

GEOVISION: SATELLITE IMAGE RECOGNITION

PHASE II REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

- In recent years, the advancement of satellite technology combined with the power of artificial intelligence has significantly improved our ability to monitor and analyze Earth's surface in real time. This project, titled "IntelliSat: Automated Landform Classification Using Satellite Imagery," focuses on the intelligent recognition and classification of terrain features such as plains, mountains, forests, and other geographical landforms from satellite-captured images. The primary objective is to develop a system that can accurately analyze satellite images and identify the type of landform depicted, thereby supporting applications in environmental monitoring, land use planning, resource management, and disaster response.
- The system leverages machine learning and deep learning techniques, particularly Convolutional Neural Networks (CNNs), for feature extraction and classification. A curated dataset of satellite images representing various landforms was used to train the model, ensuring it learns to distinguish subtle patterns and textures unique to each terrain type. Preprocessing techniques such as image normalization, resizing, and augmentation were employed to enhance the robustness and generalization of the model.
- Upon receiving a satellite image as input, the trained model processes it and outputs a classification label indicating whether the region is a plain, mountainous area, forest, desert, or other recognizable landform. The model's predictions are presented through an interactive interface built using Streamlit, allowing users to upload images and view real-time results

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LIST OF ABBREVIATIONS

S. No	ABBR	Expansion
1	CNN	Convolutional Neural Network
2	RGB	Red Green Blue (color model used in images)
3	ROI	Region of Interest
4	IoU	Intersection over Union
5	GIS	Geographic Information System
6	SAR	Synthetic Aperture Radar
7	NDVI	Normalized Difference Vegetation Index
8	ML	Machine Learning
9	DL	Deep Learning
10	AI	Artificial Intelligence
11	DEM	Digital Elevation Model
12	UAV	Unmanned Aerial Vehicle
13	GSD	Ground Sampling Distance
14	LULC	Land Use Land Cove
15	SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 GENERAL

- Satellite imagery has become an essential tool for understanding and monitoring the Earth's surface. With the increasing availability of high-resolution images captured by satellites, there is a growing need for intelligent systems that can automatically interpret these images and extract meaningful information. Traditionally, analyzing satellite images to identify landforms such as mountains, forests, plains, or deserts required manual effort by experts, which is time-consuming and prone to human error.
- This project aims to develop an automated solution for classifying different types of land features from satellite images using artificial intelligence and image recognition techniques. By training a machine learning model on a labeled dataset of satellite images, the system can learn to distinguish between various terrain types based on visual patterns and characteristics. The model takes a satellite image as input and outputs a label indicating the type of landform it represents, such as "mountain," "forest," or "plain."
- The project not only reduces the need for manual image interpretation but also speeds up the process of land classification, making it useful for applications in agriculture, environmental monitoring, urban planning, and disaster management. With a simple user interface built using Streamlit, even non-technical users can upload satellite images and receive quick, accurate classifications in real time.

1.2 OBJECTIVE

The primary objective of this project is to develop an intelligent system that can automatically classify landforms such as plains, mountains, forests, and deserts from satellite images using deep learning techniques. By leveraging image recognition algorithms, the system aims to accurately identify terrain types based on visual features in the images, thereby eliminating the need for manual interpretation. This project seeks to provide a fast, scalable, and user-friendly solution for land classification, supporting various real-world applications such as environmental monitoring, land use analysis, disaster response, and geospatial planning.

1.3 EXISTING SYSTEM

Traditional landform classification from satellite imagery largely relies on manual analysis by experts or semi-automated Geographic Information System (GIS) tools that require extensive human input and domain knowledge. These systems often involve visual inspection, predefined rule-based methods, or basic pattern recognition algorithms that are limited in scalability and accuracy. While some satellite image analysis platforms exist, many are either domain-specific, costly, or lack the adaptability to classify a wide range of landforms with high precision. Furthermore, these systems typically do not utilize advanced AI or deep learning techniques, making them less effective in handling large datasets or capturing complex patterns in high-resolution satellite imagery.

CHAPTER 2

LITERATURE SURVEY

"Satellite image recognition has been a widely researched area, particularly with the increasing availability of remote sensing data and advances in computational intelligence. Traditionally, satellite image classification was performed using supervised classification techniques such as Maximum Likelihood Classification (MLC), Minimum Distance, and Support Vector Machines (SVM). These methods relied heavily on manually selected features and required extensive preprocessing and calibration. Early systems such as Landsat-based land cover mapping employed pixel-level classification, which performed reasonably well but often struggled with mixed pixels and lacked the contextual understanding needed to identify complex terrain structures. These methods also required significant domain expertise to interpret the results, which limited their usability in broader, real-time applications.

The use of machine learning introduced a significant shift in how satellite data is processed and interpreted. Techniques like Decision Trees, Random Forests, and k-Nearest Neighbors (k-NN) began replacing traditional statistical classifiers due to their higher flexibility and ability to model non-linear relationships. In particular, Random Forests became popular for land cover classification because of their robustness to noise and high-dimensional data. These algorithms, however, still relied on hand-crafted features, meaning the performance was heavily dependent on the quality of feature engineering. Researchers found that while machine learning improved accuracy and scalability, it still lacked the ability to automatically extract deep spatial and contextual features, which are critical in complex terrain classification involving similar color patterns but different topographical structures, such as forests and mountainous regions.

With the emergence of deep learning, especially Convolutional Neural Networks

(CNNs), the field experienced a paradigm shift. CNNs introduced an end-to-end learning mechanism where feature extraction and classification are combined into a single model. These models excel at automatically learning hierarchical spatial features from raw pixel data, making them ideal for satellite imagery. Numerous studies demonstrated the superiority of CNNs in land cover classification tasks. For instance, a study by Zhong et al. (2016) used CNNs for classifying land use types from high-resolution satellite images and achieved significant accuracy improvements over traditional methods. Similarly, researchers like Zhang et al. (2018) applied deep residual networks (ResNets) and transfer learning techniques to overcome the challenge of limited labeled datasets, thereby enhancing performance and generalization in satellite image classification tasks.

In addition to CNNs, other architectures such as Fully Convolutional Networks (FCNs), U-Net, and DeepLab have been used for semantic segmentation of satellite images. These architectures allow pixel-wise classification, which is particularly useful when dealing with mixed landforms within a single image. U-Net, originally developed for biomedical image segmentation, has been widely adopted in remote sensing due to its encoder-decoder architecture that captures both low-level and high-level features. For example, Audebert et al. (2017) applied U-Net for high-resolution urban land cover classification and demonstrated its effectiveness in segmenting fine-grained objects like roads, buildings, and vegetation. When extended to natural terrains, such architectures enable precise boundary detection between different landforms such as water bodies adjacent to forests or mountainous regions.

Another critical advancement in satellite image recognition is the use of multi-spectral and hyper-spectral imaging, which incorporates data beyond the visible spectrum. These datasets capture unique spectral signatures of various landforms and are particularly helpful in distinguishing between vegetation types, soil compositions, and water bodies. Several studies have explored the integration of spectral bands with CNNs to enhance classification accuracy. For instance, studies using Sentinel-2 and

MODIS data have demonstrated that incorporating near-infrared and shortwave infrared bands improves the ability to identify water bodies and forest cover. This spectral information, combined with spatial features learned by CNNs, significantly improves the model's capability to detect subtle terrain variations and seasonal changes.

In recent years, hybrid models combining CNNs with Recurrent Neural Networks (RNNs) or attention mechanisms have been proposed to capture both spatial and temporal dependencies in satellite imagery. These models are particularly useful when analyzing time-series data to monitor landform changes over time, such as deforestation or desertification. For example, Gong et al. (2020) proposed a hybrid CNN-LSTM model for land cover classification using sequential satellite images and achieved superior performance in change detection tasks. Additionally, attention-based models like Transformers have also begun gaining traction in remote sensing due to their ability to focus on relevant parts of the image, making them highly efficient in capturing contextual information across large scenes.

Apart from model architectures, another major focus area in the literature has been the development of benchmark datasets and open-source tools for satellite image analysis. Datasets such as EuroSAT, DeepGlobe, and BigEarthNet have played a crucial role in advancing research by providing diverse, labeled satellite imagery covering multiple land types. These datasets are often used for training and evaluating deep learning models, ensuring consistency and comparability across studies. Tools like Google Earth Engine and NASA's Worldview platform have also enabled researchers to access and process satellite data at scale. Open-source libraries such as Rasterio, GDAL, and PyTorch-based deep learning frameworks further support experimentation and deployment of satellite image classification models in real-world applications.

Despite these advancements, challenges remain in satellite image recognition, particularly regarding data quality, resolution, and generalization. Satellite images

often suffer from noise due to atmospheric conditions, sensor errors, or cloud cover, which can hinder model performance. Addressing these issues requires sophisticated preprocessing techniques such as cloud masking, atmospheric correction, and data augmentation. Furthermore, the generalization of trained models to new geographical regions remains a concern, as models trained on specific datasets may not perform well in unseen environments with different terrain characteristics. To mitigate this, researchers have explored domain adaptation, transfer learning, and data fusion techniques, combining multiple data sources such as elevation maps, climate data, and LiDAR data to enrich the learning context.

The role of user-friendly interfaces and visualization tools is also emphasized in recent literature, especially in making satellite image analysis accessible to non-experts. Several projects have integrated AI models into web-based platforms or applications using frameworks like Streamlit, Flask, or Dash, enabling real-time image uploads and classification results. These platforms bridge the gap between research and practical implementation by allowing users in fields like agriculture, forestry, and disaster management to leverage AI-driven insights without deep technical knowledge. This approach is particularly beneficial in developing regions where rapid landform classification can support early warning systems, land use planning, and environmental conservation efforts.

Recent developments in artificial intelligence have brought remarkable changes to how satellite images are processed and interpreted, especially with the evolution of hybrid models that combine convolutional neural networks (CNNs) with transformer architectures. The traditional CNNs, while efficient at capturing local spatial features, often struggle with long-range dependencies within large satellite images. Transformers, originally popularized in natural language processing, have found their place in vision tasks due to their self-attention mechanisms, which allow them to understand contextual relationships across wider areas of an image. Studies have demonstrated that integrating transformer-based modules with CNN backbones leads

to more robust performance in tasks such as landform segmentation, water body identification, and terrain classification. These hybrid models help overcome the limitations of fixed kernel sizes in CNNs by dynamically weighing image regions based on learned importance, significantly improving the ability to distinguish between visually similar yet contextually different regions like plains adjacent to mountainous terrain or riverbanks within forests.

Furthermore, the integration of satellite imagery with auxiliary spatial data has proven to be a promising direction for more context-aware classification. Researchers are increasingly exploring the fusion of satellite images with geospatial data like topographic maps, soil quality indices, and meteorological records to enhance the interpretability of land features. For example, by combining digital elevation models with satellite RGB images, a classifier can not only detect the presence of a forest but also distinguish whether it lies in lowland valleys or on mountainous ridges. Similarly, the inclusion of climatic variables helps in refining predictions about water bodies, especially in areas where seasonal variation causes temporary expansions or contractions in size. These enriched models are more adaptable to dynamic environments and better suited for longitudinal studies that track landform changes over time, such as desertification, glacial retreat, or urban encroachment into forested zones.

Another significant thread in recent literature revolves around the automation of land classification pipelines using end-to-end deep learning systems. Earlier systems often relied on handcrafted feature extraction followed by traditional machine learning classifiers like support vector machines (SVM) or decision trees. However, end-to-end architectures eliminate the need for manual feature engineering by learning optimal feature representations directly from raw pixel values. These systems streamline the process of satellite image analysis and improve scalability across different regions and datasets. In addition, the introduction of semi-supervised and unsupervised training approaches enables the model to generalize better, especially in low-data regimes. Self-

supervised learning methods, in particular, have emerged as a powerful tool for pretraining models on unlabeled satellite data, allowing them to learn meaningful visual patterns and structures before fine-tuning with a small set of labeled images. These advances are especially important for regions where acquiring labeled satellite data is expensive or time-consuming.

The literature also emphasizes the increasing importance of time-series satellite imagery, which adds a temporal dimension to land classification tasks. Instead of analyzing a single image snapshot, time-series data allow researchers to monitor how landscapes evolve over time, making it possible to detect slow changes like seasonal crop cycles, forest regrowth, or the drying of water bodies. Recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and more recently, temporal convolutional networks (TCNs) have been applied to model temporal dependencies in satellite sequences. These models enable early detection of anomalies, such as unseasonal flooding, land degradation, or the emergence of urban settlements in previously uninhabited areas. The capacity to track changes not only supports proactive decision-making in environmental and disaster management but also provides crucial insights for urban planners, conservationists, and policy makers aiming for sustainable development.

One underexplored but rapidly growing domain in satellite image recognition is the use of generative models for data augmentation and synthetic image generation. Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are being leveraged to generate high-resolution satellite images that mimic real-world conditions, thus augmenting training datasets for better model robustness. These synthetic images help in overcoming class imbalance issues—such as a scarcity of labeled images of mountainous terrain or flooded regions—by artificially generating data for underrepresented classes. Moreover, GANs can simulate environmental conditions such as cloud cover, haze, or lighting variations, allowing models to learn invariant features that improve generalization. This technique is particularly useful in

emergency applications where real-time data may be limited or unavailable due to adverse weather or technical constraints.

Lastly, growing discussions in the literature are focusing on the social and ethical implications of satellite-based AI systems. While the technology holds tremendous promise for global-scale monitoring and planning, concerns related to data privacy, geopolitical misuse, and surveillance ethics are also emerging. For instance, the ability to detect changes in land use or monitor construction activities in near real-time can lead to privacy violations if used irresponsibly. Academic researchers and institutions are calling for the adoption of ethical AI principles, including transparency in model predictions, fairness across geographic regions, and accountability for potential errors or misuse. Furthermore, efforts are underway to develop open-source frameworks and datasets that democratize access to satellite AI tools while adhering to legal and ethical guidelines. These conversations are shaping the next generation of research, where technical advancements are increasingly aligned with societal values and regulatory standards.

In conclusion, the literature reveals a steady evolution from manual interpretation and basic machine learning to highly sophisticated deep learning models for satellite image classification. The integration of spectral and spatial features, the development of large annotated datasets, and the incorporation of user-centric tools have collectively advanced the field toward real-time, scalable, and accurate landform recognition systems. The current project builds on these foundations by implementing a deep learning-based system that classifies satellite images into categories such as plains, forests, mountains, and water bodies. By using a combination of CNNs and an interactive interface, it aims to offer a practical solution that is both technically sound and user-friendly, contributing to the growing body of work in intelligent Earth observation.

CHAPTER 3

PROPOSED SYSTEM

3.1 GENERAL

The proposed system aims to enhance the capabilities of satellite image recognition by leveraging advanced deep learning techniques for accurate and efficient landform classification. This system utilizes state-of-the-art convolutional neural networks (CNNs) combined with hybrid architectures, integrating multiple data sources such as digital elevation models, satellite imagery, and geographical data. The primary objective is to classify various land types, including plains, mountains, forests, and water bodies, with high precision. Additionally, the system will be designed to handle large-scale satellite datasets, ensuring scalability and real-time processing for dynamic monitoring and environmental analysis. By incorporating these advanced technologies, the proposed system aims to provide valuable insights for applications such as environmental monitoring, urban planning, and disaster management.

3.2 SYSTEM ARCHITECTURE DIAGRAM

The architecture of the satellite image recognition project consists of a structured pipeline that begins with the acquisition of raw satellite images from remote sensing sources. These images undergo preprocessing steps such as noise removal, resizing, normalization, and data augmentation to prepare them for model training. If the project uses supervised learning, the images are annotated with labels like forest, water body, plain, or mountain. The preprocessed and labeled data is then used to train machine learning models, typically Convolutional Neural Networks (CNNs), ResNet, or Vision Transformers, depending on the complexity and performance

requirements. After training, the model is evaluated using metrics such as accuracy, precision, recall, and F1-score to assess its performance. Finally, the trained model is used for inference to classify new satellite images, with the option of deploying the system as an API or web interface for end users.

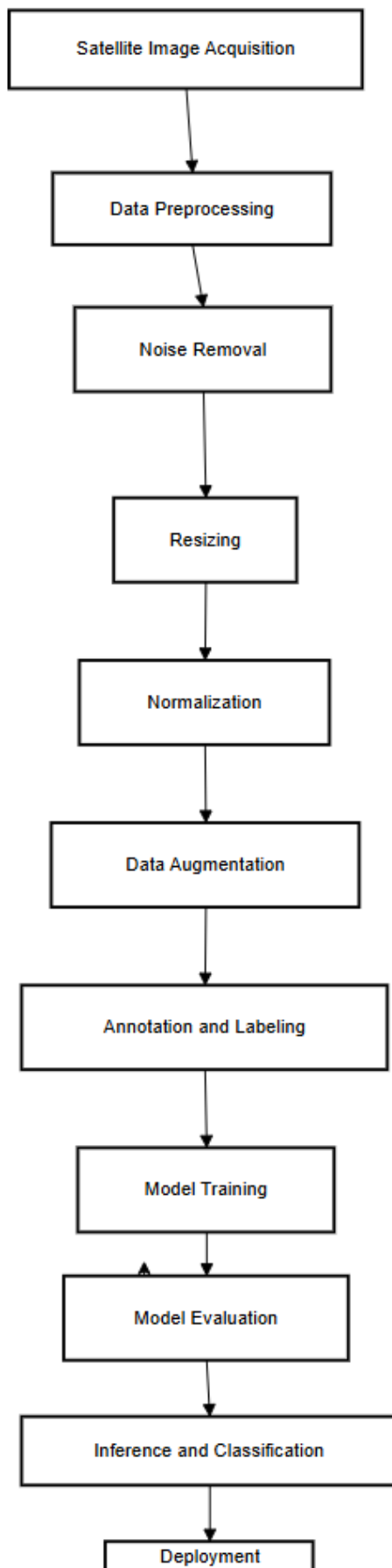


Fig 3.1: System Architecture

3.3 DEVELOPMENTAL ENVIRONMENT

3.3.1 HARDWARE REQUIREMENTS

The hardware specifications could be used as a basis for a contract for the implementation of the system. This therefore should be a full, full description of the whole system. It is mostly used as a basis for system design by the software engineers.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i3
RAM	4 GB RAM
POWER SUPPLY	+5V power supply

3.3.2 SOFTWARE REQUIREMENTS

The software requirements paper contains the system specs. This is a list of things which the system should do, in contrast from the way in which it should do things. The software requirements are used to base the requirements. They help in cost estimation, plan teams, complete tasks, and team tracking as well as team progress tracking in the development activity.

Table 3.2 Software Requirements

COMPONENTS	SPECIFICATION
Operating System	Windows 7 or higher
Frontend	ReactJS,CSS
Backend	Flask (Python)
Database	MongoDB

3.4 DESIGN OF THE ENTIRE SYSTEM

3.4.1 ACTIVITY DIAGRAM

This activity diagram illustrates the simplified workflow of a satellite image recognition system. The process begins with uploading and preprocessing the satellite image to ensure it meets the quality requirements. Next, the image is passed through a recognition model that analyzes and identifies key features, such as water bodies or land cover types. These features are then detected and visually highlighted. Finally, the results are displayed to the user and saved for further analysis or reporting, completing the recognition cycle.

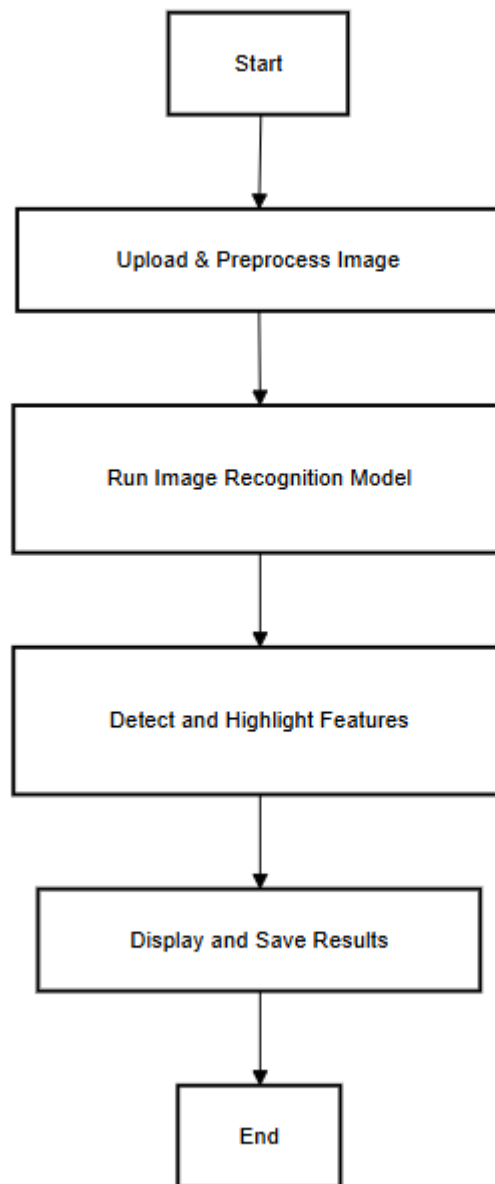


Fig 3.2: Activity Diagram

3.4.2 DATA FLOW DIAGRAM

This data flow diagram represents the core data movement in the satellite image recognition system. The process begins when the user uploads a satellite image through the input interface. The image is then sent to a preprocessing unit to enhance its quality and format. Once preprocessed, it is passed to the image recognition model, which analyzes the image and identifies relevant features such as water bodies or terrain types. These features are processed by the detection module, and the results are then displayed to the user and optionally saved for further use. The user can view or download the output, completing the data flow cycle.

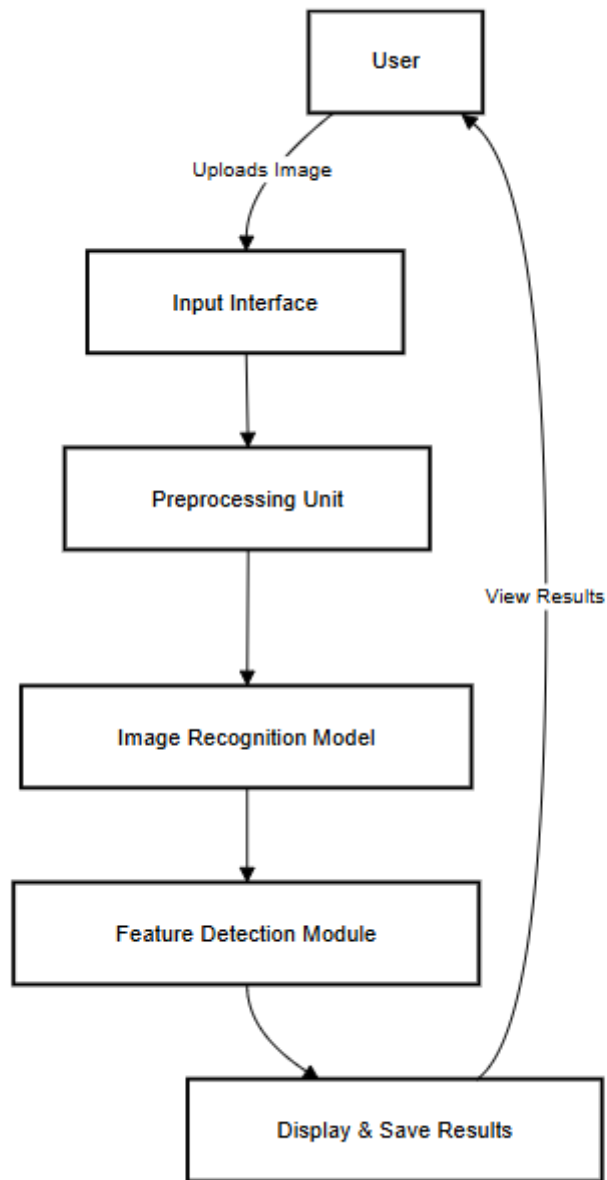


Fig 3.3:Data Flow Diagram

3.5 STATISTICAL ANALYSIS

In the statistical analysis phase of the satellite image recognition project, various metrics were used to evaluate the model's performance and accuracy. The dataset was divided into training and testing sets, and standard evaluation measures such as precision, recall, F1-score, and accuracy were computed. Confusion matrices were analyzed to assess the model's ability to correctly identify features like water bodies and vegetation. Additionally, area-based statistics such as the percentage of land covered by detected features were calculated to validate detection consistency. Statistical comparisons between predicted results and manually annotated ground truth data were performed using mean squared error (MSE) and correlation coefficients, ensuring the reliability and robustness of the model across varying image resolutions and environmental conditions.

CHAPTER 4

MODULE DESCRIPTION

The workflow for the proposed satellite image recognition system is designed to efficiently process and classify satellite imagery into distinct land types such as plains, mountains, forests, and water bodies. It follows a systematic pipeline from data acquisition to final classification and visualization.

4.1 SYSTEM ARCHITECTURE

4.1.1 USER INTERFACE DESIGN

The sequence diagram in Fig 4.1 represents the flow of satellite image classification. The user begins by uploading a satellite image through a simple graphical interface built using Streamlit. The image is then passed through preprocessing stages including resizing, normalization, and enhancement. Features are extracted and fed into a pre-trained deep learning model (e.g., CNN), which classifies the image into one of the predefined categories. The result is then displayed on the interface along with possible metadata like confidence score, classification map, and suggestions for analysis.

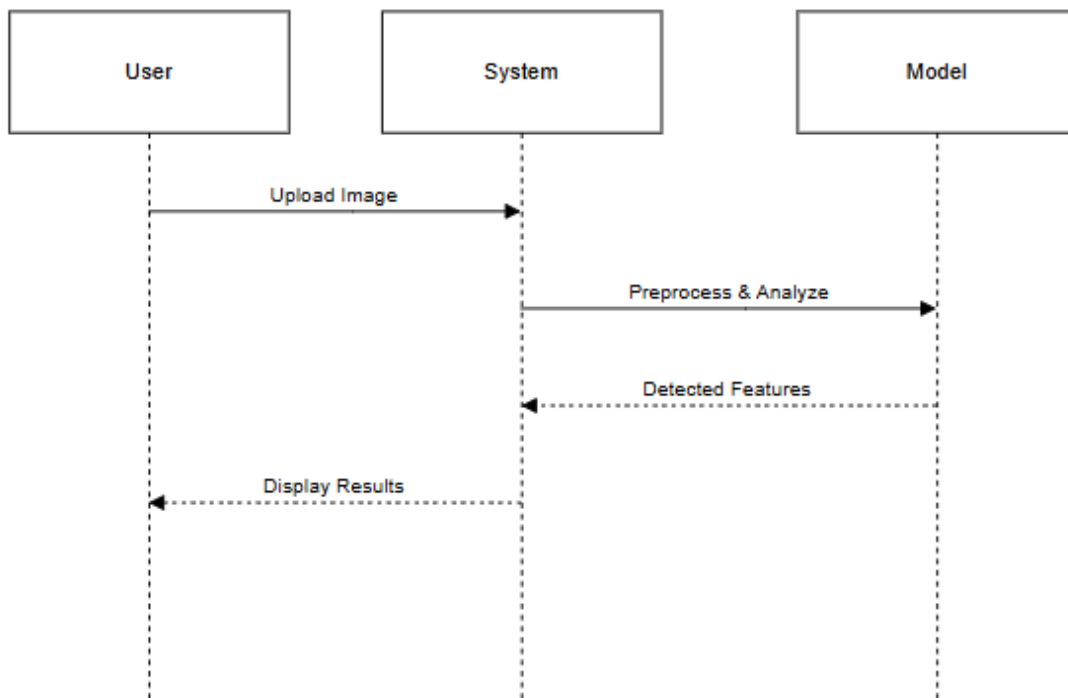


Fig 4.1: SEQUENCE DIAGRAM

4.1.2 BACK END INFRASTRUCTURE

The backend architecture integrates multiple components to handle high-resolution satellite image data. It includes a storage system (e.g., AWS S3, Google Drive, or local filesystem) to manage image datasets, preprocessing modules to clean and enhance input images, and a trained deep learning model developed using TensorFlow or PyTorch. The classification output is relayed to the frontend via a Flask or Streamlit server. Logging mechanisms are incorporated for storing predictions, model performance, and feedback, enabling periodic retraining and monitoring of accuracy.

4.2 DATA COLLECTION AND PREPROCESSING

4.2.1 Dataset and Data Labelling

The system uses publicly available satellite image datasets such as EuroSAT, UC Merced Land Use Dataset, or custom-labeled image collections. These images are labeled manually or using external metadata into classes like 'Mountain,' 'Plain,' 'Forest,' 'Water Body,' and 'Urban Area'. Accurate labeling is essential for supervised learning and to ensure correct classification during testing.

4.2.2. Data Preprocessing

The raw satellite images undergo several preprocessing steps:

- **Resizing & Normalization:** Images are resized to a fixed dimension and normalized to improve model convergence.
- **Noise Reduction:** Techniques such as Gaussian blur or sharpening filters are applied.
- **Contrast & Histogram Equalization:** Enhances the visual quality and highlights distinguishable features.
- **Augmentation:** Rotations, flips, and zooms are used to increase dataset diversity and prevent overfitting.

4.2.3 Feature Extraction and Model Training

Deep learning models like Convolutional Neural Networks (CNNs), ResNet50, or EfficientNet are employed for feature extraction. These models automatically learn high-dimensional patterns and edges from satellite data. Training is conducted using labeled images with optimizers like Adam and loss functions like cross-entropy for classification accuracy.

4.2.4 Classification and Model Selection

Multiple models are evaluated for performance:

- **CNNs** for spatial feature learning
- **ResNet** for deeper hierarchical features
- **MobileNet** for lightweight edge deployment

The best-performing model is selected based on metrics such as accuracy, precision, and F1-score.

4.2.5 Performance Evaluation and Optimization

After training, the model's performance is validated on a test dataset. Evaluation metrics include:

- **Accuracy & Confusion Matrix:** For overall prediction quality.
 - **Precision/Recall/F1:** To assess class-wise effectiveness.
 - **Cross-validation:** Ensures the model is generalizable.
- Hyperparameter tuning is performed using grid search or Bayesian optimization.

4.2.6 Model Deployment

The optimized model is deployed through a user-friendly web application using Streamlit or Flask. Users can upload images and instantly get the predicted classification result with visual feedback such as labeled maps or overlays.

4.2.7 Centralized Server and Database

A backend database (SQLite or Firebase) is used to store user uploads, prediction results, performance logs, and feedback data. This allows reusability of image records

and retraining of models based on updated feedback or datasets.

4.3 SYSTEM WORK FLOW

4.3.1 User Interaction:

Users interact with the system by uploading a satellite image through the interface. The system processes the image, extracts relevant features, and predicts the land type, displaying results such as “Mountainous Region,” “Water Body,” or “Forest Zone” along with the prediction score.

4.3.2 Image Classification and Inference

The pre-trained deep learning model classifies the uploaded satellite image by analyzing patterns, textures, and contextual elements. Each pixel or segment is assessed, and the overall label is inferred based on majority mapping and class scores.

4.3.3 Visualization and Interpretation

Once classification is complete, the result is visualized through annotated maps, overlaid masks, and detailed classification reports. Users can view prediction confidence and download reports for further usage in research or planning.

4.3.4 Feedback and Learning Loop

Users can flag incorrect predictions or provide feedback. This data is stored and periodically used to retrain the model, ensuring adaptability to new image patterns or updated class definitions.

4.3.5 Continuous Improvement

The system is designed to accept periodic updates in both datasets and model

architecture. This facilitates fine-tuning, supports additional land types (e.g., snowfields, urban slums), and ensures relevance with the latest satellite data streams.

CHAPTER 5

IMPLEMENTATION AND RESULTS

5.1 IMPLEMENTATION

The implementation of the satellite image recognition system involved several coordinated stages, beginning with the collection and organization of satellite imagery datasets representing diverse land cover types such as forests, mountains, plains, urban regions, and water bodies. These images were sourced from open satellite datasets like EuroSAT and NASA EarthData, or manually curated from reliable online repositories. The images were first preprocessed using Python libraries such as OpenCV and PIL, undergoing resizing, normalization, and contrast adjustments to standardize input formats and enhance clarity. For classification, a Convolutional Neural Network (CNN)-based architecture was developed using TensorFlow and Keras, capable of learning intricate spatial features from the satellite imagery. In certain iterations, deeper models like ResNet50 were used to improve classification precision, particularly for complex terrains. The model was trained on labeled data using GPU acceleration to speed up the learning process. Evaluation was done using validation datasets, and metrics such as accuracy, precision, recall, and confusion matrix were analyzed to ensure model effectiveness. After achieving satisfactory results, the trained model was deployed using the Streamlit framework to enable user-friendly interaction. Users could upload satellite images through the web interface, which the backend would process in real-time to return the classified land type. The final system not only provided accurate recognition of land types but also included visualization features like overlay maps and probability scores, making it practical for real-world applications in geography, agriculture, and environmental monitoring.

5.2 OUTPUT SCREENSHOTS

The graphical user interface developed using the Streamlit framework provides a clean and interactive platform for users to test the satellite image recognition model. The initial screen displays a simple homepage with the project title and a short introduction about the system's purpose. Users are prompted to upload a satellite image using a drag-and-drop file uploader. Once the image is uploaded, the interface displays the original image clearly in a centered format for verification. Upon clicking the "Classify" button, the system processes the image and outputs the predicted land type, such as *Forest*, *Mountain*, *Plain*, *Urban Area*, or *Water Body*. The prediction result appears just below the image in bold text with a color-coded label for better visual clarity. Additional output features include a bar chart or pie chart that shows the model's confidence score across different classes, helping users understand the prediction probabilities. For example, if an image of a dense green region is uploaded, the system might output "Forest" with a above 90% confidence score, and smaller percentages for other classes like "Plain" or "Mountain." Another screen showcases multiple uploaded samples and their corresponding predictions to demonstrate the batch processing capability. Screenshots also highlight how errors or unsupported file formats are handled gracefully, with messages like "Unsupported format" or "Please upload a valid satellite image." These output visuals not only validate the system's functionality but also reflect the system's responsiveness and ease of use in real-world applications.

The screenshot shows a VS Code editor with a file named `requirements.txt` open. The file contains a list of Python dependencies. Below the editor, the `TERMINAL` tab is active, displaying the output of a training process.

```

requirements.txt
1  pillow==5.5.0
2  attrs==25.3.0
3  blinker==1.9.0
4  cachetools==5.5.2
5  certifi==2025.4.26
6  charset-normalizer==3.4.1
7  click==8.1.8
8  colorama==0.4.6
9  filelock==3.18.0
10 fsspec==2025.3.2
11 gitdb==4.0.12
12 GitPython==3.1.44
13 idna==3.10
14 importlib-metadata==6.11.0
15 Jinja2==3.1.6
16 jsonschema==4.23.0
17 jsonschema-specifications==2025.4.1
18 markdown-it-py==3.0.0
19 MarkupSafe==3.0.2
20 mdurl==0.1.2
21 mpmath==1.3.0
22 narwhals==1.37.1
23 networkx==3.4.2
24 numpy==1.26.4
25 packaging==23.2

Epoch 4, Loss: 0.1699, Val Accuracy: 94.24%
Epoch 4, Loss: 0.1699, Val Accuracy: 94.24%

```

The status bar at the bottom indicates the file is at `Ln 1, Col 1`, uses `Spaces: 4`, `UTF-16 LE` encoding, and `CRLF` line endings. It also shows `pip requirements` and `Go Live` buttons.

The screenshot shows a VS Code editor with a file named `train.py` open. The file contains Python code for training a model using PyTorch and torchvision. Below the editor, the `TERMINAL` tab is active, displaying the output of the training process.

```

train.py
1  import torch
2  import torch.nn as nn
3  import torch.optim as optim
4  from torchvision import datasets, models, transforms
5  from torch.utils.data import DataLoader, random_split
6
7  # 1 Data transforms with augmentation
8  transform = transforms.Compose([
9      transforms.Resize((64, 64)),
10     transforms.RandomHorizontalFlip(),
11     transforms.RandomRotation(10),
12     transforms.ToTensor(),
13 ])
14
15 # 2 Load dataset
16 dataset = datasets.ImageFolder("data/eurosat_rgb", transform=transform)
17
18 # 3 Split into train and validation sets (80%-20%)
19 train_size = int(0.8 * len(dataset))
20 val_size = len(dataset) - train_size
21 train_dataset, val_dataset = random_split(dataset, [train_size, val_size])
22
23 # 4 Create dataloaders
24 train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
25 val_loader = DataLoader(val_dataset, batch_size=8, shuffle=False)

```

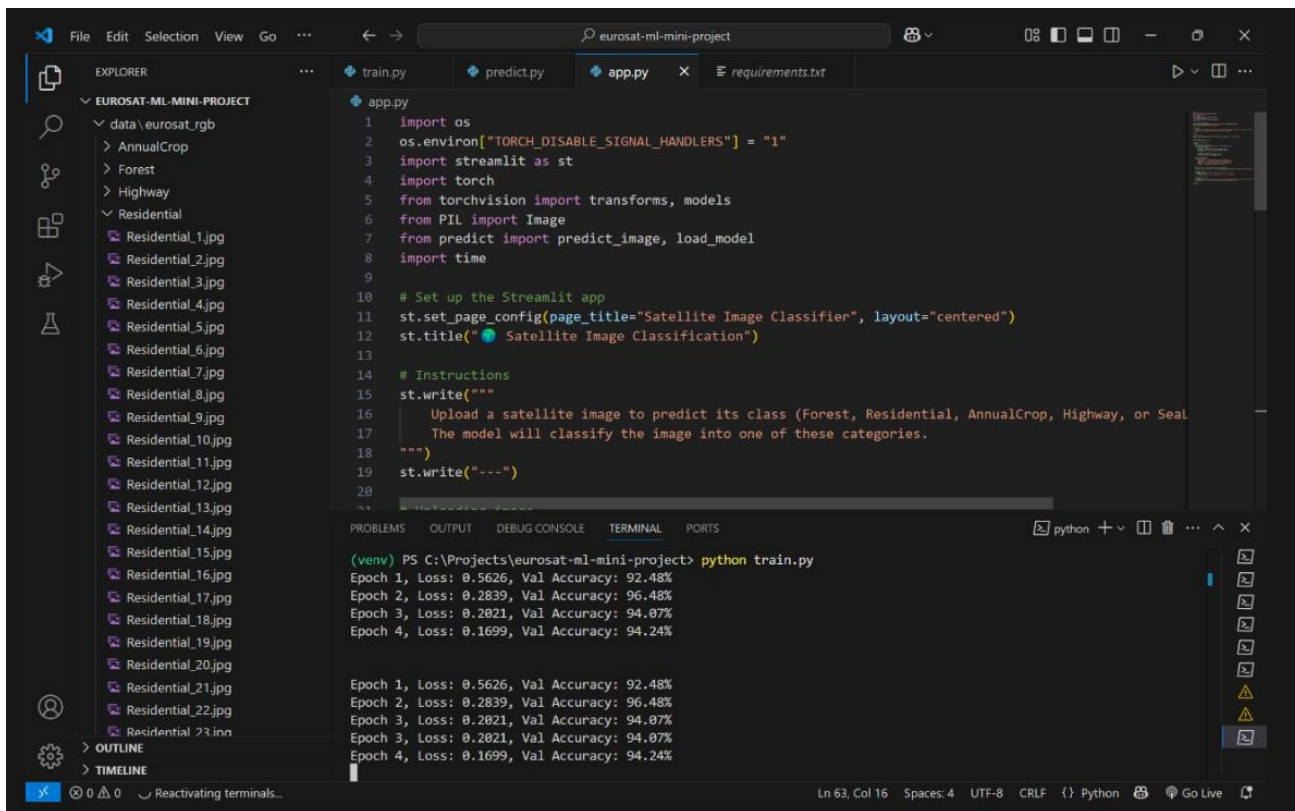
The status bar at the bottom indicates the file is at `Ln 65, Col 1`, uses `Spaces: 4`, `UTF-8` encoding, and `LF` line endings. It also shows `Python` and `Go Live` buttons.

The terminal output shows the following training results:

```

Epoch 3, Loss: 0.2021, Val Accuracy: 94.07%
Epoch 1, Loss: 0.5626, Val Accuracy: 92.48%
Epoch 2, Loss: 0.2839, Val Accuracy: 96.48%
Epoch 3, Loss: 0.2021, Val Accuracy: 94.07%


```



Satellite Image Classification

Upload a satellite image to predict its class (Forest, Residential, AnnualCrop, Highway, or Sealake). The model will classify the image into one of these categories.

Upload a satellite image



Drag and drop file here

Limit 200MB per file • JPG, JPEG, PNG

Browse files

Satellite Image Classification

Upload a satellite image to predict its class (Forest, Residential, AnnualCrop, Highway, or SeaLake). The model will classify the image into one of these categories.

Upload a satellite image



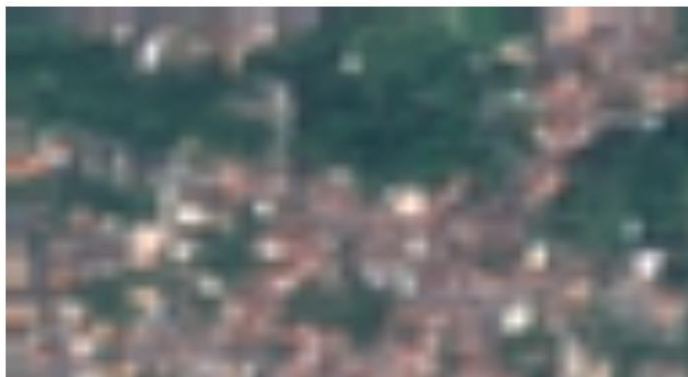
Drag and drop file here

Limit 200MB per file • JPG, JPEG, PNG

Browse files



Residential_2.jpg 4.8KB



Uploaded Image

Prediction: **Residential**

Confidence: 99.89%

Class Description: 🏠 Areas where people live (buildings, houses).

Was the prediction correct?

☒ Yes

☐ No

If you have any questions, or want to learn more about the model, feel free to explore or contact us.

[Click here for more information](#)

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

The Satellite Image Recognition System developed in this project demonstrates the effective integration of deep learning and image processing techniques for automated land type classification. By utilizing Convolutional Neural Networks (CNNs), the system accurately identifies various geographical features such as forests, mountains, plains, urban areas, and water bodies from satellite-captured images. The project showcases how machine learning can be leveraged to assist in environmental monitoring, agricultural planning, disaster management, and geographic analysis. The implementation through a user-friendly interface using Streamlit makes the system accessible to both technical and non-technical users, allowing for real-time predictions and visual feedback. The high accuracy and adaptability of the model underline its potential for scalability and application in broader remote sensing domains. Overall, the system contributes to the growing field of automated satellite imagery analysis, offering a reliable, efficient, and intelligent tool to support decision-making processes in a variety of real-world scenarios.

6.2 FUTURE ENHANCEMENT

To further improve the performance and usability of the satellite image recognition system, several future enhancements can be considered. Integrating temporal analysis using time-series satellite data can enable the detection of environmental changes such as deforestation, urban expansion, or seasonal variations.

Incorporating higher-resolution satellite imagery and hyperspectral data can enhance the accuracy of land cover classification. Additionally, leveraging advanced models like self-supervised learning or foundation models (e.g., Segment Anything Model by Meta) may reduce dependency on large labeled datasets. Real-time processing capabilities and edge deployment can make the system more responsive for use in disaster monitoring and military applications. Lastly, adding a GIS-based visualization layer can help end-users interactively explore and analyze the classified regions on a map.

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