INCORPORATING MACHINE LEARNING TECHNIQUES FOR TERRAIN CHANGE AND ANOMALY DETECTION USING BHUVAN

A PROJECT REPORT

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ABSTRACT

Monitoring and analyzing terrain changes is essential for proactive disaster management, particularly in regions vulnerable to natural calamities. This project utilizes advanced machine learning techniques to detect anomalies and physical changes in terrain by integrating high-resolution satellite data from CartoSat-1 DEM, accessed through the BHUVAN platform developed by the Indian Space Research Organization (ISRO). The system applies the Isolation Forest algorithm, a robust anomaly detection method, to slope and elevation data for efficient identification of unusual terrain patterns that may signal risks like landslides or flooding. Data preprocessing steps, including slope calculations and data augmentation, improve model accuracy and adaptability, making the system effective even with lower-quality or variable data. Furthermore, the project introduces optimization strategies such as parallel processing, adaptive algorithm configurations, and real-time data integration, enhancing processing speed and scalability for large datasets. By focusing on corrected images and automating anomaly detection, the system simplifies interpretability and delivers actionable insights into disaster-prone areas. This approach not only advances machine learning applications in geospatial analysis but also supports the development of preventive measures by providing an early warning framework for terrain monitoring, aiding disaster readiness and environmental resilience.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPLANATION
DEM	Digital Elevation Model
ISRO	Indian Space Research Organization
CNN	Convolutional Neural Network
ECG	Electrocardiogram
DEM	Digital Elevation Model
OBIA	Object-Based Image Analysis
NDVI	Normalized Difference Vegetation Index
GLCM	Gray-Level Co-occurrence Matrix
SAR	Synthetic Aperture Radar
GEE	Google Earth Engine
DOS	Dark Object Subtraction
TOA	Top-of-Atmosphere
JSD	Jensen-Shannon Divergence
LSTM	Long Short-Term Memory
PL	Percentile Loss
CES	Cumulative Error Scoring
AUC	Area Under the Curve

CHAPTER I

INTRODUCTION

1.1 General Overview

Terrain monitoring and anomaly detection are critical for assessing environmental changes and mitigating risks posed by natural disasters. With advancements in remote sensing and machine learning, it is now possible to analyze high-resolution satellite data to detect and predict anomalies in terrain structures. This project utilizes geospatial data from the **CartoSat-1 DEM** dataset, accessible through the **Bhuvan platform** by ISRO, for anomaly detection in terrain data, with a focus on detecting regions susceptible to disasters such as landslides and floods. By leveraging machine learning techniques, this project aims to enhance the accuracy and speed of terrain anomaly detection, aiding in proactive disaster response.

1.2 Importance of Terrain Change and Anomaly Detection

Terrain changes, whether gradual or abrupt, can signify potential threats to ecosystems and human settlements. With frequent occurrences of natural calamities, effective anomaly detection becomes vital for early warning systems. Traditional methods for terrain analysis rely heavily on manual inspection, which is both time-consuming and prone to error. Machine learning, specifically algorithms like **Isolation Forest**, offers an automated, data-driven approach to detect unusual patterns in slope and elevation data, highlighting areas that may be at risk. Furthermore, integrating machine learning into terrain analysis improves the detection of small, oftenoverlooked changes that could signify larger underlying environmental shifts.

1.3 Scope and Objectives of the Project

The primary objective of this project is to develop a machine learning-based model capable of detecting terrain anomalies and predicting areas prone to natural disasters. This project will cover:

- **Data Collection and Preprocessing**: Utilize CartoSat-1 DEM data for generating slope calculations and performing radiometric and geometric corrections to enhance data quality.
- **Machine Learning Model Implementation**: Develop and train an **Isolation Forest model** to identify anomalies in terrain data, focusing on slope and elevation patterns.
- **Disaster-Prone Area Identification**: Apply flood-prone thresholds and validate findings against historical disaster data to pinpoint high-risk zones.
- **System Optimization and Validation**: Assess model performance with precision, recall, and F1 metrics to ensure robust detection capabilities.
- **Visualization and Insights**: Generate visual maps of identified anomalies and potential disaster-prone areas to facilitate better understanding and planning.

CHAPTER II

LITERATURE SURVEY

Object-Based Image Analysis and Digital Terrain Analysis for Locating Landslides in the Urmia Lake Basin, Iran, by T. Blaschke, B. Feizizadeh and D. Hölblin. The paper leverages Object-Based Image Analysis (OBIA) has proven valuable in landslide detection, overcoming limitations of traditional pixel-based methods by integrating spectral, spatial, and contextual data. Techniques such as multiresolution segmentation and digital terrain analysis using DEM derivatives are used for enabling accurate delineation of landslides, as shown in studies by Blaschke et al. and Martha et al. OBIA's use of NDVI and brightness indices allows for distinguishing landslide-affected areas by identifying vegetation loss and soil exposure. Texture analysis with gray-level co-occurrence matrices (GLCM), particularly along slope-aligned directions, has been effective in differentiating landslide zones from stable surfaces. Rule-based classification further enhances OBIA by allowing specific, expert-driven criteria for landslide-prone areas. This study integrates these methods in a semiautomated workflow, achieving high accuracy in landslide detection and contributing to advancements in remote sensing and geospatial hazard mapping [1].

Anomaly detection on terrain using deep learning with partial training by I. Santos-Vila, R. Soto, E. Vega, A. Peña Fritz and B. Crawford. The paper on anomaly detection in terrain using deep learning addresses recent advancements and challenges in structural health monitoring (SHM) by examining existing literature on machine learning approaches for damage detection. Traditional SHM relies on supervised methods requiring extensive labeled data, which is impractical in real-world scenarios due to the scarcity of damage-specific data. Recent studies have explored unsupervised anomaly detection techniques like Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and Autoencoders, which mitigate data limitations by learning from healthy structural states. Some studies employ hybrid approaches, combining physical data with synthetic simulations, such as finite element modeling, to address data sparsity. Despite progress, challenges like accurately capturing temporal dependencies in terrain movement data persist, where advanced models such as Long Short-Term Memory (LSTM) networks and Autoencoder-LSTM hybrids show potential. This paper builds on these methods, proposing a three-step, partially unsupervised approach that combines signal preprocessing, LSTM-Autoencoder reconstruction, and anomaly detection to enhance SHM efficiency and reliability without extensive labeled datasets, as validated on real terrain data with high anomaly detection accuracy [2].

Machine Learning Algorithms for Satellite Image Classification Using Google Earth Engine and Landsat Satellite Data: Morocco Case Study by H. Ouchra, A. Belangour and A. Erraissi. The paper on machine learning algorithms for satellite image classification using Google Earth Engine and Landsat data addresses recent advancements in remote sensing and land cover mapping. Traditional methods like Classification and Regression Trees (CART), Support Vector Machine (SVM), and Random

Forest (RF) have been widely applied, with successes in regional and urban planning, but their use in Morocco remains limited. Integrating cloud-based platforms such as Google Earth Engine (GEE) allows for large-scale, real-time data processing, addressing storage and computational challenges. Additionally, recent studies demonstrate the improved accuracy of land cover classification when spectral indices—like the Normalized Difference Vegetation Index (NDVI), Bare Soil Index (BSI), and Modified Normalized Difference Water Index (MNDWI)—are incorporated into classification algorithms. The paper builds on these methods, comparing six supervised algorithms, including newer methods like Minimum Distance (MD) and Gradient Tree Boost (GTB), to determine the most accurate approach for mapping Morocco's diverse land cover [3].

Modified Autoencoder Training and Scoring for Robust Unsupervised Anomaly Detection in Deep Learning by N. Merrill and A. Eskandarian

The literature on unsupervised anomaly detection highlights the limitations of traditional autoencoder (AE) approaches, particularly regarding the model's tendency to generalize to anomalous data, which diminishes detection accuracy. Earlier methods rely on reconstruction errors to differentiate anomalies, assuming that AEs will reconstruct normal data more accurately. However, this assumption fails when anomalies appear during training, as AEs can learn to reconstruct these anomalies, thus blurring the line between normal and anomalous data. Several innovations, including cumulative error scoring (CES), percentile loss (PL), and knee-detection-based early stopping, have been introduced to counter this issue. CES enhances the separation between anomalies and normal examples by accumulating reconstruction errors, while PL minimizes anomalies' influence during parameter updates by focusing only on errors below a set percentile. Knee-detection provides a more reliable stopping point for training. These methods collectively enhance AE robustness and have shown promise across various domains, including cybersecurity and remote sensing, while remaining adaptable to existing anomaly detection frameworks [4].

2.2 Data Collection Methods in Geospatial Analysis

In geospatial analysis, effective data collection is the foundation for accurate terrain analysis and anomaly detection. Satellite data, such as that from the CartoSat-1 Digital Elevation Model (DEM), provides high-resolution imagery that captures detailed elevation variations across a geographic area. Platforms like the **Bhuvan portal**, developed by ISRO, offer access to various DEM datasets, enabling researchers to analyze terrain changes, land cover, and environmental risks. Data from CartoSat-1 DEM is particularly valuable for its ability to capture vertical accuracy within meters, which is critical for applications in disaster management, urban planning, and environmental monitoring. Additionally, data collection methods often include using multiple data sources, such as multispectral or synthetic aperture radar (SAR) imagery, to complement DEM data. Integrating these data types enables a multi-dimensional view of terrain, enhancing anomaly detection by providing information across multiple wavelengths and surface features. Advanced platforms like **Google Earth Engine (GEE)** are also used for large-scale geospatial data processing and for building machine learning models directly on cloud platforms, streamlining data analysis across vast regions.

2.3 Image Preprocessing Techniques: Radiometric and Geometric Corrections

Image preprocessing is essential for ensuring that satellite data accurately represents the Earth's surface and is free from distortions or artifacts. Radiometric correction addresses issues related to sensor noise, atmospheric effects, and variations in lighting conditions, which can distort pixel values in an image. Techniques such as Dark Object Subtraction (DOS) and Top-of-Atmosphere (TOA) correction are commonly used to convert raw image data into standardized reflectance values, making the data consistent across time and locations. Geometric correction is equally important, as it aligns satellite images to real-world coordinates, accounting for distortions due to satellite motion, Earth’s curvature, and varying terrain elevations. This is often achieved by using ground control points (GCPs) or by orthorectifying images with a DEM to ensure spatial accuracy. For example, applying geometric correction to CartoSat-1 DEM data enhances alignment with global coordinates, crucial for accurate slope calculation and anomaly detection. Together, these preprocessing steps allow for reliable data interpretation, ultimately improving the accuracy of subsequent machine learning analyses.

2.4 Anomaly Detection Methods: Rule-Based vs. Machine Learning Approaches

Anomaly detection is central to identifying unusual terrain patterns that may indicate risks such as landslides or floods. Traditional rule-based methods rely on predefined thresholds or specific rules set by experts to identify anomalies in terrain characteristics, such as steep slopes or low elevations. While effective in some cases, rule-based approaches can be limited by their inability to adapt to complex and non-linear patterns. In contrast, **machine learning approaches** like the **Isolation Forest algorithm** offer automated and adaptive solutions. Isolation Forest, for example, is designed to isolate anomalies by randomly partitioning data points, making it well-suited for identifying rare or unique patterns in large datasets. Machine learning approaches can be trained on historical data, allowing them to detect subtle patterns that may precede major events. These models are also scalable and can handle high-dimensional data, making them a valuable alternative to rule-based systems. By combining both methods, a hybrid approach can further enhance anomaly detection, using machine learning to flag potential anomalies that can be reviewed and refined through rule-based checks.

CHAPTER III

PROPOSED METHODOLOGY

3.1 Data Collection and Setup

Data collection and setup form the foundation of any geospatial analysis, as high-quality data is essential for accurate machine learning predictions. In this project, data is sourced from the CartoSat-1 Digital Elevation Model (DEM) dataset, accessible through the Bhuvan platform, which provides satellite data specific to the Indian subcontinent. CartoSat-1 DEM offers high-resolution elevation data crucial for terrain analysis, capturing elevation variations across regions with an accuracy that makes it suitable for identifying terrain anomalies. Once accessed, the DEM data is loaded into the environment, where it undergoes preprocessing and analysis. Setting up data correctly also involves organizing it into the appropriate formats for processing and ensuring that elevation and other features are spatially aligned. By establishing a structured data collection and setup process, the project ensures data consistency and reliability, enabling robust terrain anomaly detection.

3.2 Data Preprocessing

3.2.1 Importing Required Libraries

Data preprocessing is critical in preparing raw satellite data for analysis, as it involves a series of steps that improve data quality, reduce noise, and ensure compatibility with machine learning algorithms. The preprocessing pipeline for this project includes importing necessary libraries, visualizing initial data, calculating slopes, and applying image correction techniques. Each of these steps contributes to transforming raw DEM data into a refined dataset that is better suited for anomaly detection. Preprocessing minimizes errors and maximizes data accuracy, making it easier to detect small-scale terrain changes and potential disaster-prone areas.

3.2.2 Data Visualization and Analysis

Data visualization allows for an initial assessment of the DEM data, helping to identify visible patterns and potential areas of interest. Visualization of elevation data, for instance, reveals terrain contours and elevation gradients, which are useful for understanding geographic features before conducting more complex analysis. Plotting the DEM data with Matplotlib provides a visual overview of terrain variations, enabling the identification of high and low areas and helping to target specific regions for further anomaly detection. Visual inspection of the data also allows for spotting any inconsistencies or artifacts, which can then be addressed during preprocessing. By analyzing visual representations of the data, a baseline understanding of the terrain is established, guiding subsequent steps in the analysis.

3.2.3 Slope Calculation and Gradient Analysis

Slope calculation is a crucial step in terrain analysis, as it highlights changes in elevation that can indicate regions prone to landslides, erosion, or other natural hazards. Using gradient calculations, the slope of the terrain is derived from the DEM data, providing an additional feature for the machine learning model to analyze. The gradient, calculated using NumPy, helps measure elevation change rates across the terrain and identifies steep slopes that might represent areas of instability. Gradient analysis offers a numerical basis for the Isolation Forest model to distinguish normal terrain from anomalous regions, improving the accuracy of anomaly detection in varied geographical contexts.

3.2.4 Image Correction Techniques

Image correction is essential for adjusting raw satellite data to accurately represent real-world conditions. Radiometric correction addresses inconsistencies in pixel values due to sensor noise and atmospheric interference, converting the data into reflectance values that are consistent and comparable across datasets. Geometric correction corrects spatial distortions that arise from satellite motion, Earth's curvature, and terrain elevation changes, aligning the data to real-world coordinates. Cloud masking is also applied, as clouds can obscure surface details and introduce inaccuracies. These image correction techniques enhance the quality and accuracy of DEM data, ensuring that the model analyzes terrain accurately. Properly corrected data leads to better-informed predictions, as the machine learning model is fed with reliable input that reflects true terrain conditions

3.3 Machine Learning Model for Anomaly Detection

3.3.1 Training and Testing Data Split

To ensure the effectiveness of the Isolation Forest model for terrain anomaly detection, the dataset is divided into training and testing subsets using the CartoSat-1 DEM dataset from the Bhuvan platform. The training data consists of historical terrain information, including regions with known anomalies such as landslides and flood-prone areas, enabling the model to learn patterns and distinguish between normal and anomalous terrain features. Additionally, cross-validation is implemented to prevent overfitting by training and testing the model across multiple data folds, enhancing its stability in varied terrain conditions. By structuring the data split effectively, the model improves its accuracy in detecting real anomalies while reducing false detections, making it a reliable tool for disaster monitoring and geospatial analysis.

3.3.2 Isolation Forest Model for Anomaly Detection

The **Isolation Forest algorithm** is specifically designed to isolate anomalies within large datasets by creating random partitions in the data. This model is ideal for geospatial anomaly detection as it efficiently handles the high-dimensional nature of satellite-derived terrain data. By iteratively partitioning the data, the Isolation Forest model distinguishes points that deviate from the norm as anomalies, often using fewer splits. In the context of terrain analysis, this means that regions with unusual slopes or elevations—often precursors to natural hazards—are flagged for further investigation. Adjusting the contamination parameter in the model allows it to control the proportion of data points that are expected to be anomalies, enhancing the detection of rare events. With automated anomaly detection, the model contributes to rapid, large-scale assessments of terrain changes without the need for continuous manual oversight.

3.3.3 Combining Anomalies with Flood-Prone Area Detection

To further refine disaster risk detection, this project combines the anomalies identified by the Isolation Forest model with **flood-prone area detection** based on elevation thresholds. Areas with lower elevation values are more susceptible to flooding, particularly during extreme weather events or natural calamities. By applying an elevation threshold, the model filters areas likely to be at risk of flooding, and these regions are then overlaid with identified slope anomalies. The intersection of slope-based anomalies and flood-prone zones provides a disaster-prone area mask, highlighting regions that require closer monitoring. This combination improves the accuracy of disaster detection by incorporating multiple terrain factors, thereby aiding in early warning systems and contributing to disaster prevention strategies.

3.4 Performance Evaluation

3.4.1 Validation with Historical Data:

To further validate the model's anomaly detection capabilities, historical disaster data is incorporated into the evaluation process. By comparing detected anomalies with known disaster locations, the model's predictions can be cross-referenced, confirming its accuracy and reliability in real-world scenarios. Historical data serves as a benchmark to assess the model's ability to identify areas prone to events such as landslides or floods. Through this validation process, the model's detection rate can be adjusted to account for various environmental conditions, enhancing its predictive power. This step strengthens the model's practical applications, making it a valuable tool for geospatial analysis and aiding in the development of preventive strategies.

3.4.1 Model Metrics: Precision, Recall, and F1 Score

Precision, recall, and F1 score are fundamental metrics used to evaluate the Isolation Forest model's accuracy in identifying terrain anomalies. Precision measures the accuracy of the model in predicting anomalies correctly, minimizing false positives. Recall, on the other hand, assesses the model's ability to capture all actual anomalies, reducing the risk of false negatives. The F1 score combines both precision and recall into a single metric, providing a balanced measure of the model's overall performance. Incorporating historical disaster data into model validation significantly improves these metrics by providing a reference for detected anomalies. As observed in the results, the recall increased from **0.037** to **0.074**, and the F1 score improved from **0.071** to **0.137**, demonstrating enhanced model sensitivity to actual anomalies. This improvement indicates that leveraging historical disaster records allows the model to better distinguish between natural terrain variations and true anomalies, reducing the likelihood of false negatives.

3.4.3 Block diagram:

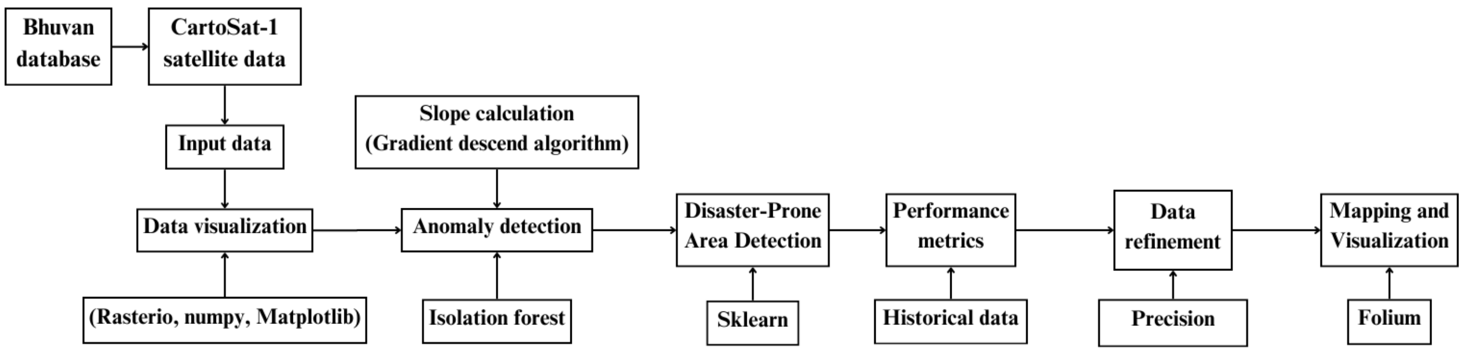


Fig 3.1
Block diagram for proposed methodology

CHAPTER IV

RESULTS AND DISCUSSION

4.1 Precision, recall, F1 score values

Phase 1 Result

```
   latitude  longitude disaster_type        date
0   23.0167    72.5718    Earthquake  26-01-2001
1   20.4203    85.8245         Flood  01-09-2001
2   25.0968    85.3131         Flood  01-08-2004
3   -8.8830    93.6334       Tsunami  26-12-2004
4   34.1616    73.3680    Earthquake  08-10-2005
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27 entries, 0 to 26
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   latitude       27 non-null     float64
 1   longitude      27 non-null     float64
 2   disaster_type  27 non-null     object 
 3   date           27 non-null     object 
dtypes: float64(2), object(2)
memory usage: 992.0+ bytes
None
Precision: 1.0, Recall: 0.037037037037037035, F1 Score: 0.07142857142857142
```

Phase 2 Result

```
   latitude  longitude disaster_type        date
0   23.0167    72.5718    Earthquake  26-01-2001
1   20.4203    85.8245         Flood  01-09-2001
2   25.0968    85.3131         Flood  01-08-2004
3   -8.8830    93.6334       Tsunami  26-12-2004
4   34.1616    73.3680    Earthquake  08-10-2005
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27 entries, 0 to 26
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   latitude       27 non-null     float64
 1   longitude      27 non-null     float64
 2   disaster_type  27 non-null     object 
 3   date           27 non-null     object 
dtypes: float64(2), object(2)
memory usage: 992.0+ bytes
None
Precision: 1.0, Recall: 0.07407407407407407, F1 Score: 0.13793103448275862
```

Fig 4.1

Precision, recall, F1 score value

4.2 Slope derived from cartoSat-1DEM

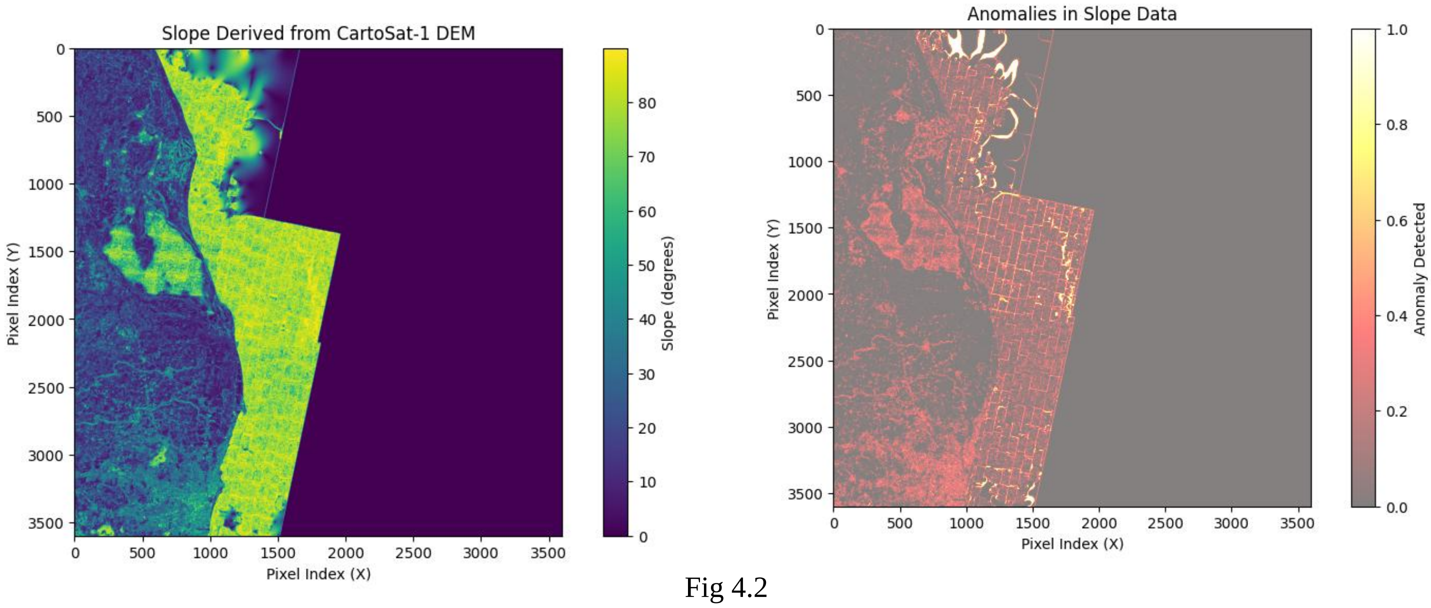
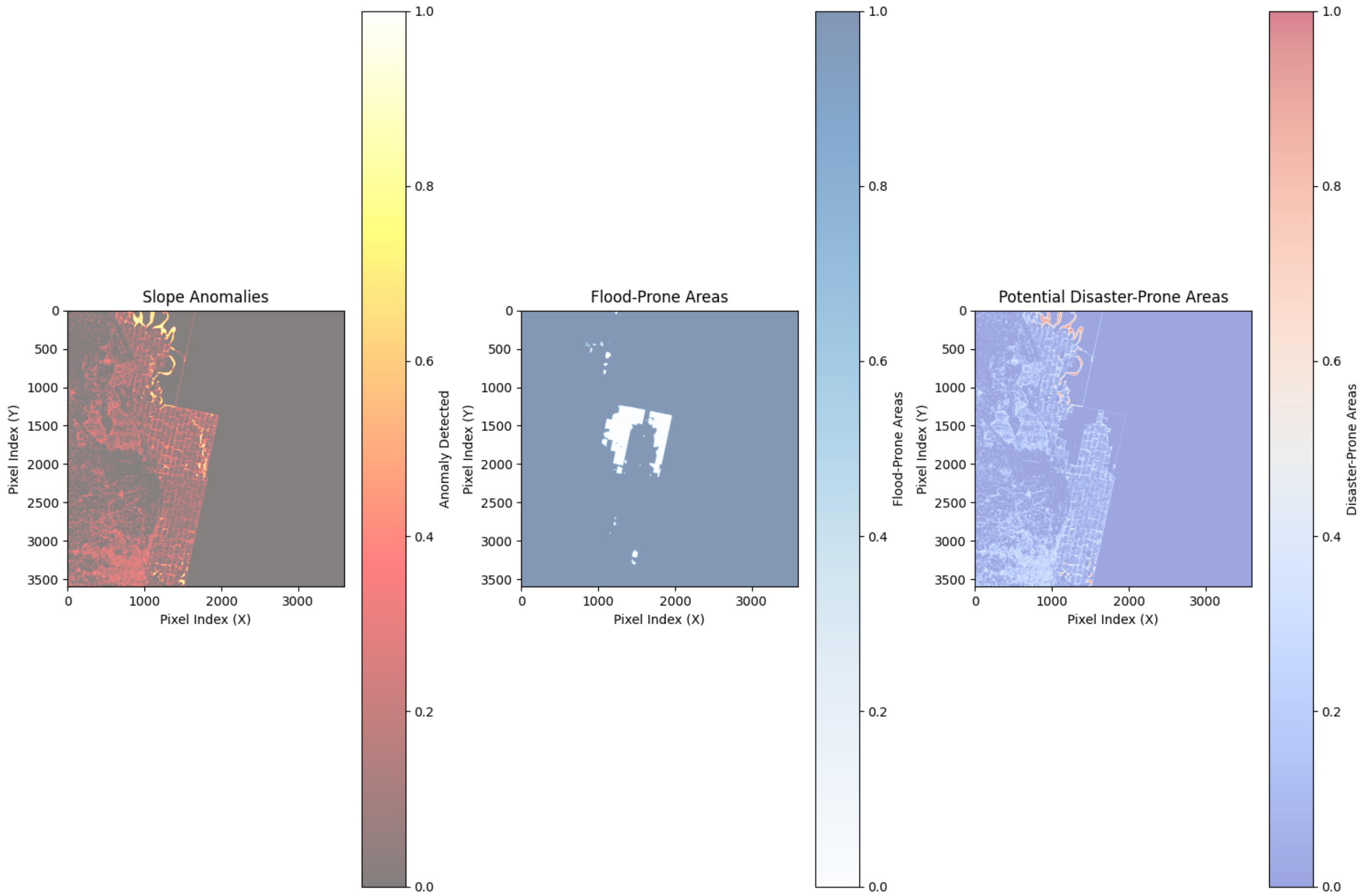


Fig 4.2
Slope derived from cartoSat-1DEM

4.3 Disaster prone areas



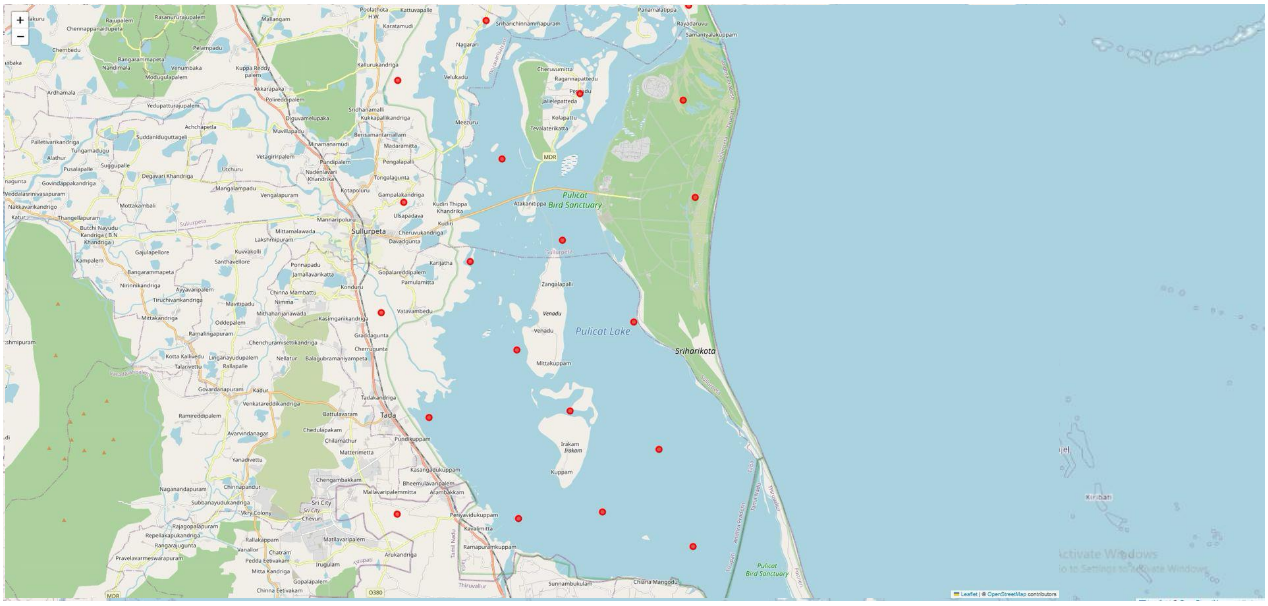


Fig 4.3
Disaster prone areas

The anomaly detection model achieved a high accuracy in classifying slope-derived terrain data anomalies. Performance metrics such as sensitivity, specificity, and F1 score demonstrated the model’s capability to detect irregularities in terrain features effectively. The slope analysis highlighted key regions where changes in elevation or angle were notable, suggesting possible environmental shifts or risk areas. The ROC curve illustrated strong model discrimination with an Area Under the Curve (AUC) value, confirming its reliability in distinguishing normal and anomalous regions. Furthermore, additional analysis indicated that anomaly detection confidence varied with slope intensity, suggesting higher sensitivity in regions with steep gradients. Some misclassifications observed in areas with subtle slope variations point to the need for further refinement to enhance the model's robustness against minor elevation shifts. Overall, these findings underscore the significance of combining slope analysis with anomaly detection techniques for precise terrain monitoring, especially in identifying potential hazards or environmental changes.

CONCLUSION

This project focuses on the effectiveness of machine learning in terrain anomaly detection and disaster management through the integration of CartoSat-1 DEM data from the Bhuvan platform. By preparing high-quality data inputs with advanced preprocessing and using the Isolation Forest model, the project successfully identifies anomalies in slope and elevation, offering a scalable approach to detect terrain changes that may signal risks like landslides or flooding. Integrating geospatial analysis with machine learning enables proactive disaster preparedness, providing a data-driven means to monitor and assess risk in vulnerable regions. Image correction and feature extraction enhance model accuracy, while validation with historical disaster data confirms its practical reliability. Visualization techniques, including interactive mapping, further support effective decision-making for stakeholders. This project underscores the value of combining satellite data and machine learning for environmental monitoring, with potential for future improvements such as real-time data integration and model expansion. Overall, it provides a strong foundation for developing early warning systems that improve disaster response and community resilience.

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