

## AI-Driven Tactical Military Asset Recognition for Enhanced Situational Awareness and Command Decision Support

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### ABSTRACT

Contemporary defense systems are increasingly dependent on intelligent technologies to enhance surveillance, reconnaissance, and strategic decision-making capabilities. The rapid growth of visual data generated from satellites and unmanned aerial platforms has made manual image analysis and traditional rule-based approaches inefficient, labor-intensive, and unsuitable for large-scale processing. To overcome these limitations, the proposed system employs advanced Machine Learning and Deep Learning techniques to automate the classification of military imagery. The framework integrates multiple algorithms, including Perceptron, Decision Tree Classifier (DTC), Deep Neural Networks (DNN), and a Hybrid Convolutional Recurrent Model (CRM). The CRM combines Convolutional Neural Networks (CNN) for robust spatial feature extraction with Long Short-Term Memory (LSTM) networks to model complex sequential relationships within the extracted features. These models are trained on well-structured military image datasets to accurately categorize assets into predefined strategic classes. Experimental results demonstrate that DNN and CRM models deliver improved accuracy and reliability, depending on dataset characteristics and training conditions. Additionally, the system is equipped with a user-friendly graphical interface that allows seamless dataset uploading, model training, prediction generation, and visualization of performance metrics. By consolidating multiple models into a single platform and identifying the most effective one for deployment, the proposed solution significantly improves the efficiency, accuracy, and robustness of automated military image analysis, thereby enhancing intelligence operations and supporting informed decision-making.

**Keywords:** Image Analysis, Surveillance Systems, Defense Intelligence, Pattern Recognition, Automated Classification, Deep Learning.

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### 1. INTRODUCTION

In recent years, military surveillance, reconnaissance, and tactical operations have led to an exponential increase in the volume of visual data generated from sources such as drones, satellites, and field-based imaging systems. Defense technology studies highlight that modern operations produce massive amounts of imagery and video data on a daily basis; however, a significant portion—often exceeding 80%—remains unstructured and underutilized due to limitations in processing capabilities and the absence of advanced automated analysis tools. This results in a critical gap between data acquisition and actionable intelligence, ultimately impacting timely and effective decision-making in mission-critical scenarios. Conventional methods that rely on manual interpretation of visual data are not only slow but also susceptible to human limitations such as fatigue, stress, and inconsistency. Research indicates that under high-pressure conditions, human analysts typically achieve an accuracy rate of only

around 65–75%, which may adversely affect operational outcomes and safety. Consequently, the adoption of machine learning and artificial intelligence has become essential to enhance situational awareness, enable automated target recognition, and support accurate and reliable classification of tactical environments in near real-time.

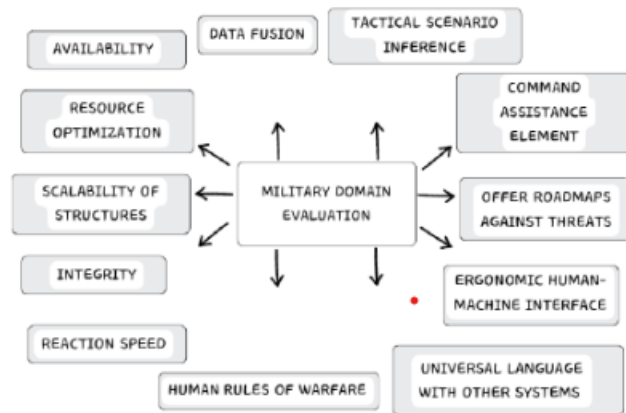


Fig.1. Key factors of military domain evolution

With the rapid advancement of computing hardware, the availability of powerful open-source machine learning frameworks, and improvements in data storage technologies, the defense sector is increasingly transitioning toward data-driven decision support systems. These systems are capable of integrating historical datasets with real-time imagery to generate a more comprehensive and dynamic operational view, as shown in Fig. 1. Consequently, military organizations are adopting data-centric methodologies to complement conventional approaches, enabling tactical decision-making to become faster, more accurate, and firmly grounded in evidence-based insights. The problem addressed in the research revolves around the efficient and reliable classification of military tactical scenarios using vast amounts of unstructured image data. Conventional manual review processes are inadequate for processing data at scale or in near-real time, which limits their usefulness in time-sensitive decision-making environments. There is a pressing need to automate the classification of critical military assets and scenarios while maintaining a high level of accuracy and consistency. Additionally, the challenge includes handling image data from varied sources, differing in quality, format, and resolution. This heterogeneity makes traditional rule-based image processing systems ineffective.

## 2. LITERATURE SURVEY

### 2.1 AI and Machine Learning in Transportation Systems

Artificial intelligence (AI) and machine learning (ML) have been extensively applied to improve safety and efficiency in transportation systems. Olugbade *et al.* [10] investigated the role of AI-driven techniques in reducing road traffic accidents and enhancing transportation management. Their study highlighted key applications such as incident detection, traffic monitoring, route optimization, predictive fleet maintenance, and real-time vehicle tracking. Furthermore, the integration of advanced technologies such as the Internet of Vehicles (IoV), vehicular ad hoc networks (VANETs), and 5G communication systems was emphasized as a critical factor in improving road safety and operational efficiency. The findings underline the importance of intelligent transportation systems in minimizing accident risks and optimizing logistics operations.

### 2.2 Deep Learning-Based Military Target Detection

Significant advancements have been made in applying deep learning for military target detection and surveillance. The authors in [11] proposed a lightweight object detection model, SMCA- $\alpha$ -YOLOv5, designed for military applications. By modifying the network architecture and replacing the focusing module, the model achieved high detection accuracy (98.4%) and real-time performance (47.6 FPS),

outperforming conventional models such as SSD and Faster R-CNN while reducing computational complexity.

In a related study, [12] introduced a framework combining Optimal Gabor Filtering with a Deep Feature Pyramid Network for military target detection using the MOD VOC dataset. The proposed method demonstrated superior performance compared to several baseline models, including Faster R-CNN, DSOD300, DSSD513, and YOLOv2, achieving improved accuracy, recall, and processing efficiency. Kong *et al.* [13] further enhanced target detection by proposing the YOLO-G algorithm, which integrates a lightweight GhostNet backbone into the YOLOv3 framework. This modification resulted in improved mean Average Precision (mAP) and increased detection speed, demonstrating the effectiveness of lightweight architectures in real-time applications.

Similarly, Wang and Han [14] introduced the YOLO-M model, focusing on improving small object detection in military scenarios. By incorporating the C3CMix module and optimizing activation functions, the model achieved high accuracy (95.2%) while significantly reducing model parameters and computational overhead, making it suitable for deployment in resource-constrained environments. Du *et al.* [15] proposed a novel military vehicle object detection model (MVIDM) based on hierarchical feature representation and refined localization. Their approach outperformed traditional models such as YOLOv3, YOLOv4, SSD, and Faster R-CNN across multiple datasets, achieving the highest mAP of 85.6% for large-scale datasets, highlighting the importance of feature refinement techniques in improving detection accuracy.

### 2.3 Sensor-Based Detection Systems in Defense Applications

Beyond visual detection, sensor-based systems have also been explored for defense applications. Nelson and McDonald [16] developed the Multisensor Towed Array Detection System (MTADS) for detecting buried unexploded ordnance. The system demonstrated a high probability of detection ( $\geq 0.95$ ), providing an efficient and cost-effective solution for identifying hazardous materials at varying depths. This work emphasizes the role of multisensor fusion in enhancing detection accuracy in complex environments.

### 2.4 AI Integration with Advanced Communication Networks

The integration of AI with next-generation communication technologies has enabled the development of intelligent mission-critical systems. Spantideas *et al.* [17] explored intelligent mission-critical services over Beyond 5G networks, focusing on proactive overload detection and control loop optimization. Similarly, Skarin *et al.* [18] investigated edge-based mission-critical control systems leveraging 5G infrastructure. These studies highlight the importance of combining AI with advanced networking technologies to support real-time decision-making and enhance system reliability in critical applications.

## 3. PROPOSED METHODOLOGY

The proposed system focuses on developing an intelligent framework for automated classification of military images using advanced ML and DL techniques. The system is designed to efficiently process large volumes of visual data collected from surveillance sources and provide accurate classification results for decision support. It integrates multiple models such as Perceptron, DTC, DNN, and Hybrid CRM to enhance performance and reliability. The framework emphasizes both spatial and temporal feature extraction using CNN and LSTM techniques. Additionally, a user-friendly interface is incorporated to simplify data handling, model training, and prediction processes as demonstrated in Fig. 2. Overall, the system aims to improve speed, accuracy, and efficiency in image-based analysis for modern defense applications.

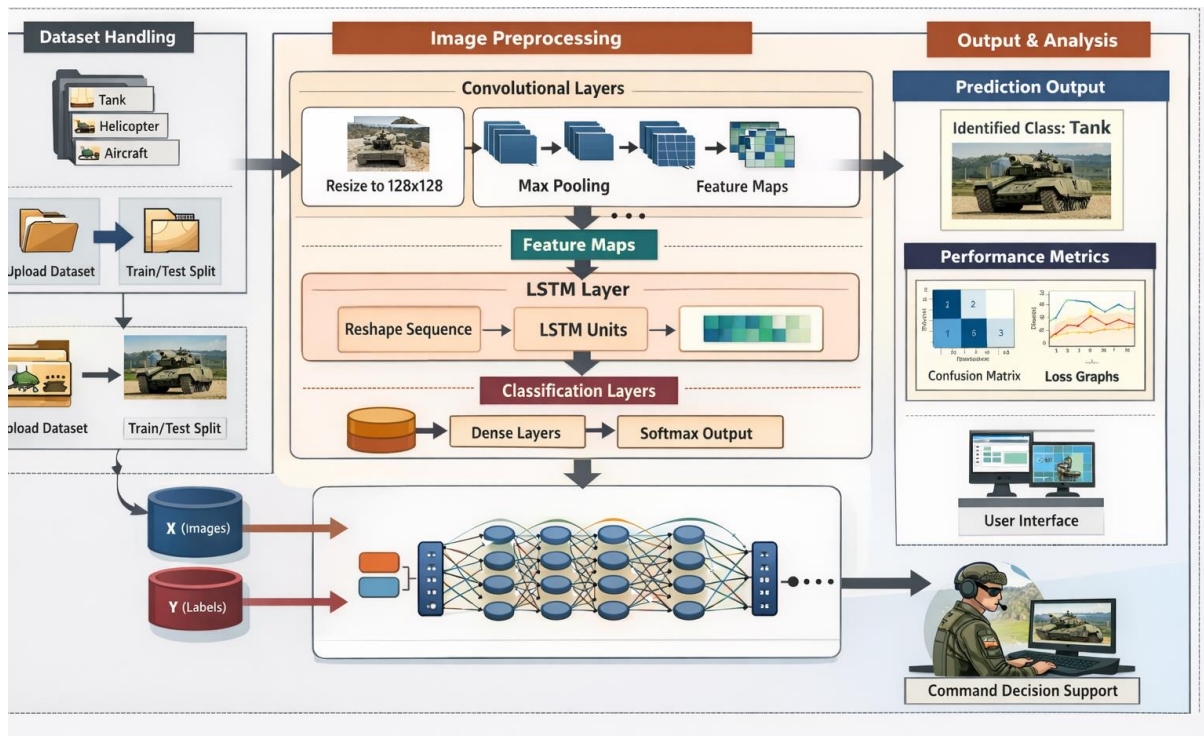


Fig. 2. Proposed system architecture for military tactical decision support system

The system begins with the collection of military image data from various sources such as surveillance systems and datasets. These images are uploaded through a user-friendly interface for further processing. The input module ensures proper handling and storage of data. This step forms the foundation for model training and evaluation. In this step, the input images are preprocessed to improve quality and consistency. Techniques such as resizing, normalization, and noise removal are applied. This helps in reducing irrelevant variations in the data. Proper preprocessing enhances the performance and accuracy of ML and DL models.

The system uses CNN to extract spatial features from images, such as shapes and patterns. LSTM is applied to capture temporal dependencies where required. This combination helps in understanding both visual structure and sequence-related information. As a result, more meaningful features are obtained for classification. Multiple models including Perceptron, DTC, DNN, and Hybrid CRM are implemented in this stage. Each model is trained using the processed dataset. The Hybrid CRM combines CNN and LSTM to improve classification performance. This step focuses on learning patterns from the data effectively. After training, all models are evaluated using performance metrics such as accuracy. The results are compared to identify the best-performing model. This helps in selecting the most suitable approach for real-time implementation. The evaluation ensures reliability and efficiency of the system. The final step involves generating predictions for new input images. The system displays classification results through a graphical interface. It also provides performance visualization for better understanding. This enables users to make quick and informed decisions based on the output.

### Hybrid RCM

The Proposed hybrid convolutional recurrent model, designed specifically to overcome the limitations of the linear Perceptron and the basic flattened DNN. The CNN components (Convolution and Pooling layers) are expertly used for automatic hierarchical feature extraction. CNNs can recognize small, local patterns (like edges and textures) and combine them into complex features (like shapes and parts of a military vehicle) while maintaining spatial context through weight sharing. The output of the CNN is then reshaped and fed into the LSTM component, a type of RNN. While LSTMs are traditionally used for sequential data (like text or time series), in this context, they treat the spatially ordered feature map outputs from the CNN as a sequence. This allows the model to analyze the relationships and

dependencies *between* the extracted spatial features, which is particularly beneficial for classifying complex objects like military hardware by analyzing patterns across the feature space, leading to a robust and context-aware tactical decision support system Fig. 3.

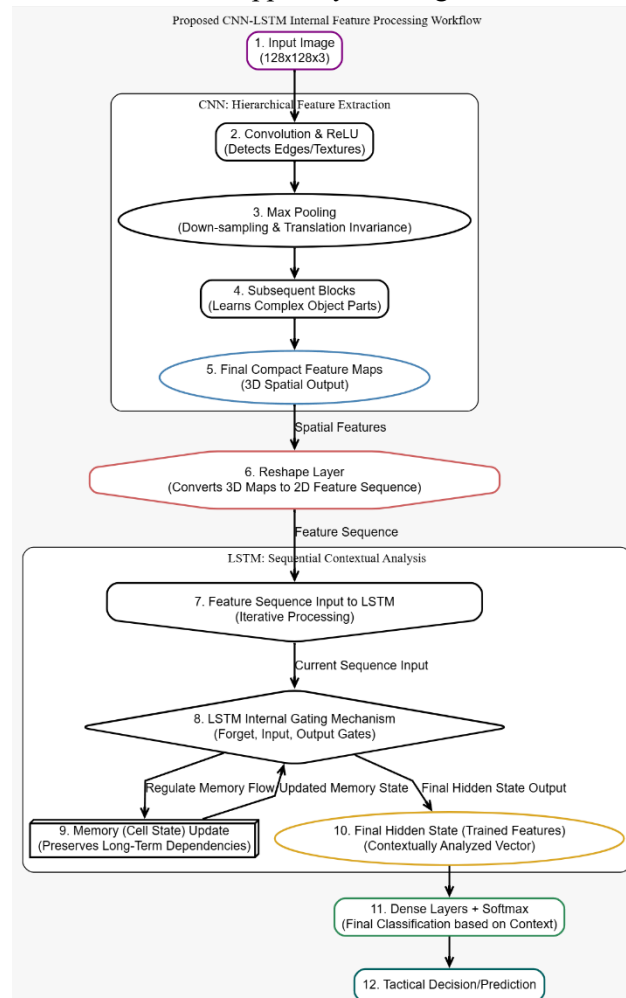


Fig. 3. Internal Workflow of Hybrid CRM model

The **LSTM** is a specialized type of RNN designed to handle sequential data and solve the long-term dependency problem. In your project, it takes the spatial features extracted by the CNN as a *sequence of inputs* and processes them iteratively. The core internal process of the LSTM is governed by three primary internal mechanisms, called **gates**, which regulate the flow of information into and out of the cell's memory state: **This gate decides which information from the previous time step's memory cell ( $C_{t-1}$ ) is no longer relevant and should be discarded.** It analyzes the new input features and the previous hidden state to output a value between 0 (forget completely) and 1 (keep completely) for each piece of old memory. This gate decides what new information from the current sequence feature ( $x_t$ ) should be stored in the memory cell. It has two parts: one decides which values to update, and the other creates a vector of new candidate values ( $C_{\sim t}$ ). Using the outputs from the Forget and Input gates, the memory cell ( $C_t$ ) is updated. It first forgets the marked-irrelevant information from  $C_{t-1}$  and then adds the new, relevant candidate information determined by the Input gate. This Cell State ( $C_t$ ) is the LSTM's memory, running straight through the entire sequence of CNN

features. Finally, this gate determines what part of the current memory cell's information will be exposed as the Hidden State (ht). The hidden state is what is passed forward to the next step in the sequence and, crucially, is what is passed out to your final Dense layers for classification after the entire sequence of CNN features has been processed.

### 9.3 Result Analysis

Fig. 4. shows the confusion matrix of the existing Deep Neural Network (DNN) classifier applied to the military equipment image dataset. Compared to the Perceptron model, the DNN demonstrates a noticeable improvement in classification performance, with stronger diagonal values for classes such as Tank, Self-Propelled Artillery, and Transport Airplane, indicating better feature learning. However, misclassifications are still observed between visually similar categories, particularly among helicopter classes, due to limited spatial feature extraction in a fully connected network. This result indicates that while the DNN improves accuracy over linear models, it still lacks the robust spatial representation capability required for complex military image classification.

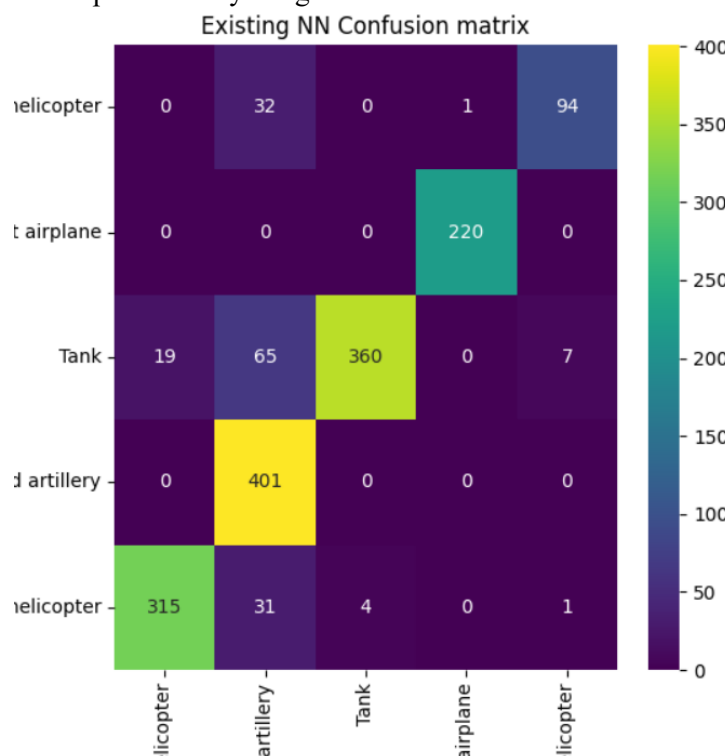


Fig. 4. Confusion matrix obtained using DNN model

Fig. 5. 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.

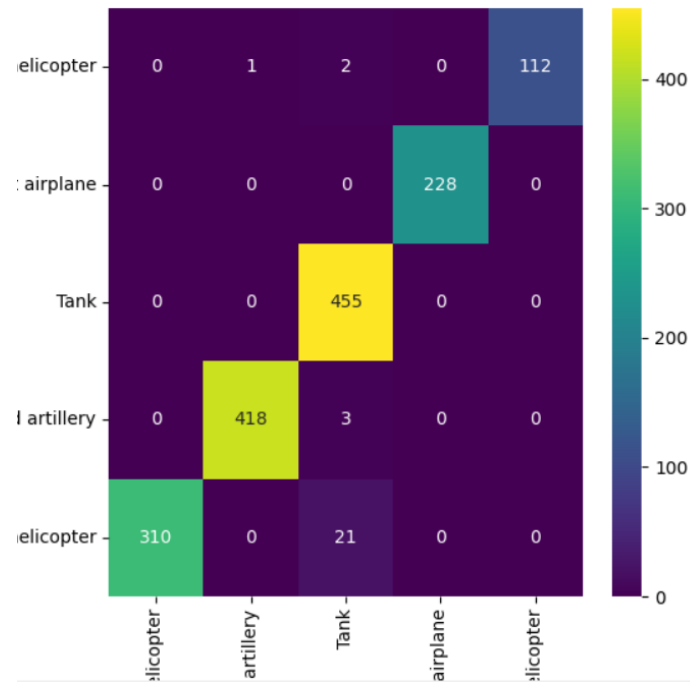


Fig. 5. Confusion matrix obtained using Hybrid Convolutional recurrent Model



Fig. 6. Prediction on test images obtained using hybrid CRM

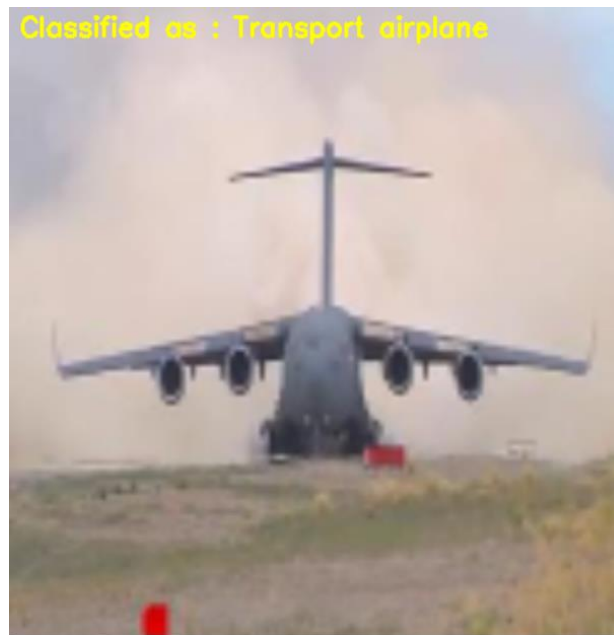


Fig. 6. Prediction on test images obtained using hybrid CRM

The Fig. 6 and 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.

Table 1: Performance comparison for the Perceptron, DTC, DNN and Proposed CRM.

Algorithms Name	Accuracy	Precision	Recall	F-score
<b>Perceptron</b>	32.90%	81.53%	41.38%	36.04%
<b>DTC</b>	90.12%	91.32%	91.97%	90.46%
<b>DNN</b>	89.67%	92.14%	88.71%	89.68%
<b>Proposed CRM</b>	98.83%	99.26%	98.89%	99.05%

Table 1 presents a detailed performance comparison of the Perceptron, DTC, DNN, and the proposed CRM 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 DTC 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

The proposed work effectively develops and implements an advanced machine learning–driven Tactical Decision Support System designed for the precise classification of military assets from image data. The system utilizes a well-structured dataset containing five major categories such as Tank, Assault Helicopter (AH), Self-Propelled Artillery (SPA), Transport Airplane (TA), and Transport Helicopter (TH)—and integrates key components such as image preprocessing, role-based access control (RBAC), and an interactive GUI to ensure a seamless end-to-end workflow. A thorough comparative study was carried out using conventional machine learning approaches, including Perceptron and DT, alongside a DNN and the proposed hybrid CRM model. The results clearly indicate that traditional algorithms are less effective when dealing with complex, high-dimensional image data, whereas the hybrid CR architecture demonstrates superior performance across all evaluation metrics, including accuracy, precision, recall, and F1-score. The strong diagonal pattern observed in the confusion matrix, combined with consistent and accurate predictions on unseen images, highlights the model’s robustness and generalization capability. Additionally, the incorporation of model saving mechanisms, performance visualization tools, and real-time prediction within a secure Tkinter-based interface enhances the system’s usability and deployment readiness. This study confirms that deep learning–based visual intelligence, particularly through hybrid CR models, offers a reliable and efficient solution for tactical decision support, making it highly applicable to real-world military surveillance, reconnaissance, and strategic operations.

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