Farmland Mapping

An Engineering Project in Community Service

Phase – II Report

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Bonafide Certificate

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This project report (Phase II) is submitted for the Project Viva-Voce examination held on ..09/05/24

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Declaration of Originality

We, hereby declare that this report entitled **Farmland Mapping** represents our original work carried out for the EPICS project as a student of VIT Bhopal University and, to the best of our knowledge, it contains no material previously published or written by another person, nor any material presented for the award of any other degree or diploma of VIT Bhopal University or any other institution. Works of other authors cited in this report have been duly acknowledged under the section "References".

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1. INTRODUCTION

Agriculture is, without a doubt, one of the most significant factors in the sustainability of any economy. It plays a key role in long-term economic growth and structural transformation, though it may vary considerably by country. In the past, agricultural activities were limited to food and crop production. Nonetheless, they have evolved in several countries to the processing, marketing, and distribution of crops and livestock products. Currently, agricultural activities constitute the first source of livelihood, improving GDP, being a source of national trade, reducing unemployment, providing raw materials for production in other industries, and overall developing the economy. And one of the tools driving this agricultural change in today's time is Agricultural Mapping. Agricultural mapping is a precision agriculture technique that allows farmers to create detailed maps of their property. These maps usually contain land boundaries, locations of buildings, fences, gateways, and water pipes located on a farm. It helps farmers record the crops planted in different sections of their fields and details of operations that were carried out in those fields. Agricultural field mapping is an increasingly important way to both monitor farmland and manage future activities. It helps us understand and map different types of information including data regarding soil health and nutrition, slopes, water and irrigation systems. When done accurately, it enables farmers to employ different sustainable practices on their land which can be designed to maximize land use, increase productivity, use resources more efficiently and reduce potentially damaging activities. It also allows farmers to correct or modify current practices to increase sustainability and yield output.

1.1 Motivation

The issue is very common in India. The restricted focus on soil and water conservation as a solution to drylands is constraining national efforts to fight land degradation. [1] Drylands cover 228.3 million hectares of land in India (about 69.6%). According to the Space Application Centre, the total area undergoing land degradation in India is 105.48 million hectares, accounting for 32.07 percent of the country's total land area, while the area undergoing desertification is 81.45 million hectares, accounting for 24.78 percent of the country's geographical area [1].

Land suitability analysis (LSA) is a method of determining suitability levels for specific uses such as agriculture, plantation, recreation, settlement, industry, watershed management, and so on, based on social, physical, and economic factors such as slope, soil, relief, humidity, drainage, rainfall, and so on [1].

LSA is an interdisciplinary decision-making method. A variety of things influence the LSA decision-making process. As a result, several researchers have used an MCDM (Multi-criteria decision-making) based on a GIS (Geographic Information System) to conduct LSA to identify potential areas for various purposes such as agriculture and plantation, settlement, and so on [1].

The study's district, Anantapur, is in southern India, where the hot, humid weather and scant precipitation lead to groundwater shortages and generally deplorable socioeconomic circumstances. A large portion of this region's groundwater levels are dropping as a result of the aforementioned processes, land degradation, and including human effects. LSA investigations are therefore necessary. On the other hand, this study concentrated more on developing alternative thematic maps and less on analyzing the findings [1].

For LS analysis, the structure and recommendations of the Food and Agriculture Organization were followed and it was found that 23.79% of the land is “highly suitable”, 20.17% of the land is “moderately suitable”, while approximately 28.28% of the total area is calculated to be “marginally suitable” for forestation, approximately 23.20% is “not suitable” for forestation [2].

As we know, India has made significant progress in human development over the past 70 years. However, as per the Global Hunger Index 2022, India ranks 107th out of 121 countries, and the level of hunger and undernutrition in the country is now at “serious” levels. A staggering 214 million people suffer from chronic food insecurity, representing 17% of the country’s total population. One in three malnourished children in the world lives in India [3]. We have witnessed numerous cases of malnutrition resulting from crop failures in our country for an extended period. This issue serves as a driving force for us to develop a solution that empowers our farmers to map their farmland and utilize resources efficiently.

1.2 Objective

The objective of our project is to make a farmland mapping project which will take location data from users using a website. Then using that data, we will get soil pictures using maps and district names. Then using different data sets we can display the common crops grown there and also give them a few unique rare grown crops suitable for their location and soil type and rainfall type and such. We also aim to provide them links to articles and videos on how to grow such crops effectively. In order to make the application more practical and useful, we also aim to add language translation into our page so that all the necessary information can be translated into the local languages for easy understanding. So in the end, the user receives practical info on which they can earn more. Farmers often lack the resources and knowledge to understand what different and more profitable crops to grow based on their soil and weather conditions. They usually follow the common trend and grow crops accordingly without taking into consideration what’s good for them and their land in the long run. So our solution provides those practical insights and helps the user in understanding the need and process to grow different crops and increase their profits and efficiency.

2. EXISTING WORK

According to the author [4], agriculture is one of the focused fields of development in Indonesia. Various technologies in agriculture are developed to improve agricultural efficiency, effectiveness, and productivity. Information and communication technology (ICT) is used in the development of information systems for agriculture. Agricultural Information System (AIS) covers a variety of related systems, ranging from land preparation, systems for farmers' data collection, agricultural activities, systems for land management, agricultural activities, crop sales and purchase systems, learning systems for farmers and farmer groups. The development of AIS has done quite a lot in various regions in Indonesia, but most of the existing systems are local and not integrated. The development of information systems in agriculture has been carried out by a development team from the Information Technology Faculty (FTI) of Duta Wacana Christian University (UKDW) since 2016. To conduct research related to the development and application of Information Technology in agriculture, a study is first carried out to see the readiness of the Indonesian agricultural community in the use of Information Technology [5] and several applications in agriculture that have been carried out [6]. After that, an integrated SIP blueprint was developed by developing an Architecture Vision [7], Business Architecture [8], and defining integrated AIS stakeholders [9]. Besides, there are several systems developed, such as the Agricultural Portal [10], Farmer and Farmer Groups Information System [11], Farmers Activity Information System [12], and Information System of Agricultural Products' Purchases and Sales [10]. Three of the four systems developed are ready to be applied in the community. Three systems that have been developed can be accessed via the website at http://dutatani.id [10]. Along with the application of the three existing systems, the next stage of the research to be carried out is to develop a system for mapping of agricultural land and agricultural activities carried out by farmers. The development of this system was carried out because there were problems faced by farmer groups in processing land ownership data, seed requirements, and the estimated amount of agricultural productivity. The manual data processing makes it difficult for farmer groups to produce information related to land area, identification of needs, and level of agricultural production in their area. Indeed, information is needed for a variety of needs including agricultural quality assurance, preparing the needs of seeds, fertilizer, and other resources supporting the agricultural process [4].

To help farmer groups overcome the problem, a system for land mapping and data collection on agricultural activities was developed. This system is developed by the Rapid Application Development (RAD) method and is intended to produce spatial information related to land use and agricultural activities that are being carried out. The system is able to integrate various data and display information in spatial form. Therefore it facilitates the analysis process and helps agricultural stakeholders to understand the data. The use of RAD is based on the suitability of sequential and iterative or incremental model characteristics in the process of developing software prototypes. This method is also used in many studies, as in [13] [4].

According to the author [4], the results they found on, the Farm Land Web Mapping System that they developed have some strengths and weaknesses. This system provides information for farmers and management/representatives of farmer groups. This information will help farmers and farmer groups manage land ownership and land processing better. This information is shown on the dashboard that is provided in this system. The limitation of developing this system lies in the mapping of farmland fields formed on the Land Combined Map which covers areas that should not be included in agricultural areas. This is due to the use of Convex Hull Graham's Scan method on the online Google Maps which only detects the outermost point, while the inside will be missed. This can cause data to be biased [4].

According to the authors [14], New remote sensing technologies have been developed for producing paddy maps, or paddy mapping, using satellite images [15]. Satellite imagery sources are often free to access, offer wide spatial range over large geographic area, and cover high temporal resolution (e.g. one year round). Due to the multi-spectral nature of satellite images, various imagery indices have been proposed to differentiate crop areas from non-crop areas [16, 17]. However, these indices require extensive expert knowledge for hand-crafting and might be subjected to adversarial conditions [18]. Common image classifiers such as VGG (Visual geometry group) and InceptionNet, are however designed for classifying natural objects on RGB (Red, green and blue) images; and thus, often ill-perform on spectral images [19]. Recent domain-specific classifiers such as SVM (Support vector machine) [20] and CNN (convolutional neural network) [17] are developed but still do not consider complex dependencies between spectral channels and neglect temporal information [14].

Challenges of remote sensing in general and of satellite images in particular vary. First, while covering a large geographic area, satellite imagery often has relatively low spatial resolution, especially for older-generation sensors, which lead to inaccurate estimation of paddy areas. Second, satellite images often suffer from adversarial conditions such as cloud shadow or solar radiation [21]. Third, the images are often produced by polar-orbiting satellites with low sampling rate, which hinders around-the-clock applications. Last, but not least, existing spectral indices for identifying vegetation areas on satellite images were empirical in nature; and thus require further domain specific calibration and validation steps when applied to different geographical locations [14].

To overcome these problems, they leverage the advances of deep learning to enable accurate and robust mapping framework for paddy monitoring and planning applications. The multi-layered nature of deep learning architectures, in particular deep neural networks, will enable to capture multispectral information of satellite images in both spatial and temporal dimensions [22]. Their approach is orthogonal to domain-specific spectral indices by the fact that the proposed deep neural network learns paddy features directly from the input data, regardless of with or without hand-crafted features. They have applied their approach to the case study data of Landsat 8 satellite system due to its state-of-the-art imagery sensors [23] and high spatial resolution (30m geo-precision) [14].

In the [14] paper the authors have proposed a novel remote-sensing rice mapping framework by leveraging spatial, spectral, and temporal information of satellite images simultaneously. The framework consists of two main components: streaming data processing to collect and clean-up raw image data against adversarial conditions of satellite imagery, and multi-temporal high-spatial resolution rice mapping using deep learning architectures to automatically capture rice and paddy features without domain-specific spectral indices for more accurate and robust 'rice' pixel classification. The empirical evaluations highlight that their techniques outperform the baselines with over 0.93 F1-score [14].

According to the authors [24], with the popularity of accessible satellite data, many studies have achieved certain results in the use of remote sensing data to extract farmland spatial distribution information [25,26,27,28,29,30]. Moreover, with the increase of the spatial resolution, the basic unit of farmland mapping is also converted from pixel to object [31]. Compared with the pixel-oriented method, the object-oriented method has obvious advantages in extracting ground information from high-resolution remote sensing images [32,33,34]. However, precise farmland spatial distribution mapping in complex scenes is still a quite challenging task [24].

2.1 Literature Review

In this chapter, we are going to focus on discussing the results or findings based on the article, journals, or any other related reference material. Some original words from the reference material may be cited in order to enhance the review. The purpose of this chapter is to explain about the selected project.

Basically, it is divided into a few subsections as well. Those sub-sections include a little explanation of basic concepts of the selected project, research of some already existing similar problem or solution done by others and the hardware, technique or method which will be applied or used in the selected project.

This chapter explains in detail regarding the techniques/method/hardware or technologies which are suitable to be adapted into the project. This chapter contains information about the study of the project in general.

2.1.1 Agricultural Mapping

Agricultural mapping involves the systematic analysis and visualization of spatial data related to agricultural activities, land use, and crop health. By leveraging advanced technologies such as satellite imagery, drones, and geographic information systems (GIS), agricultural mapping enables farmers, researchers, and policymakers to gain valuable insights into crop distribution, soil characteristics, irrigation patterns, and land productivity. Through the creation of detailed maps and spatial datasets, agricultural mapping facilitates informed decision-making in areas such as crop planning, resource allocation, pest management, and sustainable land use practices. By integrating geospatial analysis with agronomic knowledge, agricultural mapping plays a crucial role in enhancing crop yields, optimizing resource utilization, and promoting environmental stewardship in modern agriculture.

2.1.2 Land Degradation

Land degradation refers to the deterioration of land quality and productivity due to various natural and anthropogenic factors. It encompasses processes such as soil erosion, desertification, deforestation, salinization, and contamination, leading to the loss of soil fertility, biodiversity, and ecosystem services. Land degradation poses significant challenges to sustainable land management, agricultural productivity, and food security, particularly in regions prone to environmental degradation and climate change impacts. Addressing land degradation requires concerted efforts to implement land conservation measures, promote sustainable land use practices, restore degraded ecosystems, and mitigate the drivers of land degradation, including unsustainable agriculture, urbanization, and industrial activities. By combating land degradation, we can safeguard soil health, preserve biodiversity, mitigate climate change, and ensure the resilience and productivity of terrestrial ecosystems for present and future generations.

2.1.3 Land suitability analysis (LSA)

Land suitability analysis (LSA) is a comprehensive approach used to evaluate the appropriateness of land for specific uses or activities. It integrates various spatial datasets, including soil characteristics, topography, climate, land cover, and land use regulations, to assess the suitability of different areas for purposes such as agriculture, urban development, conservation, or infrastructure projects. By systematically analyzing and synthesizing spatial information, LSA helps decision-makers identify suitable locations for different land uses, taking into account environmental constraints, socioeconomic considerations, and development objectives. Through the generation of suitability maps and analysis results, LSA facilitates informed decision-making in land use planning, natural resource management, and sustainable development initiatives, contributing to the effective and responsible utilization of land resources.

2.1.4 Domain-Specific Classifier

A domain-specific classifier is a machine learning model or algorithm that is specifically designed and trained to perform classification tasks within a particular domain or application context. Unlike generic classifiers, which are trained on diverse datasets and may not capture domain-specific patterns effectively, domain-specific classifiers leverage knowledge and characteristics specific to the target domain to improve classification performance. These classifiers are tailored to handle the unique features, data distributions, and challenges present in the domain of interest, making them more effective for specialized tasks such as disease diagnosis, fraud detection, or sentiment analysis in specific industries or application areas. Domain-specific classifiers often incorporate domain knowledge, feature engineering techniques, and specialized training data to achieve higher accuracy and reliability in classification tasks within their designated domains.

2.1.5 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm widely used for classification and regression tasks. SVM works by identifying the optimal hyperplane that best separates data points into different classes in a high-dimensional space, maximizing the margin between the hyperplane and the nearest data points from each class, known as support vectors. It can handle both linearly and non-linearly separable datasets by utilizing kernel functions to map the input data into higher-dimensional feature spaces where separation is possible. In classification tasks, SVM aims to find a hyperplane that maximizes the margin, thereby enhancing robustness and generalization to unseen data. In regression tasks, SVM constructs a hyperplane that best fits the data points while minimizing the error between predicted and actual values. SVM's ability to handle high-dimensional data, flexibility with kernel functions, and resistance to overfitting make it suitable for various applications, including text categorization, image classification, bioinformatics, and finance.

2.1.6 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a class of deep neural networks commonly used for image recognition and classification tasks. CNNs are inspired by the visual cortex of the human brain and are designed to automatically and adaptively learn spatial hierarchies of features from raw pixel input. The key components of CNNs include convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply convolution operations to the input image, extracting features such as edges, textures, and shapes. Pooling layers reduce the spatial dimensions of the feature maps while preserving important information. Fully connected layers integrate the extracted features for classification or regression tasks. CNNs are known for their ability to learn hierarchical representations directly from raw data, their translational invariance, and their effectiveness in handling large-scale image datasets. They have revolutionized various fields, including computer vision, natural language processing, and medical image analysis, and are widely used in applications such as image recognition, object detection, and autonomous driving.

2.1.7 Geographic Information System (GIS)

Geographic Information Systems (GIS) are powerful tools used for capturing, storing, analyzing, and visualizing spatial or geographical data. GIS integrates various data sources, including satellite imagery, aerial photographs, and demographic data, into a single platform for analysis. GIS enables users to perform spatial analysis and modeling to gain insights into geographic patterns, relationships, and trends. It is widely used across various industries and sectors, including urban planning, natural resource management, environmental monitoring, transportation, public health, agriculture, and disaster management. GIS has diverse applications, including mapping, spatial decision support, and visualization, making it an indispensable tool for understanding and managing spatial data in today's interconnected world.

2.1.8 Bhashini API

Bhashini-Translation is designed to support the diverse linguistic landscape of India by following the ISO-639 series of language codes. This means you can easily translate content between various Indian languages with precision and accuracy.

1. ASR: Automatic Speech Recognition

Convert spoken language into written text effortlessly. Bhashini-Translation’s ASR functionality is perfect for applications that require voice-to-text conversion.

2. NMT: Neural Machine Translation

Translate text from one Indian language to another with ease. Our NMT feature employs advanced neural network models to ensure high-quality translations.

3. TTS: Text to Speech

Transform written text into spoken words. Customize your TTS output by choosing from different voices, including male and female options

4. ASR + NMT: Speech to Text Translation

Get the best of both worlds by transcribing spoken language in one Indian language and translating it directly into another. A powerful combination for multilingual applications.

5. NMT + TTS: Text Translation to Speech

Translate written text into another Indian language and convert it into natural-sounding speech. Tailor the voice to suit your preferences.

6. ASR + NMT + TTS: Speech to Speech Translation

Perform speech recognition, translation, and text-to-speech conversion in a single call. Ideal for complex language processing tasks.

3. TOPIC OF THE WORK

3.1 System Design / Architecture

- **Frontend:**
  Capture Coordinates: Using here maps javascript API to capture the coordinates of the map with appropriate zoom and utilizing javascript to determine the width and height of the captured area.
  Here Maps JavaScript API: Integrate the Here Maps JavaScript API to display satellite maps on the website and enable interactive functionalities.
  Location Search API: This maps location search API enables users to easily search for desired areas on the map.

- **Map Area Selection:**
  Develop functionality allowing users to delineate a farmland area on the map using four markers to form a rectangle.

- **Image upload**
  Soil Image Upload: Implement a feature enabling users to directly upload soil images for analysis.

- **Backend Processing:**
  Web Server: Utilize Flask, a color matching against known soil color requests and responses.
  Coordinate capture: We collect four coordinates to determine a bounding box, then calculate the centroid. This centroid, along with width, height, and zoom level, is used in a REST API request to download the corresponding image of the selected area.
  Dominant Color Extraction: Develop backend processes to extract the dominant color from the captured or uploaded images.
  Closest Soil Color Match: Calculate the Euclidean distance between the RGB (Red, green, and blue) values of the dominant color and predefined soil colors to determine the closest match.
  Output Display: Display the closest matched soil color on the website interface.

- **User Interface:**
  Design an intuitive and user-friendly interface for displaying maps, enabling area selection, uploading soil images, and presenting the results of soil color matching.

- **Bhashini API:**
  We will utilize Bhashini API to translate our web page into various different regional languages for ease of understanding for the farmers.

- **Optimization and Performance:**
  Implement optimization strategies to ensure efficient processing and response times.
  Consider implementing caching mechanisms for frequently accessed data to enhance overall system performance.

- **Testing and Validation:**
  Conduct comprehensive testing to ensure the reliability, accuracy, and functionality of the system.
  Validate the accuracy of soil color matching against known soil color references.

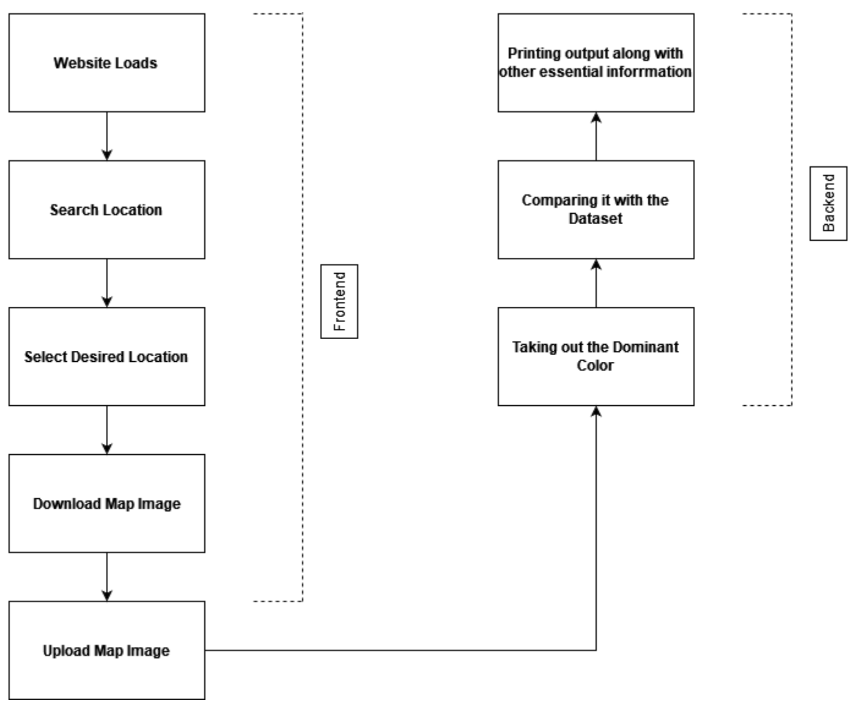

Fig1: Flowchart of the entire proposed system

3.2 Working Principle

The work proposed aims to plot the farmland area and analyze the soil color using satellite images with pinpoint accuracy. These satellite images mentioned are obtained from available APIs, and processed using suitable algorithms to segment the farmland into usable data and extract information about the various features of the soil, such as organic matter, nitrogen, potassium, pH, etc. The soil color is determined by comparing the RGB (Red, green and blue) values of the pixels

with Euclidean distance between them and then grouping them according to the similarity in color. The soil color is then matched to a stored database consisting of soil properties, such as water content, oxidation, and fertility, using Flask web framework and machine learning models.
The results obtained are displayed on a web interface, where the user can see the map of the farmland, the soil color, and the corresponding soil properties.

$$\Delta C_E = \sqrt{\Delta R^2 + \Delta G^2 + \Delta B^2},$$

$$\text{where } \Delta R = \frac{R_1 - R_2}{255},\ \Delta G = \frac{G_1 - G_2}{255},\ \Delta B = \frac{B_1 - B_2}{255}$$

Fig2. Euclidean Color Formula

Our system also has the ability to recommend suggested crops to the farmers according to the quality of the soil and the pH value of it. The pH value is an estimate and we are able to find the suitable crop for the farmer with it. We are able to do so with the help of a dataset which we have access to. In these dataset, we have access to various factors such as temperature, rainfall, pH and humidity. With all of this information, we can make an accurate prediction to suggest the type of crop which would be suitable for the farmer's land. We can use many different machine learning methods to predict the crop which we can grow. This includes K Nearest, Random Forest and Neural Networks.

temperature	humidity	ph	rainfall	label
20.87974371	82.00274423	6.502985292	202.9355362	rice
21.77046169	80.31964408	7.038096361	226.6555374	rice
23.00445915	82.3207629	7.840207144	263.9642476	rice
26.49109635	80.15836264	6.980400905	242.8640342	rice
20.13017482	81.60487287	7.628472891	262.7173405	rice

Fig3. Dataset for Crop Prediction

We have also implemented the system of pH of soil prediction. This can mainly be done using the RGB color codes for the soil. We have already been able to find the RGB color code. Using

DecisionTreeClassifier, we have found out the possible pH code. Upon testing, we received 97.2% accuracy which is quite good. Using the Forest Predict Model, we can find out pH of Soil using RGB values.

3.3 Results and Discussion

The proposed system enables us to successfully take an input image from the map. We have also successfully utilized map location searching API for easy searching of the given area. When we have found the desired area, we can select the area using the four markers and using appropriate zoom, width and height, to capture the image. Through advanced image processing techniques, the program extracts the dominant color(s) present in the soil. This dominant color is an RGB (Red, green and blue) value which we have successfully found out. We have then successfully implemented the concept of Euclidean Distance where we have found out the shortest value. We have then compared a database, which contains known soil samples with their corresponding dominant colors and associated information. The comparison involves implementing a matching algorithm that considers factors such as Euclidean distance or color similarity measures to find the closest match between the extracted color and those in the database. Once a match is identified, the program retrieves and outputs information about the soil type and its characteristics, such as fertility, texture, composition, and pH level. The expected results include accurate identification of the soil type based on color analysis, detailed information about the soil's attributes, and a user-friendly display of results. Additionally, the program should be capable of handling various challenges, including variations in lighting conditions and image quality, while maintaining accuracy. Regular updates to the soil color database can enhance the program's recognition capabilities for a broader range of soil types.We have also successfully predicted best crop to grow and found out the pH of soil with RGB value.

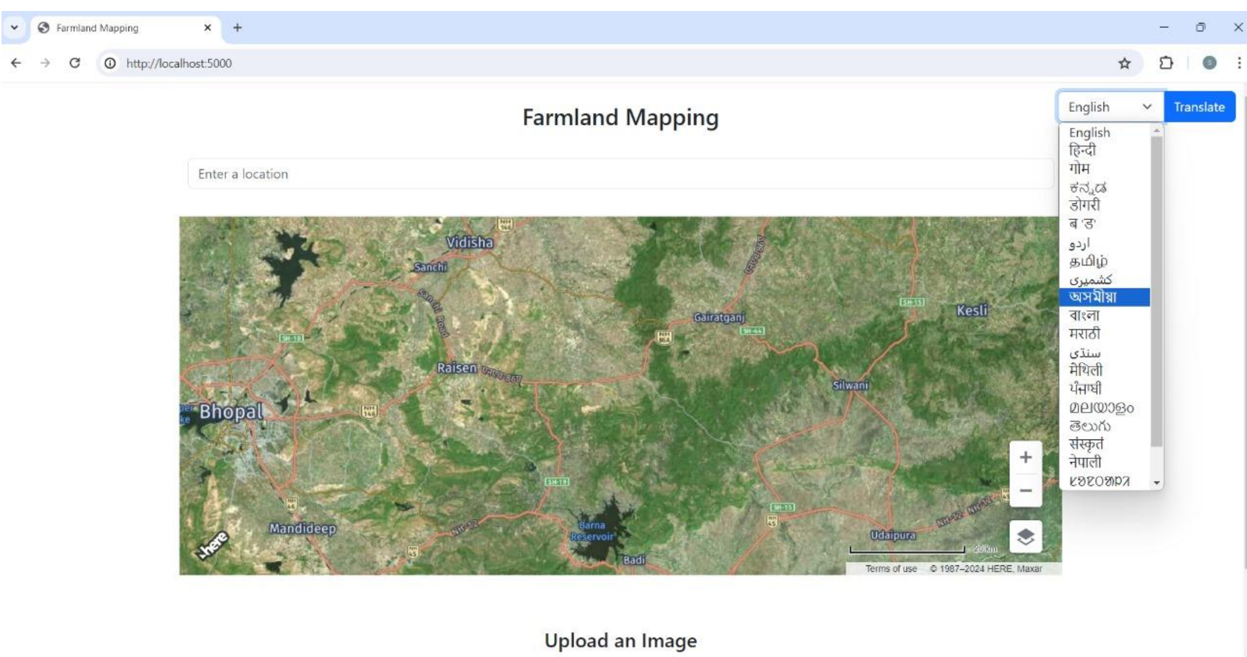

Fig3. Map API implementation and Upload Image with Translation

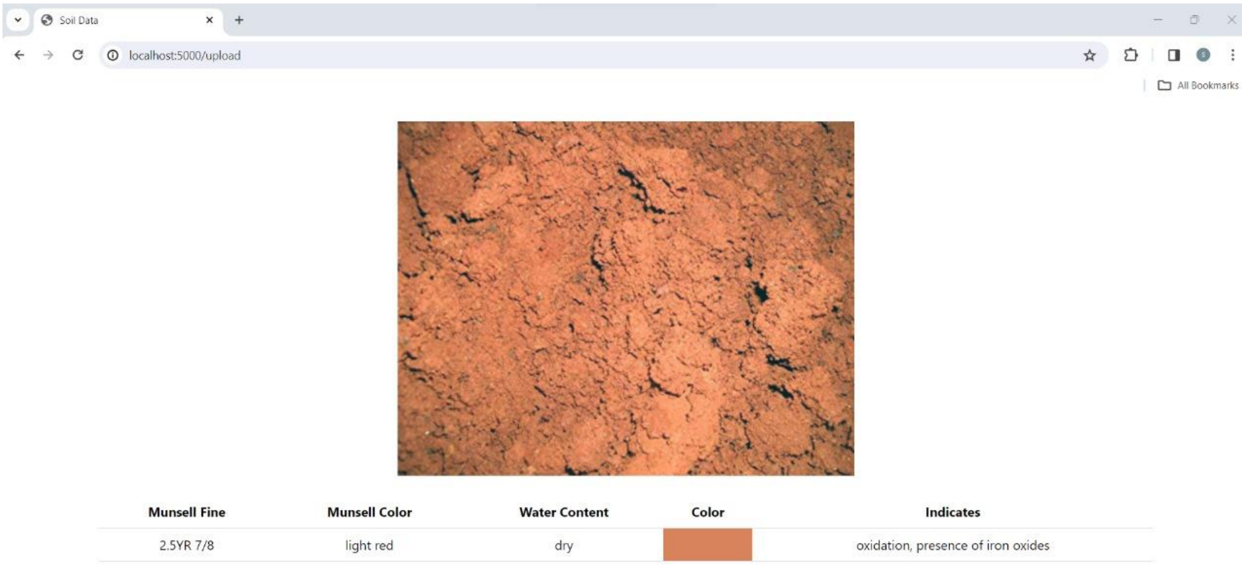

Fig4. Output of Soil image and Soil Indication

3.4 Individual Contribution by Me

Jehan Patel:

As a member of the farmland mapping project, I worked in the architecture of the program and worked to make it as robust and clear as possible. I also worked on formulating the report and making the presentation to be as clear, concise and to the point as possible. I also assisted in devising the basic system of approach for the system and helped in ideating the various paths we can choose to achieve what we are aiming for. I also went ahead and helped in overcoming the challenges faced when taking images from aerial maps due to color inaccuracies, and lack of proper cameras. We overcame it by applying a different approach of using euclidean distance to make and have higher accuracy in dominant color.

4. CONCLUSION

With the report, we can see in detail about what farmland mapping is and how it works. We have also seen how farmland mapping is being utilized by governments across the world.We have also seen the existing work done by researchers across the world and how there is a lack of guidance and proper assistance for the farmers. We have made progress on various components of the software which was to predict the soil type and color via RGB (Red, green and blue) Values and Euclidean Distance. We are able to find the RGB (Red, green and blue) color code from the software, find the dominant soil color in the image and cross refer it to the closest color code available in our database. We expect our program to further print out what kind of soil it is, water content of the soil and any other information available about the soil. This is just the first step in our procedure in helping out the farmers and assisting in India’s vision of sustainable and smart farming.

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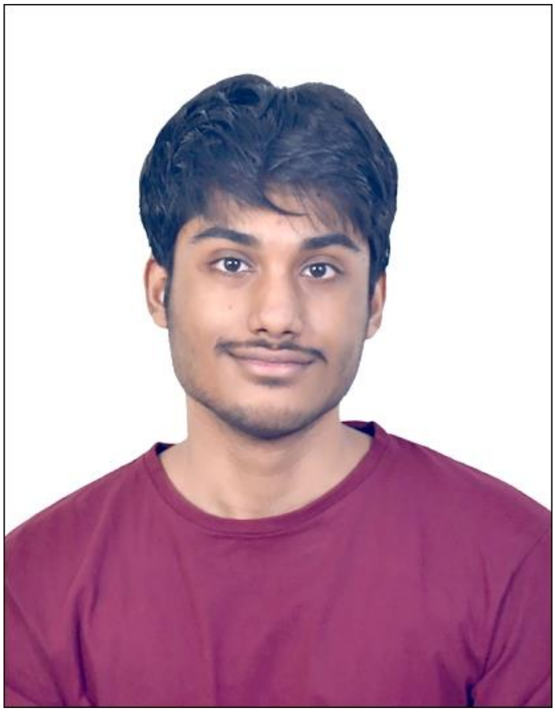
6. BIODATA WITH PICTURE

	Jehan Patel 21BCE10551 Skills: JAVA, C++, PYTHON, JAVASCRIPT, HTML, MACHINE LEARNING

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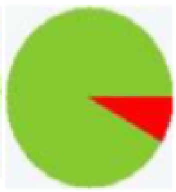

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