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Intelligent Military Decision Support Using Machine Learning and Data-Driven Tactical Analysis

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ABSTRACT

Technological advancements have fundamentally transformed modern defense operations, particularly within surveillance, reconnaissance, and battlefield decision support systems. While military environments generate vast volumes of visual data from satellites and unmanned aerial vehicles (UAVs), conventional manual interpretation remains resource-intensive and prone to human error, hindering real-time operational responses. To address these systemic bottlenecks, this research introduces an intelligent, high-assurance decision support framework for the automated classification of tactical military imagery. The proposed system transitions beyond traditional rule-based software by integrating a suite of soft computing models, including Perceptron, Decision Tree Classifiers (DTC), and Deep Neural Networks (DNN). Central to the framework is a novel Hybrid Convolutional Recurrent Model (CRM), which synergizes Convolutional Neural Networks (CNN) for spatial feature extraction with Long Short-Term Memory (LSTM) networks to capture essential temporal dependencies in dynamic battlefield scenarios. The architecture is encapsulated within a modular graphical interface designed for streamlined data ingestion, model training, and performance visualization. Experimental validation demonstrates that the integrated CRM significantly enhances processing speed and classification reliability, providing a scalable and robust technological solution for modern military intelligence and tactical decision-making.

Key words: Tactical decision support, Convolutional recurrent model, Military environments, surveillance sensors.

1. INTRODUCTION

In recent years, the volume of visual data collected through military surveillance, reconnaissance, and tactical operations has increased exponentially. According to defense technology reports, modern military operations generate terabytes of imagery and video data daily from drones, satellites, and field devices. Yet, more than 80% of this valuable data remains unstructured and unanalyzed due to limited processing capabilities and lack of advanced automated tools. This creates a huge gap between data collection and actionable intelligence, affecting critical decisions on the ground. Traditional manual analysis of images and videos in military operations is not only time-consuming but also prone to human error and fatigue. Studies indicate that human analysts have a recognition accuracy of around 65–75% under high-stress environments, which can compromise mission success and troop safety.

There are many applications for AI, including chatbots, automated drones, facial recognition, virtual assistants, cognitive automation, fraud detection, autonomous vehicles, and applications for predictive analytics. However, regardless of how AI is applied, each of these applications has something in common. Despite the variety of applications, people who have created hundreds or even thousands of AI projects know that every use case falls into one or more of seven categories, as shown in Fig. 1.

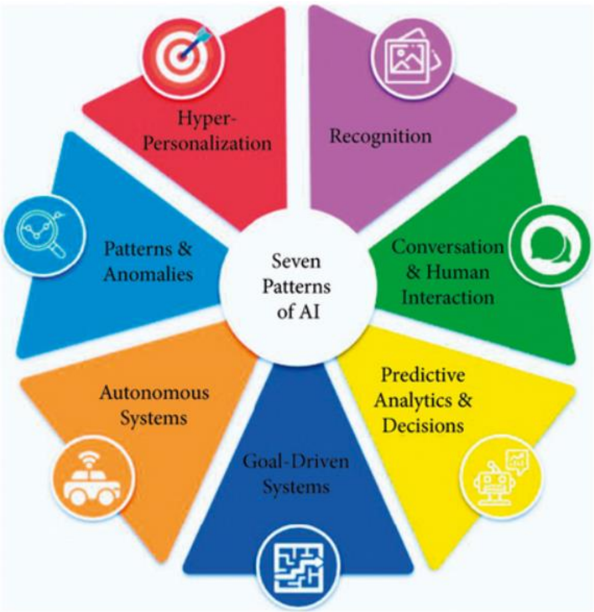

Fig. 1: Seven patterns of AI.

Leveraging machine learning and artificial intelligence is becoming a necessity to improve situational awareness, automate target recognition, and classify tactical scenarios accurately and reliably in near-real time. With the advancement of computing hardware, open-source machine learning frameworks, and better data storage facilities, the defense sector is moving toward data-driven decision support systems. 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

Artificial intelligence (AI) and machine learning (ML) technologies have increasingly been adopted in defense, surveillance, and autonomous systems to enhance situational awareness, decision-making, and operational efficiency. Zigulic et al. [1] investigated the application of deep learning for military object detection using the YOLOv5 algorithm. Their study evaluated different optimization strategies and demonstrated that the stochastic gradient descent-based model achieved superior detection performance, indicating the potential of deep learning models for reliable military object detection across diverse terrains and environments.

Simulation and machine learning have also been widely explored to analyze military combat scenarios. Costa et al. [2] reviewed the integration of ML techniques with simulation tools for beyond-visual-range (BVR) air combat analysis. Their work highlighted how ML enables adaptive tactical decision-making, threat recognition, and improved situational awareness in dynamic combat environments. Similarly, Galán et al. [4] conducted a bibliometric analysis to examine the application of machine learning in military organizations and proposed a conceptual architecture that integrates data mining, preprocessing, clustering, and decision-support mechanisms to improve military intelligence operations. The broader role of AI in military applications has been extensively studied. Bistron et al. [3] provided an overview of AI algorithms used in areas such as cybersecurity, military logistics, robotics, and object detection. Their work also discussed the societal and ethical implications of deploying AI in defense systems, particularly focusing on issues related to accountability and decision-making in autonomous systems. Alcántara Suárez et al. [6] further explored these aspects by analyzing the benefits and limitations of ML technologies in defense applications, including surveillance, target identification, and autonomous weapon systems, while emphasizing the importance of transparency and ethical considerations.

Several studies have focused on improving autonomous navigation and intelligence capabilities of unmanned systems. Skarka et al. [5] reviewed reinforcement learning approaches for autonomous navigation and obstacle avoidance in unmanned aerial vehicles (UAVs), highlighting the importance of sensor-based environmental representation and real-time decision-making. Caballero-Martin et al. [9] also examined the integration of AI in drone technologies, demonstrating how AI enables drones to perform complex missions autonomously across applications such as surveillance, logistics, and communication. Deep learning-based target detection has been a significant research focus in military applications. Researchers have proposed various optimized detection frameworks to improve performance and efficiency. The authors in [11] introduced a lightweight YOLOv5-based target detection model, achieving high detection accuracy and real-time processing capability while reducing computational complexity. Similarly, Wang and Han [14] proposed the YOLO-M algorithm, which improves small-object detection by modifying network architecture and activation functions, resulting in improved accuracy with reduced computational cost. Kong et al. [13] enhanced the YOLOv3 framework using GhostNet to develop the YOLO-G model, improving both detection accuracy and speed for military target detection.

In addition to these models, other works have explored advanced feature extraction and detection techniques for complex environments. The authors in [12] developed a military object detection framework using optimal Gabor filtering combined with a deep feature pyramid network and evaluated it on the MOD VOC dataset collected from UAV and ground-based imagery. Their approach demonstrated improved accuracy compared to several existing detection models. Similarly, Du et al. [15] proposed a hierarchical feature representation approach for military vehicle detection in diverse environments such as deserts, urban areas, and snow-covered regions, achieving improved performance compared with widely used models such as Faster R-CNN, SSD, and YOLO variants. AI-based image classification has also been applied in maritime and surveillance contexts. Karna et al. [8] proposed a hybrid AI framework combining deep learning-based feature extraction using the Inception v3 model with traditional ML classifiers such as SVM and k-nearest neighbors for maritime vessel classification. Their model demonstrated effective performance in identifying various vessel categories, contributing to improved maritime surveillance and situational awareness. Beyond military surveillance, AI has also been applied to transportation safety and intelligent infrastructure systems. Olugbade et al. [10] reviewed the application of AI and ML in road transportation systems for accident detection, traffic monitoring, and predictive maintenance. Their findings highlight the growing role of AI-driven systems in improving safety, route optimization, and real-time traffic management. Overall, the literature indicates significant advancements in AI-driven detection, autonomous navigation, and intelligent decision-support systems for defense and surveillance applications. However, several challenges remain, including improving detection accuracy for small or occluded targets, reducing computational complexity for real-time deployment, and addressing ethical and operational concerns related to autonomous systems.

3. PROPOSED METHODOLOGY

The project presents an intelligent tactical decision support system that leverages machine learning and deep learning techniques to classify military vehicles from images. The primary aim is to transform raw visual data into actionable intelligence that can support real-time decisions in military operations. Traditional military systems rely heavily on manual image interpretation, which is time-consuming and error-prone. In contrast, this system automates the classification of military assets such as tanks, helicopters, and aircraft using advanced computer vision models, enabling faster and more accurate decision-making.

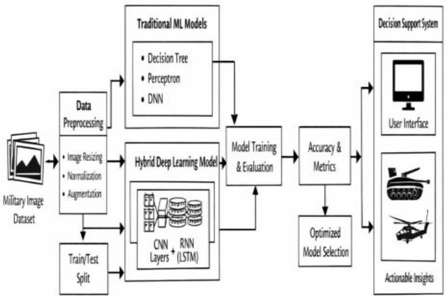

Figure 2. Proposed system architecture.

The system is developed with a user-friendly graphical user interface (GUI) that separates the roles of administrators and end-users. Administrators are responsible for uploading datasets, preprocessing images, splitting the data for training and testing, and training various machine learning models. These models include traditional classifiers like Perceptron, deep learning-based DNNs, and a hybrid Convolutional recuurent architecture. Users, on the other hand, can input unseen images to obtain real-time predictions and visual feedback on the classified military object. This modular separation enhances usability and ensures smooth interaction for different roles in military intelligence workflows. 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. The project offers a scalable, efficient, and intelligent platform to support tactical decisions in defense scenarios through automated military asset recognition.

4. RESULT ANALYSIS

Figure 3 illustrates the dataset upload interface displayed after successful Admin login in the military tactical decision support system. Through this interface, the Admin can upload the military image dataset, after which the system confirms successful loading and dynamically displays the detected classes, including Tank, Assault Helicopter, Self-Propelled Artillery, Transport Airplane, and Transport Helicopter. The interface also provides sequential action buttons for preprocessing, train–test splitting, and training multiple models such as Perceptron, Decision Tree, DNN, and the proposed convolutional recurrent. This centralized dashboard enables the Admin to manage the complete model training workflow efficiently while maintaining clear visibility of dataset status and system operations. Figure 4. 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.

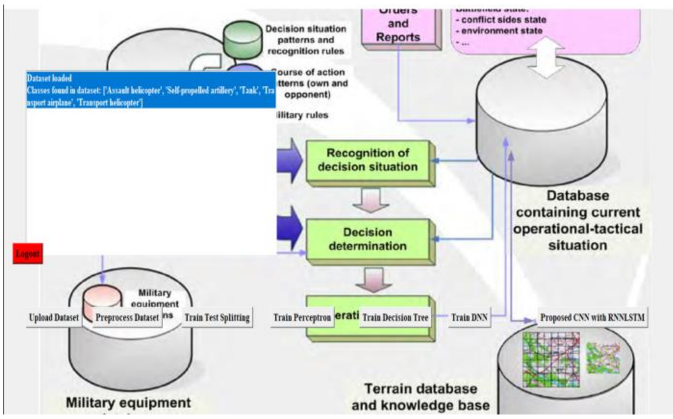

Figure 3. Dataset upload interface after admin login

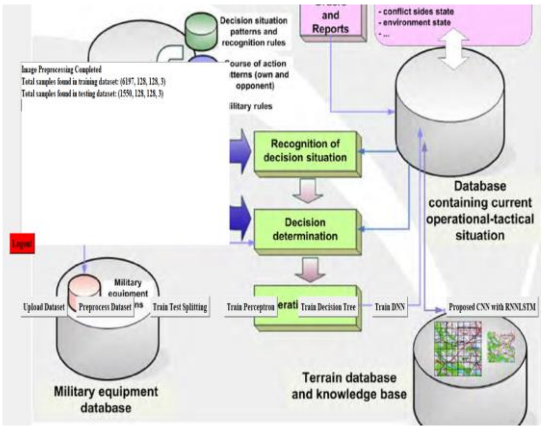

Figure 4. Data Preprocessing and splitting

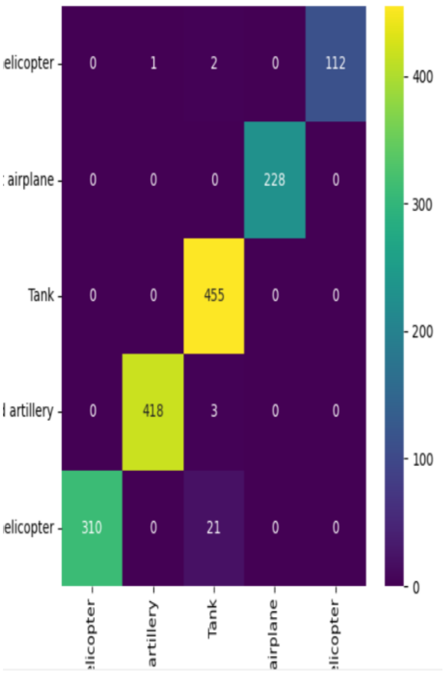

Figure 5. Confusion matrix obtained using hybrid CRM approach.

Figure 5 illustrates the confusion matrix of the proposed Convolutional recurrent model applied to the military equipment image dataset. The strong 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 6. Prediction on test images obtained using hybrid CRM approach.

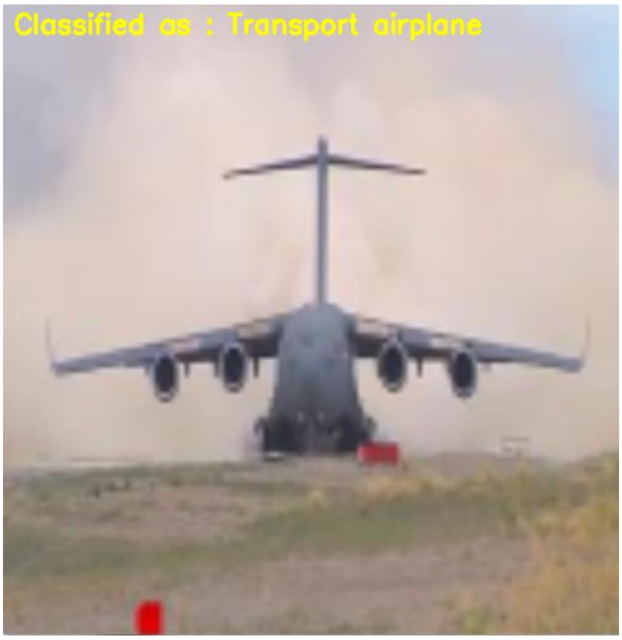

Figure 7. Prediction on test images obtained using hybrid CRM approach.

Figure 6 and Figure 7 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.

5. CONCLUSION

The project 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 DTC, DNN, and a proposed hybrid CRM approach. 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 CRM architectures, can provide reliable and efficient tactical decision support, making the system well-suited for real-world military surveillance, reconnaissance, and operational planning applications.

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