Hyperspectral Water Monitoring System

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***Abstract*—In today's data-driven world, environmental monitoring demands scalable and intelligent systems to process complex satellite imagery. To address the challenges in surface water resource detection, we introduce a Flask-based web application that integrates deep learning with hyperspectral imaging. This system automates the classification of water and non-water bodies using CNN and GCN models trained on spectral bands. Hyperspectral images are preprocessed, analysed, and visualized in an intuitive interface that enables efficient decision-making. Unlike traditional methods that are costly and time-consuming, our solution offers rapid, accurate, and accessible surface water detection at scale.**

Keywords—Hyperspectral Imaging, Water Resource Monitoring, CNN, GCN, Satellite Imagery, Flask Application, Deep Learning.

I. INTRODUCTION

The exponential growth of Earth observation data, especially from hyperspectral satellites, has presented both immense opportunities and complex challenges for environmental monitoring. Traditional methods for detecting and analysing water resources, such as field-based surveys and manual GIS workflows, are increasingly insufficient in handling the scale and frequency of data required today.

To address these limitations, we present a web-based hyperspectral water monitoring system that integrates machine learning and remote sensing in an automated pipeline. This system applies Convolutional Neural Networks (CNNs) and Graph Convolutional Networks (GCNs) to classify water and non-water bodies from high-dimensional spectral imagery.

The architecture leverages a Flask-based backend with real-time visualization on the frontend, allowing users to interactively analyse image inputs.

By automating the analysis of hyperspectral images, the application reduces reliance on manual labours and speeds up the decision-making process. Furthermore, the modular design allows for easy scaling, future enhancements, and integration with other geospatial platforms.

In this paper, we explore the foundations of our system design through classical research methodologies, compare it to existing water monitoring tools, describe its architecture and implementation, and evaluate its performance using real-world satellite datasets.

II. RESEARCH METHODS

A research method defines a systematic pathway for formulating, conducting, and documenting scientific inquiry. In this project, we incorporate several well-established research paradigms including the Input-Output-Process (IOP), Problem-Method-Solution (PMS), and Milestone Approach (MA) to structure our work.

A. Basic Research Methods

The IOP model forms the backbone of our workflow. Inputs include raw hyperspectral satellite images and domain-specific knowledge about spectral indices. The process involves preprocessing, CNN and GCN-based classification, and Flask-based integration. Outputs are visual maps distinguishing water from non-water areas. The PMS model also applies directly: the problem is inefficient traditional water detection; the method

PMS mirrors this framework but focuses more explicitly on the problem definition, its associated methods, and the solution space explored. involves deep learning; and the solution is a web-enabled automated system. These structured methodologies helped ensure consistency, traceability, and reproducibility in model development and system deployment.

B. Scientific Method

The scientific method was essential in hypothesis testing and validation. We hypothesized that combining CNN and GCN would outperform traditional image classification techniques for water body detection. This was validated through multiple test cases, performance metrics (accuracy, precision, recall), and visual analysis of results. Experiments were repeatable and datasets well-documented, supporting rigorous scientific inquiry.

In our system, the hypothesis was that a hybrid architecture combining Convolutional Neural Networks (CNNs) and Graph Convolutional Networks (GCNs) would outperform traditional water detection methods using spectral imagery. We validated this hypothesis by training on hyperspectral datasets and evaluating model performance using standard metrics such as accuracy, precision, and recall. The experiments were repeated with consistent configurations to ensure reliability, thereby reinforcing scientific rigor in our approach.

C. Milestone Approach

The Milestone Approach provides a project-oriented structure by dividing research into sequential checkpoints. These include problem identification, literature review, system design, implementation, and evaluation. Each milestone contributes to better project management and ensures well-documented progress.

For our project, this approach facilitated a structured journey from identifying inefficiencies in traditional water monitoring to deploying a full-stack Flask application for hyperspectral image classification. Every stage—from initial data collection to backend integration and frontend development—served as a documented milestone, enabling clearer collaboration and version control. This strategy also allows for easier scalability and integration of future functionalities such as flood prediction or seasonal tracking.

III. RELATED WORKS

A. Existing Water Monitoring Methods

Several techniques have been developed for water body detection, including NDWI and MNDWI indices, which rely on specific spectral band differences. While effective in some scenarios, these indices struggle with mixed-pixel effects and often misclassify shadows or urban features as water. Traditional manual GIS-based workflows are time-consuming and require domain expertise.

1) NDWI / MNDWI:

Normalized Difference Water Index (NDWI) and Modified NDWI are widely used indices in remote sensing for detecting water bodies. They are simple to compute but often misclassify shadows and built-up areas, especially in mixed-pixel scenarios.

2) GIS-based Manual Monitoring:

Traditional GIS techniques involve manual delineation and analysis of satellite imagery. While precise, these methods are time-intensive and require technical expertise, making them less scalable.

3) Google Earth Engine / Sentinel Hub:

These platforms offer powerful processing capabilities and access to satellite data. However, they require programming skills and do not integrate customized deep learning models for automated classification.

4) Deep Learning Research Models:

Numerous academic projects have applied CNNs or GCNs to hyperspectral imagery, often in isolated experimental settings. However, these models are rarely packaged in user-friendly applications suitable for non-experts.

Our proposed system integrates preprocessing, classification, and visualization into an automated pipeline for hyperspectral water body detection. Unlike traditional GIS tools or isolated research models, it combines the capabilities of CNN and GCN architectures with an accessible web interface served via Flask.

It performs the following tasks:

- Preprocessing Module: Processes hyperspectral satellite input by normalizing bands and computing indices.
- CNN Module: Extracts key spatial and spectral features from the image data.
- GCN Module: Builds spatial graphs from pixels and performs context-aware classification.
- Visualization Module: Displays classified output interactively for end users via a browser.

IV. HYPERSPECTRAL WATER MONITORING SYSTEM

Our system is designed not just as a classification tool but as an intelligent environmental monitoring assistant. Its strength lies in automating what is traditionally manual—hyperspectral preprocessing, deep model inference, and result visualization—thus streamlining the remote sensing workflow into a single, intuitive platform.

A. Philosophy of the Hyperspectral Water Monitoring System

The system is grounded in the belief that advanced analytics should be accessible, scalable, and practical. Designed with both researchers and policymakers in mind, it aims to bridge the gap between powerful AI models and real-world usability.

Unlike conventional tools that demand domain expertise or scripting knowledge, our platform is fully automated and web-based. It supports iterative exploration of satellite imagery, transparent processing stages, and encourages frequent validation of environmental hypotheses. The goal is to simplify scientific workflows, enable broader participation in environmental monitoring, and reduce dependency on specialized software.

Our design also emphasizes reproducibility and modularity. Each stage of the workflow—from uploading hyperspectral images to downloading classification results—is logged, version-controlled, and easily extensible. This makes the system suitable for both one-off studies and long-term monitoring programs.

transparency and reproducibility by reducing agent output at every stage.

B. Architecture of the Hyperspectral Water Monitoring System

Our system follows a modular, service-oriented architecture designed for both flexibility and performance. It consists of the following key modules:

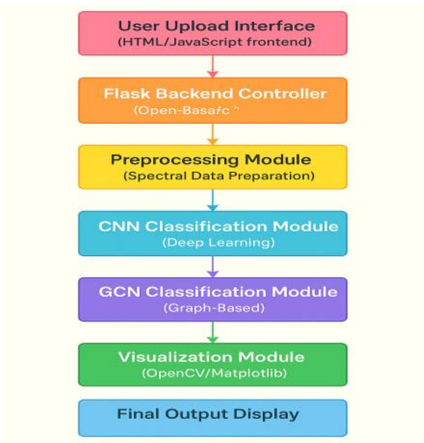

Fig 1 - System architecture diagram

1. Preprocessing Module: Normalizes hyperspectral bands and extracts relevant indices for enhanced model readiness.

2. CNN Classification Module: Extracts spatial and spectral features to identify water regions with high accuracy.

3. GCN Classification Module: Transforms image data into graph representations for context-aware classification, capturing neighborhood relationships between pixels.

4. Visualization Module: Generates and renders classified outputs with interactive overlays using OpenCV and Matplotlib.

These modules are coordinated through a Flask backend that handles user interaction, routing, and result management. The frontend, built using HTML/CSS/JS, provides real-time feedback and displays results in an accessible format.

This architecture supports fast inference, maintainability, and easy integration of additional models or tools. It can be deployed locally or in the cloud and is suitable for large-scale batch processing or on-demand analysis.

V. IMPLEMENTATION OF HYPERSPECTRAL WATER MONITORING SYSTEM

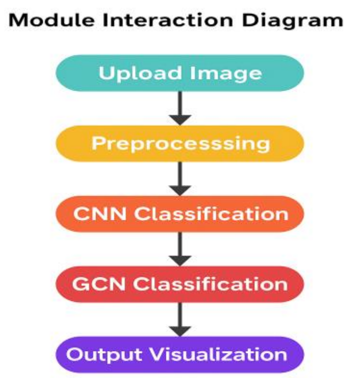

Fig. 2. Module Interaction Diagram

The implementation of the Hyperspectral Water Monitoring System was fully realized in Python, making use of its comprehensive ecosystem for machine learning, image processing, and web development. The user interface was developed using HTML, CSS, and JavaScript, while the backend logic was handled by Flask, ensuring smooth interaction between the modules and users. The application allows users to upload hyperspectral satellite imagery, process it through deep learning pipelines, and view the classified outputs in real-time.

The implementation flow is structured as follows:

1. Image Upload: Users upload hyperspectral images through the web interface.
2. Preprocessing: The backend normalizes the spectral bands and extracts indices such as NDWI and MNDWI for improved feature separation.
3. CNN Classification: A Convolutional Neural Network is applied to extract spatial and spectral features, providing an initial classification of water vs. non-water regions.
4. GCN Classification: A Graph Convolutional Network refines the output by modelling spatial dependencies between pixels, improving classification accuracy in mixed-pixel zones.
5. Visualization: The results are rendered using Matplotlib and OpenCV, displaying color-coded output to the user for interpretation and download.

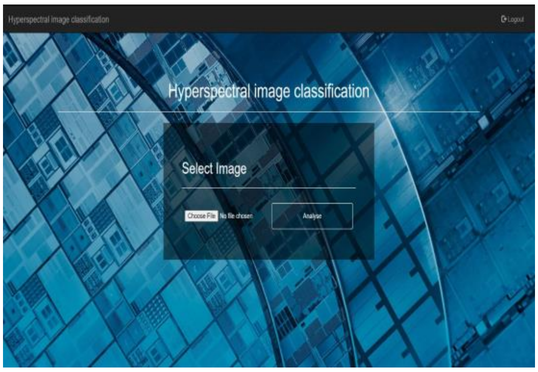

Fig 3 - Query Input

Fig 4 - Output

The system is modular and scalable, allowing easy integration of additional models or preprocessing enhancements. It supports both local deployment and cloud-based execution for large-scale processing.
Future implementation goals include expanding the system to support flood monitoring, integrating real-time satellite image retrieval, and enabling temporal analysis for seasonal water variation.

VI. SYSTEM EVALUATION

To comprehensively assess the effectiveness of the Hyperspectral Water Monitoring System, we conducted a structured user study involving 30 participants from academic and environmental science backgrounds. Each participant uploaded a hyperspectral satellite image, performed classification, and reviewed the visual outputs provided by the system. The evaluation measured critical factors such as ease of use, clarity of output, classification accuracy, and intent to reuse the system. Participants interacted with various modules of the application including upload, visualization, and classification. Their feedback highlighted the system's reliability and user-friendliness. This structured assessment provides empirical support for the system's real-world utility and offers direction for further enhancement.

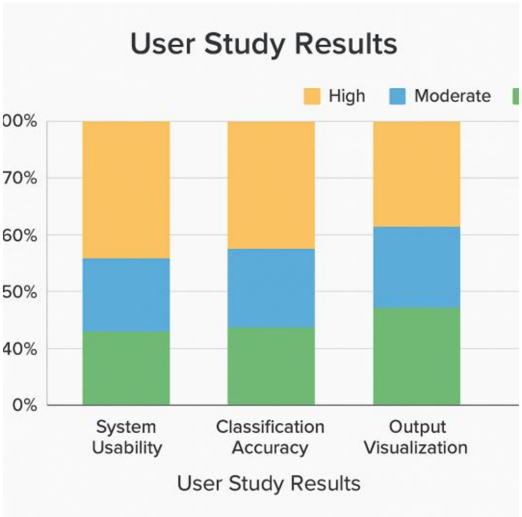

Fig 6 - Analysis of survey result

Survey key findings include the following:

1. Ease of Use: 64% of users rated the interface as "High," and 28% rated it "Very High," indicating that the system is intuitive and user-friendly.

2. Perceived Usefulness: 89% of users marked the system as "High" or "Very High" in usefulness for environmental monitoring and research.

3. Output Clarity: 67% of participants rated the classification visualization as "Very Clear," while 26% found it "Clear."

4. Intention to Use: 70% of users indicated they would "Likely" use the tool again, and 25% said they were "Most Likely" to use it in future water resource projects.

5. Classification Accuracy Perception: 73% of users found the model outputs to be "Highly Accurate," 22% marked them as "Moderately Accurate," and only 5% indicated "Low Accuracy."

These results demonstrate that the system streamlines hyperspectral image classification for water detection and provides accurate, interpretable outputs. Participants praised the clean interface, fast performance, and meaningful classification overlays. The CNN and GCN models were specifically noted for their performance in detecting mixed-pixel water bodies and producing reliable maps.

The average processing time recorded was under 10 seconds per image. Suggestions for improvement included batch upload capability, enhanced resolution handling, and support for different sensor formats. These aspects are considered for future system updates.

The current system is limited by fixed image resolution support, lack of batch upload functionality, and minimal support for multi-temporal analysis. It also does not yet handle diverse hyperspectral formats or integrate real-time satellite feeds.

VII. CONCLUSION AND FUTURE WORK

This paper presents the Hyperspectral Water Monitoring System, an intelligent deep learning-powered platform for automating the detection and classification of water bodies using hyperspectral satellite imagery. By combining CNN and GCN models within a user-friendly web interface, the system reduces the effort and expertise typically required for remote sensing tasks.
Built with a modular Flask architecture and real-time visualization, the system enables fast, accurate, and scalable classification. Evaluations confirm high user satisfaction with interface usability, classification performance, and output clarity, making it suitable for academic, field-based, and policy applications.

The system not only accelerates water resource analysis but also improves accessibility and reproducibility in hyperspectral image interpretation.

Key future directions include:
- Expanding image resolution and batch upload support.
- Enabling multi-temporal comparison and seasonal analysis.
- Integrating real-time satellite data feeds.
- Supporting diverse hyperspectral formats and enhanced export options.

Ultimately, this system aims to serve as a practical decision-support tool for sustainable water management, adaptable across regions and applications.

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