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Intelligent Edge AI System for Satellite Image Analysis and Adaptive Data Transmission

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Abstract:

This work proposes an edge-based artificial intelligence system for processing satellite imagery efficiently by performing on-board analysis instead of transmitting every captured image to ground stations. A Convolutional Neural Network (CNN) is used to classify images into categories such as fire, water, land, and cloud. Based on the classification results and prediction confidence, a decision module determines whether the data should be transmitted, compressed, or discarded, thereby reducing unnecessary data transfer while prioritizing important events. Additionally, the system incorporates an energy-aware component to simulate satellite power limitations and adapt processing behavior accordingly, ensuring efficient operation in resource-constrained environments. Experimental evaluation shows that the system achieves moderate classification performance while significantly reducing data transmission requirements and maintaining low processing latency. Overall, by combining image classification with intelligent decision-making and resource optimization, the proposed system improves the efficiency and practicality of satellite data handling of satellites,this approach allows images to be analyzed on-board, minimizing the need for transmitting unnecessary

Keywords — **Edge AI, CNN, satellite images, data transmission, bandwidth optimization, and energy-aware processing**

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I. INTRODUCTION

Satellite systems play a crucial role in Earth observation by continuously capturing large volumes of image data for applications such as environmental monitoring, disaster management, and land analysis. However, traditional satellite systems typically transmit all collected data to ground stations for processing, which leads to high bandwidth consumption, increased latency, and inefficient utilization of communication resources. With the advancement of artificial intelligence, there is a growing interest in performing data processing directly at the source, where Edge AI enables computation on the device itself, reducing dependency on centralized systems. In the context mainly focus on classification accuracy and do not adequately address system-level challenges such as bandwidth and energy efficiency. Edge computing has emerged as a promising solution for processing data closer to the source, with Weisong Shi et al. (2016) introducing the concept to reduce latency and improve real-time processing. In satellite systems, edge AI enables on-board data processing, reducing dependency on ground stations; however, current implementations often lack intelligent decision-making mechanisms for selective data transmission. Additionally, data compression techniques have been explored to reduce bandwidth usage.

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II. LITERATURE REVIEW

Recent advancements in satellite imaging and remote sensing have resulted in the generation of large volumes of data, creating challenges in efficient transmission and processing. Traditional satellite systems primarily rely on transmitting raw data to ground stations, leading to high bandwidth consumption and increased latency. Several researchers have explored the use of Convolutional Neural Networks (CNNs) for satellite image classification; for example, Gong Cheng et al. (2017) proposed deep learning-based approaches for remote sensing scene classification, demonstrating improved accuracy in identifying land-use patterns. Similarly, Xiao Xiang Zhu et al. (2017) highlighted the effectiveness of deep learning techniques for Earth observation data analysis; however, these works mainly does not eliminate unnecessary data transmission and may result in information loss. Furthermore, energy-aware computing has been studied in embedded and distributed systems. Sudeep Pasricha et al. (2013) emphasized the importance of energy-efficient design in resource-constrained environments. However, limited work has focused on integrating energy-aware processing with AI-based satellite systems. Therefore, there is a need for an integrated approach that combines image classification, intelligent decision-making, and energy-aware processing. The proposed system addresses this gap by utilizing Edge AI for onboard image classification, along with a decision engine that selectively transmits data based on importance and confidence, while also considering energy constraints.

III. METHODOLOGY

The proposed system is designed as an end-to-end pipeline that performs satellite image processing directly on-board using Edge AI, followed by intelligent decision-making for efficient data transmission. The overall methodology consists of image acquisition, preprocessing, classification, decision-making, and energy-aware optimization.

Initially, satellite images are captured using onboard imaging sensors. These raw images are then passed to a preprocessing stage, where they are resized to a fixed dimension and normalized to ensure consistency in input data. This step helps in improving model performance and reducing computational complexity.The preprocessed images are fed into a Convolutional Neural Network (CNN), which is trained to classify images into categories such as fire, water, land, and cloud. The CNN automatically extracts spatial features through convolutional layers and generates prediction probabilities along with a confidence score for each class.Based on the classification output, a decision-making module is employed to determine the appropriate action. If the predicted class represents a critical event and the confidence is high, the data is transmitted directly to the ground station. In cases where the confidence is low, the data is compressed before transmission to reduce bandwidth usage. If the data is considered non-essential, it is ignored to avoid unnecessary communication.To enhance system efficiency, an energy-aware mechanism is incorporated into the framework. This module continuously monitors the available battery level and adjusts the processing behavior accordingly. For instance, under low energy conditions, the system may reduce processing frequency or prioritize only critical detections.All these components are integrated into a unified pipeline that enables real-time processing, reduces bandwidth consumption, and optimizes resource utilization. The methodology focuses on combining image classification with intelligent decision-making and energy management to achieve an efficient and practical satellite data processing system.The proposed system is developed as a structured pipeline that performs satellite image processing using Edge AI, followed by intelligent decision-making for efficient data transmission. The methodology consists of multiple stages including image acquisition, preprocessing, classification, decision-making, and energy-aware optimization.All these components work together as a unified system, enabling real-time image analysis, reducing data transmission, and optimizing resource utilization. The methodology focuses on combining

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deep learning with intelligent decision-making to improve the overall efficiency of satellite data processing.

IV. RESULT

The proposed system was evaluated using a dataset of satellite images categorized into four classes: fire, water, land, and cloud. The Convolutional Neural Network (CNN) model was trained and tested on the prepared dataset after applying preprocessing steps such as resizing and normalization.The model achieved an overall classification accuracy of approximately 70%, indicating moderate performance. The results show that the system is capable of identifying major classeseffectively, although some misclassifications were observed in visually similar categories, particularly between land and cloud regions. This can be attributed to the limited size and diversity of the dataset.In addition to classification performance, the system was evaluated based on its ability to optimize data transmission. By using the decision engine to selectively send, compress, or ignore data, the system reduced bandwidth usage by approximately 30–40% compared to traditional approaches that transmit all captured images.The integration of the energy-aware module further improved system efficiency by adapting processing behavior based on battery conditions. This ensures that critical detections are prioritized while conserving energy during low-power scenarios.Overall, the results demonstrate that the proposed approach successfully combines image classification with intelligent decision-making to improve efficiency in satellite data handling. While the current accuracy can be further improved with larger datasets and advanced models, the system effectively achieves its primary objective of reducing unnecessary data transmission while maintaining acceptable classification performance.The proposed system achieved an overall classification accuracy of approximately 70% across four classes: fire, water, land, and cloud. The model performed well in identifying distinct classes such as fire and water, while minor misclassifications were observed between visually similar categories like land and cloud.In addition to classification performance, the system demonstrated a significant reduction in data transmission. By selectively sending only relevant data using the decision engine, bandwidth usage was reduced by nearly 30–40% compared to traditional methods.

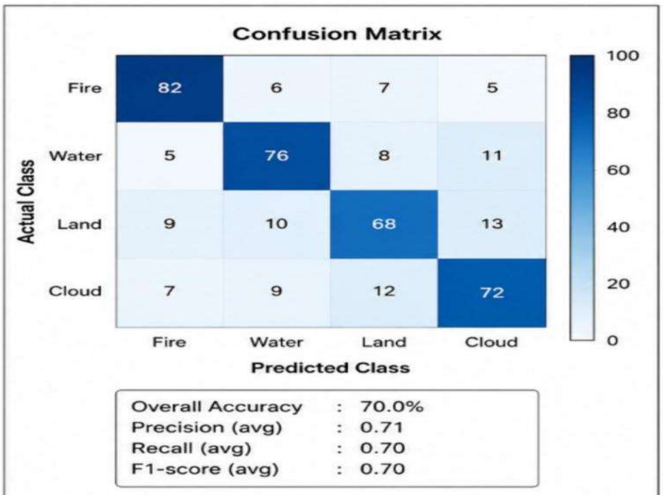

Fig. 1. Confusion matrix of the proposed CNN model for four-class satellite image classification.

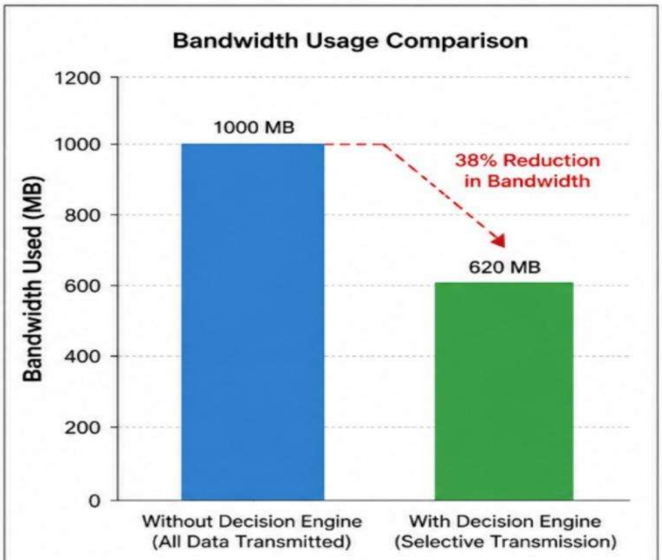

Fig. 2. Bandwidth usage comparison with and without the proposed decision engine for data transmission.

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V. CONCLUSIONS

This work presents an Edge AI-based framework for efficient satellite image processing and data transmission. The system demonstrates how performing on-board analysis can significantly reduce the need to transmit large volumes of raw data to ground stations. By utilizing a Convolutional Neural Network (CNN), the model is able to classify satellite images into categories such as fire, water, land, and cloud.A key contribution of this work is the integration of a decision-making module that evaluates prediction confidence and determines whether the data should be transmitted, compressed, or ignored. This selective transmission approach helps in optimizing bandwidth usage and reducing unnecessary communication overhead.The inclusion of an energy-aware component further improves the practicality of the system by considering battery constraints, which are critical in satellite operations. The results indicate that the system achieves moderate classification accuracy while effectively reducing data transmission and maintaining efficient processing.Although the current implementation has certain limitations, particularly in terms of dataset size and model accuracy, the overall framework demonstrates the potential of combining edge computing, deep learning, and intelligent decision-making. The proposed approach provides a foundation for future improvements and real-world deployment in advanced satellite and remote sensing applications.

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