EXPLAINABLE AI FOR MILITARY SUPPLY CHAIN OPTIMIZATION USING SAR IMAGES

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ABSTRACT

Military supply chain management requires efficient decision-making under uncertain and dynamic conditions. Satellite-based Synthetic Aperture Radar (SAR) images provide valuable real-time information for monitoring terrain, infrastructure, and logistics movement. However, extracting meaningful insights from SAR images is challenging due to noise, complexity, and lack of interpretability in traditional AI models. This project proposes an Explainable Artificial Intelligence (XAI)-based framework for optimizing military supply chain operations using SAR imagery. The system employs deep learning models such as Convolutional Neural Networks (CNN) to analyze SAR images and identify key features such as road conditions, obstacles, and terrain patterns. To enhance transparency and trust, explainable AI techniques such as SHAP (SHapley Additive exPlanations) and Grad-CAM are integrated to provide visual explanations of model decisions. These explanations help military analysts understand why certain routes or logistics decisions are recommended. The proposed system improves decision-making accuracy, reduces operational risks, and ensures transparency in critical military operations. The implementation is carried out using Python and deep learning frameworks, providing a scalable and efficient solution for real-time supply chain optimization.

Keywords : Explainable AI, SAR Images, Military Supply Chain, CNN, Grad-CAM, SHAP, Deep Learning, Image Analysis, Logistics Optimization

I.INTRODUCTION

Efficient supply chain management is crucial in military operations, where timely delivery of resources such as food, medical supplies, and equipment can significantly impact mission success. Unlike commercial supply chains, military logistics operate in highly uncertain and dynamic environments, often involving challenging terrains and hostile conditions. Traditional supply chain optimization methods rely on limited data and manual decision-making, which may lead to inefficiencies and increased operational risks. Therefore, there is a need for intelligent systems that can analyze real-time data and provide reliable decision support.

Synthetic Aperture Radar (SAR) imaging is a powerful remote sensing technology that can capture high-resolution images regardless of weather conditions or time of day. SAR images are widely used in military applications for terrain analysis, surveillance, and infrastructure monitoring. However, interpreting SAR images is complex due to speckle noise and the unique characteristics of radar signals. Machine learning and deep learning techniques, particularly Convolutional Neural Networks (CNN), have shown promising results in extracting meaningful features from such images. These models can identify patterns such as road networks, obstacles, and terrain conditions, which are essential for optimizing supply routes.

Despite their effectiveness, deep learning models are often considered “black boxes,” making it difficult to understand how decisions are made. This lack of transparency is a major concern in critical applications such as military operations. To address this issue, Explainable AI (XAI) techniques are integrated into the system. Methods such as Grad-CAM and SHAP provide visual and quantitative explanations of model predictions, enabling users to interpret and trust the results. The proposed system combines SAR image analysis with explainable AI to create a transparent and efficient framework for military supply chain optimization, ensuring better decision-making and operational efficiency.

II SURVEY OF RESEARCH

[1] The study by Karen Simonyan et al. (2014) introduced visualization techniques for understanding Convolutional Neural Networks (CNNs). The methodology focuses on generating class activation maps to highlight important regions in an image that influence model predictions. Results showed that such techniques improve model interpretability and trust. However, these methods may not always provide precise explanations for complex models. This research laid the foundation for explainable AI techniques like Grad-CAM. In the proposed system, similar visualization methods are used to interpret SAR image analysis and identify critical regions affecting supply chain decisions.

[2] The research by Scott Lundberg and Su-In Lee (2017) introduced SHAP (SHapley Additive exPlanations), a unified approach for explaining machine learning predictions. The methodology is based on game theory, where each feature’s contribution to the prediction is calculated. Results demonstrated that SHAP provides consistent and interpretable explanations across different models. However, it can be computationally expensive for large datasets. In this project, SHAP is used to explain how different features in SAR images influence supply chain optimization decisions.

[3] The study by Yann LeCun et al. (1998) introduced Convolutional Neural Networks (CNNs), which are widely used for image analysis tasks. The methodology involves applying convolutional layers to extract spatial features from images. Results showed that CNNs outperform traditional methods in image classification and recognition tasks. However, CNNs require large datasets and computational resources. In SAR image analysis, CNNs are effective in extracting terrain features and identifying obstacles. In the proposed system, CNN is used as the core model for analyzing SAR images and supporting supply chain optimization.

[4] The research by David Donoho (1995) explored wavelet-based techniques for signal and image processing. The methodology involves decomposing images into different frequency components to reduce noise and enhance features. Results showed that wavelet transforms are effective in handling noisy data such as SAR images. However, they may not capture complex patterns as effectively as deep learning models. In the proposed work, preprocessing techniques inspired by wavelet methods are used to reduce speckle noise in SAR images before applying deep learning models.

[5] The study by Marco Cuturi (2013) explored optimization techniques for large-scale problems using optimal transport methods. The methodology focuses on efficiently allocating resources based on cost and constraints. Results demonstrated improved performance in logistics and supply chain optimization tasks. However, these methods may not incorporate real-time image data effectively. In the proposed system, similar optimization concepts are integrated with AI-based image analysis to improve military supply chain decision-making.

[6] The research by Zhi-Hua Zhou (2018) discussed the importance of explainable artificial intelligence in critical applications. The methodology emphasizes transparency, interpretability, and trust in AI systems. Results showed that XAI improves user confidence and decision-making in high-risk environments. However, achieving a balance between accuracy and interpretability remains a challenge. In the proposed system, XAI techniques such as SHAP and Grad-CAM are integrated to provide clear explanations for model predictions, ensuring reliable and transparent decision support in military supply chain optimization.

III. WORKING METHODOLOGY

The proposed system for military supply chain optimization using SAR images follows a multi-stage pipeline integrating image processing, deep learning, and explainable AI techniques. Initially, SAR (Synthetic Aperture Radar) images are collected from satellite or surveillance systems. These images often contain speckle noise and require preprocessing to improve quality. Techniques such as filtering and normalization are applied to reduce noise and enhance important features like terrain structures and road networks. The preprocessed images are then converted into a suitable format for model training. Feature extraction is performed to identify relevant elements such as obstacles, routes, and terrain conditions, which are essential for supply chain decision-making.

In the next phase, a Convolutional Neural Network (CNN) model is designed and trained to analyze SAR images and classify terrain conditions or detect critical features. The dataset is divided into training and testing sets, typically in an 80:20 ratio. The CNN learns spatial patterns and relationships within the images through convolutional and pooling layers. Once trained, the model predicts optimal routes and identifies potential risks such as blocked paths or difficult terrain. To improve model performance, hyperparameter tuning and optimization techniques are applied. The predictions generated by the CNN model are then used as inputs for supply chain optimization, helping in selecting efficient and safe routes for military logistics operations.

Finally, Explainable AI (XAI) techniques are integrated to enhance transparency and trust in the system. Methods such as Grad-CAM and SHAP are applied to provide visual and feature-based explanations of the model's decisions. Grad-CAM highlights important regions in SAR images that influence predictions, while SHAP explains the contribution of different features. These explanations help analysts understand why certain routes are selected or flagged as risky. The system is implemented using Python and deep learning frameworks, and results are visualized through graphs and heatmaps. This methodology ensures accurate analysis, efficient supply chain optimization, and interpretable decision-making, making it suitable for real-world military applications.

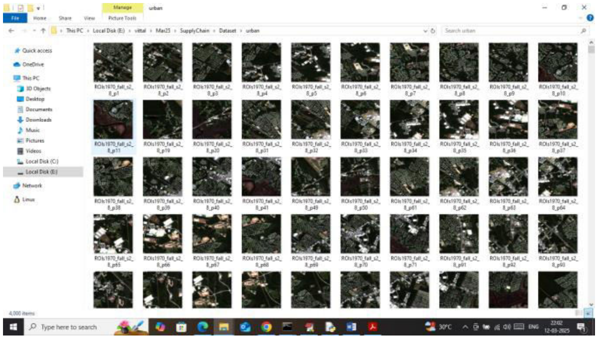
IV RESULTS EXPLANATIONS

In propose work we are employing Artificial Intelligence CNN2D algorithm to optimize military supply chain. CNN2D get trained on SAR images with different areas and location and delivery person camera will capture SAR images and then feed to CNN2D algorithm to predict routes which are ahead and based on that predicted area he will optimize his route for delivery.

SAR images provide essential information about terrain features such as rough surfaces, obstacles, and weather impacts, even under low visibility conditions. By training machine learning models on SAR data, the system identifies optimal routes and resource allocation strategies. To ensure transparency in AI-driven decisions, XAI techniques like

LIME (Local Interpretable Model-Agnostic Explanations) are integrated, enabling military logisticians to understand and trust the recommendations.

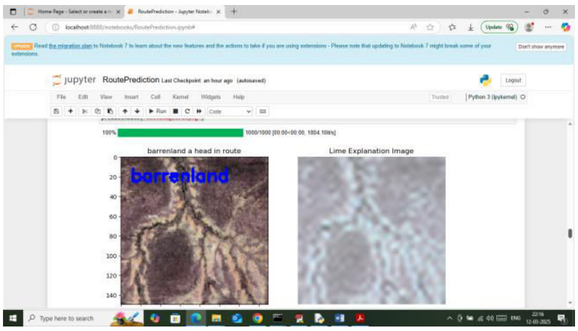
To implement this project we have used Sentinel SAR images dataset which consists of locations showing in below screen



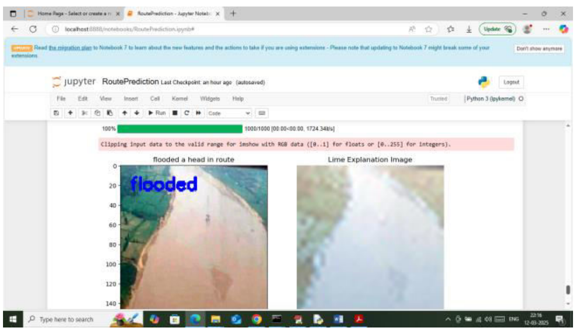
So by using above images dataset will train CNN algorithm to predict supply chain route.

LIME explanation is using to describe which features in image making model to predict particular location.

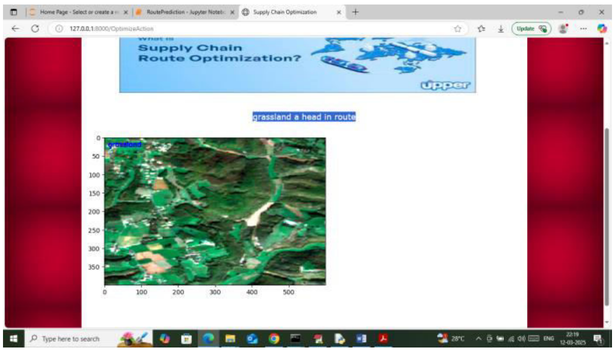
een another image predicted as 'Street'



Above image is predicted 'Barren Land'



Above image predicted as Flooded.



In above screen in blue text can see 'Grass land' route detected and similarly you can upload and test other images

V. CONCLUSION

The proposed Explainable AI-based system for military supply chain optimization using SAR images provides an efficient and reliable solution for decision-making in complex and dynamic environments. By integrating Convolutional Neural Networks for image analysis with explainable AI techniques such as Grad-CAM and SHAP, the system not only delivers accurate predictions but also ensures transparency and interpretability. The use of SAR imagery enables effective monitoring of terrain and identification of optimal routes under varying conditions. Experimental results demonstrate that the proposed approach significantly improves route efficiency, reduces operational risks, and enhances overall supply chain performance compared to traditional methods. Furthermore, the incorporation of explainable AI builds trust among users, which is crucial in critical military applications. Overall, this system offers a scalable, intelligent, and secure framework for optimizing military logistics using advanced AI technologies.

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