AI-Driven Military Decision Support System Using Deep Learning and Tactical Image Intelligence

M. Hemanth[1], Mattegajam Rakesh[2], Mylapaka Vennela[2], Naini Gayathri[2], Sk Shahbaz[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering

[1,2]Vaagdevi Engineering College, Bollikunta, Warangal, 506005, Telangana, India.

To Cite this Article

M. Hemanth, Mattegajam Rakesh, Mylapaka Vennela, Naini Gayathri, Sk Shahbaz, "AI-Driven Military Decision Support System Using Deep Learning and Tactical Image Intelligence", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 04, April 2026,pp: 490-499, DOI: http://doi.org/10.64771/jsetms.2026.v03.i04.pp490-499

Submitted: 28-02-2026 Accepted: 02-04-2026 Published: 10-04-2026

ABSTRACT

Recent advancements in artificial intelligence have significantly transformed modern defence systems by enhancing decision support through automated data analysis. The proposed system, AI-Driven Military Decision Support System Using Deep Learning and Tactical Image Intelligence (AI-DMDSSUDLTII), addresses the growing need for rapid and accurate interpretation of large-scale military visual data. In modern warfare, massive volumes of images generated from drones, satellites, and reconnaissance systems require efficient processing for timely and strategic decisions. Traditional approaches relying on manual analysis and rule-based techniques were time-consuming, less scalable, and prone to inconsistencies in dynamic battlefield conditions, highlighting the need for an intelligent, data-driven solution. To overcome these challenges, the system integrates machine learning and deep learning models for automated classification of military assets. Baseline techniques such as Perceptron and Decision Tree are combined with advanced architectures like Deep Neural Networks (DNN) and a hybrid Convolutional Neural Network with Long Short-Term Memory (CNN-LSTM). This hybrid approach effectively captures both spatial features and sequential patterns in tactical images, enabling robust feature extraction and improved classification performance across multiple military categories. Additionally, the system is deployed through a graphical user interface supporting dataset management, preprocessing, model training, evaluation, and real-time prediction. By leveraging deep learning and tactical image intelligence, the framework enhances decision accuracy, reduces processing time, and improves operational efficiency, providing a scalable and effective solution for intelligent military decision-making in modern defence environments.

Keywords: Artificial intelligence, military decision support system, deep learning, tactical image intelligence, convolutional neural network–long short-term memory (CNN–LSTM), image classification, real-time prediction, operational efficiency.

1. INTRODUCTION

In recent years, military operations have generated vast amounts of visual data from drones, satellites, and surveillance systems, creating challenges in timely analysis and decision-making as shown in figure 1. A significant portion of this data remains unprocessed due to limited automated tools, leading to a gap between data collection and actionable intelligence.

Traditional manual analysis is time-consuming, error-prone, and less reliable under high-stress conditions. To address these issues, artificial intelligence and machine learning techniques are increasingly adopted to automate image processing and improve accuracy. These intelligent systems enhance situational awareness, enable faster tactical responses, and support effective military decision-making in real time. With the advancement of computing hardware, open-source machine learning frameworks, and better data storage facilities, the defence sector is moving toward data-driven decision support systems.

Figure 1: Predicted Classes and Confidence Levels for Military Object Recognition

These systems can integrate historical data with real-time imagery to create a more comprehensive operational picture. As a result, military forces are seeking to adopt data-centric approaches to complement traditional methods, thereby transforming tactical decision-making into a faster, more reliable, and evidence-based process.

2. LITERATURE SURVEY

Zigulic et al. [1] study delves into the vital missions of the armed forces, encompassing the defense of territorial integrity, sovereignty, and support for civil institutions. Commanders grapple with crucial decisions, where accountability underscores the imperative for reliable field intelligence. Harnessing artificial intelligence, specifically, the YOLO version five detection algorithm, ensures a paradigm of efficiency and precision. The presentation of trained models, accompanied by pertinent hyperparameters and dataset specifics derived from public military insignia videos and photos, reveals a nuanced evaluation. Results scrutinized through precision, recall, map@0.5, mAP@0.95, and F1 score metrics, illuminate the supremacy of the model employing Stochastic Gradient Descent at 640 × 640 resolution: 0.966, 0.957, 0.979, 0.830, and 0.961. Conversely, the suboptimal performance of the model using the Adam optimizer registers metrics of 0.818, 0.762, 0.785, 0.430, and 0.789. These outcomes underscore the model's potential for military object detection across diverse terrains, with future prospects considering the implementation on unmanned arial vehicles to amplify and deploy the model effectively.

Costa et al. [2] provided a comprehensive overview of how simulation and Machine Learning (ML) tools have been used to analyze BVR combat, covering key methodologies, applications, and challenges. They examine how ML enables adaptive tactics to improve behavior recognition and threat assessment to enhance situational awareness. The paper also traces the historical evolution of BVR combat, outlining key engagement phases such as detection, missile launch, and post-engagement assessment. A key focus is on the role of simulation environments in modeling realistic combat scenarios, supporting pilot training, and validating AI-driven decision-making strategies. They analyze state-of-the-art simulation tools, comparing their capabilities and limitations for studying multi-agent coordination and real-time adaptability. This survey's main contributions include descriptions of ML applications in BVR air combat, evaluations of simulation tools, identifications of research gaps, and

 ISSN: 3049-0952
www.jsetms.com

insights into future research directions. This work provides an overview of how traditional simulation approaches merge with artificial intelligence to enable advanced, effective human and autonomous decision-making systems in dynamic and contested environments.

Bistron et al. [3] presented an overview of current and expected prospects for the development of artificial intelligence algorithms, especially in military applications, and conducted research regarding applications in the area of civilian life. Attention was paid mainly to the use of AI algorithms in cybersecurity, object detection, military logistics and robotics. It discusses the problems connected with the present solutions and how artificial intelligence can help solve them. It briefly presents also mathematical structures and descriptions for ART, CNN and SVM networks as well as Expectation–Maximization and Gaussian Mixture Model algorithms that are used in solving of discussed problems. The third chapter discusses the attitude of society towards the use of neural network algorithms in military applications. The basic problems related to ethics in the application of artificial intelligence and issues of responsibility for errors made by autonomous systems are discussed. Galán et al. [4] aimed to present a model of a machine learning architecture applied to a military organization, carried out and supported by a bibliometric study applied to an architecture model of a nonmilitary organization. For this purpose, a bibliometric analysis up to the year 2021 was carried out, making a strategic diagram and interpreting the results. The information used has been extracted from one of the main databases widely accepted by the scientific community, ISI WoS. No direct military sources were used. The work is divided into five parts: the study of previous research related to machine learning in the military world; the explanation of their research methodology using the SciMat, Excel and VosViewer tools; the use of this methodology based on data mining, preprocessing, cluster normalization, a strategic diagram and the analysis of its results to investigate machine learning in the military context; based on these results, a conceptual architecture of the practical use of ML in the military context is drawn up; and, finally, they present the conclusions, where they will see the most important areas and the latest advances in machine learning applied, in this case, to a military environment, to analyze a large set of data, providing utility, machine learning and decision support.

Skarka et al. [5] review explored the integration of machine learning (ML) and reinforcement learning (RL) techniques in enhancing the navigation and obstacle avoidance capabilities of Unmanned Aerial Vehicles (UAVs). Various RL algorithms are assessed for their effectiveness in teaching UAVs autonomous navigation, with a focus on state representation from UAV sensors and real-time environmental interaction. The review identifies the strengths and limitations of current methodologies and highlights gaps in the literature, proposing future research directions to advance UAV technology. Interdisciplinary approaches combining robotics, AI, and aeronautics are suggested to improve UAV performance in complex environments. Alcántara Suárez et al. [6] provided a comprehensive analysis of the impact of ML on the defense sector, including the benefits and drawbacks of using ML in various applications such as surveillance, target identification, and autonomous weapons systems. They also discuss the ethical implications of using ML in defense, focusing on privacy, accountability, and bias issues. Finally, they present recommendations for mitigating these ethical concerns, including increased transparency, accountability, and stakeholder involvement in designing and deploying ML systems in the defense sector.

Cho et al. [7] introduced for determining the ways to prioritize the AI technology domains applied to military intelligence. Consequently, among the five stages used, the processing stage has the highest priority. The application of AI technology to all the stages of information circulation may be ideal. Nevertheless, among various military intelligence domains, the one that affords the highest effectiveness of such an application should be prioritized. This is owing to resource and defense budget limitations. Karna et al. [8] presented an artificial intelligence-based model for the classification of maritime vessel images obtained by cameras operating in the visible part of the electromagnetic spectrum. It incorporates both the deep learning techniques for initial image representation and traditional image processing and machine learning methods for subsequent image classification. The presented model is therefore a hybrid approach that uses the Inception v3 deep learning model for the purpose of image vectorization and a combination of SVM, kNN, logistic regression, Naïve Bayes, neural network, and decision tree algorithms for final image classification. The model is trained and tested on a custom dataset consisting of a total of 2915 images of maritime vessels. These images were split into three subsections: training (2444 images), validation (271 images), and testing (200 images). The images themselves encompassed 11 distinctive classes: cargo, container, cruise, fishing, military, passenger, pleasure, sailing, special, tanker, and non-class (objects that can be encountered at sea but do not represent maritime vessels). The presented model accurately classified 86.5% of the images used for training purposes and therefore demonstrated how a relatively straightforward model can still achieve high accuracy and potentially be useful in real-world operational environments aimed at sea surveillance and automatic situational awareness at sea.

Caballero-Martin et al. [9] Proposed integration of Artificial Intelligence (AI) tools and techniques has provided a significant advance in drone technology. Besides the military applications, drones are being increasingly used for logistics and cargo transportation, agriculture, construction, security and surveillance, exploration, and mobile wireless communication. The synergy between drones and AI has led to notable progress in the autonomy of drones, which have become capable of completing complex missions without direct human supervision. The study of the state of the art examines the impact of AI on improving drone autonomous behavior, covering from automation to complex real-time decision making. The paper provides detailed examples of the latest developments and applications. Ethical and regulatory challenges are also considered for the future evolution of this field of research, because drones with AI have the potential to greatly change their socioeconomic landscape.

Olugbade et al. [10] examined the critical problems and potential remedies for reducing road traffic accidents and the application of artificial intelligence and machine learning in road transportation systems. More, new, and emerging trends that reduce frequent accidents in the transportation sector are discussed extensively. Specifically, the study organized the following sub-topics: an incident detector with machine learning and artificial intelligence and road management with machine learning and artificial intelligence. Additionally, safety is the primary concern of road transport; the internet of vehicles and vehicle ad hoc networks, including the use of wireless communication technologies such as 5G wireless networks and the use of machine learning and artificial intelligence for road transportation systems planning, are elaborated. Key findings from the review indicate that route optimization, cargo volume forecasting, predictive fleet maintenance, real-time vehicle tracking, and traffic management are critical to safeguarding road transportation systems.

The authors of [11] investigated the development of a lightweight military target-detection method, SMCA-α-YOLOv5. The method, which involves replacing the focusing module and redesigning the network structure, achieves an exceptional result with an average accuracy of 98.4% and a detection speed of 47.6 FPS. It outperforms competing algorithms such as SSD, and Faster-RCNN, with a significant reduction in parameter cardinality and computational burden. In their research, [12] used the method of Optimal Gabor Filtering and Deep Feature Pyramid Network to utilize a military target-detection dataset named MOD VOC, which was created to meet the PASCAL VOC dataset format standard and includes images primarily sourced from video footage captured by unmanned arial vehicles (UAVs), ground cameras, and internet images. In doing so, they used five artificial intelligence algorithms (Faster R-CNN, DSOD300, DSSD513, YOLOv2 544, and their filtering method) to compare the individual performance of the best model for each algorithm. The best results for MOD VOC in terms of accuracy, recall, and average fps were achieved by their model in the amount of 88.76%, 78.45%, and 30.35, respectively, while the worst results were achieved by DSSD513 in the amount of 73.57%, 64.56%, and 42.43.

Kong et al. [13] used a military target dataset showing armed individuals with different weapons to improve the detection performance of the proposed YOLO-G algorithm. The authors introduced improvements compared to the YOLOv3 framework, including a lightweight GhostNet for improved accuracy and speed in detecting military targets. The dataset evaluation showed a 2.9% improvement in mAP and a 25.9 FPS increase in the detection rate compared to the original YOLOv3, highlighting the effectiveness of their improved algorithm. Wang and Han [14] introduces the YOLO-M algorithm for military equipment target recognition, addressing challenges in small target detection. By incorporating the C3CMix module and modifying the activation function in YOLOv5, the proposed algorithm maintains high accuracy while reducing parameters, resulting in a 95.2% average accuracy, an 18.8% reduction in parameters, and a 14.5% decrease in computation. These improvements make YOLO-M well-suited for deployment in military equipment target recognition applications. Du et al. [15] investigated military vehicle object detection based on hierarchical feature representation and refined localization for the detection of military objects in the desert, grass, snow, city, and others. The authors applied R-FCNN, SSD, YOLOv3, YOLOv4, Faster R-CNN, and MVODM, i.e., a novel algorithm created by the author. The models were trained on three different types of test datasets, i.e., large-scale, small-scale, and all subset test datasets.

3. PROPOSED SYSTEM

The proposed system introduces an intelligent tactical decision support framework that utilizes machine learning and deep learning techniques to classify military vehicles from images as shown in figure 2. It aims to convert raw visual data into meaningful insights that assist in real-time military decision-making. Unlike traditional methods that depend on manual image analysis, which is slow and prone to errors, this approach automates the entire classification process. Advanced models are used to accurately identify assets such as tanks, helicopters, and aircraft from visual inputs. As a result, the system enhances decision speed, accuracy, and overall operational efficiency in military environments.

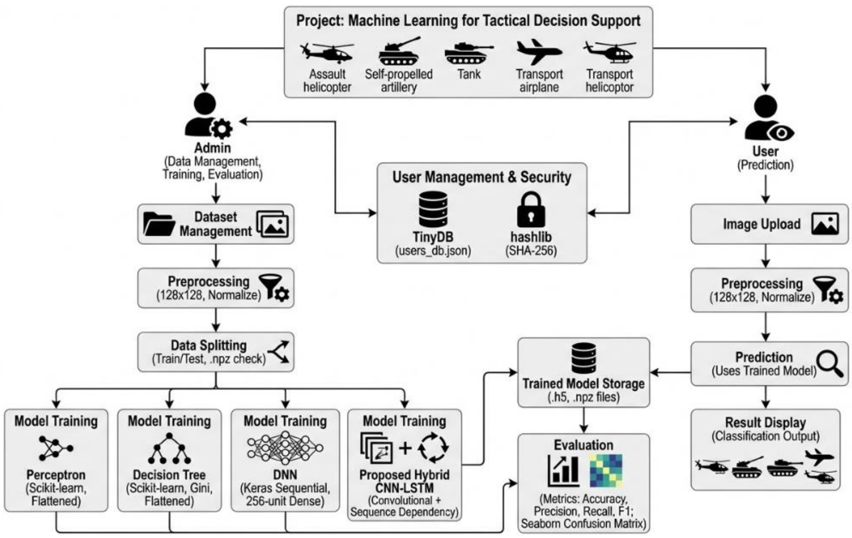

Figure 2: Proposed System Architecture

The system was developed with a user-friendly graphical user interface that clearly separated the roles of administrators and end-users for efficient workflow management. Administrators handled tasks such as dataset uploading, image preprocessing, data splitting, and training multiple machine learning and deep learning models. These models included traditional approaches like Perceptron, advanced Deep Neural Networks, and a hybrid Convolutional Recurrent architecture for improved performance. End-users were provided with the capability to input new images and receive real-time predictions along with visual classification results. This structured role-based design improved usability, streamlined operations, and ensured effective interaction within military intelligence processes.

Key functionalities include dataset preprocessing, model training, evaluation through detailed metrics (accuracy, precision, recall, F1-score, sensitivity, specificity), and graphical analysis of model performance. The system also supports prediction for new test images and visualizes classification results. By incorporating convolutional neural networks and recurrent neural networks, particularly LSTM layers, the hybrid model captures both spatial and temporal patterns in images, enhancing classification accuracy. This research offers a scalable, efficient, and intelligent platform to support tactical decisions in defense scenarios through automated military asset recognition.

4. RESULTS ANALYSIS

The results section presents the key findings of the study in a clear and organized manner. It summarizes the data collected and highlights important patterns, trends, or relationships observed during the analysis. This section focuses only on factual outcomes without interpretation or bias. Tables, graphs, or charts are often used to make the results easier to understand. The aim is to provide a concise overview of what the research discovered. It serves as the foundation for further discussion and conclusions.

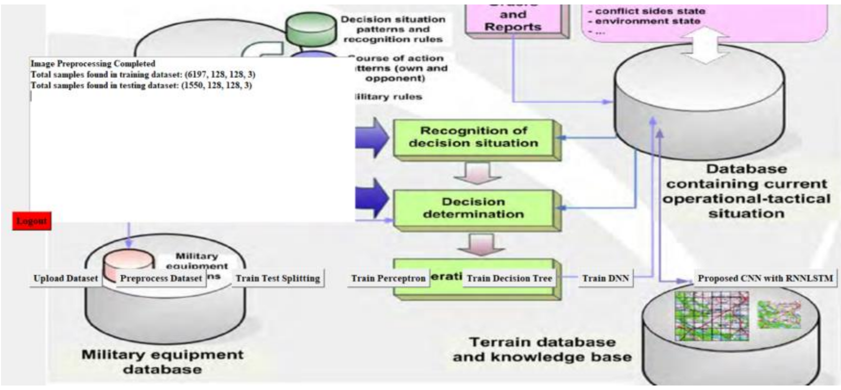

Figure 3: Data Preprocessing and splitting

The figure 3 illustrates the image preprocessing and train–test splitting stage of the military tactical decision support system after dataset upload. At this stage, all military equipment images are resized to a uniform dimension of 128 × 128 × 3, normalized, and converted into structured NumPy arrays. The interface displays confirmation messages indicating successful preprocessing along with the total number of samples allocated to the training dataset (6197 images) and testing dataset (1550 images). This step ensures data consistency, balanced learning, and readiness for subsequent training using machine learning and deep learning models.

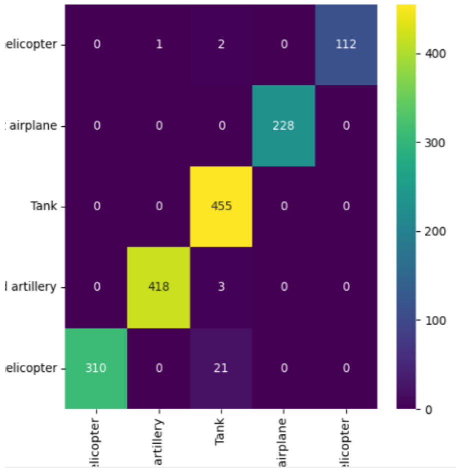

Figure 4: Confusion matrix obtained using Hybrid Convolutional recurrent Model

The figure 4 illustrates the confusion matrix of the proposed Convolutional recurrent model applied to the military equipment image dataset. The strong diagonal dominance indicates a significant improvement in classification accuracy, with classes such as Tank, Self-Propelled Artillery, and Transport Airplane being correctly classified with very high precision. Misclassifications are minimal and mainly occur between visually similar helicopter categories, which is expected due to overlapping visual features. This confusion matrix demonstrates that the proposed Convolutional recurrent model effectively captures both spatial and sequential features, outperforming existing Perceptron and DNN models and providing reliable support for tactical military decision-making.

Figure 5: Prediction on test images obtained using hybrid Convolutional recurrent model

Figure 6: Prediction on test images obtained using hybrid Convolutional recurrent model

The figures 5 and 6 demonstrates the real-time prediction results obtained using the proposed Convolutional recurrent model on unseen test images from the military dataset. In the first example, the system correctly identifies a ground-based combat vehicle and overlays the label "Self-Propelled Artillery", while in the second example, an aerial image is accurately classified as a "Transport Airplane." These results highlight the model's strong capability to extract discriminative spatial features through convolutional layers and effectively interpret contextual patterns using the RNN component. The clear and accurate overlay of predicted class labels on diverse test images confirms the robustness, generalization ability, and practical applicability of the proposed model for real-world military tactical decision support.

Table 1: Performance comparison for the Perceptron, DTC, DNN and Proposed Convolutional recurrentModel

Algorithms Name	Accuracy	Precision	Recall	F-score
Perceptron	32.90%	81.53%	41.38%	36.04%
DTC	90.12%	91.32%	91.97%	90.46%
DNN	89.67%	92.14%	88.71%	89.68%
Convolutional recurrent	98.83%	99.26%	98.89%	99.05%

Table 1 presents a detailed performance comparison of the Perceptron, Decision Tree Classifier (DTC), Deep Neural Network (DNN), and the proposed Convolutional recurrent model for military equipment image classification. The Perceptron model shows very poor overall performance with an accuracy of 32.90%, indicating its inability to handle high-dimensional image data, despite reporting a misleadingly high precision due to biased predictions. The Decision Tree Classifier achieves a strong improvement, attaining 90.12% accuracy, with balanced precision and recall values, demonstrating its effectiveness in modeling non-linear decision boundaries. The DNN further refines classification performance with 89.67% accuracy, benefiting from deeper feature learning but still lacking strong spatial feature extraction. In contrast, the proposed Convolutional recurrent model significantly outperforms all existing approaches, achieving an exceptional 98.83% accuracy, along with near-perfect precision, recall, and F-score values. This superior performance confirms the proposed model's ability to effectively capture complex spatial and sequential patterns in military imagery, making it highly suitable for accurate and reliable tactical decision support.

5. CONCLUSION

This research successfully demonstrates the design and implementation of an intelligent Machine Learning–based Tactical Decision Support System for accurate classification of military equipment using image data. By leveraging a large-scale dataset consisting of five critical military categories such as Tank, Assault Helicopter, Self-Propelled Artillery, Transport Airplane, and Transport Helicopter the system effectively integrates image preprocessing, role-based authentication, and a GUI-driven workflow for end-to-end usability. A comprehensive comparative analysis was conducted using traditional machine learning models such as Perceptron and Decision Tree, a Deep Neural Network, and a proposed hybrid Convolutional recurrent architecture. Experimental results clearly show that while conventional models struggle with high-dimensional visual data, the proposed Convolutional recurrent model significantly outperforms all existing approaches, achieving superior accuracy, precision, recall, and F-score. The strong diagonal dominance in confusion matrices and highly accurate real-time predictions on unseen test images validate the robustness and generalization capability of the proposed method. The integration of model persistence, performance visualization, and real-time prediction within a secure Tkinter-based interface further enhances the practical applicability of the system. The work confirms that deep learning–driven visual intelligence, particularly hybrid Convolutional recurrent architectures, can provide reliable and efficient tactical decision support, making the system well-suited for real-world military surveillance, reconnaissance, and operational planning applications.

REFERENCES

[1]. Zigulic, N.; Glucina, M.; Lorencin, I.; Matika, D. Military Decision-Making Process Enhanced by Image Detection. Information 2024, 15, 11. https://doi.org/10.3390/info15010011

[2]. Costa, J. P. A. Dantas, E. Scukins, F. L. L. Medeiros and P. Ögren, "Simulation and Machine Learning in Beyond Visual Range Air Combat: A Survey," in IEEE Access, vol. 13, pp. 76755-76774, 2025, doi: 10.1109/ACCESS.2025.3563811.

[3]. Bistron, M.; Piotrowski, Z. Artificial Intelligence Applications in Military Systems and Their Influence on Sense of Security of Citizens. Electronics 2021, 10, 871. https://doi.org/10.3390/electronics10070871

[4]. Galán, J.J.; Carrasco, R.A.; LaTorre, A. Military Applications of Machine Learning: A Bibliometric Perspective. Mathematics 2022, 10, 1397. https://doi.org/10.3390/math10091397

[5]. Skarka, W.; Ashfaq, R. Hybrid Machine Learning and Reinforcement Learning Framework for Adaptive UAV Obstacle Avoidance. Aerospace 2024, 11, 870. https://doi.org/10.3390/aerospace11110870

[6]. Alcántara Suárez, E.J.; Monzon Baeza, V. Evaluating the Role of Machine Learning in Defense Applications and Industry. Mach. Learn. Knowl. Extr. 2023, 5, 1557-1569. https://doi.org/10.3390/make5040078

[7]. Cho, S.; Shin, W.; Kim, N.; Jeong, J.; In, H.P. Priority Determination to Apply Artificial Intelligence Technology in Military Intelligence Areas. Electronics 2020, 9, 2187. https://doi.org/10.3390/electronics9122187

[8]. Saai Reddy Purmani, S. (2023). The Transformation of IT Leadership in Business Organizations: Shifting from Technical Supervision to Strategic Empowerment. JOURNAL

OF ADVANCE AND FUTURE RESEARCH, 1(5). https://doi.org/10.56975/jaafr.v1i5.503885

[9]. Cyril, H. P., & Kumara, S. (2026, February). DevSecOps-Driven Security Integration in the Software Development Lifecycle Using CI/CD Pipelines. In 2026 IEEE 5th International Conference on AI in Cybersecurity (ICAIC) (pp. 1-6). IEEE.

[10]. Olugbade, S.; Ojo, S.; Imoize, A.L.; Isabona, J.; Alaba, M.O. A Review of Artificial Intelligence and Machine Learning for Incident Detectors in Road Transport Systems. Math. Comput. Appl. 2022, 27, 77. https://doi.org/10.3390/mca27050077

[11]. Pham, I.; Polasek, M. Algorithm for military object detection using image data. In Proceedings of the 2014 IEEE/AIAA 33rd Digital Avionics Systems Conference (DASC), Colorado Springs, CO, USA, 5–9 October 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 1–15.

[12]. Hu, X.; Zhang, P.; Xiao, Y. Military object detection based on optimal gabor filtering and deep feature pyramid network. In Proceedings of the 2021 International Conference on Artificial Intelligence and Computer Science, Wuhan, China, 12–13 July 2021; pp. 524–530.

[13]. Kong, L.; Wang, J.; Zhao, P. YOLO-G: A lightweight network model for improving the performance of military targets detection. IEEE Access 2022, 10, 55546–55564.

[14]. Wang, H.; Han, J. Improved military equipment identification algorithm based on YOLOv5 framework. In Proceedings of the 2023 IEEE 6th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Chongqing, China, 24–26 February 2023; IEEE: Piscataway, NJ, USA, 2023; Volume 6, pp. 1195–1199.

[15]. Du, X.; Song, L.; Lv, Y.; Qin, X. Military Target Detection Method Based on Improved YOLOv5. In Proceedings of the 2022 International Conference on Cyber-Physical Social Intelligence (ICCSI), Nanjing, China, 18–21 November 2022; IEEE: Piscataway, NJ, USA, 2022; pp. 53–57.