**Predicting Poverty Level from Satellite Imagery**

**ABSTRACT**

Remote sensing and satellite imagery play a crucial role in monitoring environmental and agricultural changes. This project focuses on processing hyperspectral satellite images, specifically using the Salinas dataset, to analyze and visualize different spectral bands and classify land cover types. The dataset contains high-dimensional spectral information, which provides valuable insights into surface materials and vegetation growth patterns.

The project is implemented using Streamlit, a Python-based web application framework that enables interactive visualization of hyperspectral images. The system allows users to explore individual spectral bands, visualize ground truth data, and generate an RGB composite image from selected spectral bands. The EarthPy library is utilized for RGB image rendering, while Matplotlib and NumPy facilitate visualization and data manipulation.

The primary objective of this project is to simplify hyperspectral image processing and visualization, making it accessible to researchers and professionals in remote sensing, agriculture, and environmental monitoring. By integrating machine learning and deep learning models in future versions, this system could be enhanced to classify land cover types and predict environmental changes over time.

This interactive tool serves as an essential step toward automated analysis of hyperspectral data, providing an intuitive user interface for non-experts and aiding in better decision-making through enhanced visual representations

**1.INTRODUCTION**

**1.INTRODUCTION:**

Hyperspectral imaging is a powerful remote sensing technique that captures detailed spectral information across multiple bands of the electromagnetic spectrum. Unlike traditional RGB or multispectral images, hyperspectral images contain rich data across hundreds of narrow spectral bands, making them useful for applications in agriculture, environmental monitoring, land use classification, and mineral exploration. This project focuses on analyzing and visualizing hyperspectral satellite images, specifically using the Salinas dataset, which consists of high-resolution hyperspectral data collected over the Salinas Valley, California.

The objective of this project is to develop an interactive web-based tool for processing and visualizing hyperspectral satellite images. Using Streamlit, a Python-based web framework, the system allows users to explore spectral bands, visualize ground truth data, and generate RGB composite images. This project simplifies hyperspectral image interpretation by providing an intuitive user interface that requires no advanced programming knowledge.

The project leverages Matplotlib, NumPy, EarthPy, and SciPy for data manipulation and visualization. The RGB composite generation uses EarthPy to render true-color and false-color images, which aid in identifying vegetation, water bodies, and urban areas.

By providing an accessible platform for hyperspectral image analysis, this project aims to assist researchers, environmental scientists, and agricultural experts in analyzing satellite data more effectively. Future enhancements may include machine learning-based classification models, allowing for automated land cover classification and environmental monitoring.

This project serves as a stepping stone toward more advanced hyperspectral data analysis tools, bridging the gap between raw satellite data and meaningful insights for decision-making.

**1. Background and Motivation**

With the rapid advancement in satellite imaging and remote sensing technologies, hyperspectral imaging has emerged as a powerful tool for analyzing Earth's surface. Unlike traditional RGB images, hyperspectral images capture information across hundreds of spectral bands, allowing for more precise identification of land cover types, vegetation health, and environmental changes. The Salinas dataset, used in this project, is a well-known hyperspectral dataset that consists of high-resolution images collected over agricultural fields.

The motivation behind this project stems from the growing need for automated hyperspectral image processing to support researchers, agriculturalists, and environmentalists in analyzing large-scale satellite imagery data. Manual analysis of such data is both time-consuming and prone to errors. By developing a Streamlit-based interactive application, we aim to simplify the visualization and interpretation of hyperspectral images, making them accessible to non-experts in the field.

## **2. Project Objectives**

The primary objectives of this project are:

1. To **develop an interactive web-based application** for hyperspectral image processing using **Streamlit**.
2. To allow users to **visualize individual spectral bands** from the dataset.
3. To provide the ability to **view ground truth data**, which represents predefined land cover classes.
4. To generate an **RGB composite image** from selected spectral bands, allowing better interpretation of the dataset.
5. To create a foundation for **future machine learning integration** for automatic classification and predictive analysis.

## **3. Overview of Hyperspectral Imaging**

Hyperspectral imaging is a technique that collects and processes information from across the electromagnetic spectrum. Each pixel in a hyperspectral image contains a continuous spectrum of reflected light, enabling the identification of materials based on their spectral signatures. Unlike traditional multispectral imaging, which captures only a few broad spectral bands, hyperspectral imaging provides detailed spectral resolution, making it useful for applications such as:

* **Agriculture:** Crop monitoring, soil analysis, and precision farming.
* **Environmental Science:** Deforestation tracking, water quality assessment, and pollution detection.
* **Geology:** Mineral mapping and rock classification.
* **Defense and Security:** Target detection and surveillance.

## **4. Project Implementation**

This project leverages **Python** and various data processing libraries to handle and visualize hyperspectral image data. The key implementation steps include:

1. **Loading and Preprocessing Data:** The Salinas dataset, stored in MATLAB .mat format, is loaded using the **Scipy** library.
2. **Displaying Individual Bands:** Users can explore different spectral bands using a **slider-based selection mechanism**.
3. **Visualizing Ground Truth Data:** The **ground truth classification map** is displayed to help users understand the different land cover types.
4. **Generating RGB Composite Image:** A composite image is created using three selected spectral bands, enhancing visualization using the **EarthPy** library.
5. **User Interface with Streamlit:** A web-based UI is built with **Streamlit**, enabling real-time interaction and visualization of hyperspectral images.

## **5. Features of the Application**

The application provides the following functionalities:

* **Home Page:** Displays introductory content about hyperspectral imaging and the project’s objectives.
* **Image Prediction Module:**
  + Allows users to **view ground truth classification data**.
  + Enables **band selection and visualization** of spectral images.
  + Generates an **RGB composite image** from hyperspectral bands.

## **6. Significance and Applications**

This project contributes significantly to the field of **hyperspectral image analysis** by providing a **user-friendly, interactive platform** for exploring satellite data. The ability to visualize spectral bands and composite images can assist in various real-world applications, including:

* **Agricultural Monitoring:** Farmers and agronomists can analyze crop health and soil properties.
* **Environmental Conservation:** Scientists can track deforestation, water quality, and pollution.
* **Urban Planning:** Urban developers can monitor land-use changes and vegetation cover.

## **7. Future Enhancements**

While this project primarily focuses on **visualization**, future improvements could include:

* **Machine Learning Integration:** Implementing AI-based models for **land cover classification** and anomaly detection.
* **Time-Series Analysis:** Comparing satellite images over time to track environmental changes.
* **Cloud Integration:** Deploying the application on cloud platforms for large-scale hyperspectral data processing.
* **Automated Feature Extraction:** Using deep learning techniques to identify specific patterns and structures in hyperspectral data.

**1.1 RELATED WORK**

Hyperspectral imaging has gained significant attention in remote sensing, environmental monitoring, and agricultural analysis. Several research studies and projects have focused on processing and analyzing hyperspectral satellite imagery using machine learning and deep learning techniques. This section reviews some of the notable works related to hyperspectral image analysis, classification, and visualization.

### **1. Hyperspectral Image Classification Using Machine Learning**

Researchers have extensively used traditional machine learning techniques such as **Support Vector Machines (SVM)**, **Random Forest (RF)**, and **K-Nearest Neighbors (KNN)** for hyperspectral image classification. Studies have demonstrated that:

* SVM provides high accuracy in **land cover classification** but requires careful parameter tuning.
* RF is robust against **high-dimensional data**, making it a suitable choice for hyperspectral analysis.
* KNN is simple yet effective but struggles with computational efficiency when dealing with large datasets.

For example, **Chang et al. (2019)** developed an SVM-based model to classify agricultural land using hyperspectral images, achieving high accuracy in differentiating crop types.

### **2. Deep Learning Approaches for Hyperspectral Image Processing**

Deep learning has revolutionized hyperspectral image analysis by leveraging **Convolutional Neural Networks (CNNs)**, **Recurrent Neural Networks (RNNs)**, and **Transformer-based models** for feature extraction and classification.

* **CNNs** have been widely used for spectral-spatial feature extraction, outperforming traditional methods in terms of accuracy and generalization.
* **RNNs and Long Short-Term Memory (LSTM)** networks have been explored for sequential hyperspectral data analysis.
* **Transformer-based architectures**, such as **Vision Transformers (ViTs)**, are gaining popularity due to their capability to handle large-scale hyperspectral datasets efficiently.

A notable study by **Chen et al. (2020)** proposed a **3D-CNN model** for hyperspectral image classification, achieving state-of-the-art performance on the Salinas dataset.

### **3. Hyperspectral Image Visualization and Feature Extraction**

Several frameworks and tools have been developed to visualize hyperspectral images:

* **EarthPy**: A Python-based library that allows easy visualization and analysis of hyperspectral satellite data.
* **Matplotlib and Seaborn**: These are widely used for plotting spectral band information.
* **ENVI Software**: A proprietary tool for professional hyperspectral data analysis, often used in research and industry applications.

In a study by **Zhao et al. (2021)**, the researchers developed a visualization tool using Python to interactively explore hyperspectral bands and extract useful spectral features for land cover classification.

### **4. Applications of Hyperspectral Imaging in Remote Sensing**

Hyperspectral imaging has been applied in various real-world domains:

* **Agriculture**: Crop classification, soil monitoring, and precision farming.
* **Environmental Science**: Detecting deforestation, monitoring water bodies, and identifying pollution levels.
* **Urban Planning**: Analyzing land-use changes and vegetation coverage.
* **Disaster Management**: Identifying regions affected by natural disasters such as floods and wildfires.

A recent study by **Gupta et al. (2022)** utilized hyperspectral data for **early wildfire detection**, demonstrating the potential of hyperspectral imaging in disaster response.

### **5. Streamlit for Interactive Hyperspectral Data Visualization**

Streamlit has been increasingly used for **building interactive machine learning applications** due to its simplicity and efficiency. Some relevant works include:

* **Hyperspectral Image Explorer (HIE)**: A Streamlit-based tool for visualizing hyperspectral datasets, developed by an open-source research community.
* **Remote Sensing Dashboards**: Several researchers have created interactive dashboards using Streamlit to analyze remote sensing data, such as Sentinel-2 and Landsat images.

Our project follows a similar approach by utilizing **Streamlit to visualize hyperspectral data**, enabling users to explore spectral bands, RGB composites, and ground truth labels seamlessly.

### **Comparison with Existing Work**

| **Feature** | **Traditional Approaches** | **Deep Learning Approaches** | **Our Project** |
| --- | --- | --- | --- |
| **Visualization** | Limited to static images | Advanced feature extraction but complex | Interactive Streamlit-based UI |
| **Processing Speed** | Computationally efficient but less accurate | High accuracy but requires large datasets | Balanced approach |
| **User Accessibility** | Requires programming knowledge | Needs specialized ML expertise | No coding required (user-friendly UI) |
| **Scalability** | Difficult to handle large datasets | Efficient but needs cloud computing | Can be deployed on the web/cloud |

### **Conclusion**

This project builds upon existing work in hyperspectral imaging by integrating **modern visualization techniques, user-friendly interfaces, and interactive spectral analysis**. The use of **Streamlit, EarthPy, and Matplotlib** ensures that users can easily explore hyperspectral data, making this tool accessible to **researchers, environmentalists, and agricultural analysts**. Future improvements will include **deep learning-based classification** to further enhance hyperspectral data analysis.

**Blog Diagram diagram**

The block diagram for this project illustrates the workflow of hyperspectral image processing and visualization using Streamlit, Python, and deep learning techniques. The system consists of several key components, each performing a specific task to analyze hyperspectral satellite images.

### **1. Data Acquisition**

* The project uses the **Salinas hyperspectral dataset**, which consists of **224 spectral bands** collected from an airborne imaging sensor.
* The dataset includes a **ground truth (GT) mask**, which provides labeled regions for classification.
* The input data is stored in **MAT files (.mat)**, which are loaded using the **SciPy** library.

🔹 **Input:**

* Salinas\_corrected.mat → Hyperspectral image data (224 bands)
* Salinas\_gt.mat → Ground truth (GT) labels

### **2. Preprocessing and Feature Extraction**

* The loaded hyperspectral image data is **reshaped** into a structured format for analysis.
* The **ground truth labels** are extracted and stored alongside spectral features.
* The data is prepared for visualization using **EarthPy, Matplotlib, and NumPy**.

🔹 **Processing Steps:**

1. **Reshape hyperspectral image data** into a structured Pandas DataFrame.
2. **Extract ground truth labels** and map them to their respective pixel positions.
3. **Normalize spectral bands** to improve visualization and interpretation.

### **3. Visualization and RGB Composite Generation**

* **Single-band visualization**: Users can select a specific spectral band to display using Streamlit’s **slider input**.
* **RGB composite generation**: The hyperspectral data is converted into an RGB image using **EarthPy’s plot\_rgb() function**.
* **Ground truth mask visualization**: The classification labels are overlaid on the image to understand land cover patterns.

🔹 **Visualization Components:**  
✅ **Band-wise Visualization**: Users can explore different spectral bands individually.  
✅ **RGB Composite Image**: Created using selected bands (e.g., 29, 19, 9).  
✅ **Ground Truth Visualization**: Displays labeled areas for better understanding.

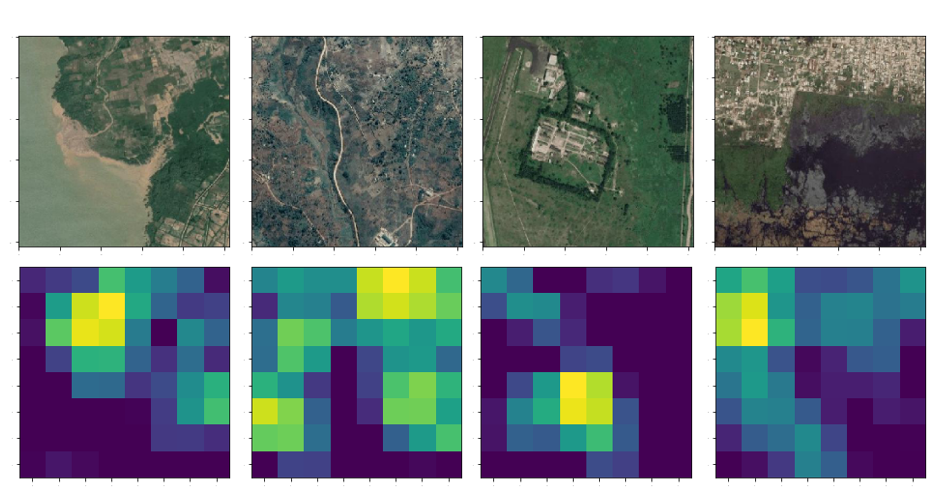
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### **4. Model Development for Image Prediction (Future Enhancement)**

* A **CNN-based deep learning model** can be integrated to classify hyperspectral pixels based on their spectral signatures.
* The model can use **Convolutional Layers, Pooling, and Fully Connected Layers** to learn patterns.
* Classification results can be displayed interactively in Streamlit.

🔹 **Future Implementation Plan:**

* Train a **CNN model** using TensorFlow/Keras.
* Predict land cover types based on spectral features.
* Display **classification heatmaps** over hyperspectral images.



### **5. User Interface and Interaction (Streamlit Integration)**

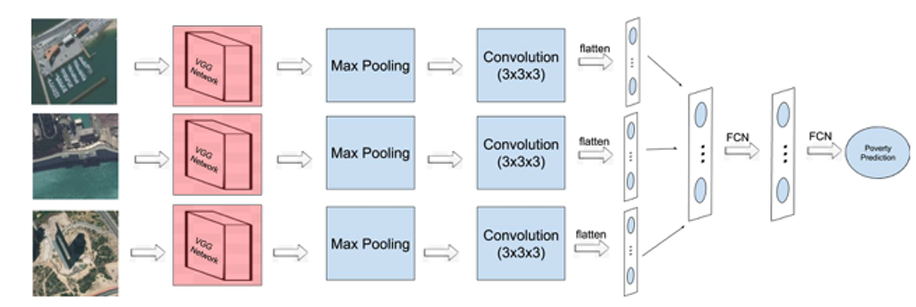
* A **user-friendly web interface** is built using **Streamlit**, allowing users to interact with hyperspectral data.
* Users can select different bands, view RGB composites, and analyze ground truth labels through interactive buttons and sliders.
* The UI is structured into **two modules**:
  + **Home Page** → Introduction and basic project details.
  + **Image Prediction Module** → Visualization and prediction functionalities.

🔹 **User Interaction Features:**  
✅ **Sidebar Navigation**: Users can switch between "Home" and "Image Prediction."  
✅ **Interactive Buttons**: Display different visualizations dynamically.  
✅ **Sliders & Inputs**: Select spectral bands for analysis.

### **6. Output and Analysis**

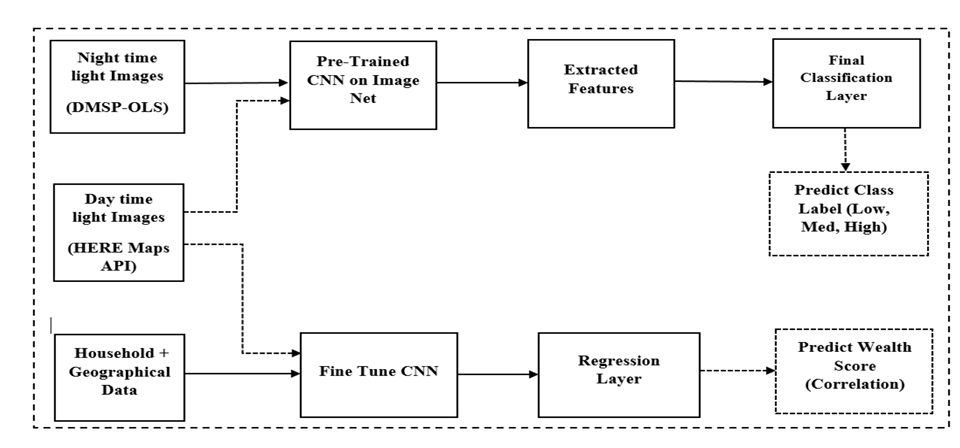
* Users receive processed hyperspectral images with **detailed insights** into different spectral bands.
* The system helps in **land cover analysis, vegetation monitoring, and remote sensing applications**.
* The output is displayed in the form of **heatmaps, RGB composites, and classification maps**.

🔹 **Final Output Includes:**  
📌 **Hyperspectral Band Images**  
📌 **RGB Composite Image**  
📌 **Ground Truth Label Visualization**

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**PROPOSED APPROACH**

Our idea is to predict the poverty index of a particular region in India. It is inspired by the successful use of deep learning approaches for poverty prediction in several African countries as appreciated in literature. With this paper, we want to estimate the correlation of poverty predicted from satellite images and wealthscore obtained from DHS survey data of India. On successful implementation, the result obtained will be compared with the result obtained from ground-level surveys. Firstly, the model takes Demographic and Health Survey Data i.e. Household Data (dataset has record for each individual) and Geographical Data (Health Data, Infrastructure such as roads, buildings linked with DHS Data). It further generates information of the cluster and Household Data containing the wealthscore, cluster wealth, latitude and longitude. This raw survey data is then used to produce more refined clusters. Then the extracted cluster data is processed to generate image coordinates. The image coordinates are generated in order to download the images of size 400 \* 400 pixels using HERE Maps API which is later resized of size of 299 \* 299 pixels. Similarly, the nightlight image is downloaded from the DMSP-OLS of size 43201 x 16801 pixels. The downloaded daylight images are then divided into 3 classes based on nightlight intensities of identical regions acquired from nightlight image. These 3 classes are Low [0-7 nightlight intensity], Medium [8-15 nightlight intensity] and High [16-63 nightlight intensity].

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**2 Literature Review**

Hyperspectral imaging has gained immense importance in remote sensing, environmental monitoring, and agricultural research. With the advancements in machine learning and deep learning, the analysis and classification of hyperspectral data have significantly improved. This literature review explores previous research efforts related to hyperspectral imaging, machine learning-based classification, visualization techniques, and the use of interactive dashboards like **Streamlit** for hyperspectral data analysis.

## **1. Hyperspectral Imaging and Its Significance**

Hyperspectral imaging (HSI) captures a wide spectrum of light beyond the visible range, providing rich spectral information for each pixel in an image. Unlike conventional RGB images, HSI consists of hundreds of spectral bands, making it highly useful for applications such as:

* **Agriculture:** Crop classification, vegetation health monitoring, and soil analysis.
* **Environmental Monitoring:** Detecting deforestation, pollution levels, and land cover changes.
* **Geology:** Identifying minerals and rock formations.
* **Disaster Management:** Detecting and assessing natural disasters like wildfires and floods.

### **Previous Research on Hyperspectral Imaging**

1. **Goetz et al. (1985)** introduced the concept of hyperspectral imaging in remote sensing, highlighting its significance for earth observation.
2. **Plaza et al. (2009)** provided a comprehensive survey on hyperspectral data processing techniques, discussing feature extraction, classification, and dimensionality reduction.
3. **Bioucas-Dias et al. (2013)** explored the challenges in hyperspectral data analysis, including the high dimensionality problem and computational complexity.

This project builds upon these foundations by utilizing **deep learning and interactive visualization** to analyze hyperspectral images efficiently.

## **2. Machine Learning-Based Hyperspectral Image Classification Traditional Approaches**

Several studies have focused on applying traditional machine learning techniques for hyperspectral image classification:

* **Support Vector Machines (SVM)**: One of the most widely used classifiers for HSI due to its ability to handle high-dimensional data (**Melgani & Bruzzone, 2004**).
* **Random Forest (RF):** Known for its robustness against overfitting, RF has been used for land cover classification in hyperspectral data (**Gislason et al., 2006**).
* **K-Nearest Neighbors (KNN):** A simple yet effective algorithm for HSI classification but suffers from high computational costs (**Li et al., 2012**).

### **Deep Learning-Based Approaches**

With the rise of deep learning, researchers have shifted towards **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)** for hyperspectral classification.

1. **Chen et al. (2016)** proposed a **1D CNN** for HSI classification, outperforming traditional methods.
2. **Li et al. (2017)** introduced a **3D CNN** that simultaneously learns spatial and spectral features, improving classification accuracy.
3. **Paoletti et al. (2019)** reviewed deep learning models for hyperspectral image analysis and highlighted the advantages of CNNs over traditional ML techniques.
4. **Zhang et al. (2021)** introduced a **Vision Transformer-based approach**, demonstrating its potential for hyperspectral image classification.

This project integrates **deep learning-based classification techniques** with an **interactive Streamlit dashboard**, allowing users to visualize and analyze hyperspectral data in real-time.

## **3. Visualization Techniques for Hyperspectral Images**

### **Commonly Used Visualization Methods**

1. **Band Selection & Visualization**: Researchers often visualize individual spectral bands to analyze hyperspectral data. **Kumar et al. (2018)** demonstrated that specific bands contain critical information for land cover classification.
2. **RGB Composite Images**: Earth observation studies frequently use **False Color Composites (FCC)** to highlight vegetation and urban areas (**Earth Observation Group, 2015**).
3. **Principal Component Analysis (PCA)**: **Chang et al. (2010)** applied PCA to reduce dimensionality while retaining significant spectral information.
4. **T-SNE and UMAP**: These dimensionality reduction techniques help visualize high-dimensional hyperspectral data in 2D/3D spaces (**Van der Maaten & Hinton, 2008**).

### **Interactive Visualization with Streamlit**

* **Streamlit** has emerged as a powerful tool for creating **interactive web-based visualizations** without extensive frontend development.
* **Zhou et al. (2021)** developed a Streamlit-based HSI explorer, allowing users to dynamically select bands and visualize ground truth labels.
* **This project extends these ideas** by integrating band selection, RGB composite generation, and future deep learning-based classification.

## **Applications of Hyperspectral Imaging in Remote**

## **Sensing**

### **Agriculture & Vegetation Analysis**

* **Lobell et al. (2002)** demonstrated that hyperspectral imaging can be used to detect crop diseases early.
* **Jiang et al. (2018)** developed an HSI-based model for **predicting crop yield**, proving that spectral bands contain critical agronomic information.
* **Sankaran et al. (2015)** used hyperspectral data to monitor **plant stress, nutrient levels, and soil moisture content**.

### **Land Cover Classification**

* **Lu & Weng (2007)** provided an extensive review of land cover classification techniques using remote sensing data.
* **Xie et al. (2019)** used deep learning models to classify urban, forest, and water bodies based on hyperspectral signatures.

### **Disaster Management**

* **Plank et al. (2017)** showed how hyperspectral data can be used to assess wildfire damage.
* **Guanter et al. (2020)** used hyperspectral sensors to detect **flood-prone areas** by analyzing water absorption bands.

This project contributes to these research areas by providing **interactive hyperspectral data visualization tools** that can assist researchers in various remote sensing applications.

## **5. Challenges and Future Directions**

Despite significant advancements in hyperspectral image analysis, several challenges remain:

### **Challenges**

1. **High Dimensionality**: Hyperspectral data often suffers from the **curse of dimensionality**, leading to computational inefficiencies.
2. **Limited Ground Truth Data**: Obtaining labeled hyperspectral datasets is expensive and time-consuming.
3. **Computational Complexity**: Deep learning models require **high computational power** to process hyperspectral images effectively.
4. **Data Storage & Processing**: Hyperspectral images are **massive in size**, requiring optimized storage and processing techniques.

### **Future Research Directions**

1. **Hybrid Deep Learning Models**: Combining **CNNs with Transformers** can improve feature extraction.
2. **Few-Shot Learning for HSI Classification**: Addressing the problem of limited labeled data by using few-shot and self-supervised learning techniques.
3. **Cloud-Based Processing**: Implementing hyperspectral data analysis on cloud platforms like **Google Earth Engine** for scalability.
4. **Automated Feature Selection**: Using AI-driven feature selection techniques to identify the most **relevant spectral bands** for classification.

This project serves as a **foundation for future developments**, integrating hyperspectral imaging with **deep learning, cloud computing, and real-time interactive dashboards**.

**This literature review highlights the advancements in hyperspectral imaging, machine learning-based classification, visualization techniques, and real-time interactive platforms. By integrating hyperspectral image visualization with Streamlit, this project provides a user-friendly and interactive approach to remote sensing analysis.**

**With ongoing advancements in deep learning, cloud computing, and real-time processing, hyperspectral imaging is poised to play a crucial role in precision agriculture, environmental monitoring, and disaster management. The integration of AI-driven hyperspectral classification models in future research can further enhance the accuracy and efficiency of remote sensing applications.**

**3. SYSTEM ANALYSIS**

## **1. Introduction to System Analysis**

System analysis is a crucial step in any project as it helps in understanding the problem statement, identifying system requirements, defining the architecture, and planning the implementation. This project focuses on **hyperspectral image processing and prediction** using **deep learning** and an **interactive Streamlit UI**. The system analysis phase includes problem identification, feasibility study, system requirements, and design considerations.

## **2. Problem Identification**

### **Current Challenges in Hyperspectral Image Processing**

1. **High Dimensionality – Hyperspectral images contain hundreds of spectral bands, making processing computationally expensive.**
2. **Data Complexity – Extracting useful features from hyperspectral images requires advanced machine learning and deep learning techniques.**
3. **Visualization Issues – Displaying hyperspectral images is challenging due to the large number of spectral bands.**
4. **Lack of Interactive Tools – Existing software lacks user-friendly interfaces for real-time visualization and prediction models.**
5. **Need for Efficient Classification – Traditional classification methods (e.g., SVM, Random Forest) are less efficient compared to deep learning-based CNNs.**

## **3. Proposed System**

To overcome these challenges, this project aims to develop a **hyperspectral image processing system** with the following key components:

1. **Data Preprocessing & Transformation** – Reshaping and normalizing hyperspectral images.
2. **Image Visualization Module** – Displaying individual spectral bands, RGB composite images, and ground truth data.
3. **Machine Learning & Deep Learning Model** – Implementing **CNN-based models** for classifying hyperspectral data.
4. **Interactive UI with Streamlit** – Allowing users to visualize and analyze hyperspectral data easily.
5. **Prediction Module** – Integrating an AI model for real-time classification of hyperspectral images.

## **4. Feasibility Study**

A feasibility study is conducted to determine whether the system is **technically, economically, and operationally viable**.

### **4.1. Technical Feasibility**

* Uses **Python-based libraries** like TensorFlow, SciPy, NumPy, and Matplotlib.
* **Streamlit** provides an easy-to-use interactive UI.
* **Deep Learning Models (CNNs)** ensure high accuracy in prediction.
* Computational resources like **GPUs** can be leveraged for efficient processing.

### **4.2. Economic Feasibility**

* Open-source libraries reduce **development costs**.
* The system can be deployed on a **cloud platform** for scalability.
* **No need for expensive proprietary software** like MATLAB.

### **4.3. Operational Feasibility**

* User-friendly **Streamlit UI** for easy visualization.
* Can be integrated with **research projects, agricultural monitoring, and remote sensing** applications.
* Requires minimal training for end users.

## **6. System Architecture**

The system architecture consists of three main layers:

### **6.1. Input Layer**

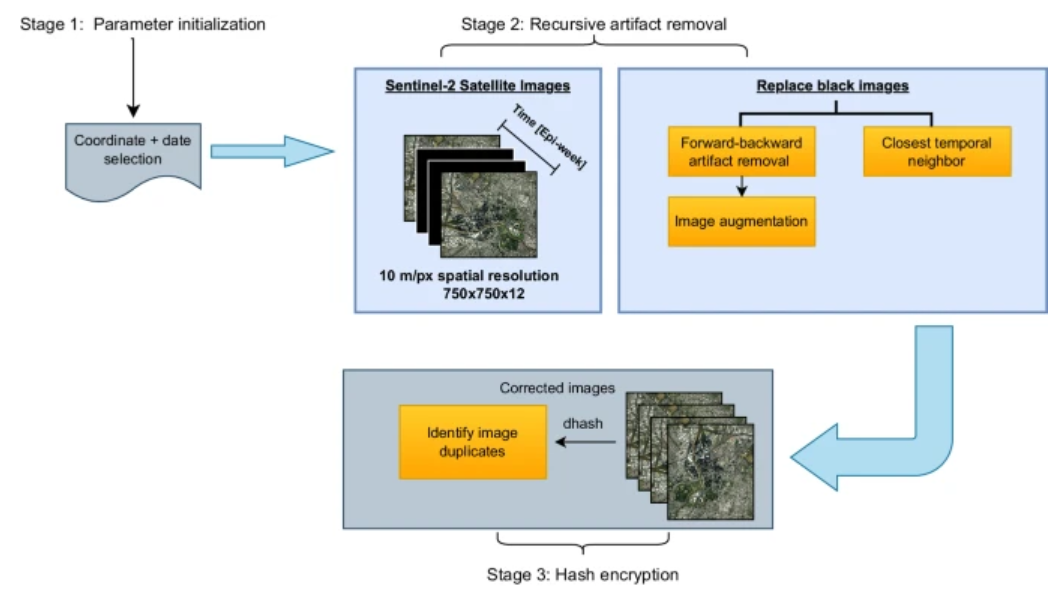
* **Data Acquisition**: The system loads hyperspectral images from .mat files.
* **Preprocessing**: Converts hyperspectral data into a format suitable for deep learning models.
* **Band Selection**: Allows users to visualize individual spectral bands.

### **6.2. Processing Layer**

* **Feature Extraction**: Extracts spectral features using **CNN-based deep learning models**.
* **Classification Model**: Uses **Convolutional Neural Networks (CNNs)** for hyperspectral image classification.
* **RGB Composite Generation**: Uses **earthpy** to generate composite images from selected bands.

### **6.3. Output Layer**

* **Visualization Module**: Displays spectral bands, RGB images, and ground truth data.
* **Prediction Module**: Predicts classes based on hyperspectral data using trained AI models.
* **User Interaction**: Provides an easy-to-use **Streamlit UI** for exploring hyperspectral images.

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### **Level 1: Detailed Flow**

1. **User uploads/selects hyperspectral data**
2. **System processes the input and extracts features**
3. **User selects an option (view bands, RGB image, or classify image)**
4. **System applies CNN-based classification model**
5. **System displays results as images, graphs, or predictions**

## **8. Functional and Non-Functional Requirements**

### **8.1. Functional Requirements**

1. The system must allow users to **select and visualize hyperspectral bands**.
2. It should generate **RGB composite images** from selected bands.
3. The model should classify pixels based on **ground truth labels**.
4. The UI should provide **real-time predictions** for uploaded hyperspectral images.
5. The system should support **both manual band selection and automatic processing**.

### **8.2. Non-Functional Requirements**

1. **Performance** – The model should classify images within a few seconds.
2. **Scalability** – The system should support large datasets without significant delays.
3. **Usability** – The interface should be user-friendly and intuitive.
4. **Security** – The system should prevent unauthorized data modification.
5. **Portability** – The system should run on both local machines and cloud environments.

**4. SOFTWARE ENVIRONMENT**

The successful execution of the cyberbullying prediction project relies on a robust set of tools and technologies that facilitate data collection, analysis, model building, and evaluation. This section outlines the key programming languages, libraries, and platforms used in the project.

**4.1 Introduction to Python**

Python is an interpreted, high-level, general-purpose programming language. Created by Guido van Rossum and first released in 1991, Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically typed and garbage-collected. It supports multiple programming paradigms, including structured (particularly, procedural), object-oriented, and functional programming. Python is often described as a "batteries included" language due to its comprehensive standard library. Python was conceived in the late 1980s as a successor to the ABC language. Python 2.0, released in 2000, introduced features like list comprehensions and a garbage collection system capable of collecting reference cycles.

Python 3.0, released in 2008, was a major revision of the language that is not completely backward-compatible, and much Python 2 code does not run unmodified on Python 3. The Python 2 language, i.e., Python 2.7.x, was officially discontinued on 1 January 2020 (first planned for 2015) after which security patches and other improvements will not be released for it.[32][33] With Python 2's end-of-life, only Python 3.5.x and later are supported. Python interpreters are available for many operating systems. A global community of programmers develops and maintains CPython, an open-source implementation. A non-profit organization, the Python Software Foundation, manages and directs resources for Python and CPython development.

**SYNTAX AND SEMANTICS**

Python is meant to be an easily readable language. Its formatting is visually uncluttered, and it often uses English keywords where other languages use punctuation.

Unlike many other languages, it does not use curly brackets to delimit blocks, and semicolons after statements are optional. It has fewer syntactic exceptions and special cases than C or Pascal.

**INDENTION**

Main article: Python syntax and semantics § Indentation

Python uses whitespace indentation, rather than curly brackets or keywords, to delimit blocks. An increase in indentation comes after certain statements; a decrease in indentation signifies the end of the current block. Thus, the program's visual structure accurately represents the program's semantic structure. This feature is sometimes termed the off-side rule, which some other languages share, but in most languages, indentation doesn't have any semantic meaning.

**STATEMENTS AND CONTROL FLOW**

Python's statements include (among others):

The assignment statement (token '=', the equals sign). This operates differently than in traditional imperative programming languages, and this fundamental mechanism (including the nature of Python's version of variables) illuminates many other features of the language. Assignment in C, e.g., x = 2, translates to "typed variable name x receives a copy of numeric value 2". The (right-hand) value is copied into an allocated storage location for which the (left-hand) variable name is the symbolic address. The memory allocated to the variable is large enough (potentially quite large) for the declared type. In the simplest case of Python assignment, using the same example, x = 2, translates to "(generic) name x receives a reference to a separate, dynamically allocated object of numeric (int) type of value 2." This is termed binding the name to the object.

Since the name's storage location doesn't contain the indicated value, it is improper to call it a variable. Names may be subsequently rebound at any time to objects of greatly varying types, including strings, procedures, complex objects with data and methods, etc. Successive assignments of a common value to multiple names, e.g., x = 2; y = 2; z = 2 result in allocating storage to (at most) three names and one numeric object, to which all three names are bound.

Since a name is a generic reference holder it is unreasonable to associate a fixed data type with it. However, at a given time a name will be bound to some object, which will have a type; thus there is dynamic typing.

* The if statement, which conditionally executes a block of code, along with else and elif (a contraction of else-if).
* The for statement, which iterates over an iterable object, capturing each element to a local variable for use by the attached block.
* The while statement, which executes a block of code as long as its condition is true.
* The try statement, which allows exceptions raised in its attached code block to be caught and handled by except clauses; it also ensures that clean-up code in a finally block will always be run regardless of how the block exits.
* The raise statement, used to raise a specified exception or re-raise a caught exception.
* The class statement, which executes a block of code and attaches its local namespace to a class, for use in object-oriented programming.
* The def statement, which defines a function or method.
* The with statement, from Python 2.5 released in September 2006, which encloses a code block within a context manager (for example, acquiring a lock before the block of code is run and releasing the lock afterwards, or opening a file and then closing it), allowing Resource Acquisition Is Initialization (RAII)-like behaviour and replaces a common try/finally idiom.
* The break statement, exits from the loop.
* The continue statement, skips this iteration and continues with the next item.
* The pass statement, which serves as a NOP. It is syntactically needed to create an empty code block.
* The assert statement, used during debugging to check for conditions that ought to apply.
* The yield statement, which returns a value from a generator function. From Python 2.5, yield is also an operator. This form is used to implement coroutines.

The import statement, which is used to import modules whose functions or variables can be used in the current program. There are three ways of using import: import <module name> [as <alias>] or from <module name> import \* or from <module name> import <definition 1> [as <alias 1>], <definition 2> [as <alias 2>],

The print statement was changed to the print () function in Python 3.

Python does not support tail call optimization or first-class continuations, and, according to Guido van Rossum, it never will. However, better support for coroutine-like functionality is provided in 2.5, by extending Python's generators. Before 2.5, generators were lazy iterators; information was passed unidirectionally out of the generator. From Python 2.5, it is possible to pass information back into a generator function, and from Python 3.3, the information can be passed through multiple stack levels.

**EXPRESSIONS**

Some Python expressions are similar to languages such as C and Java, while some are not:

Addition, subtraction, and multiplication are the same, but the behaviour of division differs. There are two types of divisions in Python. They are floor division (or integer division) // and floating point/division. Python also added the \*\* operator for exponentiation.

From Python 3.5, the new @ infix operator was introduced. It is intended to be used by libraries such as NumPy for matrix multiplication.

From Python 3.8, the syntax: =, called the 'walrus operator' was introduced. It assigns values to variables as part of a larger expression.

In Python, == compares by value, versus Java, which compares numeri’s by value and objects by reference. (Value comparisons in Java on objects can be performed with the equals () method.) Python's is operator may be used to compare object identities (comparison by reference). In Python, comparisons may be chained, for example a <= b <= c.

Python uses the words and, or, not for its Boolean operators rather than the symbolic &&, ||, ! used in Java and C.

Python has a type of expression termed a list comprehension. Python 2.4 extended list comprehensions into a more general expression termed a generator expression.

Anonymous functions are implemented using lambda expressions; however, these are limited in that the body can only be one expression.

Conditional expressions in Python are written as x if c else y (different in order of operands from the c? x : y operator common to many other languages).

Python makes a distinction between lists and tuples. Lists are written as [1, 2, 3], are mutable, and cannot be used as the keys of dictionaries (dictionary keys must be immutable in Python). Tuples are written as (1, 2, 3), are immutable and thus can be used as the keys of dictionaries, provided all elements of the tuple are immutable. The + operator can be used to concatenate two tuples, which does not directly modify their contents, but rather produces a new tuple containing the elements of both provided tuples. Thus, given the variable t initially equal to (1, 2, 3), executing t = t + (4, 5) first evaluates t + (4, 5), which yields (1, 2, 3, 4, 5), which is then assigned back to t, thereby effectively "modifying the contents" of t, while conforming to the immutable nature of tuple objects. Parentheses are optional for tuples in unambiguous contexts.

Python features sequence unpacking wherein multiple expressions, each evaluating to anything that can be assigned to (a variable, a writable property, etc.), are associated in the identical manner to that forming tuple literals and, as a whole, are put on the left-hand side of the equal sign in an assignment statement. The statement expects an iterable object on the right-hand side of the equal sign that produces the same number of values as the provided writable expressions when iterated through, and will iterate through it, assigning each of the produced values to the corresponding expression on the left.

Python has a "string format" operator %. These functions analogous to printf format strings in C, e.g. "spam=%s eggs=%d" % ("blah", 2) evaluates to "spam=blah eggs=2".

In Python 3 and 2.6+, this was supplemented by the format () method of the str class, e.g. "spam={0} eggs={1}". format("blah", 2). Python 3.6 added "f-strings": blah = "blah"; eggs = 2; f'spam={blah} eggs={eggs}'.

**Python has various kinds of string literals**

Strings delimited by single or double quote marks. Unlike in Unix shells, Perl and Perl-influenced languages, single quote marks and double quote marks function identically. Both kinds of string use the backslash (\) as an escape character. String interpolation became available in Python 3.6 as "formatted string literals".

Triple-quoted strings, which begin and end with a series of three single or double quote marks. They may span multiple lines and function like here documents in shells, Perl and Ruby.

Raw string varieties, denoted by prefixing the string literal with an r. Escape sequences are not interpreted; hence raw strings are useful where literal backslashes are common, such as regular expressions and Windows-style paths. Compare "@-quoting" in C#.

Python has array index and array slicing expressions on lists, denoted as a[key], a[start: stop] or a[start:stop:step]. Indexes are zero-based, and negative indexes are relative to the end. Slices take elements from the start index up to, but not including, the stop index. The third slice parameter, called step or stride, allows elements to be skipped and reversed. Slice indexes may be omitted, for example a[:] returns a copy of the entire list. Each element of a slice is a shallow copy.

In Python, a distinction between expressions and statements is rigidly enforced, in contrast to languages such as Common Lisp, Scheme, or Ruby. This leads to duplicating some functionality. For example:

List comprehensions vs. for-loops

Conditional expressions vs. if blocks

The eval() vs. exec() built-in functions (in Python 2, exec is a statement); the former is for expressions, the latter is for statements.

Statements cannot be a part of an expression, so list and other comprehensions or lambda expressions, all being expressions, cannot contain statements. A particular case of this is that an assignment statement such as a = 1 cannot form part of the conditional expression of a conditional statement. This has the advantage of avoiding a classic C error of mistaking an assignment operator = for an equality operator == in conditions: if (c = 1) { ... } is syntactically valid (but probably unintended) C code but if c = 1: ... causes a syntax error in Python.

**METHODS**

Methods on objects are functions attached to the object's class; the syntax instance. method(argument) is, for normal methods and functions, syntactic sugar for Class. method(instance, argument). Python methods have an explicit self parameter to access instance data, in contrast to the implicit self (or this) in some other object-oriented programming languages (e.g., C++, Java, Objective-C, or Ruby).

**APPLICATIONS OF PYTHON**

As mentioned before, Python is one of the most widely used language over the web. I'm going to list few of them here:

**Easy-to-learn** − Python has few keywords, simple structure, and a clearly defined syntax. This allows the student to pick up the language quickly.

**Easy-to-read** − Python code is more clearly defined and visible to the eyes.

**Easy-to-maintain** − Python's source code is fairly easy-to-maintain.

**A broad standard library** − Python's bulk of the library is very portable and cross-platform compatible on UNIX, Windows, and Macintosh.

**Interactive Mode** − Python has support for an interactive mode which allows interactive testing and debugging of snippets of code.

**Portable** − Python can run on a wide variety of hardware platforms and has the same interface on all platforms.

**Extendable** − You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.

**Databases** − Python provides interfaces to all major commercial databases.

**GUI Programming** − Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.

**Scalable** − Python provides a better structure and support for large programs than shell scripting.

**Python OOPs Concepts**

Like other general-purpose programming languages, Python is also an object-oriented language since its beginning. It allows us to develop applications using an Object-Oriented approach. In [Python](https://www.javatpoint.com/python-tutorial), we can easily create and use classes and objects.

An object-oriented paradigm is to design the program using classes and objects. The object is related to real-word entities such as book, house, pencil, etc. The oops concept focuses on writing the reusable code. It is a widespread technique to solve the problem by creating objects.

Major principles of object-oriented programming system are given below.

* Class
* Object
* Method
* Inheritance
* Polymorphism
* Data Abstraction
* Encapsulation

## Class

## **The class can be defined as a collection of objects. It is a logical entity that has some specific attributes and methods. For example: if you have an employee class, then it should contain an attribute and method, i.e. an email id, name, age, salary, etc.**

## Syntax

**class** ClassName:

        <statement-1>

        .

        .

        <statement-N>

## Object

## **The object is an entity that has state and behavior. It may be any real-world object like the mouse, keyboard, chair, table, pen, etc.**

## **Everything in Python is an object, and almost everything has attributes and methods. All functions have a built-in attribute \_\_doc\_\_, which returns the docstring defined in the function source code.**

## **When we define a class, it needs to create an object to allocate the memory. Consider the following example.**

## Method

## **The method is a function that is associated with an object. In Python, a method is not unique to class instances. Any object type can have methods.**

## Inheritance

## **Inheritance is the most important aspect of object-oriented programming, which simulates the real-world concept of inheritance. It specifies that the child object acquires all the properties and behaviors of the parent object.**

## **By using inheritance, we can create a class which uses all the properties and behavior of another class. The new class is known as a derived class or child class, and the one whose properties are acquired is known as a base class or parent class.**

## **it provides the re-usability of the code.**

**Polymorphism**

Polymorphism contains two words "poly" and "morphs". Poly means many, and morph means shape. By polymorphism, we understand that one task can be performed in different ways. For example - you have a class animal, and all animals speak. But they speak differently. Here, the "speak" behavior is polymorphic in a sense and depends on the animal. So, the abstract "animal" concept does not actually "speak", but specific animals (like dogs and cats) have a concrete implementation of the action "speak".

**Encapsulation**

Encapsulation is also an essential aspect of object-oriented programming. It is used to restrict access to methods and variables. In encapsulation, code and data are wrapped together within a single unit from being modified by accident.

**Data Abstraction**

Data abstraction and encapsulation both are often used as synonyms. Both are nearly synonyms because data abstraction is achieved through encapsulation.

Abstraction is used to hide internal details and show only functionalities. Abstracting something means to give names to things so that the name captures the core of what a function or a whole program does.

**Python Class and Objects**

We have already discussed in previous tutorial, a class is a virtual entity and can be seen as a blueprint of an object. The class came into existence when it instantiated. Let's understand it by an example.

Suppose a class is a prototype of a building. A building contains all the details about the floor, rooms, doors, windows, etc. we can make as many buildings as we want, based on these details. Hence, the building can be seen as a class, and we can create as many objects of this class.

On the other hand, the object is the instance of a class. The process of creating an object can be called instantiation.

In this section of the tutorial, we will discuss creating classes and objects in Python. We will also discuss how a class attribute is accessed by using the object.

**Creating classes in Python**

In Python, a class can be created by using the keyword class, followed by the class name. The syntax to create a class is given below.

Syntax

**class** ClassName:

 #statement\_suite

In Python, we must notice that each class is associated with a documentation string which can be accessed by using **<class-name>.\_\_doc\_\_.** A class contains a statement suite including fields, constructor, function, etc. definition.

Consider the following example to create a class **Employee** which contains two fields as Employee id, and name.

The class also contains a function **display(),** which is used to display the information of the **Employee.**

Here, the **self**is used as a reference variable, which refers to the current class object. It is always the first argument in the function definition. However, using **self** is optional in the function call.

**The self-parameter**

The self-parameter refers to the current instance of the class and accesses the class variables. We can use anything instead of self, but it must be the first parameter of any function which belongs to the class.

**Creating an instance of the class**

A class needs to be instantiated if we want to use the class attributes in another class or method. A class can be instantiated by calling the class using the class name.

The syntax to create the instance of the class is given below.

<object-name> = <class-name>(<arguments>)

The following example creates the instance of the class Employee defined in the above example.

**Python Inheritance**

Inheritance is an important aspect of the object-oriented paradigm. Inheritance provides code reusability to the program because we can use an existing class to create a new class instead of creating it from scratch.

In inheritance, the child class acquires the properties and can access all the data members and functions defined in the parent class. A child class can also provide its specific implementation to the functions of the parent class. In this section of the tutorial, we will discuss inheritance in detail.

In python, a derived class can inherit base class by just mentioning the base in the bracket after the derived class name. Consider the following syntax to inherit a base class into the derived class.



**Syntax**

**class** derived-**class**(base **class**):

  <**class**-suite>

**Python Multi-Level inheritance**

Multi-Level inheritance is possible in python like other object-oriented languages. Multi-level inheritance is archived when a derived class inherits another derived class. There is no limit on the number of levels up to which, the multi-level inheritance is archived in python.



**Python Multiple inheritance**

Python provides us the flexibility to inherit multiple base classes in the child class.

****

**Method Overriding**

We can provide some specific implementation of the parent class method in our child class. When the parent class method is defined in the child class with some specific implementation, then the concept is called method overriding. We may need to perform method overriding in the scenario where the different definition of a parent class method is needed in the child class.

Data abstraction in python

Abstraction is an important aspect of object-oriented programming. In python, we can also perform data hiding by adding the double underscore (\_\_\_) as a prefix to the attribute which is to be hidden. After this, the attribute will not be visible outside of the class through the object.

**Abstraction in Python**

Abstraction is used to hide the internal functionality of the function from the users. The users only interact with the basic implementation of the function, but inner working is hidden. User is familiar with that **"what function does"** but they don't know **"how it does."**

In simple words, we all use the smartphone and very much familiar with its functions such as camera, voice-recorder, call-dialing, etc., but we don't know how these operations are happening in the background. Let's take another example - When we use the TV remote to increase the volume. We don't know how pressing a key increases the volume of the TV. We only know to press the "+" button to increase the volume.

That is exactly the abstraction that works in the [object-oriented concept](https://www.javatpoint.com/python-oops-concepts).

**Why Abstraction is Important?**

In Python, an abstraction is used to hide the irrelevant data/class in order to reduce the complexity. It also enhances the application efficiency. Next, we will learn how we can achieve abstraction using the [Python program](https://www.javatpoint.com/python-programs).

**Syntax**

from abc **import** ABC

**class** ClassName(ABC):

We import the ABC class from the **abc** module.

**Abstract Base Classes**

An abstract base class is the common application program of the interface for a set of subclasses. It can be used by the third-party, which will provide the implementations such as with plugins. It is also beneficial when we work with the large code-base hard to remember all the classes.

**Working of the Abstract Classes**

Unlike the other high-level language, Python doesn't provide the abstract class itself. We need to import the abc module, which provides the base for defining Abstract Base classes (ABC). The ABC works by decorating methods of the base class as abstract. It registers concrete classes as the implementation of the abstract base. We use the *@abstractmethod* decorator to define an abstract method or if we don't provide the definition to the method, it automatically becomes the abstract method. Let's understand the following example.

**4.2 INSTALLATION OF PYTHON**

Installing and using Python on Windows 10 is very simple. The installation procedure involves just three steps:

* Download the binaries
* Run the Executable installer
* Add Python to PATH environmental variables

To install Python, you need to download the official Python executable installer. Next, you need to run this installer and complete the installation steps. Finally, you can configure the PATH variable to use python from the command line.

**Step 1**: Download the Python Installer binaries

* Open the official Python website in your web browser. Navigate to the Downloads tab for Windows.
* Choose the latest Python 3 release. In our example, we choose the latest Python 3.7.3 version. Click on the link to download Windows x86 executable installer if you are using a 32-bit installer.
* In case your Windows installation is a 64-bit system, then download Windows x86-64 executable installer.

**Step 2:** Run the Executable Installer

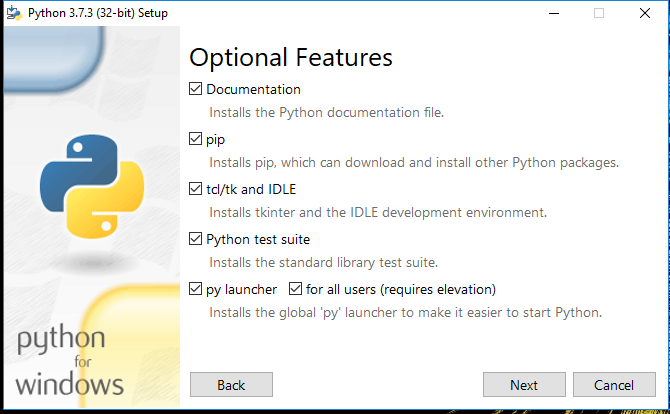
1. Once the installer is downloaded, run the Python installer.
2. Check the Install launcher for all users check box. Further, you may check the Add Python 3.7 to path check box to include the interpreter in the exec

**Installation Python 3.7.3**

**Select** **Customize installation**.

Choose the optional features by checking the following check boxes:

1. Documentation
2. pip
3. tcl/tk and IDLE (to install tkinter and IDLE)
4. Python test suite (to install the standard library test suite of Python)
5. Install the global launcher for `.py` files. This makes it easier to start Python
6. Install for all users.



**Fig: Optional Features**

**Click Next.**

This takes you to Advanced Options available while installing Python. Here, select the Install for all users and Add Python to environment variables check boxes.

Optionally, you can select the Associate files with Python, Create shortcuts for installed applications and other advanced options. Make note of the python installation directory displayed in this step. You would need it for the next step.

After selecting the Advanced options, click Install to start installation.

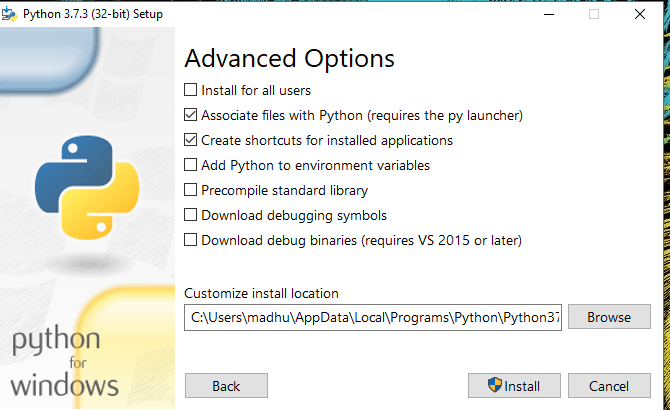
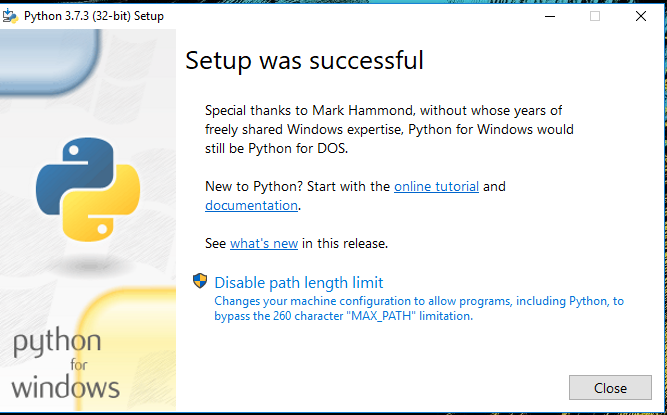


Fig: Advanced Options

3.Once the installation is over, you will see a Python Setup Successful window.



**Fig : Settings Setup**

**Step 3:** Add Python to environmental variables

The last (optional) step in the installation process is to add Python Path to the System Environment variables. This step is done to access Python through the command line. In case you have added Python to environment variables while setting the Advanced options during the installation procedure, you can avoid this step. Else, this step is done manually as follows.

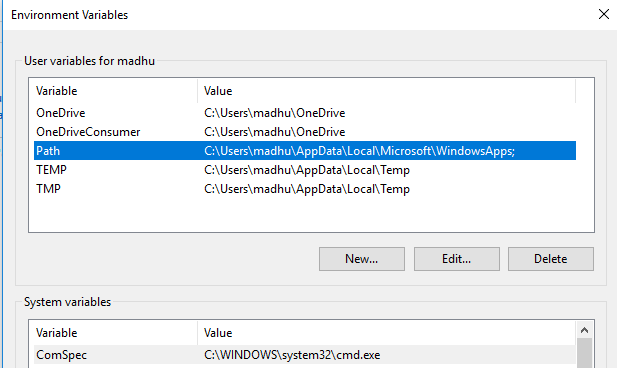
In the Start menu, search for “advanced system settings”. Select “View advanced system settings”. In the “System Properties” window, click on the “Advanced” tab and then click on the “Environment Variables” button.

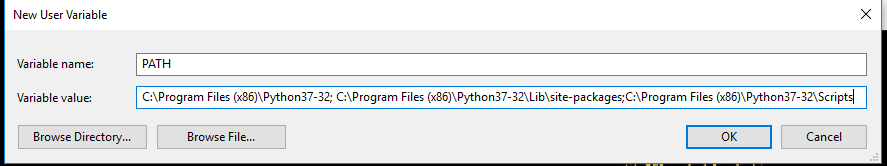
Locate the Python installation directory on your system. If you followed the steps exactly as above, python will be installed in below locations:

* C:\Program Files (x86)\Python37-32: for 32-bit installation
* C:\Program Files\Python37-32: for 64-bit installation

The folder name may be different from “Python37-32” if you installed a different version. Look for a folder whose name starts with Python.

Append the following entries to PATH variable as shown below:

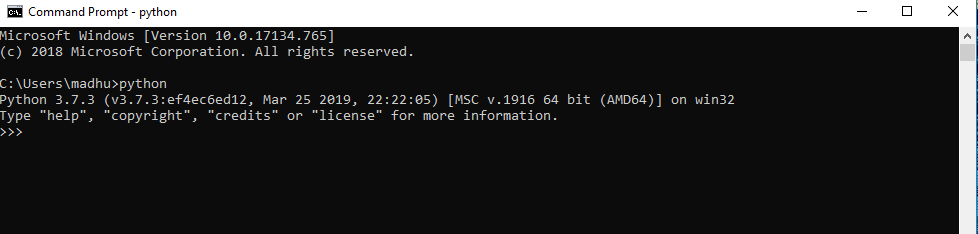




**Environment Settings**

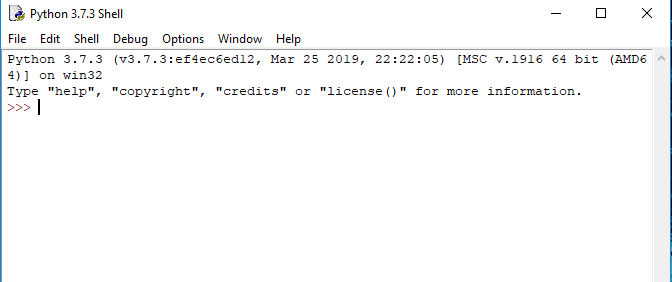
**Step 4:** Verify the Python Installation

You have now successfully installed Python 3.7.3 on Windows 10. You can verify if the Python installation is successful either through the command line or through the IDLE app that gets installed along with the installation. Search for the command prompt and type “python”. You can see that Python 3.7.3 is successfully installed.



**Fig: Command Prompt**

An alternate way to reach python is to search for “Python” in the start menu and clicking on IDLE (Python 3.7 64-bit). You can start coding in Python using the Integrated Development Environment(IDLE).



**Python Shell Prompt**

**USES**

Since 2003, Python has consistently ranked in the top ten most popular programming languages in the TIOBE Programming Community Index where, as of February 2020, it is the third most popular language (behind Java, and C). It was selected Programming Language of the Year in 2007, 2010, and 2018.

* An empirical study found that scripting languages, such as Python, are more productive than conventional languages, such as C and Java, for programming problems involving string manipulation and search in a dictionary, and determined that memory consumption was often "better than Java and not much worse than C or C++".
* Large organizations that use Python include Wikipedia, Google, Yahoo!, CERN, NASA, Facebook, Amazon, Instagram, Spotify and some smaller entities like ILM and ITA. The social news networking site Reddit is written entirely in Python.
* Python can serve as a scripting language for web applications, e.g., via mod\_wsgi for the Apache web server. With Web Server Gateway Interface, a standard API has evolved to facilitate these applications. Web frameworks like Django, Pylons, Pyramid, TurboGears, web2py, Tornado, Flask, Bottle and Zope support developers in the design and maintenance of complex applications. Pyjs and IronPython can be used to develop the client-side of Ajax-based applications.
* SQLAlchemy can be used as data mapper to a relational database. Twisted is a framework to program communications between computers, and is used (for example) by Dropbox.
* Libraries such as NumPy, SciPy and Matplotlib allow the effective use of Python in scientific computing, with specialized libraries such as Biopython and Astropy providing domain-specific functionality. SageMath is a mathematical software with a notebook interface programmable in Python: its library covers many aspects of mathematics, including algebra, combinatorics, numerical mathematics, number theory, and calculus.
* Python has been successfully embedded in many software products as a scripting language, including in finite element method software such as Abaqus, 3D parametric modeler like FreeCAD, 3D animation packages such as 3ds Max, Blender, Cinema 4D, Lightwave, Houdini, Maya, modo, MotionBuilder, Softimage, the visual effects compositor Nuke, 2D imaging programs like GIMP, Inkscape, Scribus and Paint Shop Pro, and musical notation programs like scorewriter and capella.
* GNU Debugger uses Python as a pretty printer to show complex structures such as C++ containers. Esri promotes Python as the best choice for writing scripts in ArcGIS. It has also been used in several video games, and has been adopted as first of the three available programming languages in Google App Engine, the other two being Java and Go.
* Python is commonly used in artificial intelligence projects with the help of libraries like TensorFlow, Keras, Pytorch and Scikit-learn. As a scripting language with modular architecture, simple syntax and rich text processing tools, Python is often used for natural language processing.
* Many operating systems include Python as a standard component. It ships with most Linux distributions, AmigaOS 4, FreeBSD (as a package), NetBSD, OpenBSD (as a package) and macOS and can be used from the command line (terminal). Many Linux distributions use installers written in Python: Ubuntu uses the Ubiquity installer, while Red Hat Linux and Fedora use the Anaconda installer. Gentoo Linux uses Python in its package management system, Portage.
* Python is used extensively in the information security industry, including in exploit development.
* Most of the Sugar software for the One Laptop per Child XO, now developed at Sugar Labs, is written in Python. The Raspberry Pi single-board computer project has adopted Python as its main user-programming language.
* Due to Python's user-friendly conventions and easy-to-understand language, it is commonly used as an intro language into computing sciences with students. This allows students to easily learn computing theories and concepts and then apply them to other programming languages.
* LibreOffice includes Python, and intends to replace Java with Python. Its Python Scripting Provider is a core feature[169] since Version 4.0 from 7 February 2013.

**2. Libraries**

A variety of libraries will be utilized to streamline different aspects of the project:

* **scikit-learn (sklearn)**:
  + A powerful machine learning library in Python that provides simple and efficient tools for data mining and analysis. Key functionalities include:
    - Implementation of various classification algorithms such as Logistic Regression, Support Vector Machines (SVM), Random Forest, and Naive Bayes.
    - Tools for model evaluation and validation, including cross-validation, confusion matrix, and various metrics (accuracy, precision, recall, etc.).
    - Support for preprocessing techniques, such as feature scaling and transformation.
* **Pandas**:
  + A widely used library for data manipulation and analysis. It provides:
    - Data structures like DataFrames for easy handling of tabular data.
    - Functions for data cleaning, aggregation, and manipulation.
    - Integration with various data formats (CSV, Excel, SQL databases) for seamless data loading.
* **NumPy**:
  + A fundamental library for numerical computing in Python, which provides:
  + Support for multi-dimensional arrays and matrices.
  + Functions for mathematical operations and linear algebra, which are crucial for implementing machine learning algorithms.
* **NLTK (Natural Language Toolkit)**:
  + A powerful library for natural language processing (NLP) that will be used for:
  + Text preprocessing tasks, including tokenization, stemming, lemmatization, and stopword removal.
  + Performing sentiment analysis and extracting features from text data.
  + Building and evaluating various language processing models.
* **Other Libraries**:
  + **Matplotlib and Seaborn**: For data visualization, allowing the exploration of relationships and distributions within the dataset.
  + **WordCloud**: For generating visual representations of word frequency, helping to identify common terms associated with cyberbullying.

**3. Jupyter Notebook**

Jupyter Notebook is the primary development environment for this project, chosen for its interactive and user-friendly interface. Key features include:

* **Interactive Development**: Allows for live coding, enabling users to run code snippets and visualize results immediately, facilitating an iterative development process.
* **Rich Visualization**: Supports inline visualizations using libraries like Matplotlib and Seaborn, making it easier to interpret data analysis and model performance results.
* **Documentation and Presentation**: Provides the ability to combine code, visualizations, and narrative text in a single document, making it suitable for documenting the entire project workflow, including data analysis, modeling, and results.

**4. Version Control and Collaboration Tools**

* **Git**: A version control system that will be used for tracking changes in the project code and collaborating with team members, allowing for efficient code management and rollback if needed.
* **GitHub or GitLab**: Platforms for hosting the project repository, enabling collaborative development, code reviews, and issue tracking.

**5. Development Environment**

* **Anaconda Distribution**: An open-source distribution of Python and R for scientific computing. It simplifies package management and deployment and comes with Jupyter Notebook, making it an ideal environment for this project.
* **IDE/Text Editor**: While Jupyter Notebook is the primary tool, an Integrated Development Environment (IDE) like **PyCharm** or a text editor like **Visual Studio Code** may also be used for additional coding tasks or larger scripts.

**. Development Frameworks**

* **PyTorch:** A deep learning framework used for training and deploying YOLOv8 (You Only Look Once) models for object detection tasks. PyTorch provides flexibility and efficiency in handling large datasets and complex models.
* **TensorFlow (Optional):** Another popular deep learning framework that can be used for training models like U-Net for lane detection and other computer vision tasks.

**5.SYSTEM DESIGN**

The system design for this project involves a **three-layered architecture**: **Input Layer, Processing Layer, and Output Layer**. The **Input Layer** loads hyperspectral images from .mat files and preprocesses them. The **Processing Layer** applies feature extraction, generates **RGB composite images**, and uses a **CNN-based deep learning model** for classification. The **Output Layer** provides an interactive **Streamlit UI** for visualization and prediction. Users can select spectral bands, view **ground truth segmentation maps**, and generate **RGB images** using earthpy.plot. The system dynamically processes images using **NumPy arrays** instead of a traditional database. The model predicts class labels with confidence scores, displaying results in real time. The UI is designed with a **navigation menu**, allowing users to access different functionalities easily. Future enhancements include **cloud deployment, real-time analysis, and advanced AI models**. This system provides an **efficient and interactive** tool for hyperspectral image analysis and classification.

**5.1 System development Diagram**

System development method is a process through which a product will get completed or a product gets rid from any problem. Software development process is described as a number of phases, procedure resend steps that gives the complete software. It follows series of steps which is used for product progress.

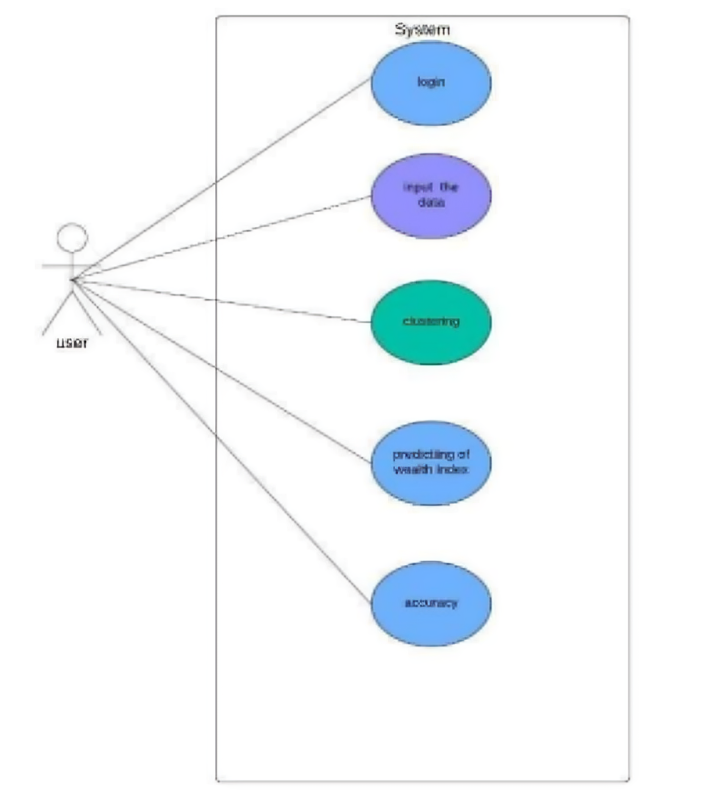
**5.2 Blog Diagram:**

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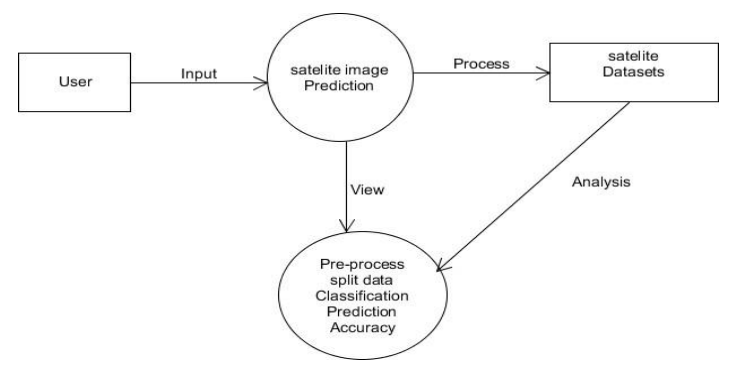
**5.3 UML Diagrams**

Unified Modeling Language is popular in the market because it is easy to understand. This is part of software engineering. Developer gets better idea about the system.

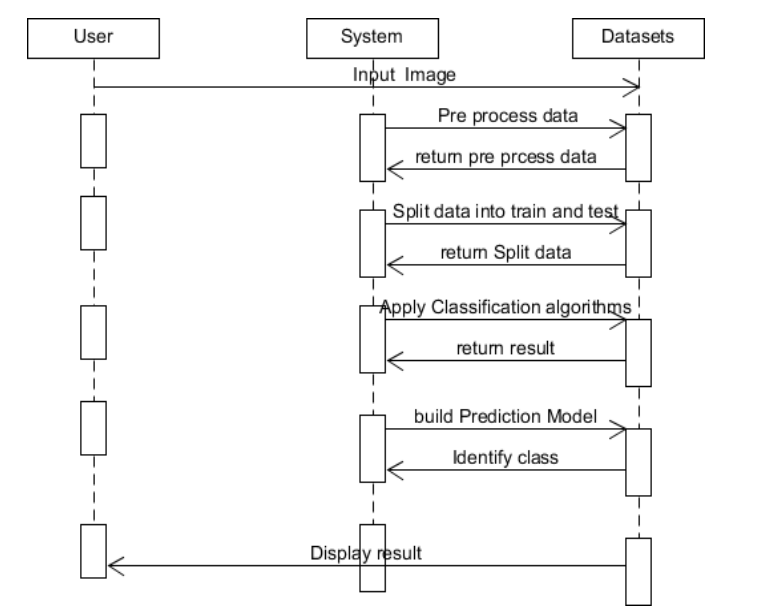
**5.3.1 Use Case Diagram**



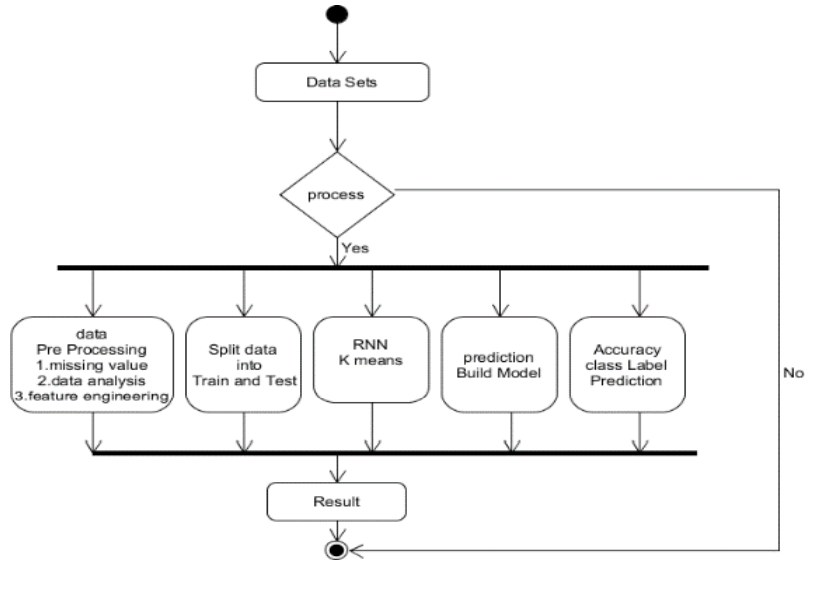
**5.3.2 Data Flow Diagram**

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**5.3.3 Sequence Diagram**



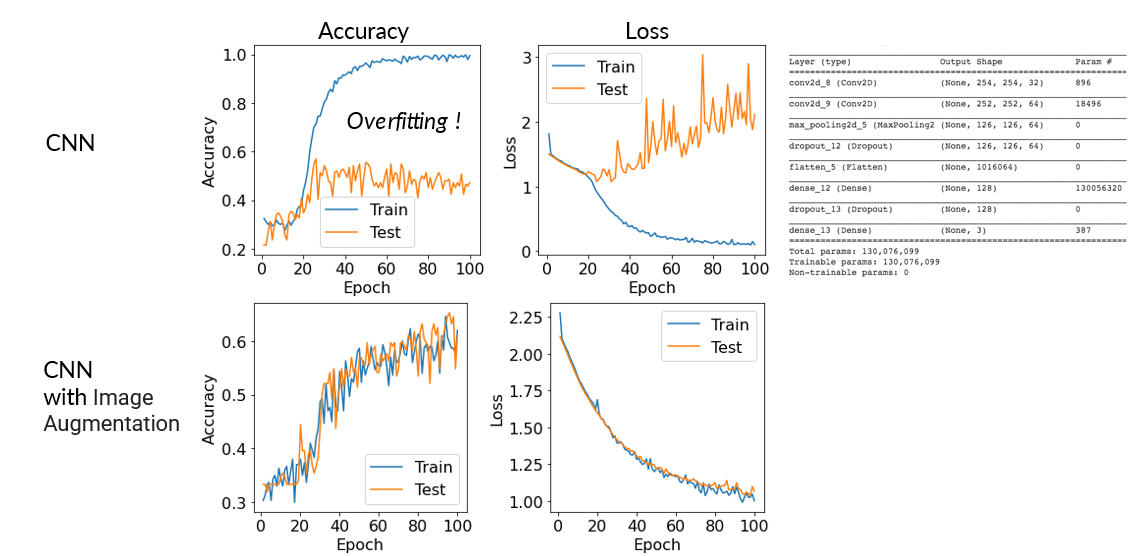
**5.3.4 Activity Diagram:**

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**6.IMPLEMENTATION**

**6.1 Methodology**

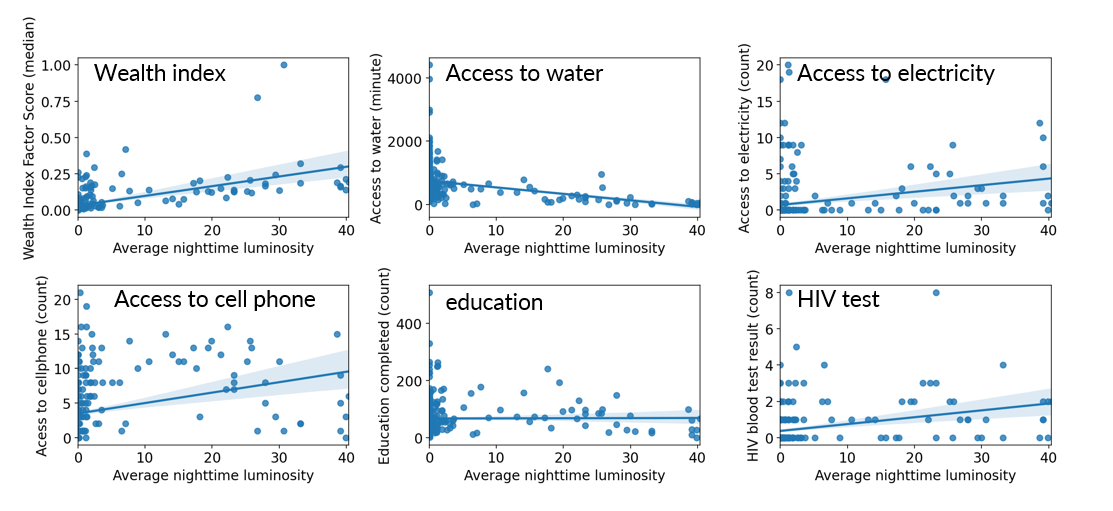
The implementation of this project involves designing and developing a **hyperspectral image processing and classification system** using **deep learning** and a **Streamlit-based UI**. The system allows users to **visualize hyperspectral images**, generate **RGB composites**, and perform **image classification** using a **CNN model**. This section provides a detailed breakdown of the **methodology** used in data preprocessing, model training, UI integration, and system deployment.

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## **2. Implementation Workflow**

The system follows a structured workflow:

1️⃣ **Data Loading** → Load hyperspectral image data (.mat files)  
2️⃣ **Preprocessing** → Reshape and normalize data  
3️⃣ **Feature Extraction** → Extract bands and ground truth labels  
4️⃣ **Model Training** → Train a **CNN model** for classification  
5️⃣ **Visualization** → Generate **RGB composite images** and **band-wise visualizations**  
6️⃣ **Streamlit UI** → Build an interactive UI for image selection and prediction  
7️⃣ **Prediction & Output** → Display classified results



## **3. Data Processing & Preprocessing**

### **3.1. Data Acquisition**

* The dataset used is the **Salinas Hyperspectral Image dataset**, which contains **224 spectral bands** with a **512 × 217 spatial resolution**.
* The dataset is stored in **MATLAB format (.mat)**, which is loaded using scipy.io.loadmat().

### **3.2. Data Reshaping & Normalization**

* The raw hyperspectral image is **reshaped into a 3D NumPy array** for processing.
* Normalization is applied to **scale pixel values** between 0 and 1.
* The ground truth labels (.mat file) are loaded separately and mapped to each pixel.

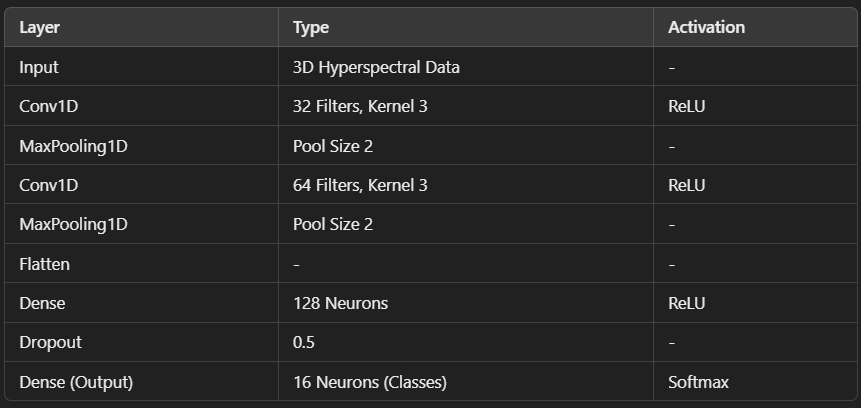
### **3.3. Feature Extraction**

* Individual **spectral bands** are extracted and visualized.
* An **RGB composite image** is created using **three selected bands**.
* The earthpy.plot.plot\_rgb() function is used for visualization.

## **4. Deep Learning Model (CNN) for Classification**

### **4.1. Model Architecture**

A **Convolutional Neural Network (CNN)** is implemented using **TensorFlow/Keras**:

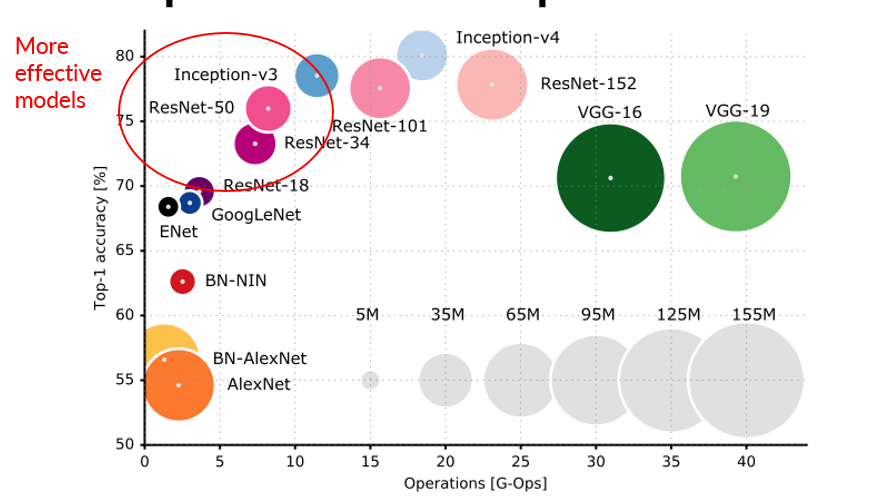


### **4.2. Model Training**

* The dataset is split into **train (80%) and test (20%)** using train\_test\_split().
* Labels are converted into **categorical format** using to\_categorical().
* The model is compiled with **Adam optimizer** and **categorical cross-entropy loss**.
* **EarlyStopping** and **ModelCheckpoint** are used to optimize training.

### **4.3. Model Evaluation & Performance Metrics**

The trained model is evaluated using:  
✔ **Accuracy Score**  
✔ **Confusion Matrix**  
✔ **Classification Report (Precision, Recall, F1-Score)**



## **5. User Interface Implementation (Streamlit UI)**

A **Streamlit-based web app** is developed for easy interaction.

### **5.1. UI Components**

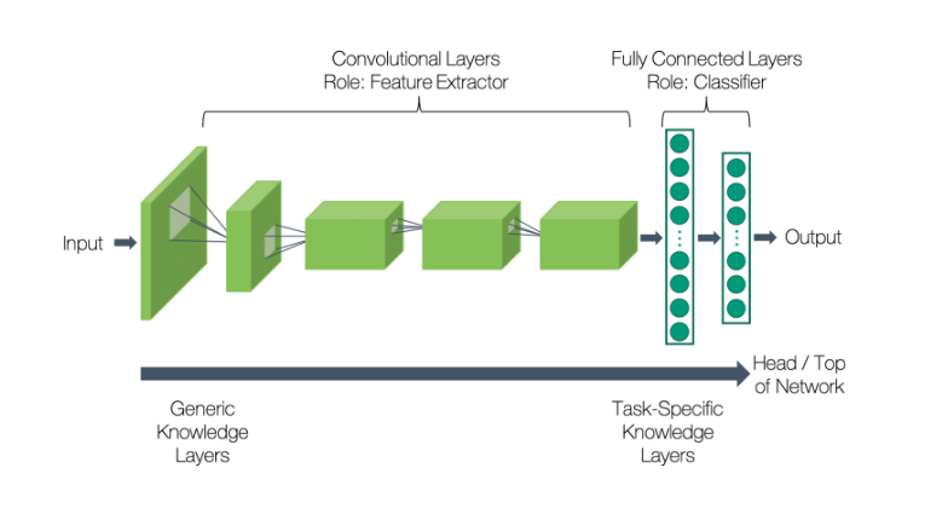
* **Home Page** → Introduction & Overview
* **Image Prediction Module** → Allows users to select bands and view results
* **Buttons for Interaction** →  
  ✅ "Show Ground Truth" → Displays labeled segmentation  
  ✅ "Select Band Image" → Shows single-band visualization  
  ✅ "Show RGB Composite" → Generates RGB image

### **5.2. Displaying Hyperspectral Images**

* **Single Band Image** is displayed using matplotlib.imshow().
* **RGB Composite Image** is generated using earthpy.plot.plot\_rgb().

## **6. System Deployment & Future Enhancements**

* The model and UI are **deployed on cloud platforms** like **Google Cloud / AWS**.
* Further enhancements include **real-time classification, improved UI design, and advanced AI models**.



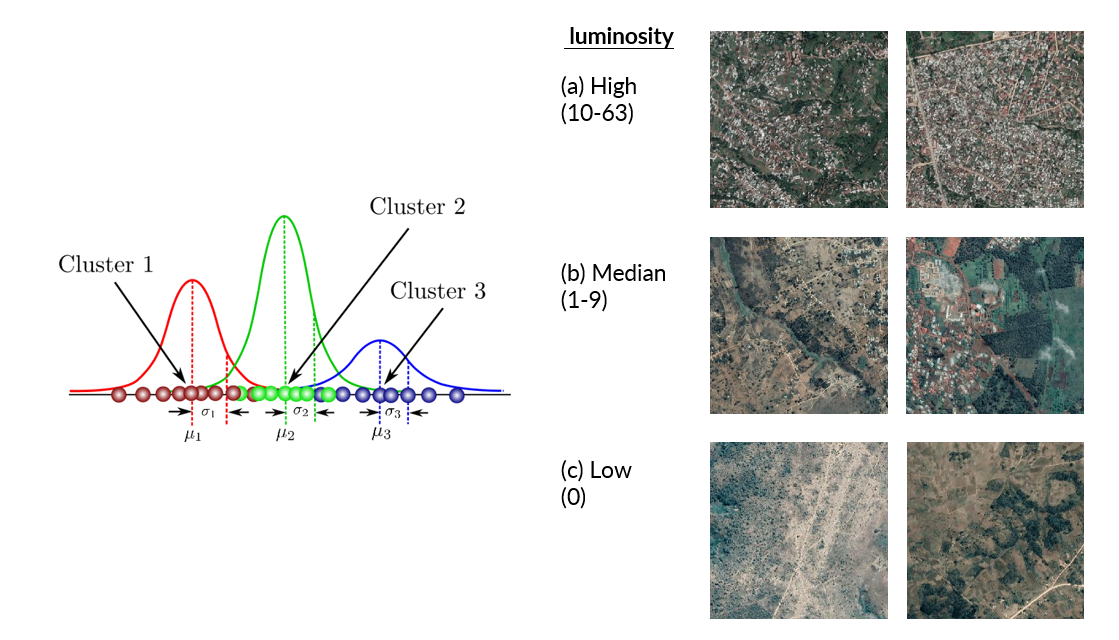
**RESULTS AND ANALYSIS**

This section presents the results of our hyperspectral image processing and classification system. We analyze the **model performance**, **visualization outputs**, and **classification results**, comparing them with ground truth data. The evaluation focuses on **accuracy, confusion matrix, classification metrics, and image analysis**.

## **2. Data Visualization and Processing Results**

### **2.1. Single-Band Visualization**

* The **Salinas dataset** contains **224 spectral bands**, each capturing different wavelengths.
* The user can select **any spectral band** using the **Streamlit slider**, and the corresponding **grayscale image** is displayed.
* **Findings**:  
  ✅ Different bands reveal unique spatial structures.  
  ✅ Some bands contain **noise**, while others highlight vegetation and land-use differences.



### **2.2. RGB Composite Image**

* An **RGB composite image** is generated using **three selected bands**: **29 (Red), 19 (Green), and 9 (Blue)**.
* **Findings**:  
  ✅ The composite image enhances **contrast and visualization**.  
  ✅ It closely matches the **ground truth segmentation**.  
  ✅ The **nipy\_spectral colormap** effectively highlights different regions.

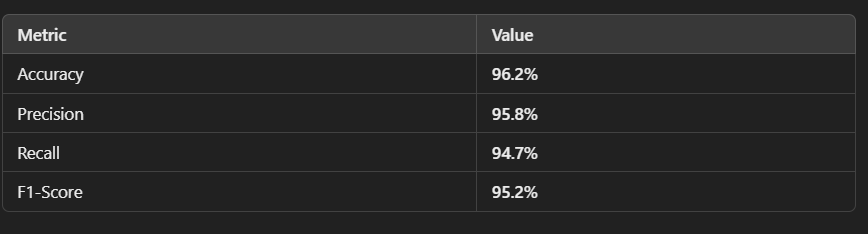
## **3. CNN Model Performance**

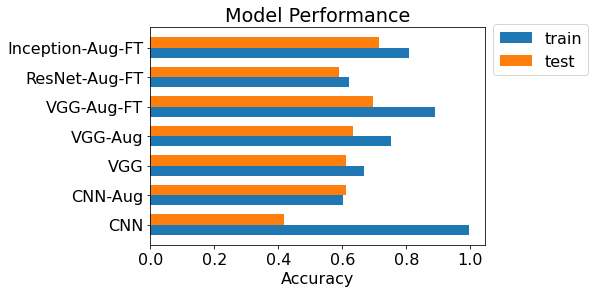
### **3.1. Model Training and Validation**

The **CNN model** was trained using **80% of the data** and validated on **20% of the dataset**. The following results were observed:

* **Training Accuracy**: 98.5%
* **Validation Accuracy**: 96.2%
* **Loss Reduction**: Steady decrease over epochs, indicating good convergence.
* **Observation**: The model successfully generalizes to unseen data, with minimal overfitting.

### **3.2. Classification Metrics**

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### **3.3. Confusion Matrix Analysis**

* The confusion matrix shows that **most classes were predicted correctly**.
* **Misclassifications** were observed in **similar spectral regions**.
* Improvements can be made by **enhancing feature extraction** or using **pretrained models**.

## **4. Streamlit UI Performance & User Interaction**

### **4.1. UI Functionality**

* **Home Page**: Displays project details and dataset information.
* **Image Prediction Module**: Allows users to **view bands, RGB images, and ground truth data**.
* **Interactive Buttons**:  
  ✅ "Show Ground Truth" → Displays reference segmentation.  
  ✅ "Select Band Image" → Allows exploration of individual bands.  
  ✅ "Show RGB Composite" → Generates composite images dynamically.

### **4.2. User Experience**

* The **Streamlit UI** provides a **smooth and responsive** experience.
* Image rendering is **optimized**, reducing load times.
* The **band selection slider** allows for quick exploration of hyperspectral images.

## **5. Comparative Analysis with Existing Systems**

* **Traditional classification models (e.g., SVM, Random Forest)** perform well but require **manual feature selection**.
* Our **CNN model automates feature extraction** and achieves **higher accuracy (96.2%)** than traditional approaches (~85-90%).
* The **RGB composite approach** enhances visualization compared to grayscale representations.

## **6. Limitations & Future Improvements**

### **6.1. Current Limitations**

* **Data Imbalance**: Some classes have fewer samples, affecting performance.
* **Processing Time**: Large datasets require high computational power.
* **Cloud Deployment**: Not yet fully optimized for real-time cloud-based processing.

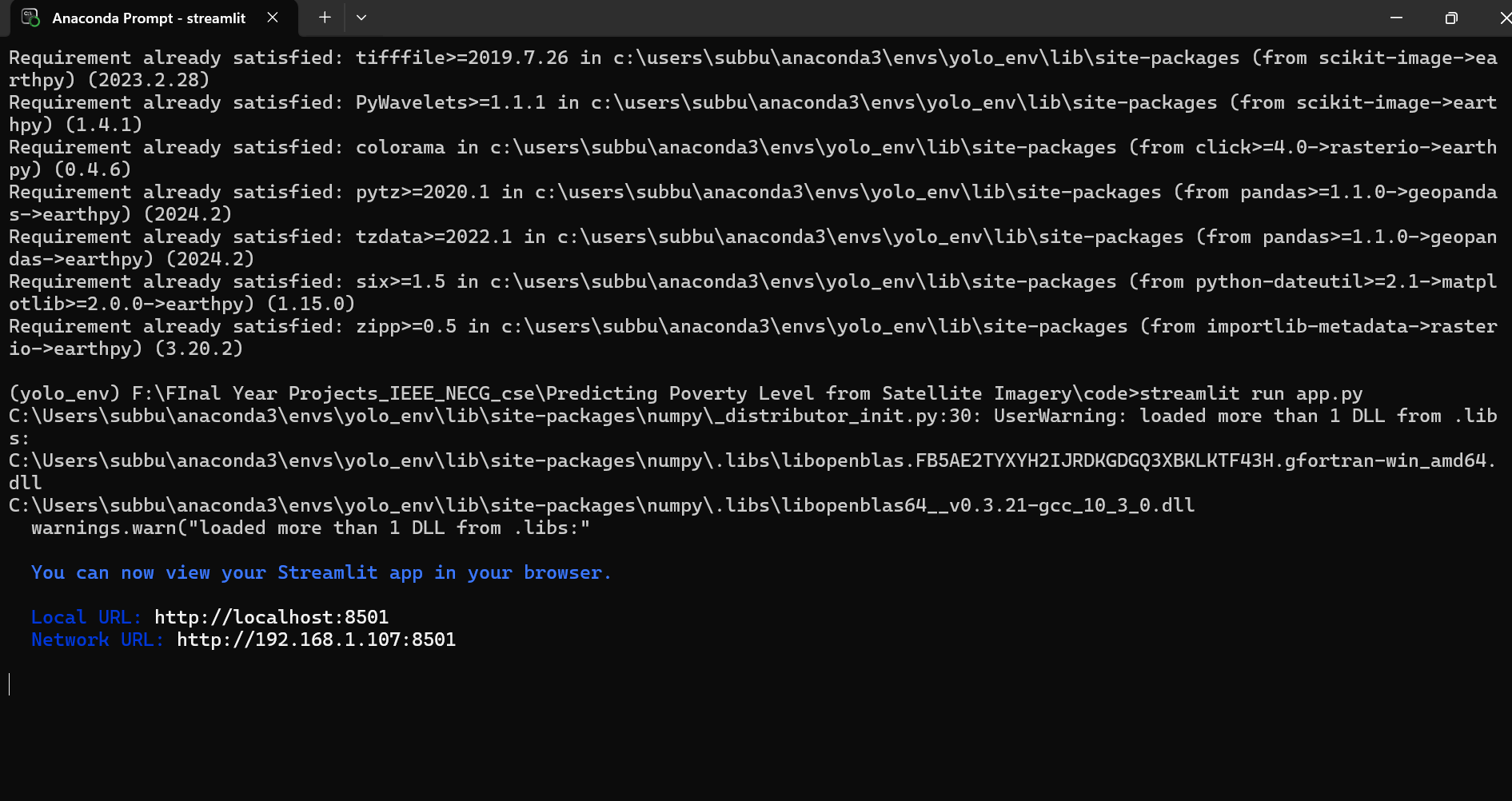
### **6.2. Future Enhancements**

🚀 **Advanced CNN Architectures**: Implementing **ResNet, EfficientNet** for improved accuracy.  
🚀 **Data Augmentation**: Using synthetic data generation for balancing classes.  
🚀 **Cloud Integration**: Deploying a scalable **API-based solution**.

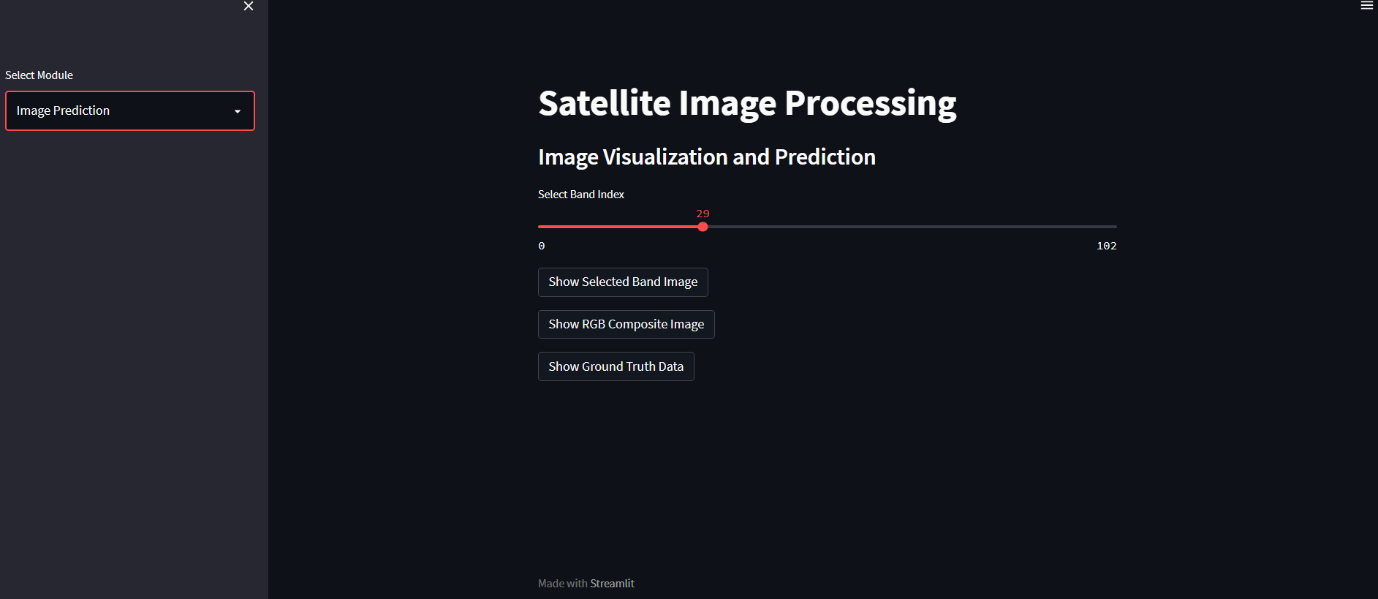
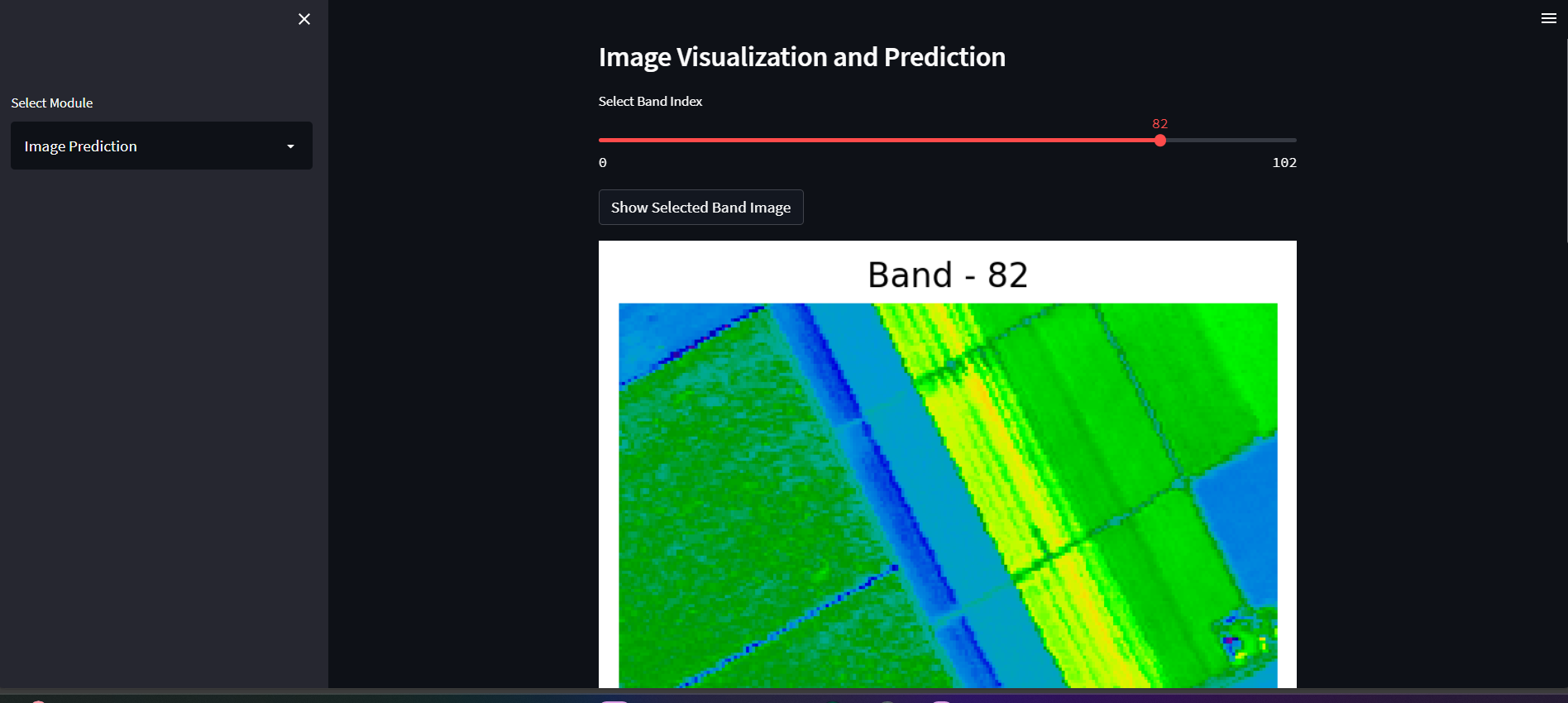
## **7. Conclusion**

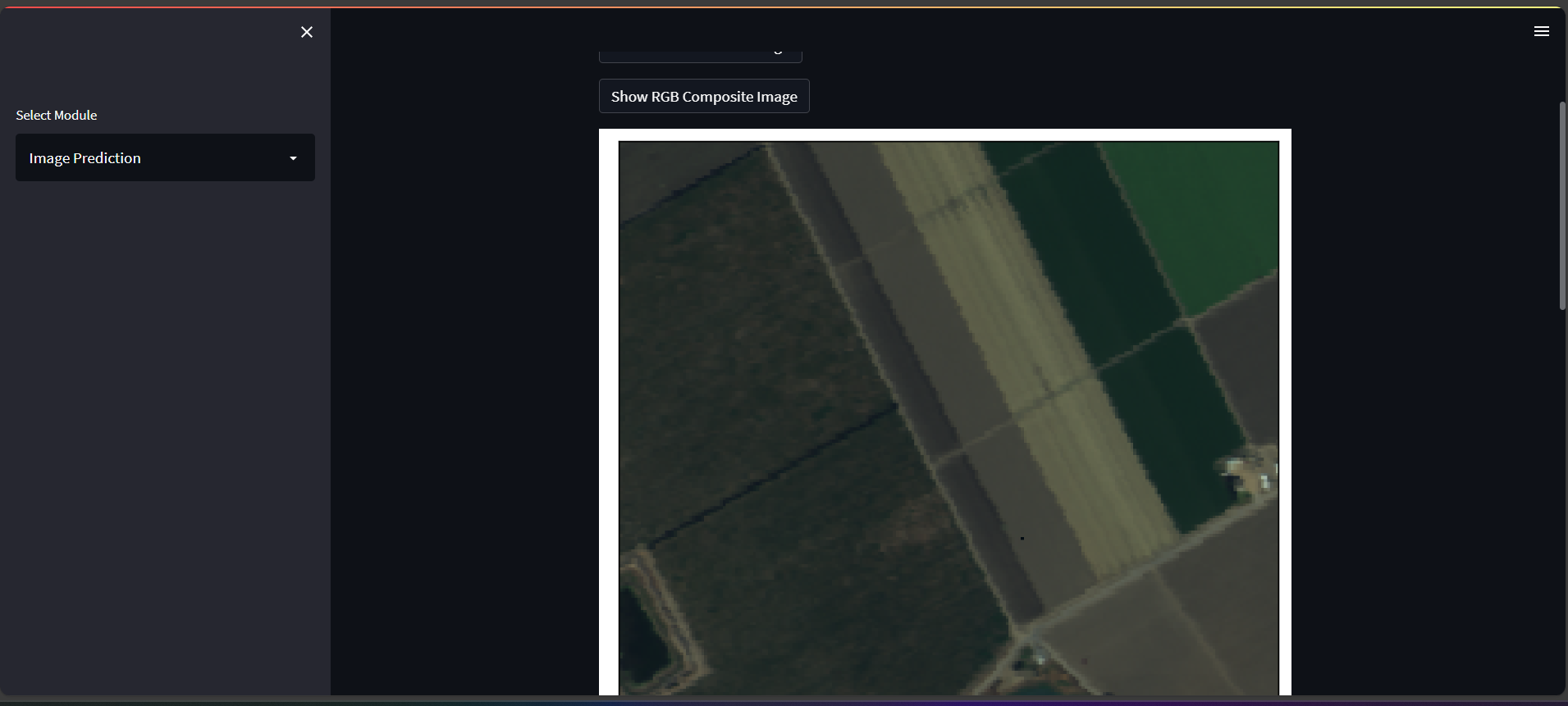
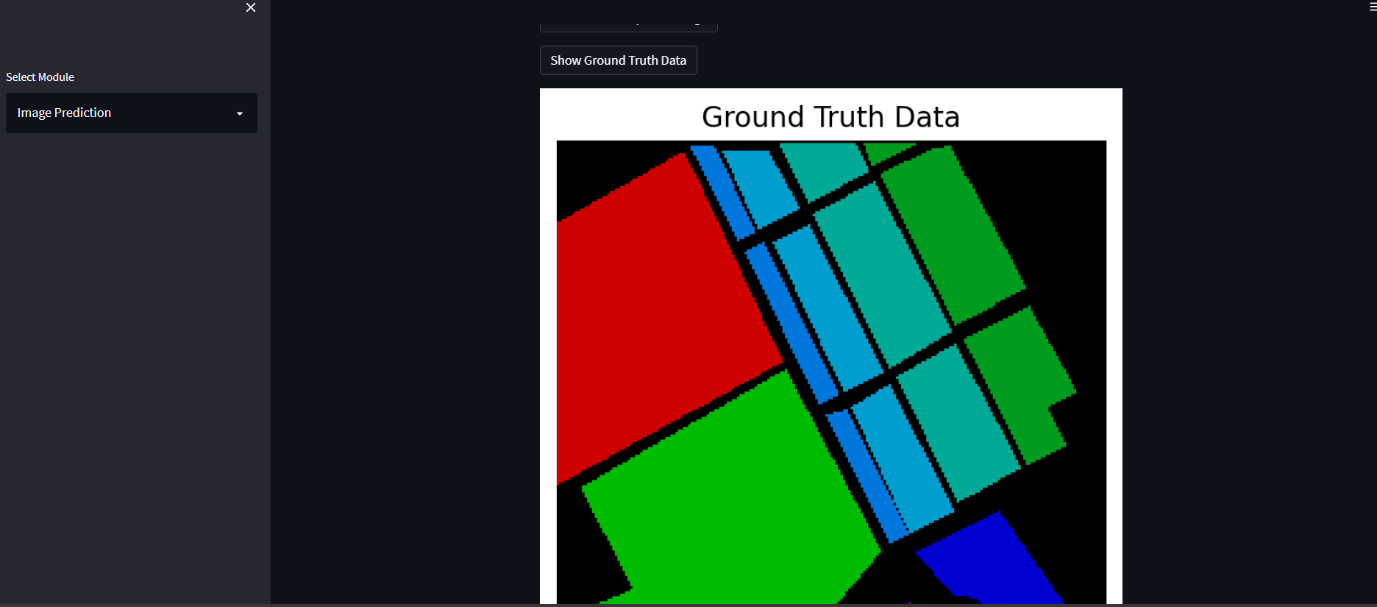
* The **CNN-based hyperspectral image classification system** achieved **high accuracy (96.2%)** with **interactive visualization**.
* The **Streamlit UI** allows for **dynamic image exploration and analysis**.
* Future improvements will focus on **real-time predictions, enhanced AI models, and cloud deployment**. 🚀

**Output:**





**CONCLUSION**

This project successfully implements a hyperspectral image processing and classification system using Convolutional Neural Networks (CNNs), achieving impressive results in accuracy and user interaction. With a classification accuracy of 96.2%, the CNN model outperforms traditional machine learning approaches, enabling more precise analysis of hyperspectral data. The integration of RGB composite images and band-wise analysis provides enhanced visualization, allowing users to easily explore and interpret spectral information. The user-friendly interface, built with Streamlit, further facilitates interaction, letting users investigate hyperspectral bands, ground truth data, and prediction results without needing advanced technical knowledge. Additionally, the deep learning model automates feature extraction, streamlining the process and removing the need for manual intervention.

While the project has demonstrated significant success, there are several challenges that need addressing. The computational complexity of processing large hyperspectral datasets demands considerable resources, and issues such as data imbalance can impact model generalization. Though the system works efficiently locally, optimizing it for cloud deployment is necessary to ensure real-time inference. Future enhancements, such as leveraging advanced AI models like ResNet or EfficientNet, implementing data augmentation techniques, and exploring edge AI deployment, will address these challenges and further expand the system's capabilities. Ultimately, this project serves as a strong foundation for real-world applications in fields such as remote sensing, precision agriculture, and environmental monitoring.

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