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RESEARCH PROJECT ON

"Utilizing hyperspectral non-imagine data to identify materials used in ancient structures"

Submitted in partial fulfillment of the requirements for the degree of

M. Sc. Artificial Intelligence

Submitted By

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Under the Guidance of

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NAAC Re-accredited with 'A+' Grade

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Department of Computer Science and Information Technology

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Certificate

This is to certify that the research project titled

"Utilizing hyperspectral non-imagine data to identify materials used in ancient structures"

Has been successfully completed as a partial fulfillment of the requirements for the degree of Master of Science in Artificial Intelligence.

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This is to certify that **Mr. Dhananjay Manik Kamble** has successfully completed a research project on **"Utilizing hyperspectral non-imagine data to identify materials used in ancient structures"**, Practical Code: SRD246564P for the partial fulfillment of **M.Sc (Artificial Intelligence) Semester-IV** during academic year 2024-25.

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Sincerely,

Mr. Dhananjay Manik Kamble

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Abstract

This research focuses on the noninvasive identification of materials used in ancient structures by analyzing hyperspectral non-imaging data. Traditional methods of material identification in historical buildings are often invasive, time-consuming, and can cause damage to the structures. Hyperspectral non-imaging data provides a non-destructive alternative, allowing for the analysis of spectral signatures of materials without physical contact. This study aims to develop a comprehensive spectral library of ancient construction materials and apply machine-learning techniques, to classify and identify these materials accurately. The research is conducted on ancient structures located in Chhatrapati Sambhajinagar, with a focus on materials such as Ancient limestone and organic additives like bel-fruit (Aegle marmelos), jaggery (Saccharum officinarum), Ambada vegetable (Hibiscus sabdariffa) and udid dal (Vigna mungo). The results demonstrate the effectiveness of hyperspectral nonimaging data in material identification, with an SVM model accuracy of 93.60%. This research contributes to the preservation and restoration of historical structures by providing a reliable and efficient method for material analysis.

1. Introduction

India, with its rich history and diverse cultural heritage, is home to countless ancient structures that span thousands of years.Ancient structures are invaluable treasures that connect us to our past, showcasing the creativity and skills of earlier civilizations. These structures were not just architectural wonders but also cultural landmarks. From the rockcut caves of Ajanta and Ellora to the grand forts of Rajasthan, these buildings were constructed using locally sourced materials like stone, bricks, clay, and natural additives such as bel fruit, jaggery, and udid dal. Ancient builders often mixed these materials with natural additives to improve their strength and durability.

Fig.1.1 Ancient Structure

Over time, these structures have started to degrade due to environmental factors like weather, pollution, and human activities such as urbanization and tourism. To restore these structures effectively, it is crucial to understand the exact composition of the materials used in their construction. Traditional methods of material identification, such as chemical analysis or physical sampling, often require removing small pieces of the structure, which can cause further damage. This is particularly problematic for ancient structures, where even minor changes can lead to a loss of historical authenticity.

In recent years, advancements in technology have introduced noninvasive methods for material analysis, offering a safer and more efficient alternative. One such method is the use of hyperspectral nonimaging data. This technique involves capturing and analyzing the spectral signatures of materials using light, without any physical contact. By examining how different materials reflect or absorb light at various wavelengths, hyperspectral data provides detailed information about their composition. This nondestructive approach is particularly beneficial for studying ancient structures, as it allows for thorough analysis without causing harm.It provides a way to identify materials in ancient structures without causing damage. By creating a spectral library and using machine learning, the study improves the accuracy of material identification. This helps in preserving and restoring historical structures. The findings of this research can also be used in future studies to protect and conserve ancient buildings.

This research project focuses on using hyperspectral non imaging data to identify materials in ancient structures, particularly in **Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar.** In this ancient structures are believed to have been built using limestone and natural additives, which were commonly used in ancient Indian architecture. The study aims to create a spectral library of these materials and apply machine learning techniques to classify and identify them accurately. This approach not only helps us understand ancient construction techniques but also provides a reliable tool for the conservation and restoration of historical sites.

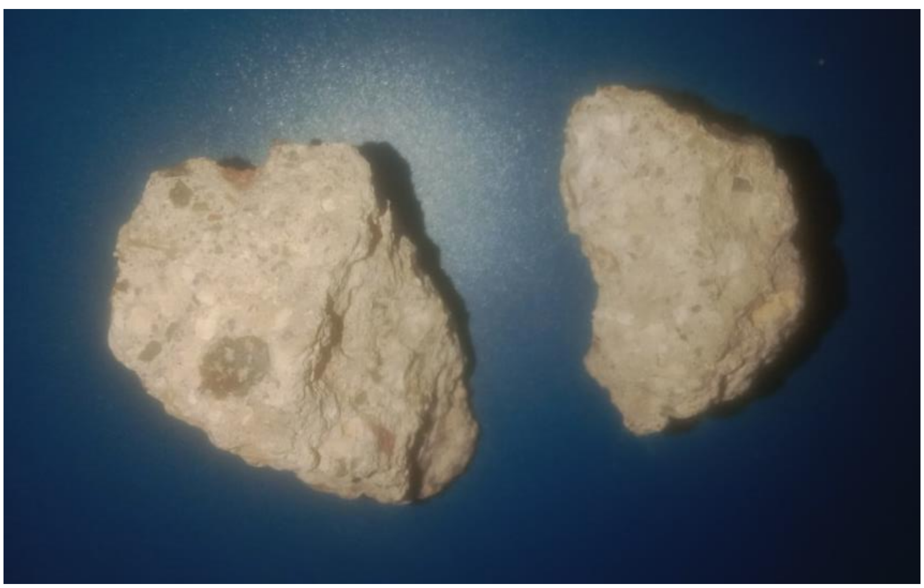


Fig.1.2 Ancient Limestone

2. Literature review

Vijay dhangar's in his paper investigates the development of a spectral library for food samples using the ASD FieldSpec4 spectroradiometer and ENVI 5.5 software. Spectral signatures, which are unique patterns of electromagnetic radiation absorbed, emitted, or reflected by materials, play a crucial role in identifying and analyzing different substances. The study leverages remote sensing techniques, widely used in fields like agriculture, ecology, and environmental science, to collect and analyze spectral data from food samples such as tea, turmeric, and chili powder. The ENVI software, known for its advanced spectral image processing capabilities, was utilized to create a spectral library by integrating data from the ASD FieldSpec4 spectroradiometer. The research followed a systematic approach, including sample collection, database creation, spectral library building, and visualization. Samples were collected from various market brands and homemade sources, and their spectral data was captured within the 350–2500 nanometer range [1].

This paper explores the use of a spectroradiometer to predict the compressive strength of mortar cubes nondestructively. Traditionally, concrete quality testing involves breaking samples, but this study introduces a remote sensing approach using spectral analysis. The researchers used a Field Spec 3 spectroradiometer to capture spectral data from mortar samples and analyzed the relationship between reflectance and mechanical strength. They also experimented with replacing fine aggregate with industrial waste (foundry sand) to assess its impact on mortar strength. The study developed a predictive model using Partial Least Squares Regression (PLSR), achieving high accuracy in estimating compressive strength. This method offers a fast, costeffective alternative for realtime concrete quality monitoring, reducing reliance on destructive testing [2].

This paper discusses how to accurately measure spectral reflectance using the ASD FieldSpec spectroradiometer. Spectral reflectance is essential in remote sensing applications, as it helps identify and analyze materials based on how they reflect light. However, various factors can affect the accuracy of spectral measurements, such as environmental conditions, instrument calibration, measurement timing, and viewing geometry. The paper outlines a standardized method for collecting spectral data, emphasizing the importance of warming up the spectroradiometer, optimizing settings, taking white reference readings, and accounting for dark current. It also explains how to calculate the Field of View (FOV) to ensure accurate data collection. The study highlights the significance of precise spectral measurements for applications like agriculture, mining, material quality assessment, and environmental studies, where reliable data is crucial for detection and classification [3].

This paper explores the use of the ASD FieldSpec 4 Spectroradiometer to build a spectral database for food samples. The device measures how different food items reflect light across a wide spectral range (350–2500 nm) to analyze their composition. Researchers collected spectral data for various food items, including homemade and market samples of chili powder, turmeric, and tea, under controlled laboratory conditions. Factors such as calibration, white reference, and optimization were considered to ensure accurate measurements. The collected spectral signatures were analyzed using statistical and machine learning techniques to identify patterns and differences in food quality. The study highlights the importance of precise spectral measurements for detecting food adulteration and improving quality control in the food industry [4].

This paper examines the use of the ASD FieldSpec4 Spectroradiometer to analyze Wheat Leaf Rust (WLR) disease in winter wheat crops. Remote sensing techniques, specifically hyperspectral measurements, were used to detect and differentiate between healthy and infected wheat leaves. The study focused on spectral data within the 450–1000 nm wavelength range, where WLR infection is most noticeable. Researchers collected spectral signatures from both healthy and diseased leaves and applied statistical analysis to identify significant differences in reflectance. The results showed that diseased leaves had lower spectral reflectance compared to healthy ones, indicating a clear spectral distinction. The study highlights the potential of remote sensing for early disease detection, which can aid farmers in monitoring crop health and improving wheat yield. Future research aims to integrate machine learning techniques to enhance disease severity prediction and automate analysis [5].

Here is the table representation of the literature review:

No.	Author(s)	Title	Year	Key Focus
1	Dhangar et al.	Creating a spectral library of food samples through spectroscopic device integration with ENVI software	2024	Spectral library creation for food samples using ENVI software.
2	Bhojaraja et al.	Compressive Strength Predictive Analysis using Spectroradiometer	2024	Non-destructive evaluation of mortar strength using spectral analysis.
3	Janse et al.	Standard spectral reflectance measurements for ASD FieldSpec Spectroradiometer	2018	Standardization of spectral reflectance measurements for accuracy in spectral analysis.
4	Dhangar, Vijay	Exploring the Spectral Database of Food Samples Using ASD Field Spec 4 Spectroradiometer	2024	Spectral analysis of food samples using ASD Field Spec 4 for quality assessment.
5	Maid & Deshmukh	Statistical analysis of WLR (wheat leaf rust) disease using ASD FieldSpec4 spectroradiometer	2018	Remote sensing-based detection of wheat leaf rust disease.
6	Fang et al.	Machine Learning-Based Crack Detection Methods in Ancient Buildings	2024	Machine learning techniques for detecting cracks in ancient structures.
7	Jiang et al.	Explainable AI for ancient architecture and lacquer art	2023	AI-based interpretation of ancient architectural and artistic materials.
8	Fais et al.	Non-destructive diagnosis of architectural elements of ancient historical buildings	2018	Innovative non-destructive techniques for analyzing ancient structures.
9	Wei et al.	Application of advanced analytical techniques in organic cultural heritage	2022	Use of advanced analytical methods in preserving ancient architecture.
10	Ye	Machine Learning Algorithm for Repair Materials in Ancient Ceramics via Additive Manufacturing	2025	AI-based repair material development for ancient ceramics.
11	Xin et al.	Non-destructive evaluation of ancient timber properties using ML	2022	Machine learning for evaluating density and strength of ancient wooden structures.
12	Perumal & Venkatachalam	ML-based automated crack detection in ancient monuments	2024	Image processing for automated detection of cracks in heritage sites.

No.	Author(s)	Title	Year	Key Focus
13	Santhanam et al.	Characterisation of ancient mortar in Chettinadu house, Tamil Nadu	2021	Analysis of traditional mortar composition in heritage structures.
14	Smith & Mohanty	Ancient Composite Materials: Experimental study on Artificial Laterite	2017	Experimental reconstruction of ancient composite materials in Odisha.
15	Ray & Chakrabarti	Studies in ancient Indian technology and production: A review	1975	Review of ancient Indian technological advancements and production methods.
16	Reddy et al.	Ancient Indian Plasters and Mortars: A Review on Traditional Organic Composites	2022	Study of organic components in ancient Indian construction materials.

Table 2.1 Literature survey

3. Problem Statement

- Traditional methods for identifying materials in ancient structures are invasive, time-consuming, and may cause.
- Hyperspectral non imagining data offers a nondestructive alternative but presents challenges in data processing, interpretation, and distinguishing between similar materials.
- There is a lack of comprehensive spectral libraries specifically tailored for ancient construction materials.
- Advanced analytical models and machine learning techniques are needed to effectively classify and identify materials from hyperspectral non imaging data.

4. Objectives

- To study the spectral data of materials used in ancient structures.
- To create a comprehensive spectral library for ancient materials.
- To analyze the spectral data.
- To develop a machine learning model that can accurately identify materials.

5. Ancient Structure Buildings

Ancient structures are a testament to the creativity, engineering skills, and cultural values of past civilizations. These buildings were constructed using a variety of materials and techniques, depending on the civilization, geographical location, and the purpose they served.

Based on their function and design, ancient structures can be classified into several types:

5.1 Megalithic Structures (Prehistoric & Early Civilizations):

Megalithic structures are among the earliest forms of ancient architecture, built using large stones or "megaliths." These structures were primarily constructed during prehistoric times and early civilizations. Examples include stone circles, dolmens, and menhirs. Megalithic structures were often used for religious, ceremonial, or burial purposes. For instance, Stonehenge in England and the Dolmens of Antiquary in Spain are iconic examples. These structures were built using massive stones, carefully arranged without the use of mortar, showcasing the advanced knowledge of early builders in handling heavy materials.

5.2 Religious & Temple Structures:

Religious and temple structures were built to honor deities, serve as places of worship, and reflect the spiritual beliefs of a civilization. These buildings often feature intricate carvings, grand designs, and symbolic elements. Examples include the Egyptian pyramids, Greek temples like the Parthenon, and Indian temples such as those in Khajuraho and Hampi. These structures were constructed using durable materials like stone, marble, and limestone, often decorated with sculptures and inscriptions. They were designed to inspire awe and devotion, and many have survived for centuries due to their robust construction.

5.3 Palaces & Forts:

Palaces and forts were built to serve as residences for royalty and as centers of power and administration. These structures were often grand and luxurious, reflecting the wealth and status of the rulers. Examples include the Palace of Versailles in France, the Red Fort in India, and the Forbidden City in China. Forts, on the other hand, were built for defence and protection, often featuring thick walls, watchtowers, and strategic designs. The Great Wall of China and the

Mehrangarh Fort in India are notable examples. These structures were built using materials like stone, brick, and wood, with a focus on durability and security.

5.4 Civic & Public Buildings:

Civic and public buildings were constructed to serve the community and facilitate public activities. These include amphitheaters, baths, markets, and government buildings. The Roman Coliseum and the Baths of Caracalla are famous examples of such structures. These buildings were designed to accommodate large gatherings and were often built using materials like concrete, stone, and marble. They reflect the social and cultural life of ancient civilizations and their emphasis on public welfare and entertainment.

5.5 Residential Structures:

Residential structures were built to provide shelter and living spaces for people. These ranged from simple huts and houses to more elaborate villas and mansions. In ancient times, residential buildings were constructed using locally available materials like mud, clay, wood, and stone. For example, the Pueblo dwellings in North America and the courtyard houses of ancient China and Rome are notable examples. These structures were designed to meet the daily needs of the inhabitants and often reflected the local climate and culture.

5.6 Defensive Structures:

Defensive structures were built to protect cities, settlements, and empires from invasions and attacks. These include city walls, fortresses, and castles. Examples include the Walls of Constantinople, the Castles of Medieval Europe, and the Kumbhalgarh Fort in India. These structures were designed with strategic features like moats, drawbridges, and battlements to withstand enemy attacks. They were built using strong materials like stone and brick, with a focus on strength and durability.

6. Application Areas of Hyperspectral Imaging

Hyperspectral imaging is a powerful technology that captures and analyzes the spectral signatures of objects across a wide range of wavelengths. This technology has a wide range of applications across various fields due to its ability to provide detailed information about the composition and properties of materials.

6.1 Geology and Mining

Hyperspectral imaging is extensively used in geology and mining for mineral exploration, mapping, and analysis. By analyzing the spectral signatures of rocks and minerals, geologists can identify the composition of the Earth's surface and detect valuable mineral deposits. This technology helps in:

- Identifying and mapping mineral resources like gold, copper, and iron ore.
- Studying soil composition and detecting contaminants.
- Creating detailed maps of rock formations and geological features.
- Optimizing mining operations by identifying high value areas and reducing environmental impact.

For example, hyperspectral imaging has been used to detect rare earth elements and map large-scale geological formations, making it a valuable tool for the mining industry.

6.2 Defence

In the defence sector, hyperspectral imaging is used for surveillance, target detection, and reconnaissance. Its ability to detect subtle differences in spectral signatures makes it ideal for identifying camouflaged objects or hidden threats.

- Identifying military vehicles, equipment, and personnel, even in camouflaged conditions.
- Monitoring borders and sensitive areas for unauthorized activities.
- Gathering detailed information about terrain and enemy positions.
- Identifying hazardous materials or chemical agents in the environment.

For instance, hyperspectral imaging can detect hidden landmines or identify chemical spills, making it a critical tool for military and security operations.

6.3 Environmental Monitoring

Hyperspectral imaging plays a crucial role in environmental monitoring by providing detailed data about ecosystems, pollution, and natural resources.

- Assessing vegetation health, detecting deforestation, and monitoring biodiversity.
- Detecting pollutants, algae blooms, and sedimentation in water bodies.
- Monitoring glaciers, ice caps, and changes in land use over time.
- Assessing damage after natural disasters like floods, earthquakes, or wildfires.

For example, hyperspectral imaging can detect oil spills in oceans or monitor the health of coral reefs, helping environmentalists take timely action to protect ecosystems.

6.4 Agriculture

In agriculture, hyperspectral imaging is used to improve crop management, monitor plant health, and optimize yields. It provides valuable insights into soil conditions, plant stress, and nutrient levels.

- Detecting diseases, pests, and nutrient deficiencies in plants.
- Assessing soil moisture, fertility, and composition.
- Optimizing the use of water, fertilizers, and pesticides to increase crop yields.
- Estimating crop yields based on vegetation health and growth patterns.

For instance, hyperspectral imaging can identify areas of a field that need more irrigation or detect early signs of plant diseases, enabling farmers to take preventive measures.

6.5 Material Science

In material science, hyperspectral imaging is used to analyze the composition, quality, and properties of various materials. It is particularly useful in industries like manufacturing, construction, and archaeology.

- Identifying and classifying materials based on their spectral signatures.
- Detecting defects or impurities in manufactured products.
- Analyzing ancient artifacts and paintings to identify materials and detect damage.
- Assessing the condition of building materials like concrete, bricks, and metals.

For example, hyperspectral imaging can be used to study ancient structures, identify the materials used in their construction, and plan restoration efforts without causing damage.

7. Most Common Materials Include

7.1 Stone

- **Limestone**: Used in structures like the Egyptian Pyramids and Bibi Ka Maqbara.
- Sandstone: Used in Indian temples and forts.
- Granite: Used in South Indian temples (e.g., Brihadeeswara Temple).
- Marble: Used in the Taj Mahal and Mughal architecture.

7.2 Bricks & Clay

- Sundried (mud) bricks:Used in Mesopotamian structures.
- Fired bricks:Used in Indus Valley Civilization (MohenjoDaro, Harappa).
- Terracotta:Used in Chinese and Indian architecture.

7.3 Mortar & Binding Agents

- Lime Mortar:A mix of lime, water, and sand, used in many historical buildings.
- Mud Mortar: Used in ancient Indian and Mesopotamian structures.
- Gypsum Plaster:Used in Egyptian pyramids.

7.4 Natural Additives

- **Bel fruit (Wood apple pulp):** Used in Bibi Ka Maqbara construction.
- **Jaggery (Unrefined sugar):** Added to mortar for strength.
- **Ambada Vegetable (Roselle plant extract):** Used as a binding agent.
- **Udid Dal (Black gram paste):** Added for durability in Indian structures

8. Data collection

These materials were chosen for their natural adhesive, binding, and waterproofing properties, making them essential in ancient construction techniques.

- **Bel – Fruit (Aegle marmelos)**
    - The pulp of the Bel fruit, when mixed with other materials, acts as a natural binding agent due to its sticky and adhesive properties. It was used in ancient times to strengthen mortar or plaster.
- **Jaggery (Saccharum officinarum)**
    - Jaggery, when mixed with lime, enhances the binding properties of mortar. It also acts as a retardant, slowing down the setting process, which was useful for largescale construction projects.
- **Ambada Vegetable (Hibiscus sabdariffa)**
    - The extract from the Roselle plant contains mucilage, which acts as a natural adhesive and waterresistant agent. It was used to improve the durability and waterproofing of construction materials.
- **Udid Dal (Vigna mungo)**
    - Black gram paste, when mixed with lime, acts as a strong binding agent and improves the plasticity and strength of mortar. It was commonly used in ancient Indian construction for its durability and resistance to weathering.

9. Tools/Devices

9.1 ASD Field Spec 4 (Analytical spectral device)

ASD fieldspec4 spectroradiometer over 25 years ago the ASD develop the science of field and lab spectroscopy and world's most trusted field and lab spectrometers. These instruments are also used for many remote sensing applications including crop, plant, vegetation climate, snow, soil analysis, mining material analysis, defence sector, analysis of environmental conditions, material quality analysis etc. ASD field spec 4 spectroradiometer can measure radiant energy (radiance and irradiance).

ASD spectroradiometer is the learning of interaction among the physiochemical features and spectral signature features of object. ASD field spec 4 spectroradiometer finds more information and the best spectroradiometer in the field spec line according to the needs. ASD spectroradiometer have been used in detection, identification, verification and quantification of object. This device is having three distinct detectors: UV/VNIR range (3001000), for the SWIR1 range (1,000–1,800 nm) and the SWIR2 range (1,800–2,500 nm).

Fig. 9.1 Dark room setup of ASD Field Spec 4

9.2 RS^3 Software

RS^3 (pronounced "RS cubed") is a spectral acquisition software developed by ASD Inc., designed primarily for field use with ASD's portable spectroradiometers, such as the Field Spec 4 series. This software enables continuous data collection and is particularly suited for applications like ground trothing, glacial studies, largescale mapping, and pollution research. When paired with appropriate calibration files, RS^3 facilitates the realtime collection of absolute reflectance and radiometric measurements. It offers a userfriendly interface compatible with Windows operating systems, allowing for efficient data collection, storage, and display. For postprocessing and analysis of the collected spectral data, ASD provides the View Spec Pro software, which complements RS^3 by offering advanced data visualization and interpretation tools.

For collection of spectral signature we use RS^3 software. When we start RS3, splash screen appear as shown in following figure. There should be WiFi connectivity or Ethernet connectivity.

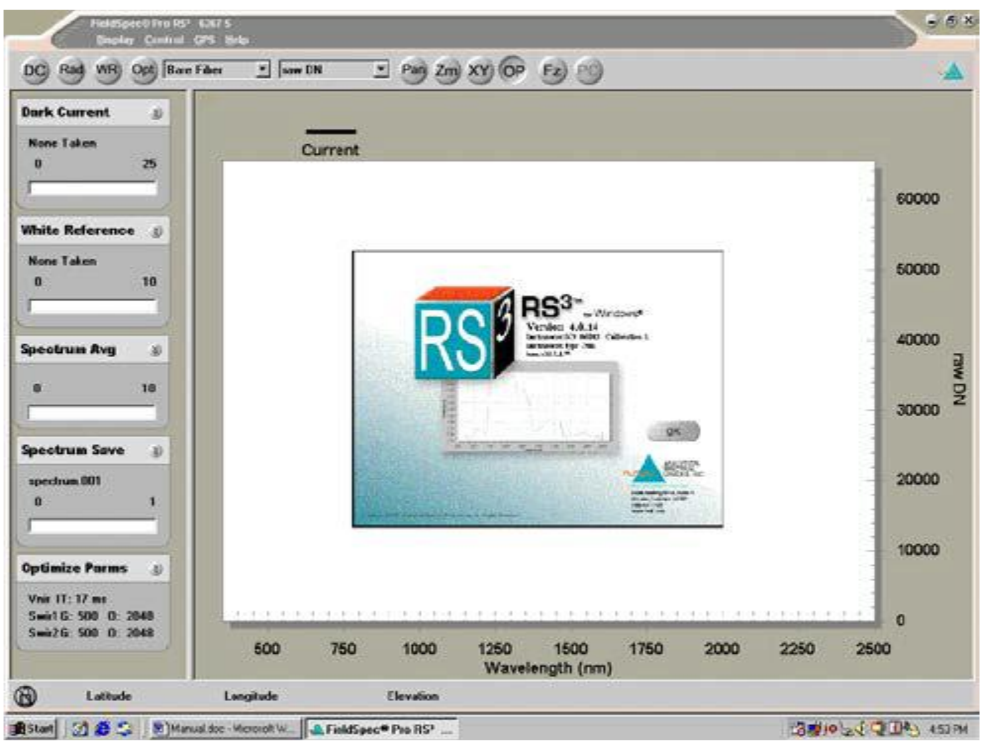


Fig. 9.2 RS^3 Software

In fig, we can see the straight line, this means 100% light is reflected back and that reflected energy is captured by the spectroradiometer.

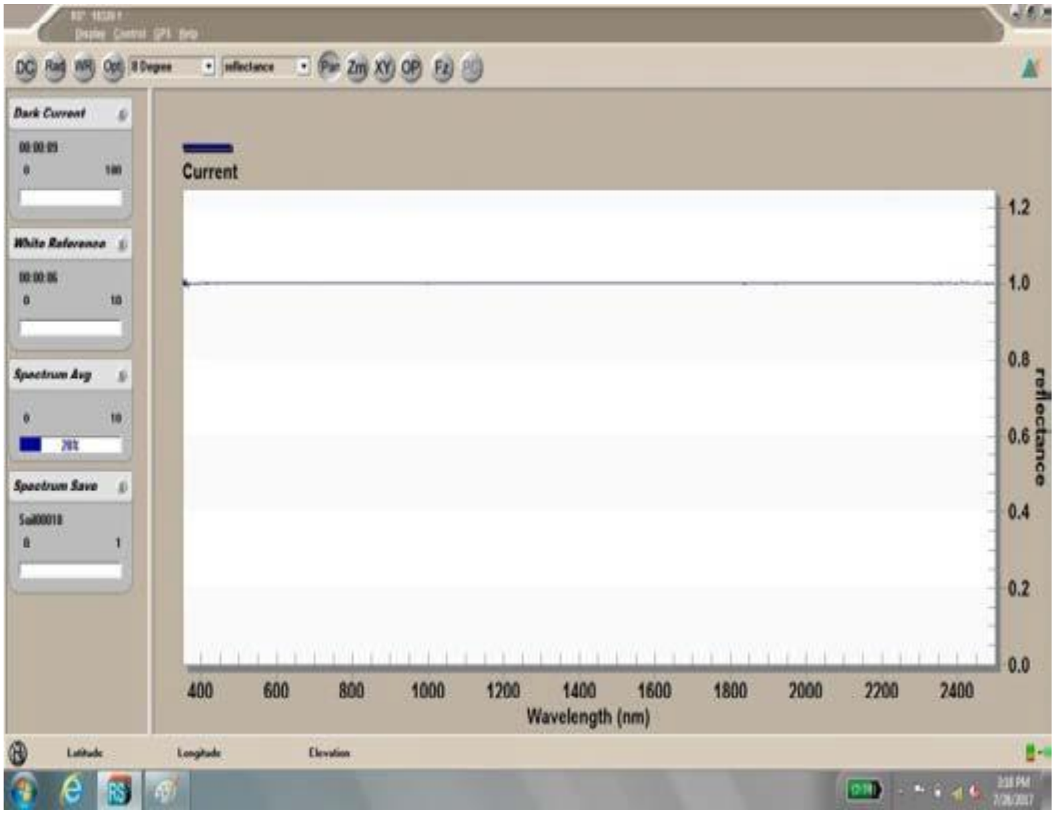


Fig. 9.3 Initialize Dark Current

White reference is also called as 'baseline'. We know the property of white surface, total energy incident on white surface will be reflected back in environment. So the white reference is the calibration or reference panel which gives the 100 percent reflectance of incident illumination to calibrate the target reflectance. When spectral in lab data is collected or in the field, it is necessary to take white reference reading after every 10 to 15 minutes for better reflectance spectra.

9.3 View Spec pro

View Spec Pro is post processing software developed by ASD Inc. for analyzing spectral data collected with ASD instruments. It allows users to visualize, process, and interpret spectra files saved during data acquisition. The software can be launched directly from the RS³ software via the "Control" menu or by clicking the View Spec Pro desktop icon.

9.3.1 Features of View Spec pro:

- ViewSpec Pro provides tools to display spectral data graphically, enabling users to examine spectral features and assess data quality.
- The software offers functionalities such as averaging multiple spectra, applying splice corrections, and performing other spectral manipulations to prepare data for analysis.
- Designed to work seamlessly with ASD's RS³ software, ViewSpec Pro ensures a smooth transition from data collection to post processing.

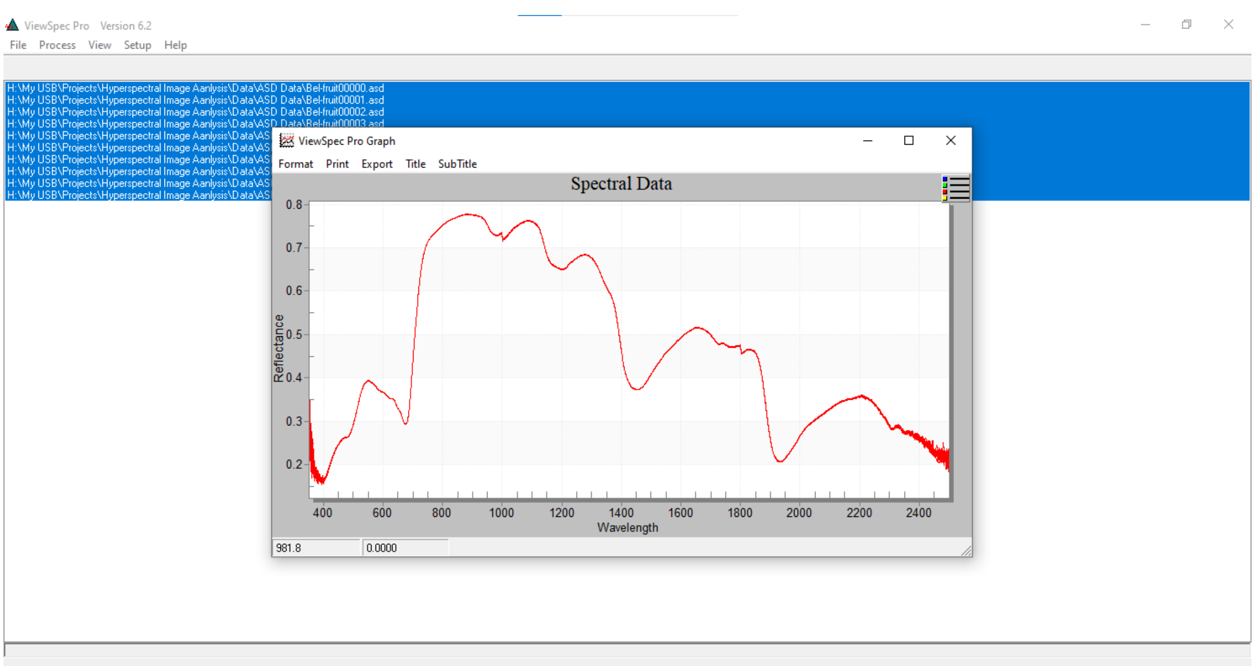


Fig. 9.4 View Spec Pro interface of spectral signature

10. Methodology

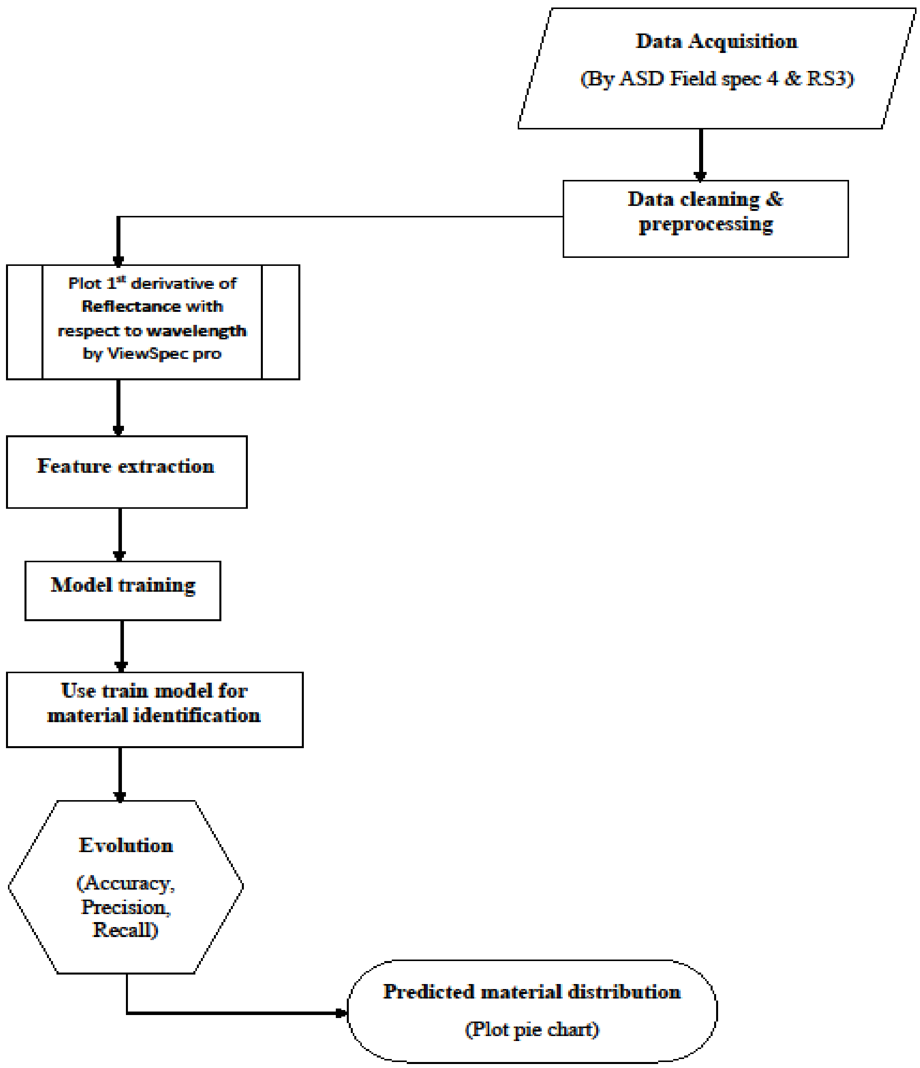


Fig. 10.1 Methodology of ML model

10.1 Data Acquisition

The first step in this research was to collect data. We used a device called ASD Field Spec 4, which is a spectroradiometer. This device measures the light reflected or absorbed by materials across different wavelengths. We also used RS³software to record and process the data. The data collected included the spectral signatures of materials like limestone, and natural additives like belfruit, ambada vegetable, jaggery, udiddal.

After collecting ASD data, we converted it into ASCII binary format for model training. This conversion ensured that the data was efficiently structured and compatible with our machine learning algorithms.

10.2 Data Cleaning and Preprocessing

The raw data collected from the spectroradiometer had some noise and saturation. To make the data usable, we cleaned it by removing unnecessary information and correcting errors. We also normalized the data to ensure consistency. This step is important because clean data leads to better results in the analysis.

10.3 Plot 1st derivative of reflectance with respect to wavelength

An essential step in the analysis was plotting the first derivative of reflectance with respect to wavelength. This technique enhances feature extraction by highlighting subtle variations in spectral reflectance and absorbance patterns. By analyzing these firstderivative spectra, we could better distinguish materials based on their unique spectral characteristics, ultimately improving the accuracy of our classification model.

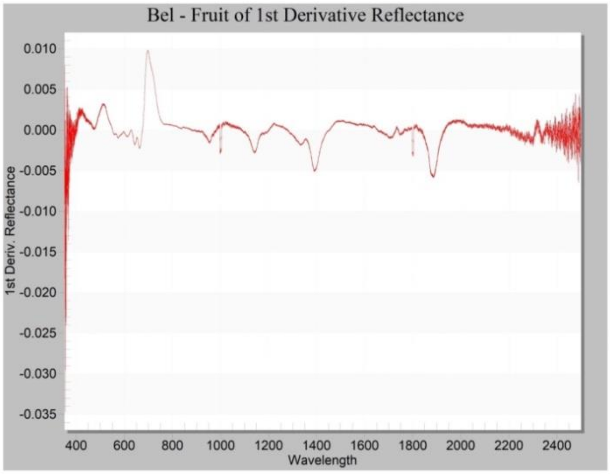


Fig.10.2 1st Derivative reflectance of Bel Fruit

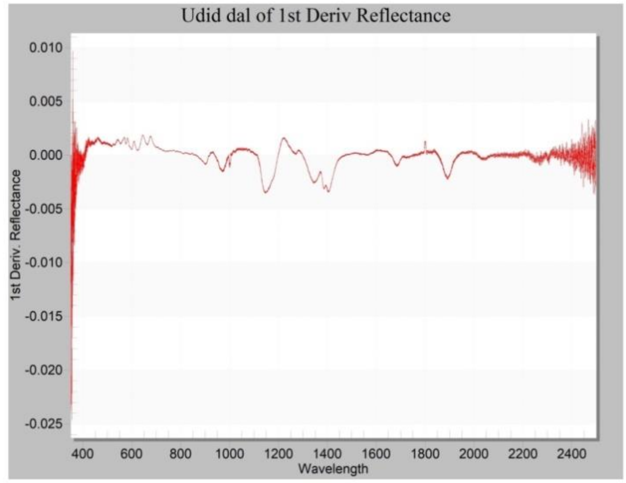


Fig.10.3 1st Derivative reflectance of Udid dal

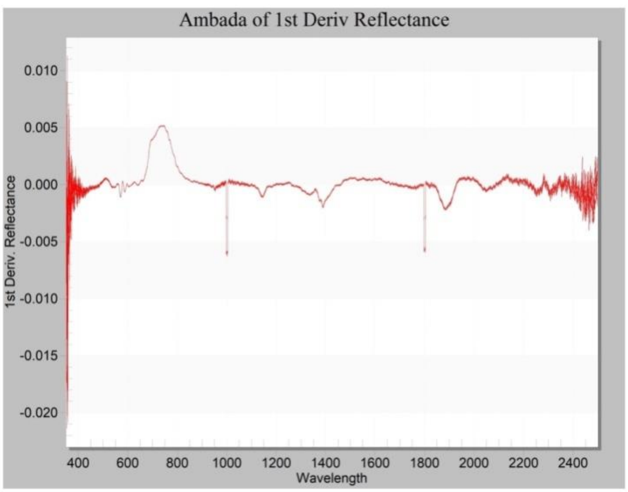


Fig.10 1st Derivative reflectance of Ambada

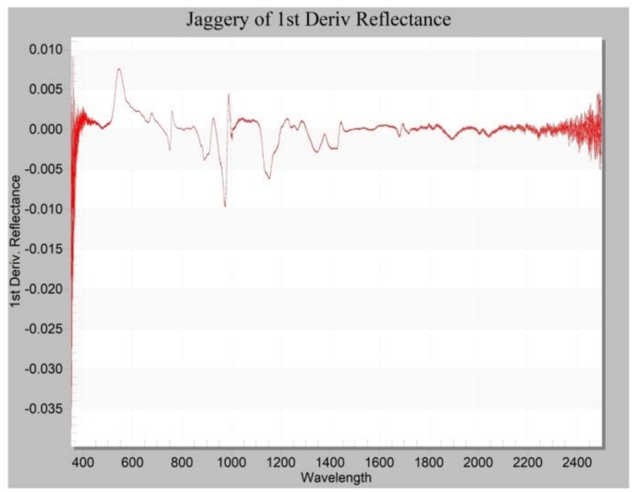


Fig.10.5 1st Derivative reflectance of Jaggery

10.4 Feature Selection

We selected the most significant features for analysis. Features are the key characteristics that help in accurately identifying materials based on their spectral properties. To achieve this, we used View Spec Pro software to plot the first derivative of the reflectance and absorbance spectra. This allowed us to pinpoint the specific wavelengths where each material exhibited unique spectral patterns. These distinct wavelength ranges were then used as input features for training the machine learning model.The table below presents the selected wavelength ranges for each material, which serve as distinguishing features:

Sr. No	Name of Data	Wavelength
1	Bel Fruit	600nm – 800nm, 1000nm – 1200nm, 1350nm – 1450nm, 1800nm – 1900nm.
2	Ambada Vegetable	650nm – 820nm, 1100nm – 1300nm, 1350nm – 1450nm, 1850nm – 2000nm.
3	Udid Dal	1300nm – 1450nm, 1800nm – 2000nm.
4	Jaggery	500nm – 650nm, 850nm – 1000nm, 1100nm – 1300nm.
5	Ancient Limestone	400nm – 2400nm.

Fig 10.1 Table of selected features

10.5 Model Training

We used the **Support Vector Machine (SVM)** model to classify the materials based on their spectral signatures. The model was trained using the hyperspectral data we collected, where it learned to recognize patterns and associate them with specific materials.

- **Feature and Label Selection:** Used X_train (training features) and y_train (corresponding labels) to train the model.
- **Kernel Selection:** Chose the **Radial Basis Function (RBF) kernel** (kernel='rbf' in SVC()) to effectively handle nonlinear relationships in hyperspectral data.
- **Regularization Parameter:** Set C=1.0 to control the tradeoff between achieving a low error and maintaining a simpler decision boundary. Higher values enforce stricter classification boundaries.
- **Gamma Adjustment:** Used gamma='scale', which automatically adjusts the influence of training samples on the decision boundary based on feature distribution.

10.6 Use train model for material identification

After training the **Support Vector Machine (SVM)** model, we tested its performance on unseen data to classify materials based on their spectral signatures. The trained model predicted the material types using the test dataset.

- **Generating Predictions:** The trained model predicted material labels using y_pred.
- **Decoding Labels:** Used label_encoder to convert numerical labels back into their original class names for easier interpretation (labels=label_encoder.classes_).

10.7 Evaluation Metrics

To evaluate the model's performance, we used key metrics such as accuracy, precision, and recall. The model achieved **93% accuracy**, indicating that it correctly classified materials in most cases. Precision measured how many of the predicted materials were actually correct, while recall assessed how many actual materials were successfully identified. Additionally, we used a confusion matrix to analyze the model's classification errors by visualizing true positives, false positives, and false negatives. This helped identify misclassifications and understand areas where the model could be improved. With high accuracy and a balanced precisionrecall tradeoff, the model demonstrated strong reliability in material identification, making it a valuable tool for analyzing hyperspectral data.

11. Workflow of developing spectral library

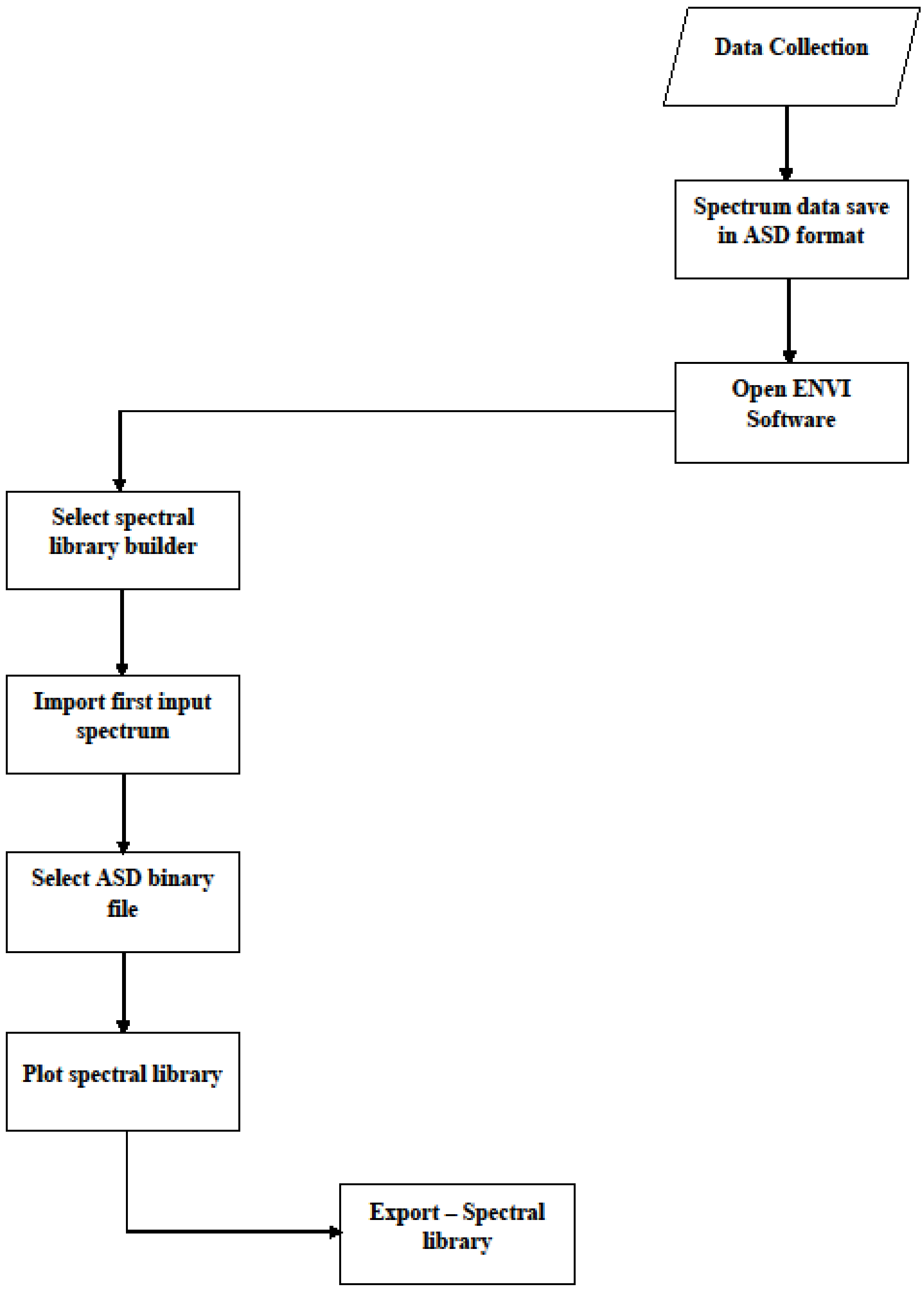
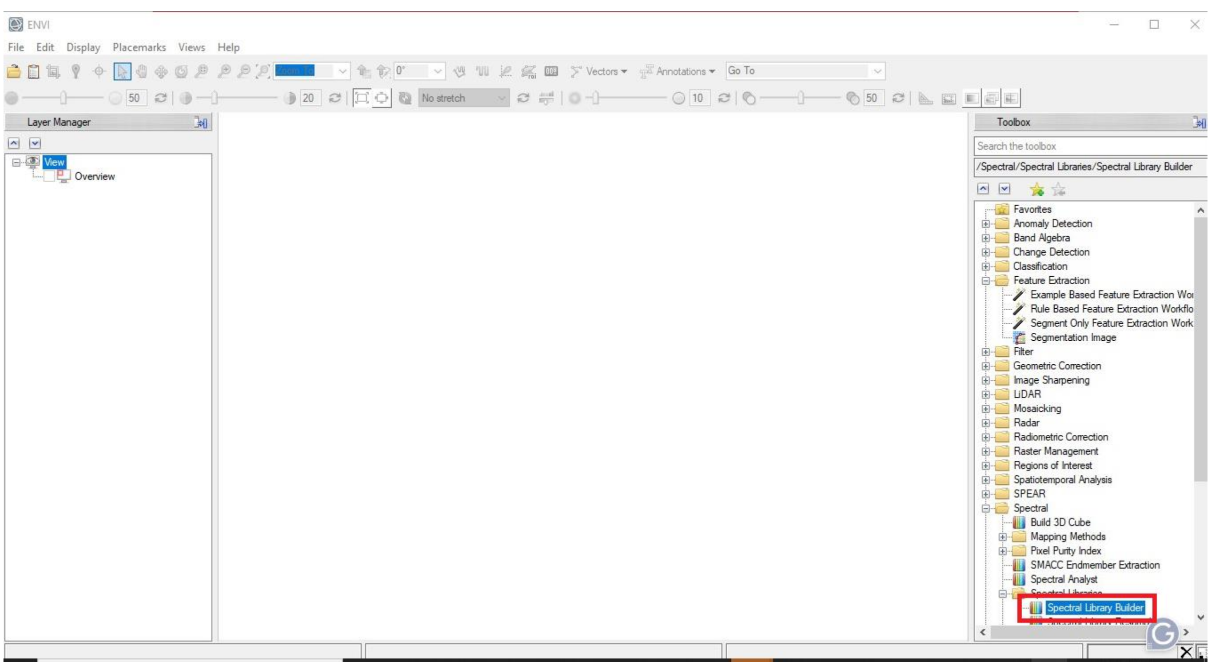


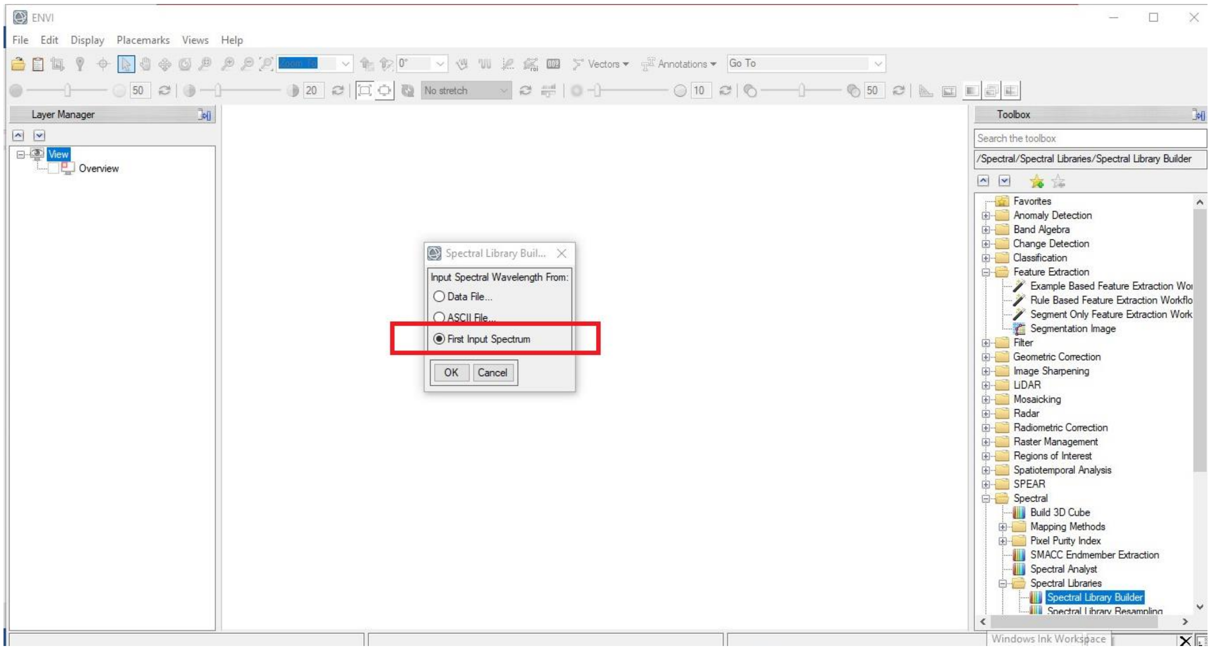
Fig. 11.1 Workflow of Spectral Library Builder

Step1: Open ENVI software

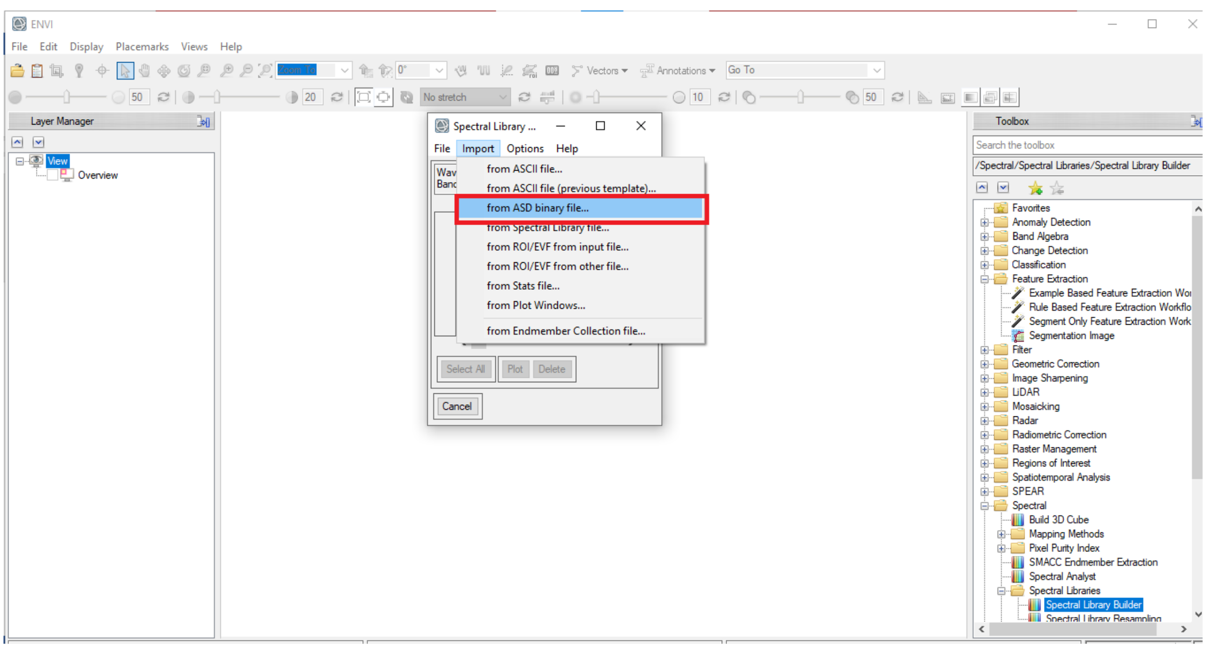
Step 2: Select Spectral Library Builder



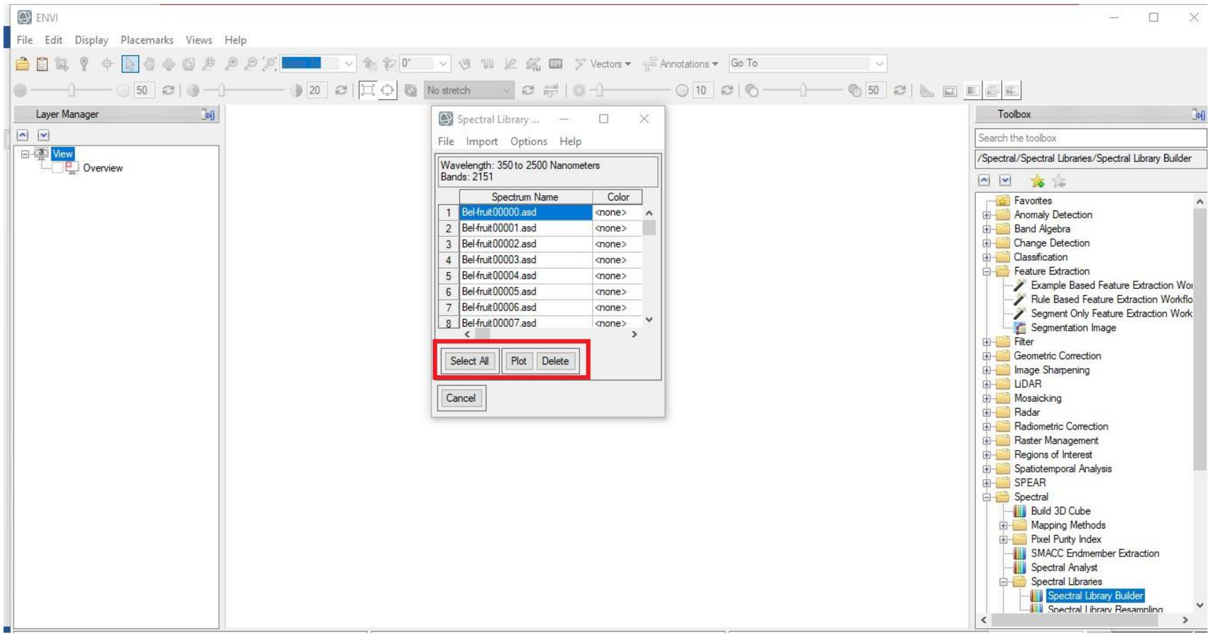
Step 3: Click on first input spectrum



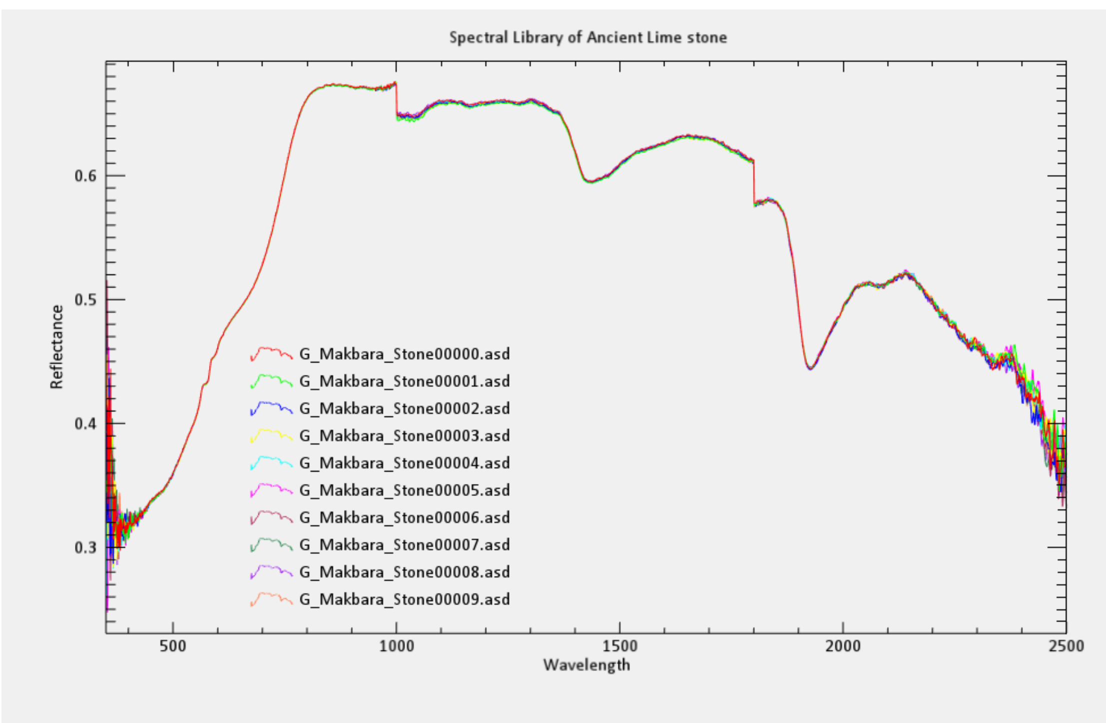
Step 4: Import ASD binary file



Step 5: Select all data samples



Step 6: Plot spectral Library (Bel – Fruit)



12. Results and Discussion

12.1 Predicted Material Distribution

The SVM model achieved **93.60%** accuracy in classifying materials within ancient structures. This high accuracy suggests the model's reliability in identifying the composition of these structures. The chart reveals that Ancient Limestone was the most prevalent material, comprising **53.6%** of the identified components, highlighting its dominance in the construction. Following Limestone, Ambada Vegetable constituted **14.9%**, indicating a significant, though lesser, presence. Bel Fruit and Jaggery were also notable components, representing **13.3%** and **11.3%** respectively, suggesting a diverse range of materials utilized. Lastly, Udid Dal was identified as the least common material, accounting for only **6.9%** of the composition. This visual representation effectively communicates the relative proportions of each material, offering valuable insights into the construction practices and resource utilization of the ancient builders.

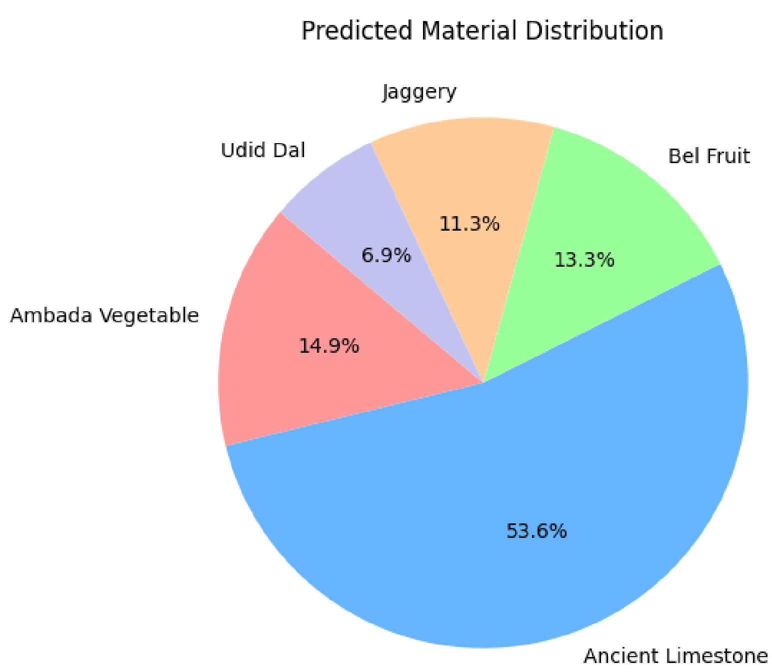


Fig.12.1 Material identified in the ancient structures.

12.1.2 Comparative study of ML algorithm

ML Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.5142	0.38	0.51	0.36
SVM	0.9360	0.94	0.89	0.91

Table 12.1 Comparison of ML model

12.1.2.3 Support vector machine

Class	Precision	Recall	F1-Score	Support
0	0.79	0.96	0.87	157
1	0.93	0.99	0.96	601
2	1.00	0.87	0.93	181
3	1.00	0.88	0.94	151
4	1.00	0.73	0.84	106

Table 12.2 Classification report of SVM

12.1.2.4 Logistic Regression

Class	Precision	Recall	F1-Score	Support
0	0.00	0.00	0.00	157
1	0.51	1.00	0.67	601
2	0.00	0.00	0.00	181
3	1.00	0.09	0.17	151
4	0.00	0.00	0.00	106

Table 12.3 Classification report of logistic regression

12.2 Confusion Matrix

This confusion matrix illustrates the performance of a classification model across five distinct classes, labeled 0 through 4. Organized as a 5x5 grid, the rows represent the true, or actual, classifications of the data, while the columns indicate the model's predicted classifications. The diagonal cells, such as the cell at (0, 0) containing 100, signify correct predictions – in this case, 100 instances were correctly identified as belonging to class 0. Similarly, the model accurately predicted 395 instances of class 1, 106 instances of class 2, 90 instances of class 3, and 55 instances of class 4. However, the offdiagonal cells reveal the model's errors. For example, 5 instances of class 0 were incorrectly predicted as class 1, and conversely, 5 instances of class 1 were misclassified as class 0, indicating some confusion between these two classes. Furthermore, 15 instances of class 2 and 11 instances of class 3 were both incorrectly predicted as class 1, suggesting a tendency to misclassify these classes. Class 4 appears to be the most challenging, with 14 instances misclassified as class 0 and 1 instance misclassified as class 1. Overall, the model demonstrates strong performance in predicting class 1, which may be due to its prevalence or distinct characteristics. Classes 2 and 3 exhibit moderate performance, while class 4 presents the most significant challenges, highlighting areas for potential model improvement.

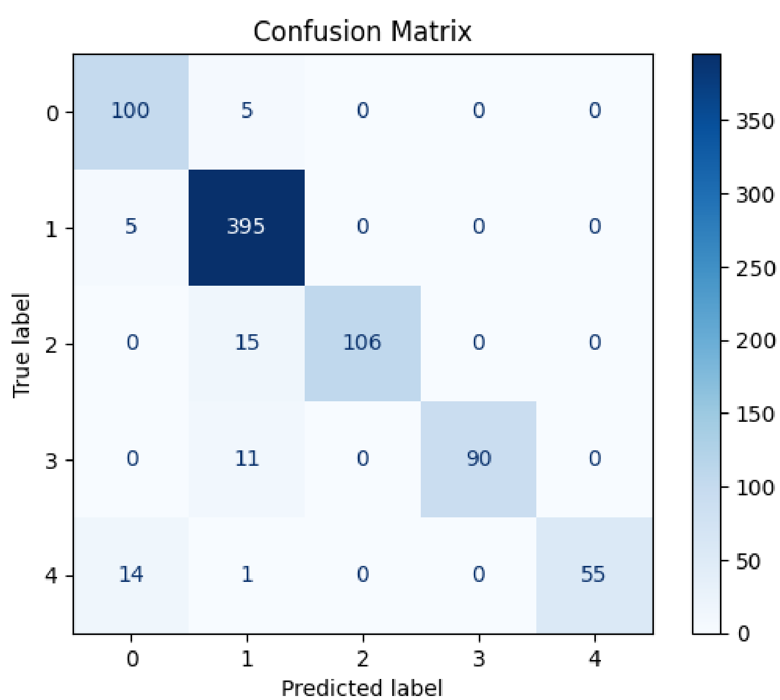


Fig 12.2 Confusion matrix of SVM model

12.3 Spectral Library Development

We created a spectral library that contains the spectral signatures of various ancient materials. This library is a valuable resource for future research. It can be used to identify materials in other ancient structures and improve the accuracy of material classification.

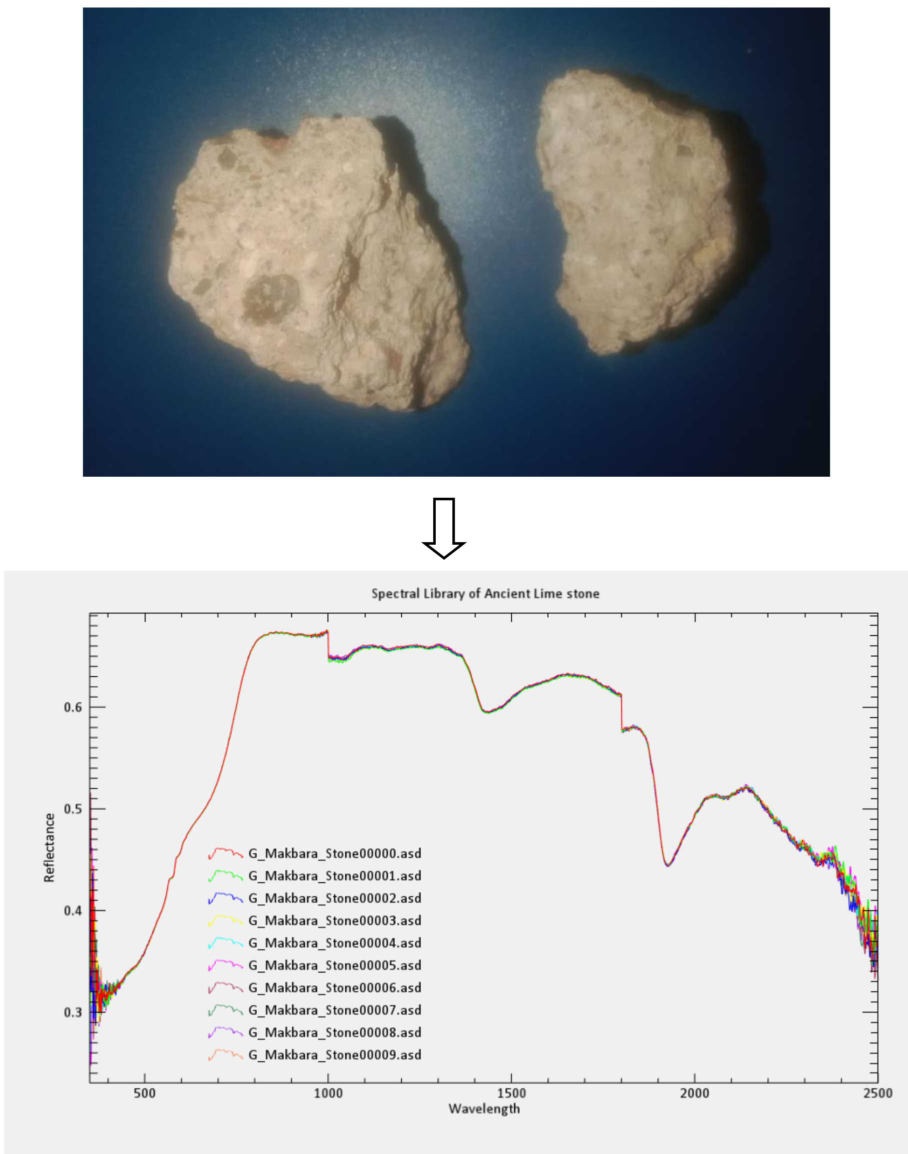


Fig.12.3 Spectral Library of Ancient limestone

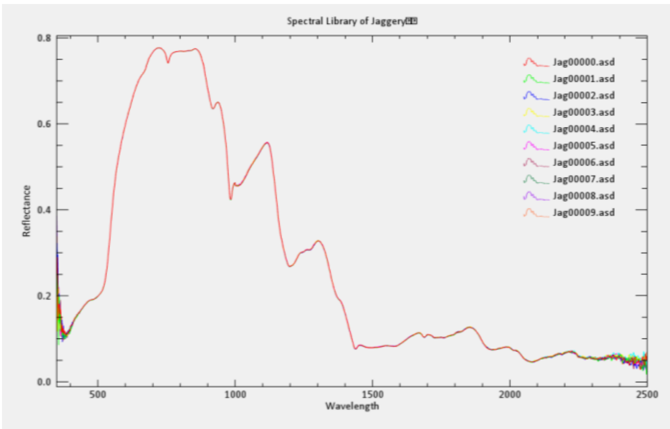


Fig.12.4 Spectral Library of Jaggery

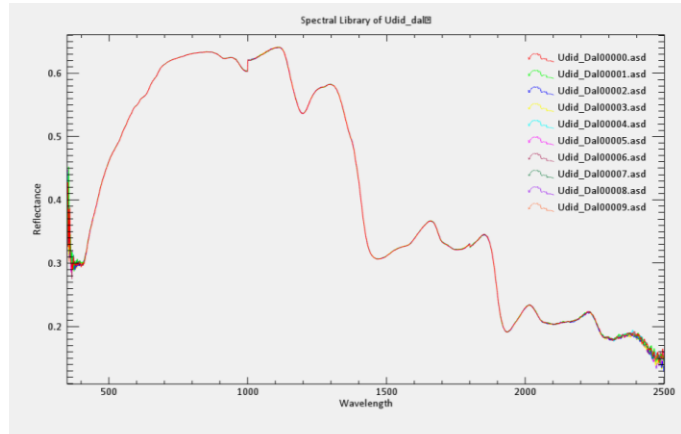


Fig.12.5 Spectral Library of Udid - dal

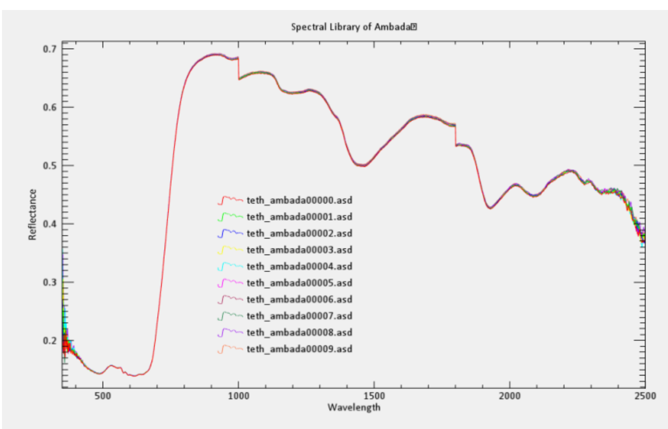


Fig.12.6 Spectral Library of Ambada

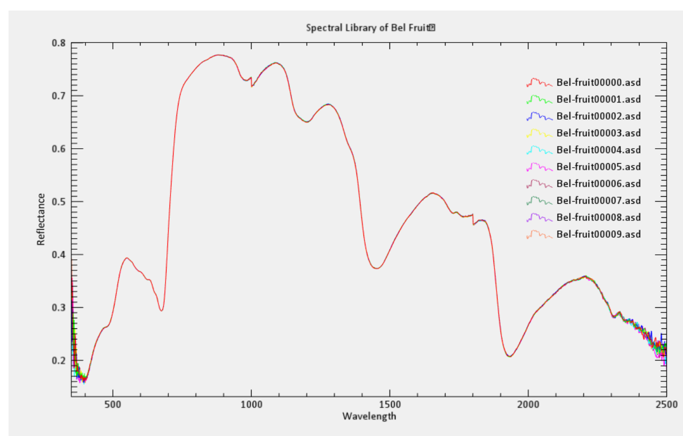


Fig.12.7 Spectral Library of Bel - Fruit

13. Conclusion

This research successfully demonstrates the potential of hyperspectral non imaging techniques and machine learning for revolutionizing the study and conservation of ancient structures. By achieving **93.60%** accuracy in material identification using an SVM model, the project validates the efficacy of this nondestructive approach, offering a significant advancement over traditional invasive methods. The development of a detailed spectral library for ancient construction materials, coupled with the ability to accurately classify these materials, provides a valuable resource for archaeologists, historians, and conservationists. The dominance of Ancient Limestone, as revealed by the pie chart, underscores its importance in the region's historical architecture, while the presence of natural additives like Bel Fruit, Jaggery, Ambada Vegetable, and Udid Dal highlights the ingenuity of ancient builders in utilizing locally available resources. Moving forward, this methodology can be expanded to analyze other ancient sites, refine the spectral library, and explore the use of advanced machine learning algorithms to further enhance accuracy. The ability to identify and map materials noninvasively opens new avenues for understanding the construction techniques, trade networks, and cultural practices of past civilizations, ultimately contributing to the preservation and appreciation of our shared heritage.

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