtered out. A confidence threshold acts as a cutoff, ensuring that only predictions with a certain level of confidence are considered. Initially, when applied to the handpicked test data from the unified dataset, we achieved an average of 0.922 mAP@0.5. This metric, ranging from 0 to 1, indicates the model's accuracy in correctly identifying and localizing military targets in images. An mAP@0.5 score of 0.922 suggests a high level of precision in the predictions, considering a 50% IoU overlap threshold. In essence, the model exhibits robustness and effectiveness in its ability to recognize military targets with a notable degree of accuracy.

Furthermore, the displayed confusion matrix in Fig. 10 indicates that the model can label most of the data quite accurately and with high precision when it comes to depicting classes of Military Targets, it does not overlap them with each other which ensures proper and accurate target recognition.

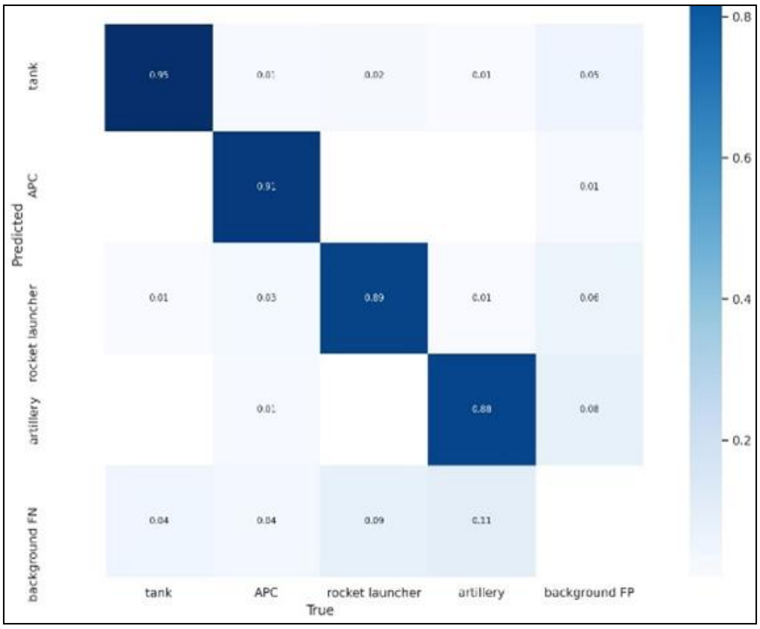

Fig. 10. Confusion Matrix of the model

Additionally, Fig. 11 shows that the model can accurately confirm the presence of a Military Target in the image.

The obtained value and prediction results depicted in the performance graphs in Fig. 12 demonstrate a significant potential to use the YOLOv8 algorithm for real-time detection of Military Targets during drone surveillance.

The confidence value of the Military Targets recognized by the model is notably high. Furthermore, the performance of the proposed model applied to validation data can be observed in Fig. 8.

а б

Fig. 11. Predicted Output Examples

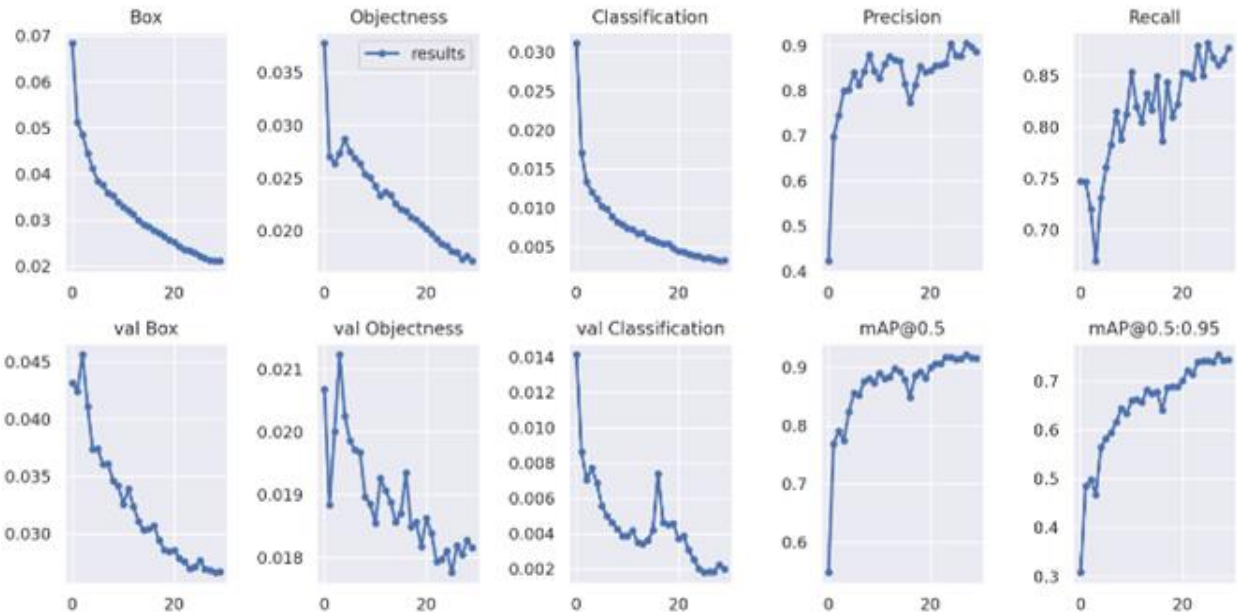

Fig. 12. Graphs illustrating Model Training and Validation Results

Box Accuracy refers to how accurately the model is able to predict the bounding boxes around objects in the images. High box accuracy shown in Fig. 12 means that the predicted bounding boxes closely match the actual positions of the objects in the test data. Objectness measures how well the model distinguishes between object and non-object regions in an image. A high objectness score as shown in Fig. 12 indicates that the model is effective at identifying regions containing relevant objects. Classification Accuracy assesses how accurately the model classifies the detected objects. As shown in Fig. 12, high classification accuracy means that the model correctly assigns the appropriate class labels to the recognized objects, such as different types of military targets. Precision as the ratio of true positive predictions to the total number of positive predictions made by the model. A high precision as shown in Fig. 12 indicates that the model is making accurate positive predictions, minimizing false positives. Recall or sensitivity, is the ratio of true positive predictions to the total number of actual positive instances in the dataset. High recall as shown in Fig. 12 means that the model is adept at capturing a significant portion of the positive instances in the data, minimizing false negatives.

Having all these metrics at very high levels collectively suggests that the model is well-optimized, demonstrating strong performance in accurately detecting, localizing, and classifying military targets.

The model is lightweight and sufficiently fast for deployment. It can be integrated with built-in capturing tools, such as Surveillance Cameras mounted on COTS drones, to predict recognition in almost real-time with minimal delays.

In contrast to this, the results may vary depending on the image quality, therefore, another challenge to get the desired results from this model is to secure a constat good image quality feed. In the operational environment this can be a challenging task, and depends on multiple factors, but mostly weather conditions. The first step in mitigating those issues would be manually fine-tuning YOLOv8 on datasets specifically captured in rainy or foggy scenarios to improve its robustness. However, that focuses on the model itself rather than image feed quality, and it overall may bring better detection results, it will not eliminate the problem completely. Furthermore, image feed quality needs to be filtered properly before getting to the model, so the model can perform at its highest capacity and achieve the results which are presented in this study. To effectively mitigate weather conditions impact on the image feed several algorithms can be employed, depending on the severity and the impact of negative factors. First and foremost, is image dehazing. According to recent studies, Dehazing algorithms can be utilized to mitigate the impacts of fog and haze on the image feed up to certain heights and those algorithms include; Dark Channel Prior (DCP), Color Attenuation Prior (CAP), and Fast Guided Filter Dehazing **[59]**.

Alongside fog and haze, rain streaks can significantly degrade image quaility, therefore, motion compensation, temporal filtering, and deep learning-based rain removal networks can be utilized to mitigate its effects to a certain extent

Additionally, other image processing algorithms and tools may be utilized to improve the overall image quality. Contrast enchantment techniques like histogram equalization or adaptive contrast stretching can make objects more distinguishable for the pre trained YOLOv8 detection model. Gamma Correction can also be utilized to improve brightness and overall image quality, furthermore it can compensate for variations caused by weather conditions. Alongside with that, denoising filters (e.g., Gaussian, median) can be used to reduce noise caused by raindrops or fog. White Balance Correction can be used to adjust color balance to compensate for color shifts due to weather conditions, while proper white balance ensures accurate color representation **[60]**.

With successful employment of the beforementioned algorithms and solutions, camera feed from the drone to the YOLOv8 model can be brought to a decent enough level so that even in negative operating conditions the model can perform on its highest levels.

Conclusion

The evolution of military capabilities has been closely linked to the relentless integration of advanced technologies into modern combat operations. Advances in science and technology have ushered in a new era, significantly enhancing the efficiency and effectiveness of military units. This transformation is particularly evident in the utilization of unmanned aerial vehicles (UAVs) equipped with artificial intelligence (AI) and advanced technical instruments within the C5IRS system. The integration of UAVs into the C5IRS system represents a quantum leap in increasing the operational efficiency of military units engaged in combat. The versatility of these vehicles, equipped with high-resolution cameras, infrared and thermal cameras, microphones, various sensors, guided and non-guided missiles, and other accessories, provides a comprehensive solution for real-time battlefield information. This capability not only facilitates the destruction of targets without risking human lives but also ensures the swift transmission of critical data to central command centers.

The wide range of applications for UAVs extends beyond combat scenarios, encompassing humanitarian efforts such as the delivery of medical supplies and essential equipment to operational areas. Despite the undeniable advantages, it is crucial to acknowledge the potential shortcomings of the proposed model. The risk of misidentifying non-military objects as actual targets, particularly at long range and with poor imagery is a significant challenge. Addressing these issues requires sustained efforts, including longer training times, expansive datasets, and improvements in accuracy to minimize false positives.

Looking ahead, the integration of modern C6ISR systems with existing combat frameworks emerges as a focal point for future research. This seamless integration holds the promise of optimizing military operations across diverse scenarios, aligning with the dynamic nature of modern warfare. The imperative for ongoing refinement and adaptation of these systems underscores the commitment to maintaining strategic advantages on the contemporary battlefield. The comprehensive literature review provides insights into the diverse applications of UAVs in military operations. Researchers have explored the possibilities of using drones in urban environments, protecting and monitoring of land security zones, effectiveness in modern armed conflicts, combat use in counter-terrorism operations, and integration with C5IRS systems for military needs. These studies collectively contribute to the growing body of knowledge on the subject, addressing challenges and proposing innovative solutions.

The following sections discuss the definition and classification of unmanned aircraft, emphasizing the need for a standardized classification system. The EUROUVS classification based on various factors such as purpose, flight altitude, duration, speed, and dimensions provide a foundation for understanding the categorization of UAVs. Control and management models further delineate categories based on take-off weight, maximum range and take-off weight.

The discussion focuses on combat operations, underscoring the foundational role of land-based military operations in overall military endeavors. Operations, characterized by tactical actions with a common purpose, unfold across diverse physical environments and vary in scale and duration. The complex operational environment necessitates leaders with a nuanced understanding of both the science and art of operations. While the science includes factors like combat power ratios and weapons ranges, the art encompasses intangible human factors that often determine the outcomes of operations.

The focus then shifts to combat operations, which are defined as intense, direct engagements with enemy forces aimed at achieving specific tactical goals. The elements of direct engagement, tactical objectives, fire and maneuver tactics, close combat, and the strategic context define the nature of combat operations. The discussion acknowledges the inherent risk and uncertainty in combat situations, emphasizing the importance of adaptability and the combined use of arms for success. The subsequent section explores the application of drones with AI in military combat operations. Drones, with their diverse capabilities, significantly enhance military capabilities by providing crucial information about enemy movements and targets. The integration of artificial intelligence further enhances the capabilities of drones, enabling autonomous operation and rapid analysis of real-time data. The advantages range from improved situational awareness to the rapid identification of threats and targets. The discussion highlights the transformative impact of drone technology on modern warfare.

The literature review covers a wide range of studies analyzing the use of drones in various military contexts, including urban operations, land security, counter-terrorism, reconnaissance, and cooperation with C5IRS systems. These studies contribute valuable insights into the practical applications and challenges associated with drone technology in military settings. The subsequent sections delve into the YOLOv8 method for enhanced military drone surveillance with AI software capabilities. The methodology involves training a YOLOv8 model on a customized dataset of military targets, including trucks, tanks, artillery, and other vital objects. The results indicate a high potential for real-time detection of military targets during drone surveillance, with a focus on lightweight and efficient deployment. The developed and validated algorithm may also be successfully used in COTS drones, increasing their functionality.

In conclusion, the integration of advanced technologies, particularly UAVs with AI capabilities, represents a paradigm shift in modern military operations. The versatility and efficiency of these systems offer strategic advantages while addressing complex challenges. The ongoing research and development efforts, coupled with a nuanced understanding of operational dynamics, enable the military to navigate the evolving landscape of contemporary warfare. As technology continues to advance, the commitment to innovation and adaptation remains paramount in ensuring military readiness and effectiveness on the global stage.

In conclusion, despite the achievements in integrating drones with artificial intelligence into military operations, future research can focus on optimizing performance, minimizing target identification errors, and enhancing drone autonomy. Continued research should aim to further integrate modern C6ISR systems with existing military frameworks, exploring how this integration can further optimize operations in diverse scenarios. Keeping abreast of technological advancements and adapting systems to new challenges on the battlefield remains crucial for maintaining military effectiveness and strategic advantage in the future.

As we look ahead, ongoing investigations may delve into refining the YOLOv8 algorithm for even more accurate real-time detection of military targets during drone surveillance. Addressing any remaining limitations, such as potential misidentifications and errors, particularly over longer distances, will be crucial for advancing the capabilities of the proposed model. Additionally, future studies could explore the deployment of advanced AI models in conjunction with drones to enhance decision-making processes and situational awareness in dynamic military environments.

The evolution of drone technology and artificial intelligence continues to reshape modern warfare, and further research will play a pivotal role in harnessing these advancements for more effective and precise military operations.

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Вивільнення автономних сил:
інтеграція безпілотних літальних апаратів із штучним інтелектом у сучасну військову стратегію

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Анотація. Вплив штучного інтелекту (ШІ) на міжнародну безпеку на сьогодні є безсумнівним, оскільки тепер машини здатні виконувати завдання, які традиційно покладені на людський інтелект. Ця зміна породжує безліч викликів у міжнародній безпеці, впливаючи як на звичайні військові можливості, так і на гібридні загрози. Водночас ШІ відкриває нові можливості для вирішення цих викликів, впливаючи на ключові аспекти колективної оборони, кооперативних систем безпеки та управління кризами. Враховуючи його глибокі наслідки для процвітання та безпеки, ефективне управління ШІ вимагає спільних зусиль. Обсяг перспектив і небезпек, пов’язаних зі штучним інтелектом, величезний, що вимагає колективних дій для пом’якшення ризиків безпеці та використання його потенціалу для реструктуризації операційних процесів, підтримки місій і оптимізації операцій. Ця стаття в основному зосереджена на представленні дронів, оснащених штучним інтелектом і можливостями автономного навчання, досліджуючи їх застосування у військових умовах. У статті розглядається потенціал незалежного використання безпілотних літальних апаратів із штучним інтелектом як у бойових, так і в небойових армійських операціях. Завдяки використанню ГІС, C5IRS (командування, управління, комп’ютери, зв’язок, кіберзахист, розвідка, спостереження та розвідка) і штучного інтелекту ці дрони забезпечують значну перевагу на полі бою, працюючи автономно та адаптуючись до динамічних наземних ситуацій. У бойовому просторі, де поєднання людських, інформаційних і фізичних компонентів має вирішальне значення для стратегічної переваги, оперативна сумісність стає життєво важливим фактором.

Ключові слова: БПЛА, YOLOv8, дрон, ГІС, штучний інтелект, безпека, C5IRS.