International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Urban Feature Extraction From Satellite Images Using Machine Learning

Harshad Ashok Gidaye[1],Sakshi Suhas Naphade[2], Vedant Rahul Karle[3], Suraj Shashikant Mitake[4]

[1]Final year BE, Sinhgad college of Engineering pune, Coimbatore gidayeharshad37@gmail.com
[2]Final year BE, Sinhgad college of Engineering pune, Coimbatore sakshinaphade3@gmail.com
[3]Final year BE, Sinhgad college of Engineering pune, Coimbatore vedantkarle03@gmail.com
[4]Final year BE, Sinhgad college of Engineering pune, Coimbatore surajmitake2003@gmail.com

ABSTRACT

Urban intelligence meets automation in this data-driven age of geospatial technology. The project titled **Urban Feature Extraction from Satellite Images using Machine Learning** introduces a system that blends traditional image processing with smart machine learning algorithms to deliver accurate, real-time identification of urban land features. The platform—scalable and interactive—analyzes high-resolution satellite images to detect roads, green zones, water bodies, and built-up areas using segmentation techniques such as the Densitometry 3-Channel Algorithm and Watershed Method. Designed with a user-focused interface, it empowers planners and environmental analysts to explore urban growth, infrastructure layout, and ecological zones efficiently. Enhanced with intelligent classification and visual overlays, the system transforms raw satellite data into actionable urban insight. The fusion of smart processing and visual clarity allows this system to serve not just city planners but anyone seeking spatial awareness—bridging data science and urban management under one intelligent platform.

Keywords: Urban Feature Extraction, Satellite Image Processing, Machine Learning, Watershed Algorithm, Densitometry, KNN.

Introduction

The urban development landscape is undergoing a significant transformation powered by Artificial Intelligence (AI) and Machine Learning (ML), unlocking new possibilities in spatial data analysis, city planning, and environmental management. With the increasing availability of high-resolution satellite imagery, urban researchers and planners are seeking intelligent systems capable of extracting and interpreting key land features such as roads, water bodies, green zones, and built-up areas with precision and speed.

Traditionally, the interpretation of satellite imagery has relied on manual mapping and human expertise—approaches that are time-consuming, prone to error, and difficult to scale across growing urban landscapes. The introduction of AI and ML technologies into this domain offers a shift from static, manual workflows to dynamic, data-driven automation. These technologies empower urban systems to analyze complex geospatial patterns, detect changes in infrastructure, and provide actionable insights for sustainable development. Similar to how AI in fashion uses user behavior data to deliver personalized experiences, AI in urban mapping leverages pixel-based patterns and spectral data to segment and classify land cover automatically.

The integration of image processing algorithms—such as the Densitometry 3-Channel method for detecting color-specific regions and the Watershed algorithm for boundary segmentation—provides the backbone for automated feature extraction. These models interpret satellite images not as raw visual data but as structured, quantifiable patterns, enabling fast and accurate categorization of urban spaces.

As city populations expand and climate challenges intensify, the need for real-time, intelligent urban monitoring becomes critical. AI-driven systems not only enhance the speed and accuracy of spatial analysis but also support long-term strategic planning, disaster preparedness, and smart infrastructure design. Just as AI is redefining product design, customer experience, and operations in fashion, it is becoming an indispensable tool for responsive, inclusive, and sustainable urban governance.

With continuous improvements in ML model accuracy, accessibility to satellite data, and scalable computational tools, the potential applications of AI in urban planning are limitless—paving the way for smarter, greener, and more adaptive cities of the future.

IMPLEMENTATION

Frontend: React, Vite, and Tailwind CSS

1. **React**

   React was used for building the web-based user interface of the Urban Feature Extraction System (UFES). Its component-based architecture enables modular design and reusability. React efficiently updates the user interface through its Virtual DOM, ensuring optimal rendering performance. It is scalable, lightweight, and easily integrates with third-party tools and APIs for a seamless user experience.

2. **Vite**
   Vite, a modern frontend build tool, was employed to enhance the development workflow with features like rapid startup and hot module replacement. It offers a highly optimized production build pipeline, significantly reducing load times and improving developer productivity during the UI development of UFES.
3. **Tailwind CSS**
   Tailwind CSS, a utility-first CSS framework, was used to streamline the UI design process. With pre-defined utility classes for spacing, colors, typography, and responsive layouts, it enabled rapid prototyping and consistent styling across the application. This reduced the need for writing custom CSS, ensuring maintainability and speed in design iterations.

Backend: Python, Node Js, express

1. **Python**
   Python served as the backend engine, enabling the integration of machine learning models with image processing libraries. Its extensive ecosystem supports libraries like OpenCV, NumPy, and Scikit-learn, making it ideal for handling geospatial data processing, model training, and real-time segmentation.
2. **Node.js**
   Node.js, a powerful JavaScript runtime, was employed to build the server-side architecture. It enabled non-blocking, event-driven operations, allowing the backend to handle multiple concurrent requests efficiently—especially useful for real-time applications and data streaming.
3. **Express.js**
   Express.js, a lightweight and flexible web application framework for Node.js, was used to develop the backend APIs and manage routing. It simplified the creation of RESTful services, middleware integration, and response handling, streamlining the communication between the frontend and backend.

Core Tools and Models

1. **OpenCV**
   OpenCV (Open Source Computer Vision Library) was the cornerstone for image preprocessing and feature extraction. It was used for operations such as resizing, edge detection, and grayscale conversion. OpenCV also supported integration with custom segmentation algorithms to identify water bodies, green areas, and urban structures.
2. **Densitometry 3-Channel Algorithm**
   This color-based segmentation method was used to isolate green zones and water bodies. It works by applying thresholding across RGB channels to detect regions matching the spectral signatures of vegetation and water. This lightweight approach is both fast and effective for high-contrast satellite images.
3. **Watershed Segmentation**
   Watershed is a morphology-based algorithm that treats grayscale images as topographic maps. It was applied to segment roads and built-up areas by simulating water flooding over pixel intensity basins. It helped differentiate overlapping urban features and refine boundaries with high accuracy.
4. **Scikit-learn (sklearn)**
   Scikit-learn was used for building and evaluating the machine learning models used in feature classification. It provided a wide range of tools for clustering, classification, and validation. For UFES, classifiers like K-Nearest Neighbors (KNN) and Decision Trees were evaluated based on performance.
5. **Pandas and NumPy**
   Pandas was utilized for handling structured metadata such as image statistics, extracted feature logs, and user inputs. NumPy was used for array manipulation, pixel matrix processing, and performance optimization in mathematical operations required during model training and segmentation.
6. **Matplotlib & Seaborn**
   These libraries were used to visualize the performance of the segmentation and classification models, as well as to generate analysis plots such as accuracy trends, confusion matrices, and area coverage statistics.
7. **Principal Component Analysis (PCA)**
   PCA was applied for dimensionality reduction in cases where high-dimensional satellite image feature vectors needed to be compressed for efficient model processing. It helped in highlighting key features by removing redundant information.
8. **Cloud Hosting & Storage (Optional for Deployment)**
   For future scalability, the system is compatible with deployment on cloud platforms like AWS or Google Cloud. This ensures high availability and supports the processing of large satellite image datasets in real time.

RESULT AND DISSCUSION

The Urban Feature Extraction System (UFES) illustrates how traditional machine learning and image processing techniques can be effectively applied to real-world problems like urban analysis. Throughout the project, significant attention was paid to selecting algorithms that balance accuracy with computational efficiency. The Densitometry 3-Channel Algorithm proved effective for detecting water bodies and green spaces, while the Watershed Algorithm helped refine segmentation for complex features like roads.

One of the key strengths of the system is its simplicity and interpretability. Instead of relying on deep learning models that demand extensive computational resources and large datasets, the project uses classical approaches that are easier to implement, explain, and optimize. This makes the system well-suited for deployment in environments with limited infrastructure or in smaller municipalities.

However, the project also faced challenges such as variability in image quality, limited generalizability across regions, and the manual tuning of thresholds in segmentation. These issues highlight the importance of incorporating adaptive methods and potentially integrating hybrid approaches in the future.

Overall, the project serves as a proof of concept that demonstrates the practicality and impact of automated urban feature extraction for planning and environmental management. It lays a solid foundation for further enhancements, including deep learning integration, real-time satellite data feeds, and more detailed feature classification.

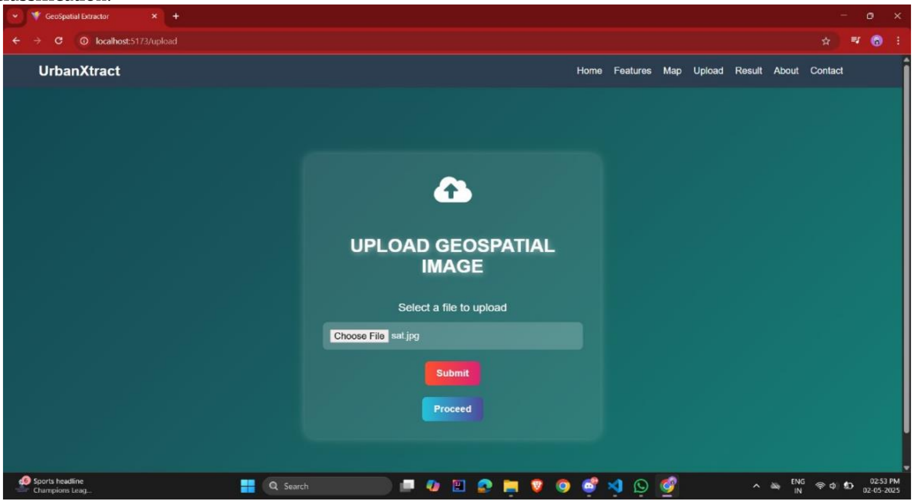
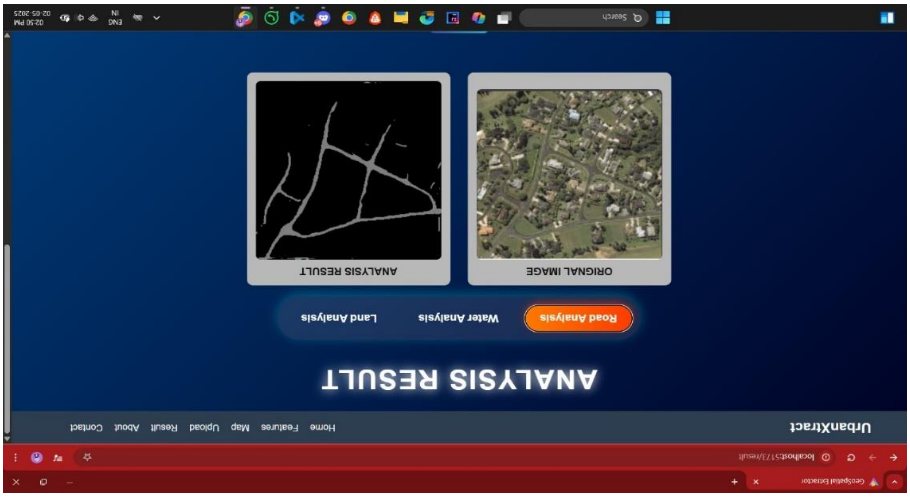
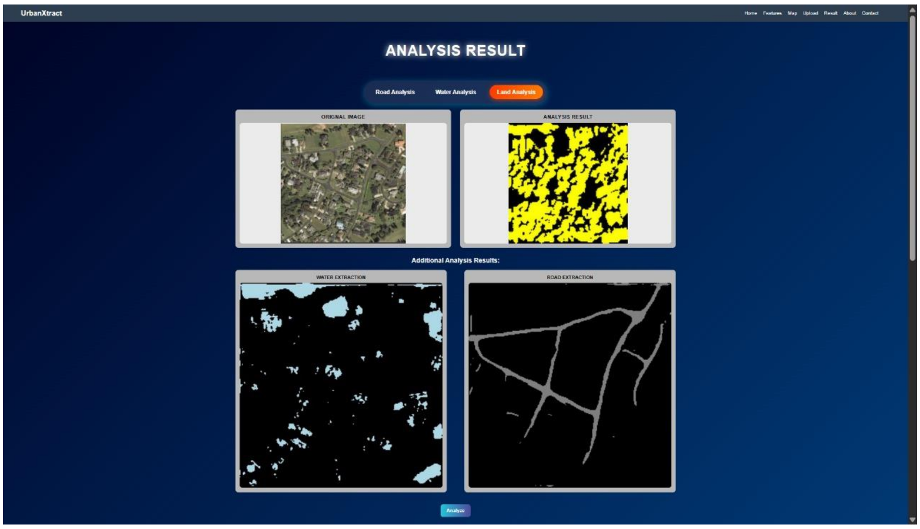


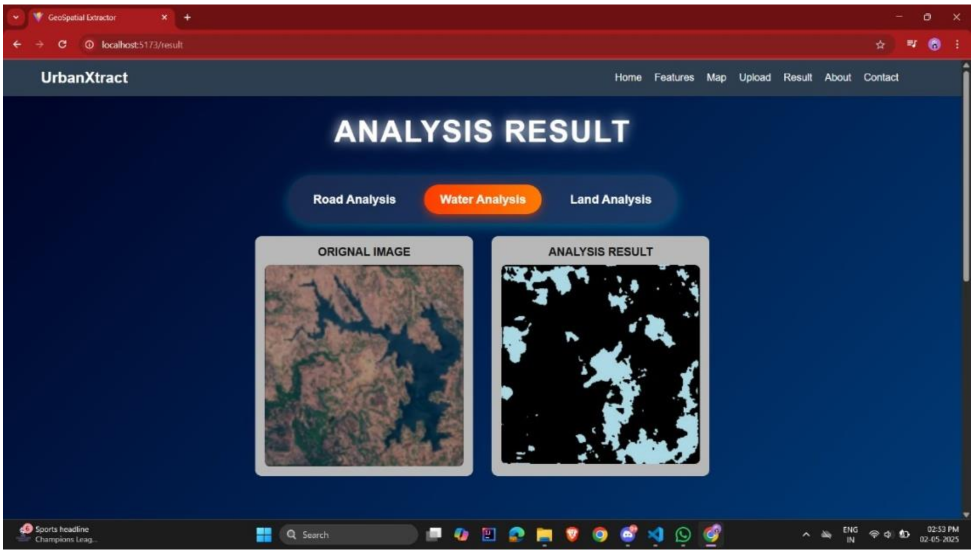
Image Upload Page



Road Analysis Result



Land Analysis Result



Water Analysis Output

CONCLUSION

The Urban Feature Extraction System (UFES) developed in this project successfully demonstrates the potential of traditional machine learning and image processing techniques for analysing satellite imagery to support urban planning. By integrating algorithms such as the Densitometry 3-Channel and Watershed segmentation methods, the system can accurately identify and classify key urban features such as roads, water bodies, green spaces, and built-up areas. The results achieved, supported by extensive testing and validation, indicate that the system is capable of delivering reliable and timely insights with a high degree of accuracy.

The incorporation of a user-friendly web interface allows non-technical stakeholders like urban planners and environmental analysts to interact with the system efficiently, enabling real-time visualization and decision-making. Moreover, the modular design and use of scalable technologies ensure that the system can be expanded and adapted to a wide range of geographic and urban contexts.

Overall, this project contributes to the growing need for automated, data-driven approaches in urban planning and environmental monitoring. It provides a practical and effective tool for supporting smart city initiatives and sustainable development goals.

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