BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

Application Of Bayesian Networks To Assess Soil Quality FOR FARMERS

STUDENT NAME: **Keith S Nasuku**

REG NUMBER: **B200976B**

SUPERVISOR: **Mr W. Kanyongo**

Preface

The research contained in this project was completed by the candidate while based in the Department of Computer Science, at the Bindura University of Science Education.

The contents of this work have not been submitted in any form to another university and, except where the work of others is acknowledged in the text, the results reported are due to Investigations by the candidate.

Candidate Signature...

Supervisor Signature..

Date ....

Approval form

The undersigned certify that they have supervised the student Keith Nasuku`s dissertation entitled Application of Bayesian Networks to assess soil quality submitted in Partial fulfilment of the requirements for the Bachelor of Information Technology Honors Degree at Bindura University of Science Education

Keith Nasuku

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Name of student Date

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Name of supervisor Date

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Name of chairperson Date

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External examiner Date

Declaration

I can confirm that this work was done under my supervision, and it is the candidate's original work. As the candidate's supervisor, I have approved this dissertation for submission.

Supervisor Signature...

Date ....

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Abstract

Modern agriculture faces the dual challenge of maximizing crop yields to feed a growing population while minimizing environmental impact. Traditionally, assessing soil quality and managing nutrients for optimal crop growth relies on time-consuming laboratory analyses and may not capture the dynamic nature of soil conditions. This research investigates the application of Bayesian networks, a specific type of probabilistic graphical model, to tackle complex problems and overcome existing challenges. The research investigates the efficacy of Bayesian networks in predicting soil quality and nutrient levels for farmers. It examines how these models can be built using diverse data sources, including historical soil image data. The research evaluates the impact of Bayesian networks on decision-making processes, considering factors like technological preparedness and long-term effects on soil health. The study also explores the limitations of this approach, including data availability and generalizability across different agricultural settings. By integrating Bayesian networks into agricultural practices, farmers can gain deeper insights into their soil conditions, leading to more sustainable and productive farming methods. This research contributes to the advancement of precision agriculture and highlights the importance of data-driven decision-making for a more sustainable and environmentally responsible agricultural future.

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CHAPTER 1: PROBLEM IDENTIFICATION

1.1 Introduction

This study investigates the application of Bayesian networks in predicting soil quality for farmers, leveraging diverse data sources, including historical soil image data. The objectives are to integrate diverse data sources for training and evaluation, develop a Bayesian network model that predicts soil quality, and evaluate the practical implications using suitable metrics. The research questions guiding this study include identifying relevant and accessible datasets, determining key variables influencing soil quality, and addressing potential challenges in deploying this technology. The research hypothesis is that Bayesian networks are effective in predicting soil quality, contrary to the null hypothesis. This study is justified by the need for precise decision-making and optimization of crop yields in modern agriculture, and its contributions align with the era of precision agriculture, enabling farmers to make data-driven decisions and improve economic viability through efficient nutrient management. The assumptions underlying this study are that the principles of Bayesian networks can be effectively applied across various agricultural settings.

1.2 Background to the study

Agriculture has been a cornerstone of human civilization, providing sustenance and livelihoods for millennia. As the global population continues to expand, the demands on agriculture are greater than ever. To meet the world's growing food requirements, farmers must optimize crop yields while simultaneously addressing environmental and sustainability concerns.

Soil quality plays a central role in this endeavour. The Food and Agriculture Organization (FAO, 2015) emphasizes that soil is the fundamental foundation of agriculture, influencing crop success and sustainable food production. Soil quality is characterized by numerous factors, including pH, organic matter content, moisture levels, and nutrient concentrations, which collectively dictate its fertility and capacity to support crop growth.

Nutrient management is intricately tied to soil quality. Essential nutrients such as nitrogen, phosphorus, and potassium are vital for plant growth. However, imbalances or deficiencies in these nutrients can lead to reduced yields, poor crop quality, and increased vulnerability to pests and diseases. As a result, maintaining the proper nutrient balance in the soil is a critical aspect of modern agriculture (Havlin et al., 2017).

Yet, the task of assessing soil quality and managing nutrient levels is a multifaceted challenge. Soil conditions vary greatly from one location to another and can change over time due to factors such as weather, land use, and crop rotation. Traditional methods of soil assessment often rely on labour-intensive and time-consuming laboratory analyses, which are costly and impractical for real-time decision-making in the field (Stoorvogel et al., 2013).

Traditional methods play a vital role in assessing soil quality. Experienced farmers can glean valuable information through visual inspection of soil texture, color, structure, and presence of earthworms. Tools like penetrometers measure compaction, while laboratory analysis provides detailed data on soil chemistry, including pH, macronutrients, micronutrients, and organic matter content. Biological analysis assesses the health of the soil ecosystem by measuring microbial populations, respiration rates, and enzyme activity (Majeed et al., 2023). Finally, physical analysis focuses on properties like texture, bulk density, and porosity, all impacting factors like drainage, aeration, and water holding capacity.

These traditional methods offer established techniques with known limitations. They are often relatively inexpensive and provide detailed information on specific soil properties. However, they can be time-consuming and labor-intensive, with laboratory analysis requiring sample collection and wait times for results. Point-specific measurements might not capture the full picture of spatial variability across a field, and these methods have limited ability to predict future changes in soil quality (Lal, 2020).

This is where Bayesian networks, a probabilistic graphical model, come into play. Bayesian networks offer a powerful tool for addressing the complex and uncertain nature of soil quality and nutrient management. By modelling the probabilistic relationships between various soil attributes and nutrient levels, they enable farmers to make data-driven decisions and predictions. These networks have gained recognition for their versatility and effectiveness in various fields, including environmental science, healthcare, and finance (Jensen & Nielsen, 2007).

In the realm of agriculture, the potential of Bayesian networks to revolutionize soil quality and nutrient assessment is increasingly recognized. These models not only provide a means to analyze complex, interconnected data but also offer a platform for continuous learning and adaptation. With the dynamic nature of agriculture influenced by climate change, evolving crop varieties, and sustainable farming practices, Bayesian networks can keep agricultural systems up-to-date and responsive to changing conditions (Smith & Marshall, 2010).

However, while the promise of Bayesian networks in agricultural applications is evident, there is a need for further exploration, validation, and dissemination of this technology. This study seeks to contribute to the understanding and practical implementation of Bayesian networks in assessing soil quality and nutrient levels for farmers, to improve agricultural sustainability, productivity, and resource efficiency.

In the subsequent sections, we will delve into the development of Bayesian network models, the integration of various data sources, and the practical implications for agricultural decision-making. By harnessing the power of Bayesian networks, farmers can gain deeper insights into their soil conditions, leading to more sustainable and productive agricultural practices.

1.3 Statement of the Problem

Modern agriculture faces the pressing need to optimize crop yields, ensuring food security for a growing global population while simultaneously mitigating the environmental and economic impacts of intensive farming practices. A fundamental challenge in achieving this balance lies in assessing soil quality and effectively managing nutrient levels to support healthy and productive crops. Traditional soil assessment methods, which rely heavily on labour-intensive and time-consuming laboratory analyses, are both costly and impractical for providing real-time guidance to farmers in the field. Furthermore, soil conditions are dynamic, influenced by factors such as changing weather patterns, land use practices, and crop rotations, making it challenging to maintain accurate and up-to-date soil quality information.

1.4 Research Aim

The aim of the research is to investigate the efficacy and implications of employing Bayesian networks for the assessment of soil quality and nutrient levels in agricultural contexts. The research aims to evaluate the impact of Bayesian networks on farmers' decision-making processes, considering factors such as technological preparedness, environmental sustainability, and long-term effects on soil health.

1.5 Research Objectives

1. Integrate diverse data sources, including historical soil image data for training and evaluation using Bayesian networks.

2. Develop a Bayesian network model that can predict the soil quality for a farmer.

3. Evaluate the practical implications of Bayesian network-based soil quality using suitable metrics.

1.6 Research questions

1. What existing datasets containing historical soil images are relevant and accessible for this project?
2. What are the key variables influencing soil quality that should be included as nodes in the Bayesian network model?

3. What are the potential challenges in deploying this technology for on-farm soil quality assessment?

1.7 Research hypothesis

- **Null Hypothesis (H0):** Bayesian networks are not effective in predicting soil quality.
- **Alternative Hypothesis (H1):** Bayesian networks are effective in predicting soil quality.

1.8 Justification of the study

The application of Bayesian networks to assess soil quality and nutrient levels for farmers holds paramount significance for modern agriculture. In a world striving for sustainable food production and resource efficiency, the use of Bayesian networks enables precise decision-making and optimization of crop yields (Sylvester-Bradley & Kindred, 2009). This technology addresses the challenge of real-time decision support, empowering farmers with immediate insights into soil conditions (Gebbers & Adamchuk, 2010), while also offering a means to adapt to changing environmental conditions, such as climate change and evolving crop varieties (Lobell et al., 2009). Additionally, the economic viability of farming is improved through more efficient nutrient management, reducing input costs and enhancing profitability (Pannell et al., 2006). The research's data-driven approach aligns with the era of precision agriculture and the need for harnessing diverse data sources (Gómez-Barbero et al., 2015). Overall, this study contributes to sustainable, economically viable, and environmentally responsible farming practices.

1.9 Assumptions

It is assumed that the principles underlying Bayesian networks can be effectively applied across a wide range of agricultural settings, encompassing varied soil types, climates, and cropping systems.

1.10 Limitations

While this study offers valuable insights into the application of Bayesian networks for assessing soil quality in agriculture, it is essential to acknowledge several limitations.

First, the effectiveness of Bayesian networks relies heavily on data quality, availability, and comprehensiveness. The accuracy of the models developed is contingent upon the precision and reliability of input data. Second, the practical implementation of Bayesian networks in real-world farming contexts may face challenges related to data collection and integration. Some farmers may lack access to the required technology or resources for continuous data monitoring. Third, the generalizability of findings may be constrained by variations in soil types, climates, and farming practices. The study's applicability may vary across diverse agricultural settings. Lastly, the study does not delve into the specific technical aspects of Bayesian network modelling, which might require specialized expertise for farmers to fully harness. These limitations highlight the need for further research and the importance of considering local and contextual factors when applying Bayesian networks in agriculture.

1.11 Scope of the research

The research scope encompasses a comprehensive examination of the application of Bayesian networks in the assessment of soil quality and nutrient levels for farmers. Geographically, to ensure our investigation is well-rounded, we will gather data from a wide range of locations. This will allow us to account for the natural variations in soil types, climatic conditions, and the farming practices employed in different regions. It explores the performance of Bayesian networks across different crop types, considering both monoculture and polyculture systems. Special attention is given to the availability and quality of data necessary for model construction, incorporating assessments of existing databases, remote sensing technologies, and on-field measurements. The research investigates the technological preparedness of farmers, assessing digital literacy, technology accessibility, and the willingness of farmers to integrate advanced tools into their decision-making processes. Environmental impact analysis focuses on resource use efficiency, reduction in environmental pollutants, and the overall sustainability of farming practices. The study delves into the influence of Bayesian networks on farmers' decision-making processes, comparing their effectiveness with traditional methods for soil quality and nutrient assessment. Long-term implications on soil health, economic considerations, and stakeholder involvement are integral components, providing a comprehensive framework to advance sustainable and datadriven agricultural practices.

1.12 Definition of terms

Bayesian Networks:

Bayesian networks are probabilistic graphical models that represent a set of variables and their conditional dependencies via a directed acyclic graph. In the context of this research, Bayesian networks are employed as a computational tool to model and analyse the relationships among various factors influencing soil quality and nutrient levels in agriculture.

Soil Quality:

Soil quality refers to the capacity of soil to perform its functions, supporting plant and animal productivity, maintaining or enhancing water and air quality, and promoting plant and animal health. In this research, soil quality is a key parameter being assessed concerning its impact on agricultural productivity and sustainability.

Nutrient Levels:

Nutrient levels refer to the concentration and availability of essential elements such as nitrogen, phosphorus, potassium, and other micronutrients in the soil. The research focuses on evaluating and managing these nutrient levels to optimize crop yields while minimizing environmental impact.

Geographical Scope:

Geographical scope denotes the extent and range of geographical areas covered in the research. It involves considering diverse locations with variations in soil types, climates, and agricultural practices to ensure the applicability and effectiveness of findings across different environments.

Technological Preparedness:

Technological preparedness relates to the readiness and ability of farmers to adopt and integrate technological innovations into their agricultural practices. In this research, it includes assessing factors such as digital literacy, access to technology, and the willingness of farmers to embrace advanced tools like Bayesian networks.

1.13 Chapter Summary

In conclusion, Chapter 1 has set the stage for a comprehensive exploration of the application of Bayesian networks in assessing soil quality and nutrient levels for farmers. The introductory chapter has highlighted the pivotal importance of this research topic in the context of modern agriculture, where the dual objectives of optimizing crop yields and minimizing environmental impact present ongoing challenges for farmers. The delicate balance between soil health and agricultural productivity underscores the necessity for informed decision-making.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

A literature review serves as an academic document that showcases a comprehensive understanding of scholarly literature related to a specific subject within a broader context. This type of review involves not only summarizing the existing literature but also critically evaluating the materials. This critical evaluation is the reason it is termed a literature review rather than a mere literature report. Essentially, it encompasses both the process of examining existing literature and the act of composing a piece of writing on the subject.

2.1 Agriculture in Zimbabwe

The agricultural sector stands as a significant contributor to the overall value added in Zimbabwe, serving as the largest employer and the second-largest source of export earnings for the country. This Selected Issues Paper (SIP) delves into the trajectory of agricultural production in Zimbabwe since the year of independence in 1980. The primary focus lies on the consistent decline in agricultural productivity witnessed over the past two decades and the widening disparity between the potential agricultural output of Zimbabwe and the actual achievements. Employing a cross-country analysis, we pinpoint the crucial factors influencing and hindering agricultural productivity in Zimbabwe. These factors encompass structural, regulatory, and financial obstacles that impede sustainable growth (International Monetary Fund ,2019).

Furthermore, we scrutinize the role played by government support and subsidy programs designed for the agricultural sector, taking into account the considerable fiscal burdens associated with these subsidies. In conclusion, we propose fiscally sustainable reforms aimed at enhancing agriculture as a catalyst for inclusive growth in Zimbabwe. This approach seeks to present an original perspective on the evolution of Zimbabwe's agricultural sector and the potential avenues for improvement, referencing the work without directly replicating the language used in the original text (Akwabi-Ameyaw, 1997)

2.2 Soil Nutrients

In the 20th century, modern farming practices shifted away from traditional methods that used cover crops and diverse rotations, instead relying heavily on tillage, chemical fertilizers, and pesticides. Since the 1940s, agricultural research has prioritized maximizing crop yields, protein content, and pest control through chemical-based methods, leading to increased food production. However, this approach may have unintentionally resulted in the depletion of essential micronutrients and phytochemicals in crops, compromising their nutritional value. Nevertheless, the emerging understanding of soil biota's influence on crop nutrient density raises concerns about the sustainability and long-term consequences of these conventional practices, highlighting the need for a shift towards more holistic and sustainable agricultural approaches that prioritize soil health and ecosystem services. (Montgomery & Biklé, 2016).

Throughout history, both farmers and early scientists have worried about soil washing away and losing its richness. Efforts to enhance soils in the United States date back to colonial times, drawing inspiration from practices independently embraced by indigenous peoples globally. The perception of soil fertility has evolved from a divinely bestowed blessing in ancient times to an intrinsic feature influenced by climate and geology, subject to radical modification through farming practices and soil management (Uphoff, 2013).

Soil health is a multifaceted concept encompassing both biotic and abiotic components, defined as the soil's capacity to function as a viable ecosystem supporting plant growth, animal life, and human well-being (Lehmann, 2020). Agricultural practices have a profound impact on soil health, leading to erosion and degradation through the loss of topsoil, depletion of organic matter, and damage to soil structure and biota (Bünemann, 2018). Both organic and conventional farming methods have contributed to soil degradation, particularly through intensive tillage practices (Montgomery, 2007). The significance of soil biota in maintaining soil fertility and influencing crop nutritional profiles has been recognized since the mid-20th century (Balfour, 1943). Recent advances in soil ecology have further underscored the critical role of soil health in sustaining ecosystem services and promoting agricultural productivity (Uphoff, 2013).

Agriculture has already degraded up to one-third of the world's potential farmland, and current trends indicate a potential degradation of another third by the end of this century (Pimental 1995). In the past century, a significant portion of the topsoil in the U.S. Corn Belt was eroded, resulting in a 6% reduction in overall crop yields despite extensive use of synthetic chemical fertilizers (Thaler, 2021). Post-colonial farming practices in North America have led to roughly a 50% reduction in soil organic matter, contributing to land degradation that affects over 3 billion people globally (Baumhardt et al., 2015). Given the pivotal role of soil health in facilitating nutrient cycling and delivery to crops through microbial symbioses, there exists a significant potential for agricultural practices to substantially influence crop micronutrient and phytochemical content, with implications for crop quality and human nutrition.

Early concerns about the impact of conventional farming practices on food nutrient density emerged in the 1920s and 1930s, as evidenced by experiments conducted by Rowlands and Wilkinson (1930) involving rats and the vitamin content of grains. Although conflicting results and debates about the definition of a nutrient have persisted, recent research has broadened these concerns to encompass phytochemicals, which, while not traditionally considered nutrients, exert significant influences on human health and well-being.

Nutrient density, defined as the ratio of nutrient content to energy intake. It is a critical parameter in assessing the nutritional value of food. While nutritional science has historically focused on determining adequate intake levels for macronutrients and micronutrients, no recommended dietary intake levels have been established for phytochemicals such as polyphenols, flavonoids, and anthocyanins, despite their recognized antioxidant and anti-inflammatory effects on human health (Krzyzanowska, 2010). A substantial body of research over the past few decades has consistently demonstrated that soil biota significantly influences both mineral uptake and phytochemical production in various crops, highlighting the importance of soil health in determining crop nutritional quality (Adak, 2016).
This review paper provides a comprehensive synthesis of the current state of knowledge regarding the impact of agricultural practices on soil health and subsequent effects on

nutrient density, highlighting both the disruptive and cultivatory effects of farming practices on beneficial soil biota and their role in shaping crop nutritional quality (Rilling et al., 2020). Recognizing these links between soil and crops, this paper revisits research comparing the nutrient content of conventionally and organically farmed food. It suggests that analyzing how farming methods affect soil health might be a more reliable way to understand the impact on the nutritional value of our crops.

2.3 Farming Practices

Conventional soil evaluations have focused on physical and chemical properties, but the importance of soil ecology and biodiversity is increasingly recognized. The concept of soil health now encompasses biological factors like soil organic matter content and biodiversity, in addition to traditional physical and chemical parameters (Lehmann, 2020). Promoting farming practices that enhance soil health is crucial for sustainable agriculture, maintaining ecosystem services, and ensuring long-term environmental sustainability. While the development of quantitative soil health indices remains a challenge due to regional variability in soil properties and biota, there is a growing consensus that promoting farming practices that enhance soil health is crucial for the development of sustainable agricultural systems.

Traditionally, soil quality has been judged by its ability to grow crops, focusing on physical and chemical properties. However, the importance of soil life is gaining recognition. This shift in perspective means that maintaining and improving overall soil health is becoming a top priority in modern agriculture. These modifications can have significant cascading effects on various soil processes, including nutrient cycling, crop mineral uptake, and phytochemical production, ultimately influencing the nutritional quality and productivity of crops (Lu & Weng, 2007).

While tillage is a widely used method for weed control, it can have a negative impact on soil organic matter. Tillage disrupts the soil and increases oxygen exposure, which stimulates the activity of microbes that decompose organic matter, leading to its degradation. A seminal review published in 1995, synthesizing evidence from over 100 peer-reviewed studies, conclusively demonstrated that tillage practices substantially disrupt soil food webs (Wardle, 1995). Earthworms, a key component of these ecosystems, are particularly vulnerable to tillage, with numerous studies reporting significant declines in earthworm biomass, often exceeding 50%, in conventionally managed fields (Blakemore, 2018). These findings underscore the profound impact of tillage on soil ecological integrity and highlight the need for sustainable management practices that prioritize soil biota conservation. Long-term comparisons have indicated that no-till farming preserves earthworm populations, while conventionally tilled fields exhibit reduced microbial activity and fewer worms (Ross, 2002)

Tillage not only disrupts soil food webs but also diminishes the diversity of soil microorganisms, including fungi and bacteria, thereby disrupting the delicate balance of soil ecosystems. The destruction of fungal hyphae, which play a crucial role in mineral delivery to plants, is particularly noteworthy. Ploughing typically shifts the soil microbial community structure towards a more bacterial-dominated composition, characterized by a lower fungal-to-bacterial biomass ratio (Jansa, 2006). Different agricultural practices significantly influence nutrient cycling by altering crop-microbe symbioses, with no-till systems promoting fungal and earthworm communities, and tilled systems favoring bacterial populations. contrast, reduced tillage intensity has been linked to improved soil structure (Nunes, 2020).

Fertilizer use, especially synthetic nitrogen fertilizers, also has an impact on soil life. High nitrogen fertilizer usage reduces the abundance and diversity of mycorrhizal fungi, critical for nutrient uptake by crops (Egerton-Warburton & Allen, 2000). Nitrogen-rich fertilizers select less mutualistic fungi, potentially affecting the delivery of essential minerals like zinc and phosphorous to crops. Studies have consistently demonstrated that mycorrhizae enhance zinc concentrations in crops. Moreover, excessive nitrogen from fertilizers can reduce the production of phenolic compounds in foliage, affecting plant defense mechanisms (Brandt, 2011).

The combination of reduced tillage and cover cropping has been shown to enhance soil health by increasing soil organic matter levels, microbial biomass, and plant-available zinc in the soil (Nunes, 2018). Cover crops, in particular, promote mycorrhizal colonization of crop. Crop rotation also influences the diversity of mycorrhizal fungi, with rotated crops exhibiting greater richness and diversity compared to continuously cultivated ones (Jansa, 2006). The adoption of no-till, cover cropping, and organic amendments has been associated with increased soil health through enhanced soil organic matter and microbial biomass.

Comparative analyses of conventional and organic farming practices have revealed significant differences in soil microbial diversity and abundance. Organic farming systems tend to promote healthier soils with higher organic matter content, whereas conventional farming practices often result in reduced microbial biomass and diversity (Lori, 2017). The application of livestock manure has been shown to enhance soil health and crop growth, with the benefits varying depending on manure properties, farming practices, soil type, and regional climate (Rayne & Aula, 2020). Furthermore, research has demonstrated that the use of diverse cover crops, compost, and other soil healthbuilding practices can contribute to the suppression of soil-borne plant pathogens (De Corato, 2020). These findings highlight the importance of adopting sustainable agricultural practices that prioritize soil health and ecosystem services.

A 14-year study in France compared conventional, organic, and conservation agriculture practices, revealing that both organic farming and conservation agriculture significantly increased soil life abundance and biomass (Henneron, 2015). Organic farming, in particular, enhanced microbial diversity and abundance, despite facing challenges in weed control through tillage. This study highlights the potential of organic farming and conservation agriculture to promote soil biota and ecosystem services, leading to more sustainable agricultural practices. National comparisons across the United States have indicated that organic farming supports healthier soils with higher organic matter content than conventional practices (Ghabbour, 2017). Direct comparisons of paired conventional and organic fields over extended periods consistently show higher microbial biomass, microbial activity, and diversity in organically farmed soils (Lori, 2017).

Given the intricate connections between soil health, microbial communities, and crop nutritional profiles, the impact of farming practices on the nutritional composition of crops becomes a crucial consideration (Gardner & Clancy, 1977). The vitality of soil, measured by its teeming microbial life, varied ecosystem, and dynamic processes, serves as a crucial indicator of how agricultural methods impact the nutritional value of crops, including their micronutrient and phytochemical content, providing a valuable lens through which to examine the effects of farming practices on food quality. In light of these findings, it is plausible to hypothesize that alongside genetic variation, disruptions in microbial communities. The deterioration of soil health, brought on by unsustainable farming methods, has led to a significant decrease in the mineral micronutrients and phytochemicals present in crops over time. Research has been highlighting this link between soil degradation and nutrient depletion in crops since the early days of industrial agriculture, sounding a warning about the long-term consequences of neglecting soil health.

2.4 Nutrient Density

It is widely acknowledged that organic farming typically promotes more active soil biology, leading to greater nutrient cycling (Bulluck, 2002). Despite ongoing research, the nutritional differences between conventionally and organically grown crops remain a topic of disagreement among scientists, farmers, and consumers. While some studies suggest organic crops may have higher levels of certain nutrients and antioxidants, others find little evidence of significant differences. The controversy highlights the need for more robust and comprehensive research to clarify the nutritional implications of farming practices. The debate over the health benefits of organically grown foods is complicated by varying study designs and confounding factors, making it challenging to draw conclusive evidence. Additionally, factors like crop variety, soil quality, and weather conditions significantly influence nutrient density. This review of previous studies highlights the importance of defining what constitutes a "nutrient" - whether it's limited to essential dietary components or also includes phytochemicals that support overall health to accurately assess the impact of farming practices on nutrition.

A 12-year study found that crops fertilized with natural materials like manure or compost had significantly higher nutritional value compared to those grown with chemical fertilizers (Marschner & Rengel, 2023). Organic farming methods resulted in increased protein, vitamin C, phosphorus, potassium, calcium, and iron levels, with spinach showing a remarkable 77% increase in iron content. In contrast, crops treated with synthetic fertilizers had elevated levels of nitrates and sodium. However, a subsequent study found no significant differences in essential nutrients in vegetables grown using organic or commercial fertilizers, fueling ongoing debates about the nutritional differences between organic and conventionally grown produce. These conflicting findings highlight the need for further research to fully understand the impact of organic farming practices on crop nutritional value.

In 1984, a German study found that using composted farmyard manure as fertilizer resulted in crops with lower nitrate levels and higher vitamin C content compared to synthetic nitrogen fertilizer. Further experiments showed that increasing compost application reduced nitrate content in spinach, even with increased total nitrogen supply. A study comparing lettuce from conventional and organic farms found that organic lettuce contained lower levels of nitrates, indicating that organic farming practices may result in reduced nitrate levels and improved nutritional quality. Furthermore, a review of German agricultural research revealed that conventionally grown produce tends to have higher levels of nitrates and pesticides compared to organically grown produce, highlighting the potential benefits of organic farming methods for food quality and safety (Lampkin & Padel, 1994).

A landmark study published in the Journal of Applied Nutrition investigated the mineral content of organic and conventional produce in Chicago-area grocery stores over a twoyear period. The results showed a significant increase in essential mineral content in organically grown staples and fruits, ranging from 60% to 125% higher levels of iron, zinc, calcium, and potassium compared to conventionally grown counterparts. This finding suggests a substantial nutritional benefit associated with organic produce (Lacoste et al., 2022). While subsequent studies and meta-studies have reported varying results, researchers have identified consistent patterns and trends when synthesizing data from multiple studies and comparing organic and conventional farming practices in paired experiments. These patterns indicate that organic farming may lead to improvements in certain aspects of nutritional quality, including higher levels of antioxidants, vitamins, and minerals, and lower levels of harmful compounds like pesticides and heavy metals.

2.5 Machine Learning

Machine Learning can be classified into three types which are:

1. Supervised Learning

2. Unsupervised Learning

3. Reinforcement Learning

2.5.1 Supervised Learning

Supervised learning is a fundamental technique in machine learning where a model learns to make predictions based on labelled examples (Burkart & Huber, 2021). The algorithm learns to recognize patterns and relationships in the input data and maps it to the corresponding output data. Supervised learning aims to find a mapping function or model that can accurately predict the output variable (target variable) based on the input variables (features). The goal is to learn a mapping function that can make predictions on new, unseen data, given the input features.

Supervised learning is powerful, but it works best when you have a good amount of labeled data. If you have unlabeled data and want to find hidden patterns, you might explore unsupervised learning, a different machine learning approach (Egbueri, 2023). In the realm of machine learning, supervised learning emerges as a cornerstone technique, enabling machines to transform from passive observers to astute prognosticators. Just as a seasoned pedagogue guides a student towards mathematical mastery by presenting problems with well-defined solutions, supervised learning empowers models to glean insights from experience (Hvitfeldt & Silge, 2021). This analogy captures the essence of the process: labeled data serves as the foundation.
Each data point within this meticulously constructed dataset acts as a meticulously crafted training example, meticulously crafted to illuminate the intricate relationship

between inputs and outputs. The input data, the raw material from which knowledge is forged, can manifest in various forms – numerical data, text fragments, intricate images, or even a captivating blend of these elements (Bansal & Singhrova, 2021). The output, often referred to as the label, represents the coveted prediction the model strives to make. In the realm of classification tasks, the output assumes the form of a categorical label, akin to the confident declaration of "cat" or "dog" within the captivating world of image recognition. Conversely, regression tasks necessitate the prediction of a continuous value, analogous to forecasting house prices based on a complex interplay of size and location.

During this crucial training phase, the model embarks on a captivating journey of discovery, meticulously analyzing the labelled data to unearth the hidden patterns and the profound relationships that bind the inputs to their corresponding outputs. Imagine the model as a discerning scholar meticulously sifting through a treasure trove of knowledge, progressively internalizing the underlying "rules" that govern the mapping of specific inputs to their destined outputs (Bharadiya, 2023). Once this period of diligent training concludes, the model transcends its prior limitations and is presented with entirely new, unseen data. Armed with the arsenal of knowledge gleaned from the training examples, the model can now make confident predictions about the outputs for this uncharted territory.

In essence, supervised learning presents a transformative paradigm for machines, empowering them to learn from the wisdom of the past and make reliable predictions about the future. This potent technique underpins a captivating array of applications, its fingerprints evident in the realm of spam filtering, the captivating world of image recognition, the intricate dance of stock price forecasting, and even the life-saving domain of medical diagnosis. As we delve deeper into the future, supervised learning promises to unveil even more remarkable possibilities, forever transforming the landscape of artificial intelligence (Taye, 2023).

2.5.2 Unsupervised Learning

In the captivating world of machine learning, unsupervised learning emerges as a complementary technique to supervised learning. Unlike its counterpart, which thrives on the clarity of labeled data, unsupervised learning delves into the enigmatic realm of the unknown. Imagine a vast library filled with uncatalogued books, this is the essence of unlabeled data. Unsupervised learning algorithms act as the ingenious librarians, tasked with uncovering the hidden patterns and structures within this sea of information, all without the benefit of pre-defined categories or labels. (Verkerken et al., 2022).

The process is akin to an investigative detective meticulously analyzing seemingly random pieces of evidence. The model identifies similarities and differences within the data, progressively teasing out underlying relationships. This might involve clustering data points and grouping those that share common characteristics (Naeem et al., 2023). For instance, the model might uncover distinct clusters within customer data, revealing hidden segments with unique purchasing behaviors.

Unsupervised learning unlocks a treasure trove of applications. One valuable technique is dimensionality reduction. Imagine a complex dataset with numerous features. Unsupervised learning can simplify this complexity by identifying the most significant underlying factors, making data analysis more manageable. Another application is anomaly detection, where the model flags data points that deviate significantly from the norm. This is crucial for tasks like identifying fraudulent transactions on a credit card, where outliers might indicate suspicious activity (Kyriienko, & Magnusson, 2022). Furthermore, unsupervised learning plays a starring role in recommendation systems. By analyzing user data and identifying patterns in their behavior or preferences, these systems suggest products or services that are likely to resonate with each individual user.

The algorithms employed in unsupervised learning function like the minds of creative explorers venturing into uncharted territories. Clustering algorithms, for example, group data points based on similarities, allowing for customer segmentation or image categorization (Usmani et al., 2022). Principal Component Analysis (PCA) acts like a skilled mapmaker, reducing the complexity of high-dimensional data while preserving the most critical information. Autoencoders, a type of neural network, function like codebreakers. They compress and reconstruct data, uncovering hidden patterns within the process.

While unsupervised learning may lack the explicit guidance of labeled data, it offers a powerful lens for understanding the vast quantities of unlabeled data that surround us in the real world. From image and document analysis to market research and scientific discovery, unsupervised learning plays a pivotal role in unlocking the secrets hidden within our data (Banitalebi-Dehkordi, Gujjar & Zhang, 2022). It is a testament to the ingenuity of machine learning, empowering us to find meaning in the uncharted territories of information. The data analysis toolkit comprises a range of algorithms, including K-Means Clustering for identifying patterns and groupings, K-Nearest Neighbors (KNN) for predictive modelling and classification, Neural Networks for complex pattern recognition and learning, the Apriori Algorithm for uncovering associations and frequent patterns, and Singular Value Decomposition (SVD) for reducing dimensionality and imputing missing data.

2.5.3 Reinforcement Learning

In the ever-evolving field of machine learning, reinforcement learning (RL) stands out as a revolutionary approach that mimics human-like learning. Unlike traditional methods reliant on meticulously labeled datasets, RL empowers agents to actively engage with their environments (Kayhan & Yildiz, 2023). This paradigm shift opens a door to fascinating possibilities, where agents learn through trial and error, much like we do.

Envision an AI for a complex game, constantly experimenting with strategies and refining its moves based on in-game rewards. These are just a glimpse into the captivating potential of RL. The core challenge of RL lies in the delicate dance between exploitation and exploration machines (Moerland et al., 2023). Should the agent leverage its current knowledge, sticking to proven tactics, or should it venture out to explore uncharted territory? This "explore vs exploit" dilemma is the driving force behind innovation and long-term success in RL. By cleverly balancing these forces, the agent continuously refines its understanding of the environment, learning the true value of different actions in various situations.

This ability to grasp the long-term impact of choices makes RL a powerful tool for tackling problems that traditional, data-driven approaches might struggle with. From training robots in dynamic environments to developing AI that can conquer intricate games, reinforcement learning is pushing the boundaries of what's possible, paving the way for a future filled with fascinating and intelligent (Morales & Escalante, 2022). Reinforcement learning is enabled by algorithms such as Q-learning and Deep Qlearning, which facilitate learning from interactions with environments to maximize rewards. Q-learning updates an action-value function to determine optimal actions, while Deep Q-learning leverages neural networks to approximate the action-value function, enabling more complex decision-making.

2.6 Bayesian networks on Image Analysis

In array-based image processing, Bayesian techniques are employed through the construction and computation of Bayes networks, which are graphical models representing probabilistic relationships between random variables. The nodes of the graph denote random variables, while the edges symbolize conditional dependencies between them. The process commences with conventional image feature extraction, followed by the application of Bayesian inferential methods to the extracted feature data (George & Renjith, 2021). This approach relies on fundamental concepts in Bayesian statistics, including random variables and conditional dependencies, which enable the modeling of uncertainty and probabilistic relationships in image data. The Bayes network provides a robust framework for inferring probabilistic distributions over the unknown variables, given the observed data.

Following the work of Opper and Winther, Bayesian optimal prediction is characterized as an inference task, where the goal is to predict correct labels for points x, denoted as the binary optimal prediction (Schuurmans et al., 2001). Equation encapsulates this Bayesian optimal prediction task, aligning with the principles described in the referenced paper. In this context, the letter 'y' represents the binary optimal prediction, and D m is the training set, which serves as the dataset for training the classifiers. The Bayesian 'prior' p is the probability distribution reflecting beliefs about the quantity of interest before considering existing evidence.

Bayesian image processing commonly addresses challenges in object hypotheses, prediction, and sensor fusion. Various versions of standard Bayesian algorithms, such as naïve Bayes, Gaussian Naive Bayes, Multinomial Naive Bayes, Averaged OneDependence Estimators (AODE), Bayesian Belief Network (BBN), and Bayesian Network, have been implemented for mainstream toolkits like MLlib, Mahout, and H2O, catering to both serial and distributed processing requirements (Smolla & Bartlett, 2017).

Recent progress in semantic image understanding has focused on exemplar-based methods that rely on extracting low-level features and classification. However, the future of semantic image understanding lies in the ability to extract both low-level features and high-level semantic features, and integrate different feature types. This integrated approach is expected to significantly enhance the field, enabling more accurate and nuanced image understanding capabilities. By combining multiple feature types, researchers aim to move beyond simplistic classification and unlock deeper insights into image meaning and context. Bayesian networks (BN), also known as belief networks, have proven to be effective knowledge representation and inference engines in artificial intelligence and expert systems research (Schuurmans, 2019). The success of these models can be attributed to the incorporation of domain expertise into the network architecture and the simplification of complex probability distributions into manageable conditional independence relationships. By explicitly integrating domain knowledge, the models leverage prior knowledge to guide the learning process, while the reduction to conditional independence relationships enables efficient modeling and inference.

In my research, I have developed a versatile knowledge integration framework utilizing Bayesian networks to combine both low-level and semantic features. My findings demonstrate the effectiveness of this framework through three applications focused on enhancing the semantic understanding of pictorial images. Specifically, I have applied this framework to successfully detect main photographic subjects, select the most appealing image from an event, and classify images into indoor or outdoor scenes. These results showcase the potential of this framework to improve image analysis and understanding in various contexts. Through these diverse examples, we illustrate that robust inference engines can be constructed within this potent and adaptable framework, tailored to specific domain knowledge and available training data, effectively addressing inherently uncertain vision problems (Amit Shingal, 2004).

2.7 CNN on image analysis

Convolutional Neural Networks (CNNs) have transformed the landscape of image analysis and computer vision. These specialized neural networks are uniquely designed for processing image data, leveraging a series of convolutional layers to extract local features through filter operations. The subsequent pooling layers down sample these features, creating spatial hierarchies that capture abstract information. Fully connected layers then interpret the learned features, making predictions based on the network's understanding (Abdou, 2022). Activation functions, such as ReLU and Softmax, introduce non-linearity and aid in classification tasks. The training process involves backpropagation and optimization algorithms to minimize the difference between predicted and actual outputs. CNNs find widespread application in image classification, object detection, segmentation, face recognition, medical image analysis, and more. Leveraging pre-trained models and transfer learning further enhances their efficiency. Despite challenges like overfitting and computational complexity, CNNs remain indispensable in advancing computer vision, pushing the boundaries of image analysis capabilities.

2.8 ANN on image analysis

Artificial Neural Networks (ANNs) are pivotal in the realm of image analysis, providing a versatile framework for discerning intricate patterns within visual data. In this computational model, the input layer represents pixel values, while hidden layers employ interconnected neurons with adjustable weights, employing activation functions like sigmoid or ReLU. During training, backpropagation optimizes these weights to minimize the difference between predicted and actual outputs, with common loss functions such as mean squared error guiding the process. Transfer learning, leveraging pre-trained models, enhances the network's capability to generalize across tasks. ANNs find applications in image classification, object recognition, segmentation, and even generative tasks like style transfer and facial recognition (Chao et al., 2022). Despite challenges such as overfitting and computational demands, ANNs stand as a powerful tool in advancing image analysis, showcasing their efficacy in diverse visual recognition tasks across various domains.

2.9 Reviews of previous researchers

Developing a method to standardize magnetic resonance images across multiple sites without the need for physical phantom models to travel between locations

Enhancing the consistency of MRI data analysis across various instruments and locations, data harmonization is a crucial step. In addressing this, Liu and Yap present an effective deep neural network method capable of separating site-specific details from site-invariant anatomical information in MRI images. This innovative approach offers the potential to harmonize data from a diverse array of existing studies conducted with varying imaging protocols, thus contributing to a more unified and comparable analysis framework (Siyuan Liu & Pew-Thian Yap ,2021).

Enhancing the accuracy and reliability of deep neural networks by reducing background bias, achieved through layer-wise relevance propagation optimization, leading to improved generalization and robustness

Enhancing the generalization and robustness of deep neural networks to background bias is a crucial goal in image processing. In this context, the authors introduce a novel approach where the optimization of Layer-wise Relevance Propagation explanation heatmaps is utilized to mitigate the impact of background features, thereby improving the network's ability to generalize effectively, particularly in out-of-distribution scenarios (Sergio et al., 2019).

Restoring degraded time-lapse microscopy images using near-infrared imaging technology to enhance image quality and improve data accuracy

The process of Image restoration in degraded time-lapse microscopy data is innovatively addressed through InfraRed-mediated Image Restoration (IR2). This technique harnesses the power of deep learning to amalgamate the advantages of deeptissue imaging using near-infrared (NIR) probes with the convenience of imaging through Green Fluorescent Protein (GFP). The application of IR2 results in significant improvements in time-lapse imaging of embryogenesis, offering a promising approach for enhanced microscopy data quality (Nicola et al., 2018).

Petascale pipeline for precise alignment of images from serial section electron microscopy

Addressing the challenge of precise alignment in serial section electron microscopy (ssEM), the authors present a petascale pipeline that significantly improves the segmentation accuracy of ssEM images. This computational pipeline is designed to align 2D section images seamlessly, creating a comprehensive 3D image stack. The effectiveness of this approach is demonstrated through its application to a whole fly brain dataset, showcasing its potential to enhance the alignment process in ssEM and contribute to more accurate segmentation outcomes (Seung et al., 2017).

Machine Learning Algorithm for Soil Analysis and Classification of Micronutrients in IoT-Enabled Automated Farms

An assessment of the nutrient status in mulberry gardens across Tamil Nadu districts has been conducted. The evaluation involved soil classification based on various features, including fertility indices for boron, organic carbon, potassium, phosphorus, and available boron, in addition to soil pH levels. This analysis provides a comprehensive understanding of the soil's nutrient status, enabling informed decisions for optimal mulberry cultivation. A total of 10 steps are used for cross-validation purposes wherein in every step, the data involves 10% for validation and the remaining for training data (Sutton & Barto, 2018). A rapid and efficient classification approach, known as the Extreme Learning Method (ELM), is employed to analyze the data and accurately identify the micronutrients present in the soil.

The methodology is optimized using various activation functions, including hard limit, triangular basis, hyperbolic tangent, sine-squared, and Gaussian radial basis, to enhance the accuracy of nutrient classification. Through this analysis, the optimal soil conditions are identified and proposed for different regions in Tamil Nadu. The study reveals that the soils in Tamil Nadu exhibit normal electrical conductivity and are characterized by a red color, indicating specific properties that can inform agricultural practices and nutrient management strategies.. They are found to be rich in potassium (35% of the samples), nitrogen (80% of the samples), and sulphur (75% of the sample) and sufficient or poor in magnesium, boron, zinc, and copper (Arumugam & Manida, 2023).

2.10 Chapter Summary

This chapter serves to outline the previous researches that have been done by various authors. The author serves to explain the much-needed information to prove the feasibility of the system with respect to other researches that has paved a way. Henceforth in addition the author explains in detail how the author is going to tackle the problem at hand with technological practical solutions. This helps the researcher in the deep research.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design

The research design is a dynamic and iterative process that evolves throughout the project, with a focus on creating a functional, efficient, sustainable, and reliable system. In the design stage, the various modules and their intended functions are defined, with the goal of developing a robust and effective system. This study employs machine learning techniques, specifically the decision tree algorithm, to inform the research design and ensure a systematic approach to achieving the project's objectives. Additionally, the author employs the Python programming language and leverages the Flask framework for the deployment of the developed model. This comprehensive approach integrates machine learning techniques, a specific algorithm, and a combination of programming tools to design, train, and deploy the predictive model. The decision tree algorithm, Python, and Streamlit collectively contribute to the research's methodology, enabling the creation and deployment of an effective machine learning model. I chose to employ an experimental research design, which enabled me to conduct a controlled investigation and observe the effects of manipulating specific variables on the behavior and responses of systems and objects. This design allowed for the systematic analysis of cause-and-effect relationships, enabling me to draw causal inferences and gain a deeper understanding of the phenomena being studied. By controlling and varying factors, I observed and measured the resulting changes, providing valuable insights into the dynamics of the system or object under investigation.

3.1.1 Requirements Analysis

At this stage, it is essential to meticulously document both the functional and nonfunctional requirements of the desired system. To achieve this, I carefully organized and analysed all relevant data, taking into account potential limitations from the customer's perspective, and crafted a clear and concise specification that aligns with their needs. Additionally, I considered various constraints, such as time and budget limitations, that could impact the design process, ensuring that the specification is not only comprehensive but also feasible to implement within the given constraints.

3.1.1.1 Functional Requirements

- The system ought to predict soil quality.
- The user should upload a picture of a soil sample.

3.1.1.2 Non-Functional Requirements

- The system should possess rapid prediction capabilities, delivering results in a brief timeframe.
- The system should be designed for hassle-free installation, ensuring a seamless setup process.
- The system should maintain high availability, providing effortless predictions at all times.

- The system should respond swiftly, with minimal delay, and make decisions quickly.

3.1.1.3 Hardware Requirements •

Laptop core i3 and above

3.1.1.4 Software Requirements

- Windows 10 Operating system
- Visual Studio Code
- Python 3.9
- Flask framework
- Xampp

3.2 System Development

This documentation provides a comprehensive overview of the system's development process, detailing how it was designed and built to achieve the desired outcomes. It also offers a detailed account of the software tools and models employed during the development process, providing a thorough understanding of the system's architecture and functionality.

3.2.1 System Development tools

In software engineering, a methodology refers to a systematic approach or framework that guides the design, development, and implementation of an information system. It provides a structured process for organizing, planning, and managing the various activities involved in software production, ensuring a disciplined and controlled approach to creating a high-quality software system. Numerous frameworks have been identified by researchers for various projects, each with its own set of strengths and weaknesses based on its application. I selected the Prototyping Software model for this project due to its simplicity and the project's limited scope and tight deadline. However, upon further consideration, the Waterfall model emerged as a more suitable choice, given that all project requirements have been clearly defined and the necessary tools are already in place. The Waterfall model's linear and sequential approach is well-suited for projects with well-defined requirements and a fixed timeline, making it an ideal fit for this project.

3.2.2 Prototype Model

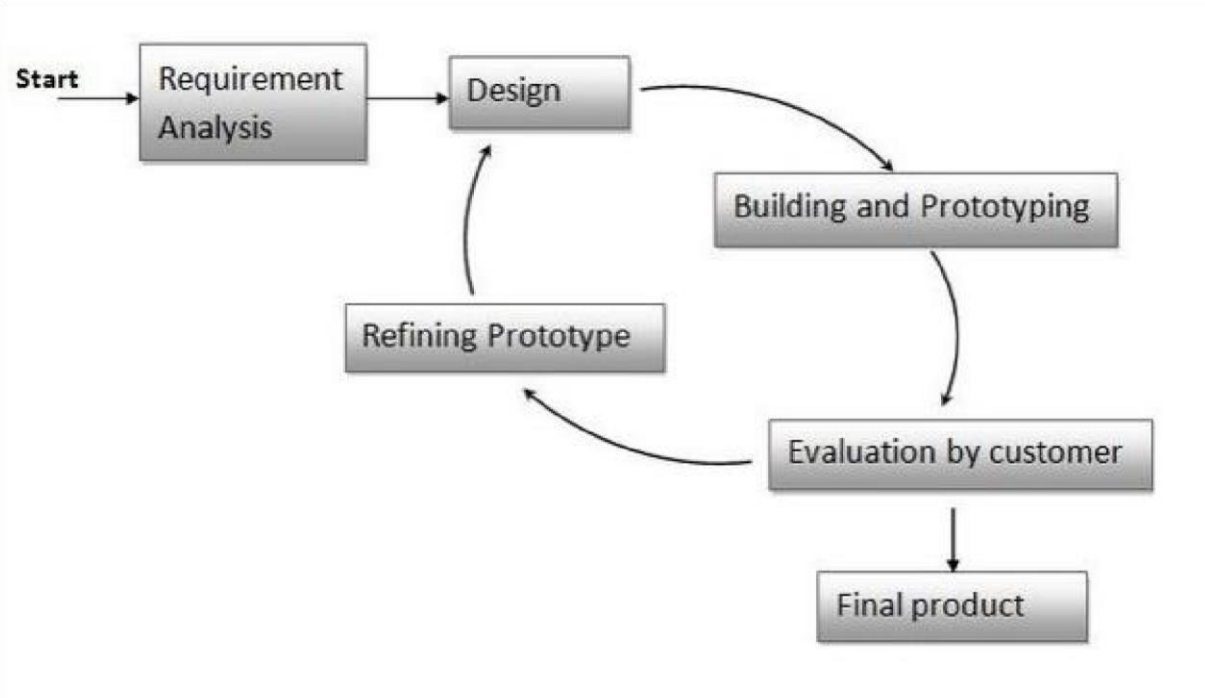


Figure 1

Prototype Model

Apart from the methodology the system was also developed using the following tools:

Python

Python is a versatile and widely-used programming language that prioritizes clear and readable code through the use of indentation. It is a dynamic language that does not require explicit type definitions, and it also features automatic memory management through garbage collection. Python supports a range of programming approaches, including structured, object-oriented, and functional programming, making it a flexible and powerful tool for software development.

Flask

Flask is an open-source framework that enables rapid development and deployment of web applications focused on machine learning and data science. Built on Python, this library is tailored specifically for machine learning engineers, providing a streamlined platform to create and share visually appealing web apps.

Dataset

A data set is a compilation of data, and in the context of tabular data, it is equivalent to one or multiple database tables. In these tables, each column represents a specific variable or field, and each row represents a single observation or record within the data set, containing values for each of the variables.

3.3 Summary of how the system works

A soil quality prediction system utilizing a naïve bayes algorithm operates by leveraging soil images data to predict the likelihood of soil quality. Initially, relevant features are analysed using neural networks. The dataset is divided into training and testing sets, and the Bayesian Network algorithm is applied to the training data. The algorithm uses metrics like entropy or Gini index to recursively split the data, creating a tree structure. This process continues until a stopping criterion is met, resulting in a decision tree with decision nodes based on features and leaf nodes with predicted outcomes. The trained model is then applied to new data to predict climate risks, and its performance is evaluated using metrics like accuracy and precision. Fine-tuning may be done as needed, and the deployed model provides a valuable tool for real-time soil quality prediction, enabling proactive decision-making and mitigation strategies.

3.4 System Design

The requirements specification document is analysed and this stage defines how the system components and data for the system satisfy specified requirements.

3.4.1 Dataflow Diagrams

Data flow diagrams (DFDs) provide a visual representation of the relationships and interactions between various components of a system, showcasing how input data is processed and transformed into output results through a series of functional steps. By labeling the data flows, DFDs clarify the nature of the data being used. As a valuable tool for information development, DFDs offer insight into the transformation of information as it moves through the system, ultimately revealing how the output is displayed. This visualization enables a deeper understanding of the system's architecture and data processing mechanisms.

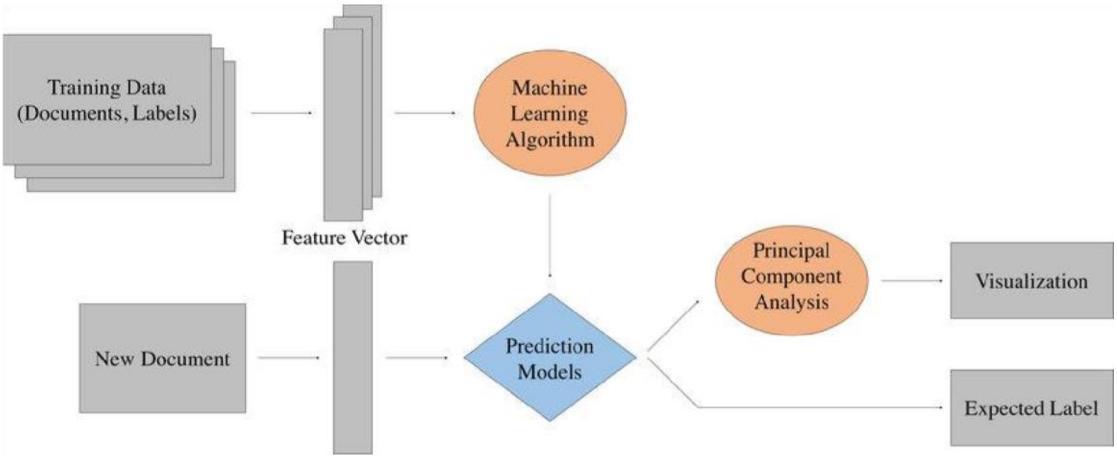


Figure 2

3.4.2 Proposed System flow chart

Flowcharts are a powerful tool for communicating complex information in a concise and intuitive way, helping to bridge the gap between technical and non-technical stakeholders. By using a limited set of symbols and connectors, flowcharts can effectively distill large amounts of data into a clear and easily understandable visual representation, making it easier for programmers and end-users to collaborate and understand the logic and processes involved.

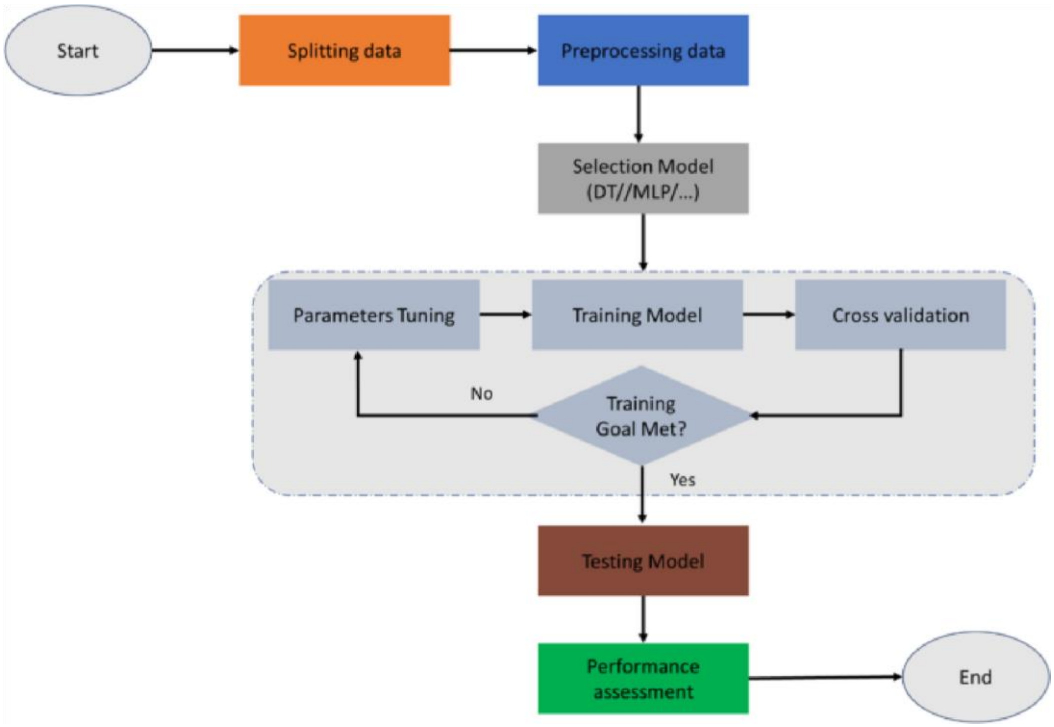
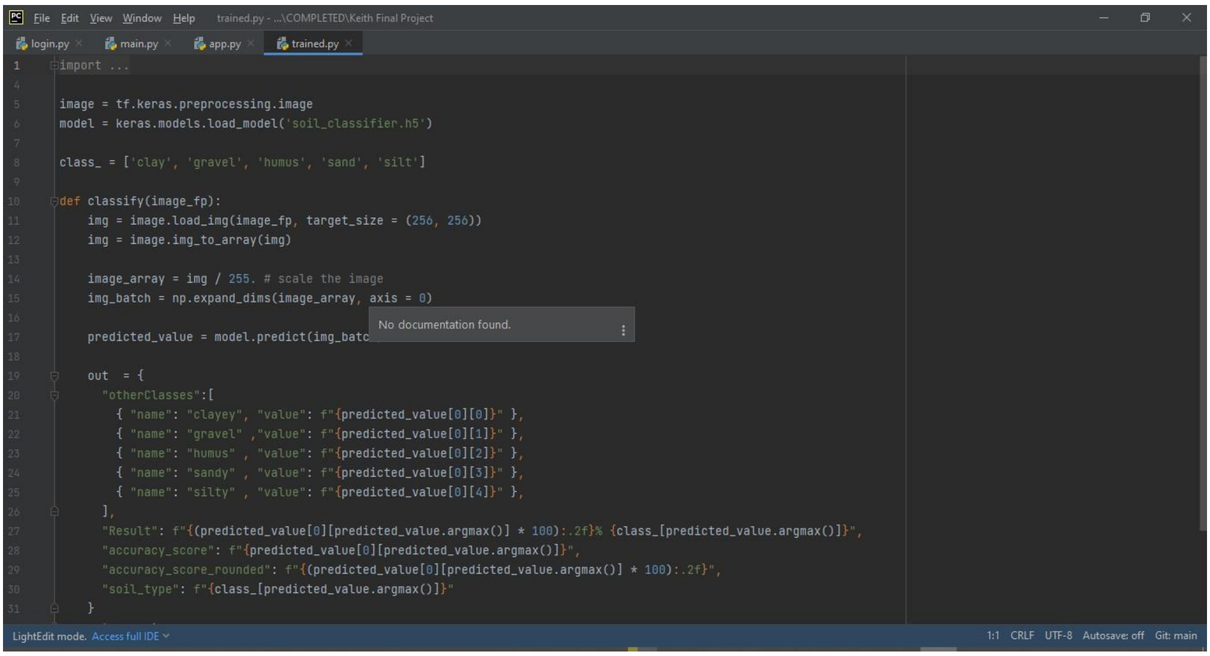


Figure 3

3.4.3 Solution Model Creation



```
import ...

image = tf.keras.preprocessing.image
model = keras.models.load_model('soil_classifier.h5')

class_ = ['clay', 'gravel', 'humus', 'sand', 'silt']

def classify(image_fp):
    img = image.load_img(image_fp, target_size = (256, 256))
    img = image.img_to_array(img)

    image_array = img / 255. # scale the image
    img_batch = np.expand_dims(image_array, axis = 0)

    predicted_value = model.predict(img_batc

    out  = {
      "otherClasses":[
        { "name": "clayey", "value": f"{predicted_value[0][0]}" },
        { "name": "gravel" ,"value": f"{predicted_value[0][1]}" },
        { "name": "humus" , "value": f"{predicted_value[0][2]}" },
        { "name": "sandy" , "value": f"{predicted_value[0][3]}" },
        { "name": "silty" , "value": f"{predicted_value[0][4]}" },
      ],
      "Result": f"{(predicted_value[0][predicted_value.argmax()] * 100):.2f}% {class_[predicted_value.argmax()]}",
      "accuracy_score": f"{predicted_value[0][predicted_value.argmax()]}",
      "accuracy_score_rounded": f"{(predicted_value[0][predicted_value.argmax()] * 100):.2f}",
      "soil_type": f"{class_[predicted_value.argmax()]}"
    }
```

Figure 4

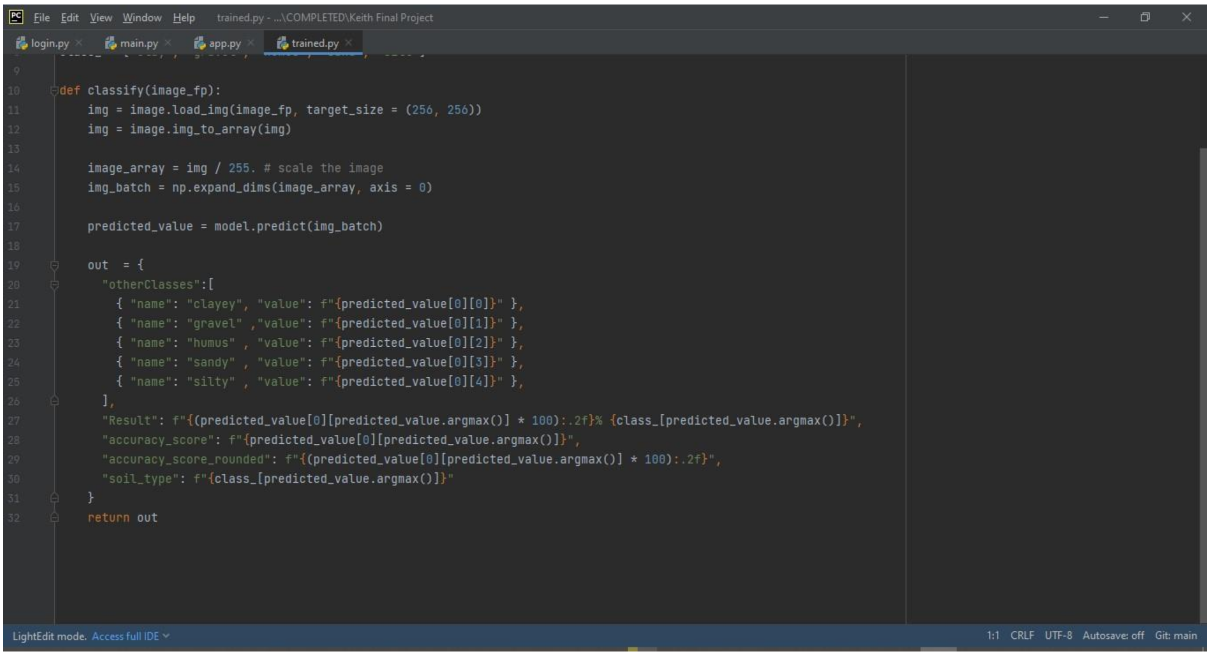
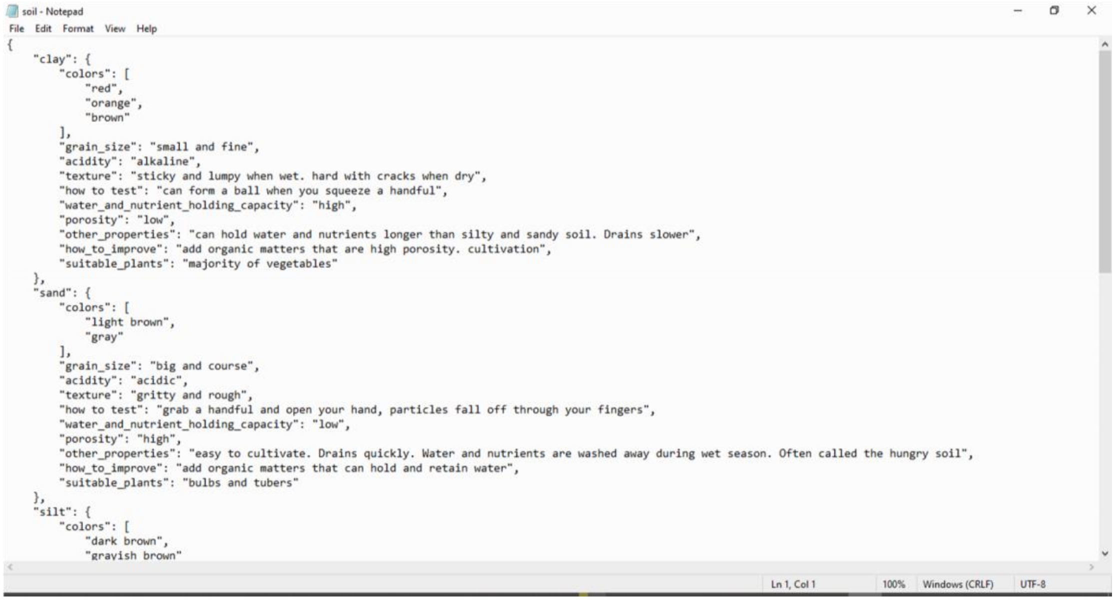


Figure 5

Model Developed

3.4.4 Dataset

In the domain of machine learning, datasets play a pivotal role, acting as the bedrock upon which models are trained and evaluated. A training dataset consists of input-output pairs that allow the model to learn patterns and make predictions, with the model adjusting its parameters to reduce the difference between predicted and actual outcomes. Meanwhile, a validation dataset helps refine model hyperparameters and evaluate its ability to generalize. Finally, the testing dataset serves as a neutral evaluation, providing an unbiased assessment of the model's performance on new, unseen data, ultimately determining its effectiveness. Unlabelled datasets come into play in unsupervised learning scenarios, where the model discerns patterns without explicit labels. Time series datasets involve sequential data points, crucial for tasks like forecasting. Image datasets, rich with labelled images, fuel applications like image classification and object detection. Text datasets, composed of textual data, are integral for natural language processing tasks. Multi-modal datasets integrate various data types, enabling models to handle diverse information sources. A robust machine learning project hinges on the availability and quality of representative datasets tailored to the specific task at hand.



soil - Notepad

File Edit Format View Help

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            "orange",
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    "sand": {
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            "gray"
        ],
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        "acidity": "acidic",
        "texture": "gritty and rough",
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        "water_and_nutrient_holding_capacity": "low",
        "porosity": "high",
        "other_properties": "easy to cultivate. Drains quickly. Water and nutrients are washed away during wet season. Often called the hungry soil",
        "how_to_improve": "add organic matters that can hold and retain water",
        "suitable_plants": "bulbs and tubers"
    },
    "silt": {
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            "dark brown",
            "gravish brown"
```

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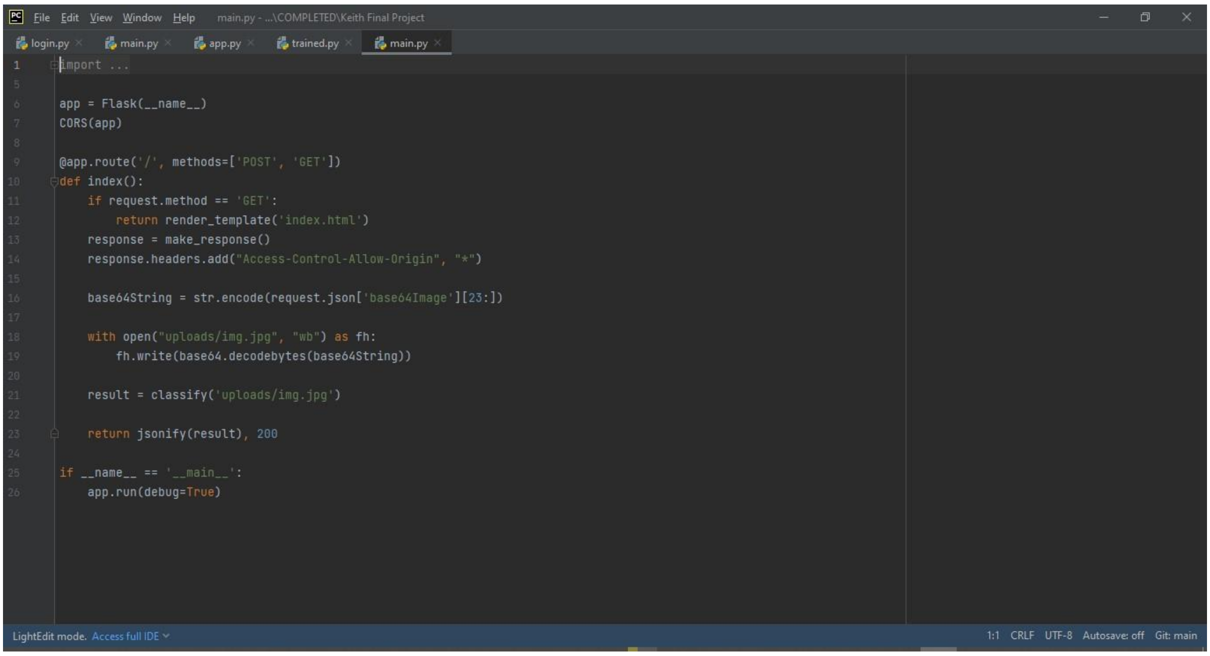
Figure 6

3.4.4.1 Training Dataset



File Edit View Window Help main.py - ...\COMPLETED\Keith Final Project

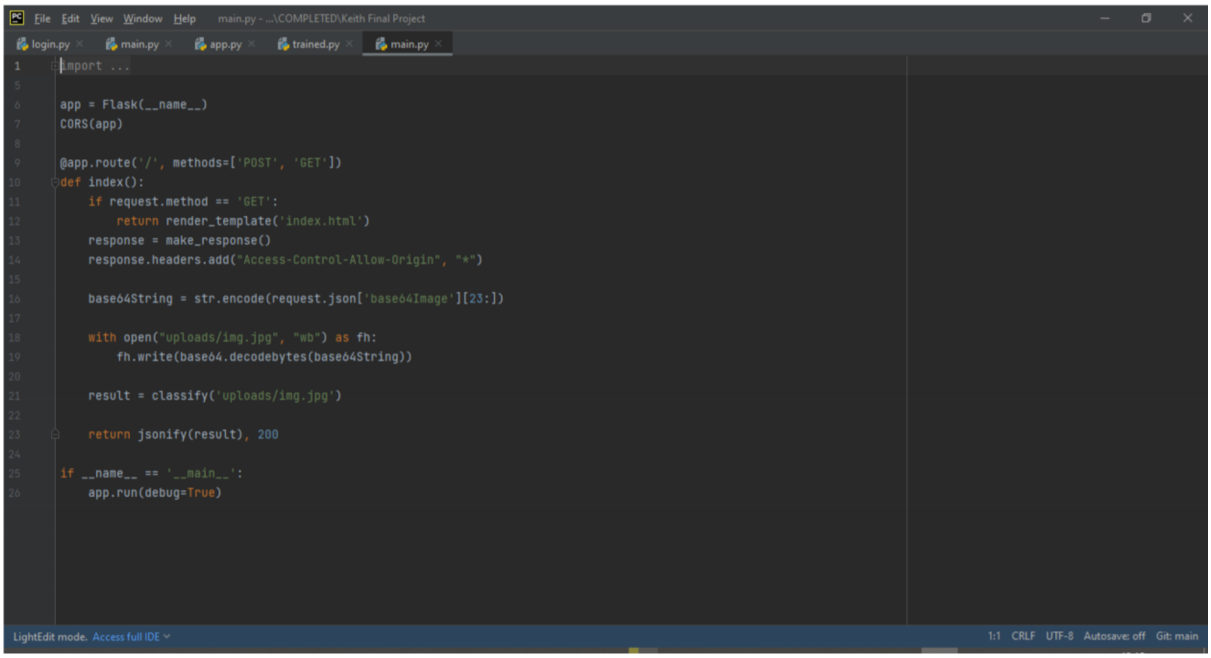
login.py | main.py | app.py | trained.py | main.py

```python
import ...

app = Flask(__name__)
CORS(app)

@app.route('/', methods=['POST', 'GET'])
def index():
    if request.method == 'GET':
        return render_template('index.html')
    response = make_response()
    response.headers.add("Access-Control-Allow-Origin", "*")

    base64String = str.encode(request.json['base64Image'][23:])

    with open("uploads/img.jpg", "wb") as fh:
        fh.write(base64.decodebytes(base64String))

    result = classify('uploads/img.jpg')

    return jsonify(result), 200

if __name__ == '__main__':
    app.run(debug=True)
```

LightEdit mode. Access full IDE | 1:1 CRLF UTF-8 Autosave: off Git: main

Figure 7

3.4.4.2 Evaluation Dataset



```
import ...

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def index():
    if request.method == 'GET':
        return render_template('index.html')
    response = make_response()
    response.headers.add("Access-Control-Allow-Origin", "*")

    base64String = str.encode(request.json['base64Image'][23:])

    with open("uploads/img.jpg", "wb") as fh:
        fh.write(base64.decodebytes(base64String))

    result = classify('uploads/img.jpg')

    return jsonify(result), 200

if __name__ == '__main__':
    app.run(debug=True)
```
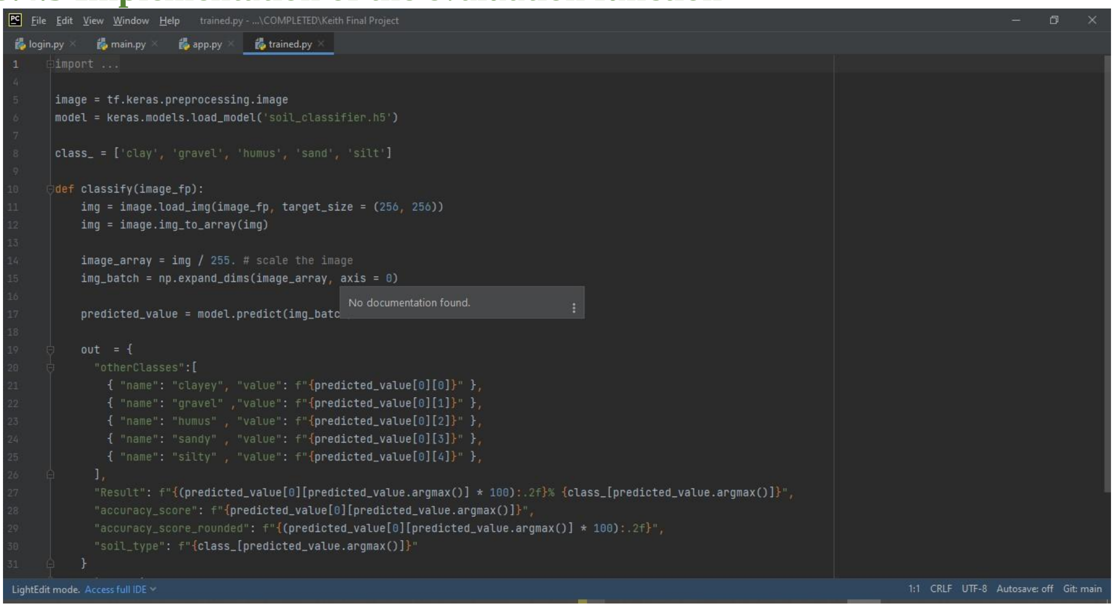

Figure 8

3.4.5 Implementation of the evaluation function



```
import ...

image = tf.keras.preprocessing.image
model = keras.models.load_model('soil_classifier.h5')

class_ = ['clay', 'gravel', 'humus', 'sand', 'silt']

def classify(image_fp):
    img = image.load_img(image_fp, target_size = (256, 256))
    img = image.img_to_array(img)

    image_array = img / 255. # scale the image
    img_batch = np.expand_dims(image_array, axis = 0)

    predicted_value = model.predict(img_batc

    out  = {
      "otherClasses":[
        { "name": "clayey", "value": f"{predicted_value[0][0]}" },
        { "name": "gravel" ,"value": f"{predicted_value[0][1]}" },
        { "name": "humus" , "value": f"{predicted_value[0][2]}" },
        { "name": "sandy" , "value": f"{predicted_value[0][3]}" },
        { "name": "silty" , "value": f"{predicted_value[0][4]}" },
      ],
      "Result": f"{(predicted_value[0][predicted_value.argmax()] * 100):.2f}% {class_[predicted_value.argmax()]}",
      "accuracy_score": f"{predicted_value[0][predicted_value.argmax()]}",
      "accuracy_score_rounded": f"{(predicted_value[0][predicted_value.argmax()] * 100):.2f}",
      "soil_type": f"{class_[predicted_value.argmax()]}"
    }
```

Figure 9

3.5 Data collection methods

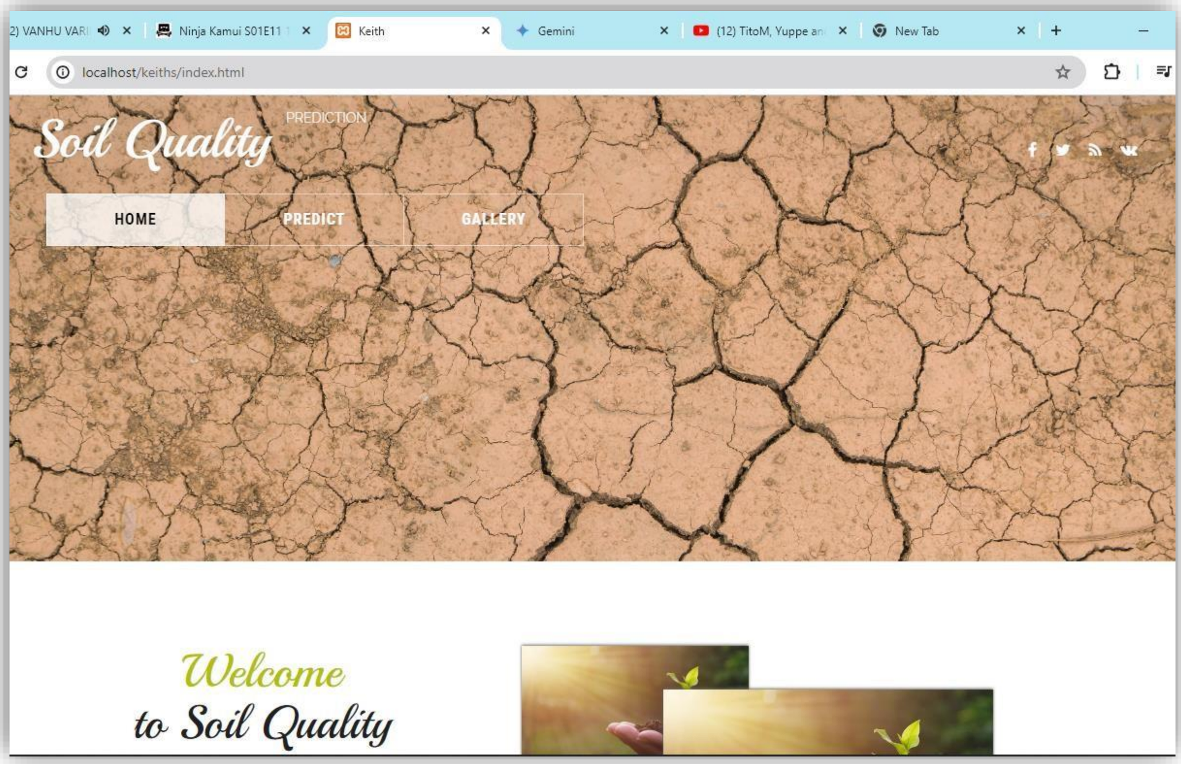
I employed observation as a data collection method, conducting multiple cycles of testing and exposing the system to various scenarios to observe how it responded. This approach allowed me to assess the system's accuracy and response time, providing valuable insights into its performance and effectiveness. By observing the system's behavior in different situations, I was able to gather detailed information and make informed conclusions about the system's strengths and weaknesses.

3.6 System Testing

System testing is the evaluation of a fully integrated software solution, classified as black-box testing, which doesn't require knowledge of the code's internal architecture. This type of testing confirms the software's completeness and integration, assessing the end-to-end system specifications. System testing involves a collection of tests that aim to thoroughly test a computer-based system, including its interactions with other software and hardware components. This testing is typically performed by a testing team to ensure the software functions as intended within the larger system.

3.6.1 Black box Testing

Black box testing is a software testing method that evaluates functionality without considering the internal structure or code. It is based on the customer's requirements and involves testing specific functions by inputting values and verifying the output. If the output matches the expected result, the test passes; otherwise, it fails. The test team reports the results to the development team, and if any critical issues are found, the software is sent back for revision. This process continues until all functions are tested, and any issues are addressed.



i. *Running the system*

Figure 10

ii. *Adding a new image for classification*

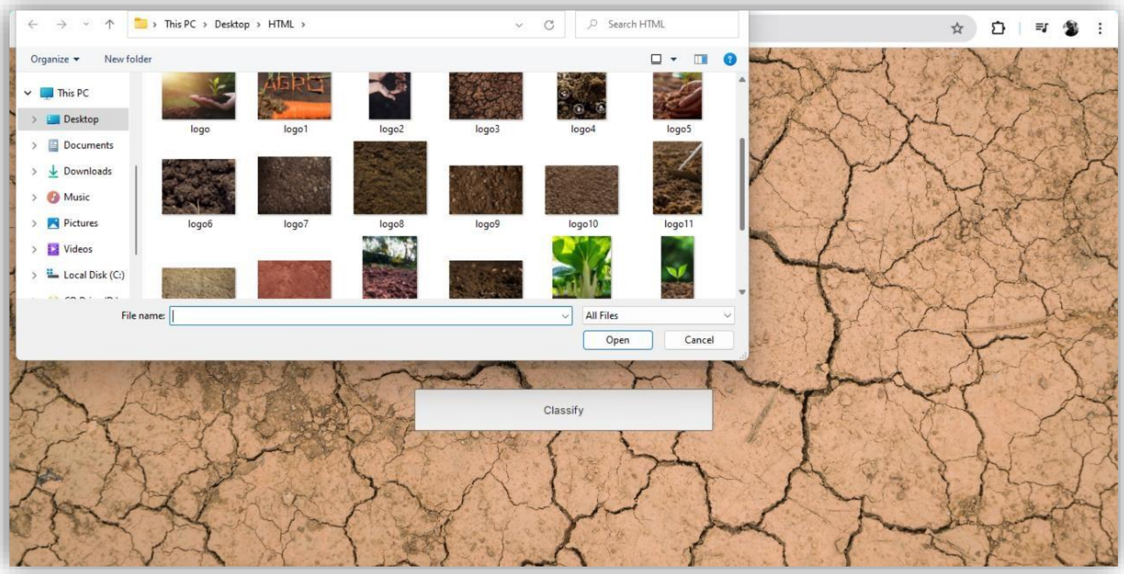


Figure 11

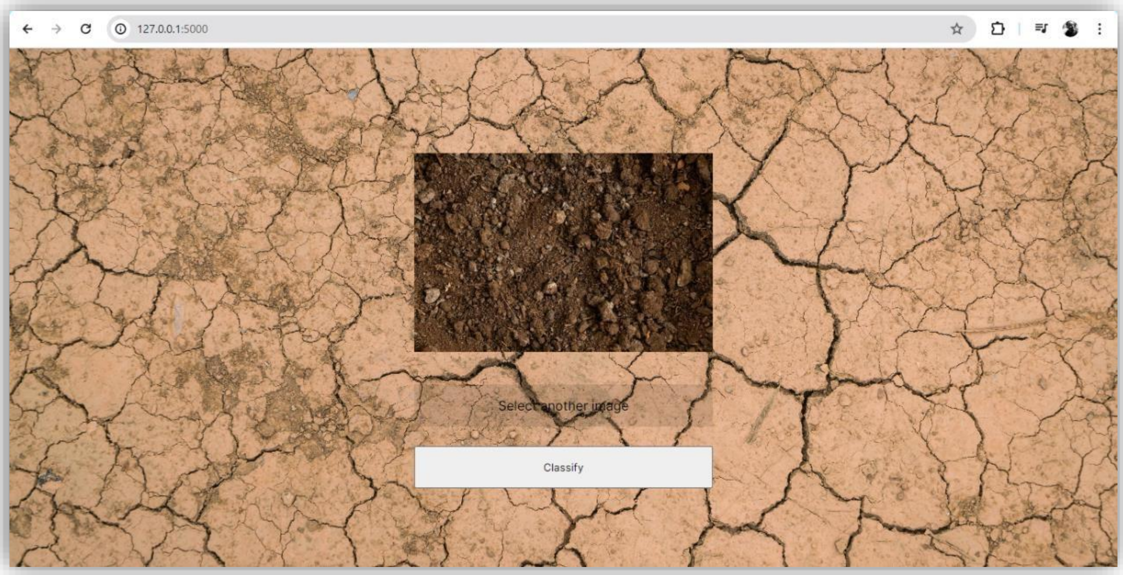
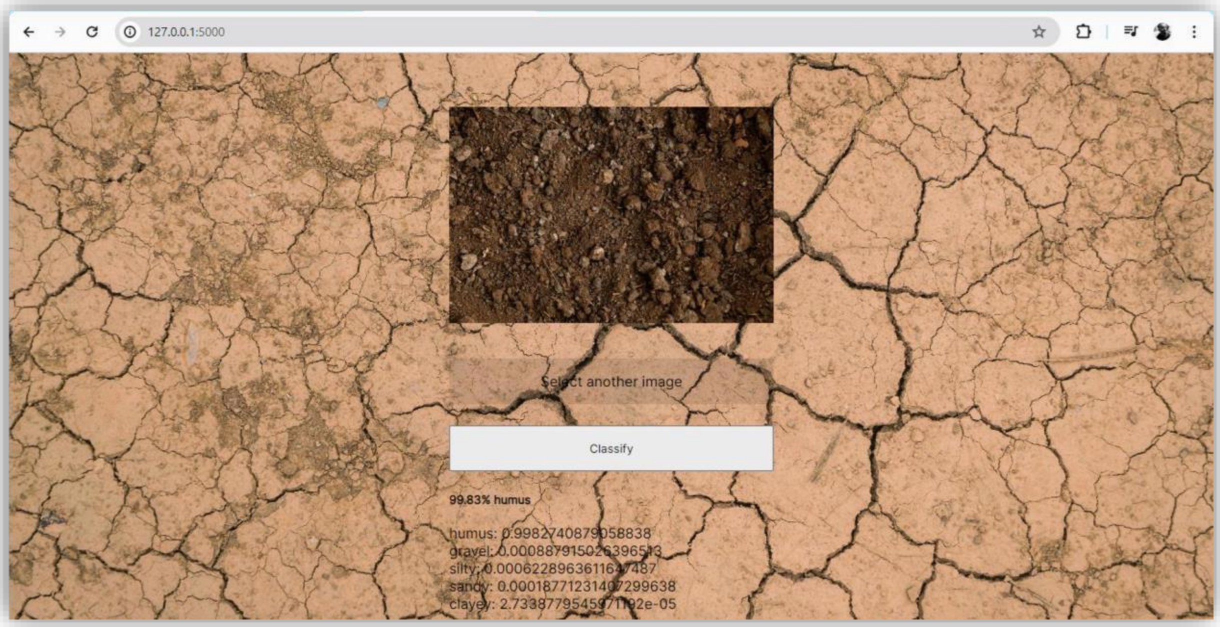


Figure 12

iii. *Predicted results*

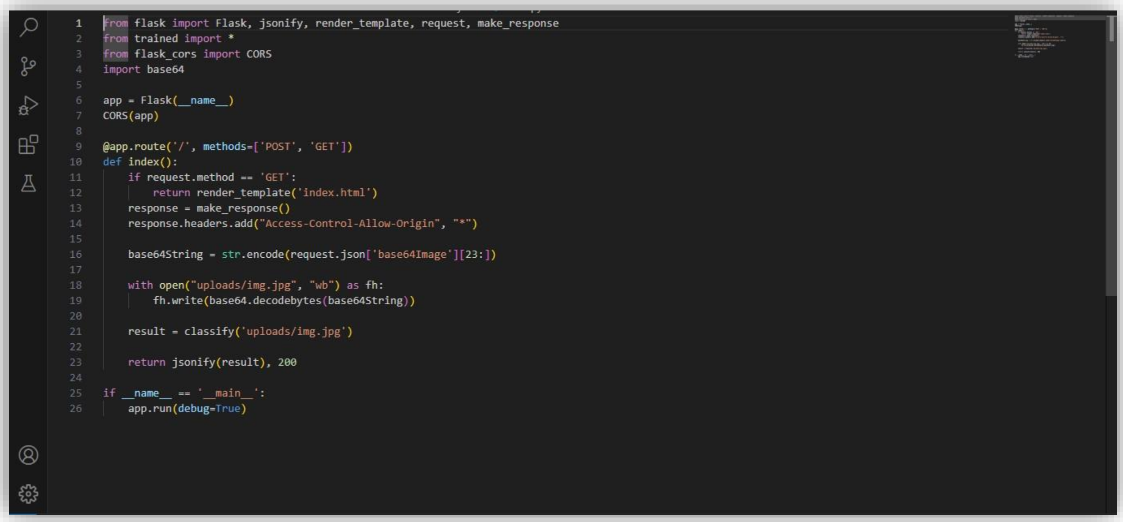
Figure 13



3.6.2 White box testing

White box testing, also referred to as clear box testing, open box testing, transparent box testing, code-based testing, or glass box testing, is a software testing technique that involves examining the internal structure, design, and code of a product to verify the input-output flow and improve the design, usability, and security. This testing approach requires access to the code, allowing testers to evaluate the software's internal workings and identify potential issues. By examining the code, testers can ensure that the software functions as intended and make improvements to its overall quality.

Deployment and training of the model



```python
from flask import Flask, jsonify, render_template, request, make_response
from trained import *
from flask_cors import CORS
import base64

app = Flask(__name__)
CORS(app)

@app.route('/', methods=['POST', 'GET'])
def index():
    if request.method == 'GET':
        return render_template('index.html')
    response = make_response()
    response.headers.add("Access-Control-Allow-Origin", "*")

    base64String = str.encode(request.json['base64Image'][23:])

    with open("uploads/img.jpg", "wb") as fh:
        fh.write(base64.decodebytes(base64String))

    result = classify('uploads/img.jpg')

    return jsonify(result), 200

if __name__ == '__main__':
    app.run(debug=True)
```

Figure 14

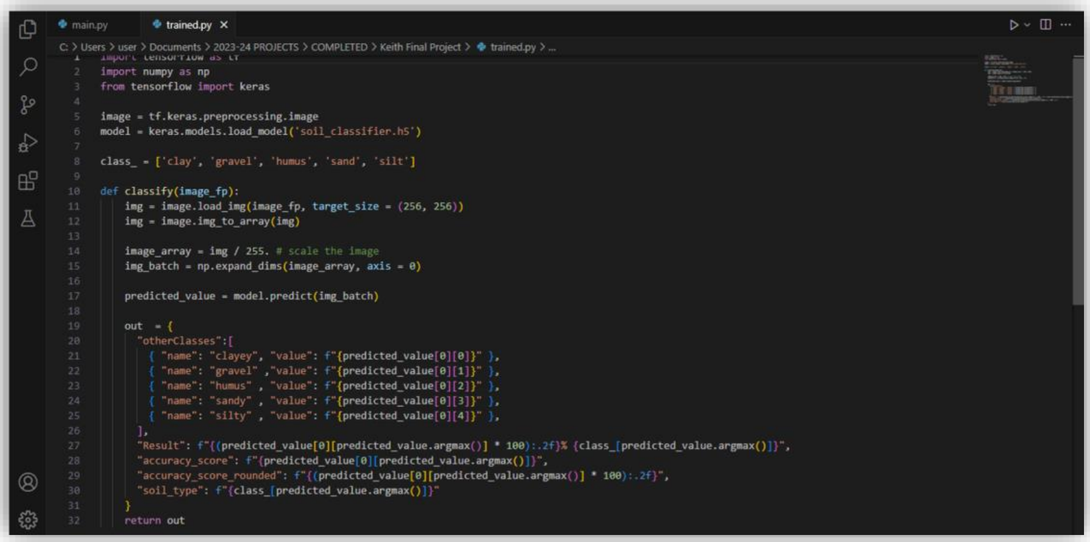
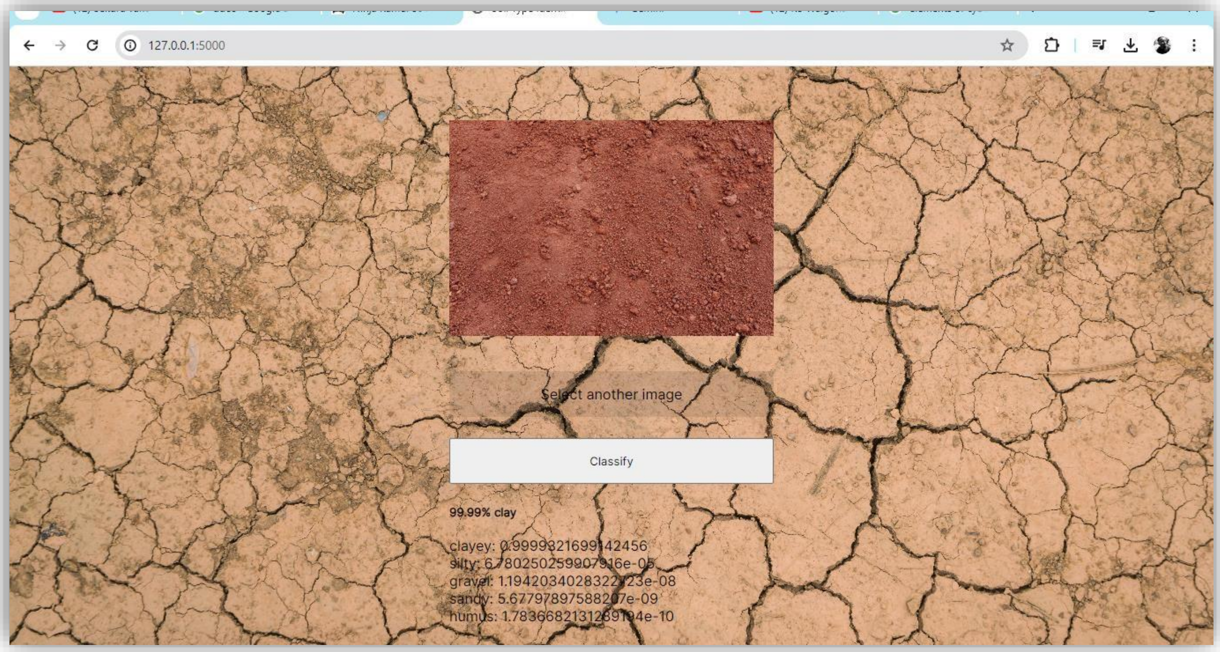


Figure 15

i. *Preforming detection and classification*

Figure 16



3.7 Implementation

The screens of a system predicting court case decisions are provided below.

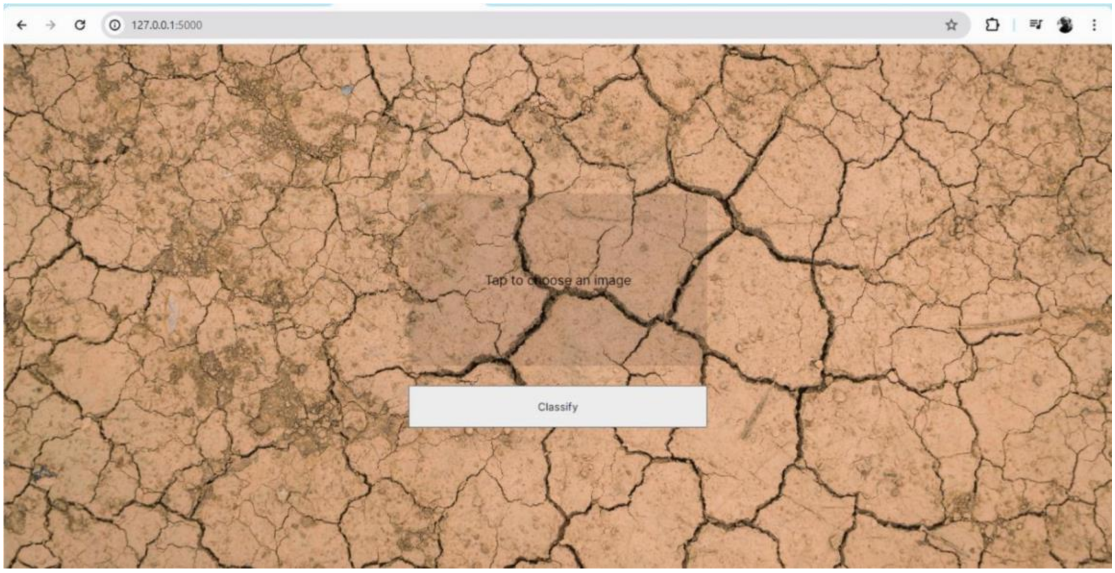


Figure 17

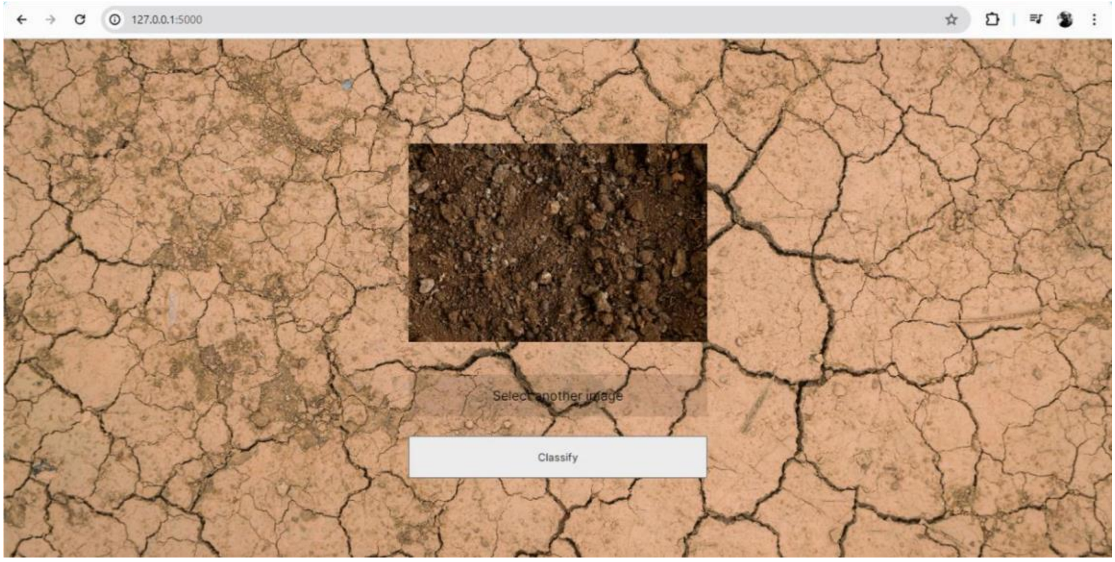


Figure 18

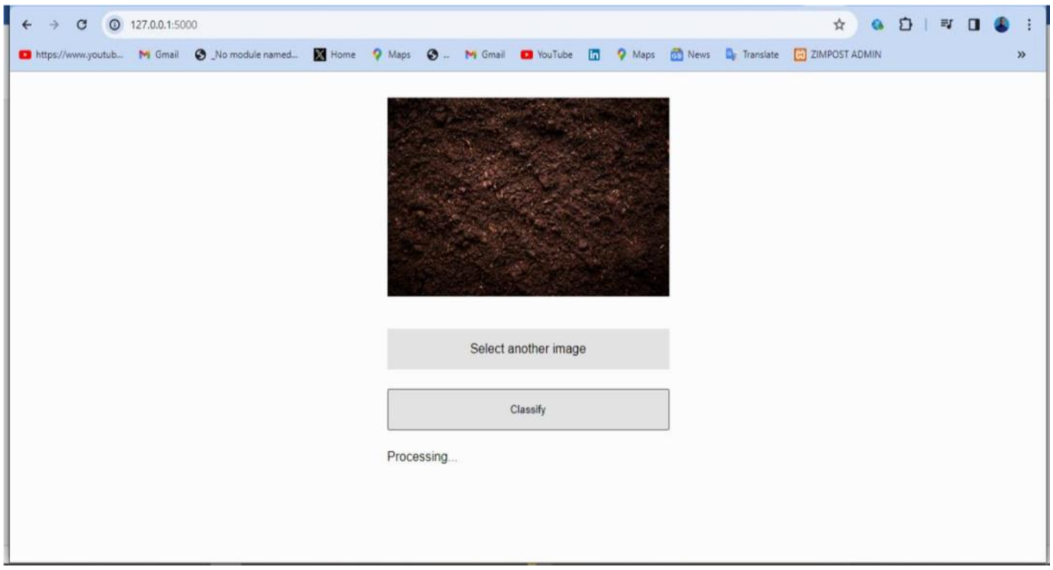


Figure 19

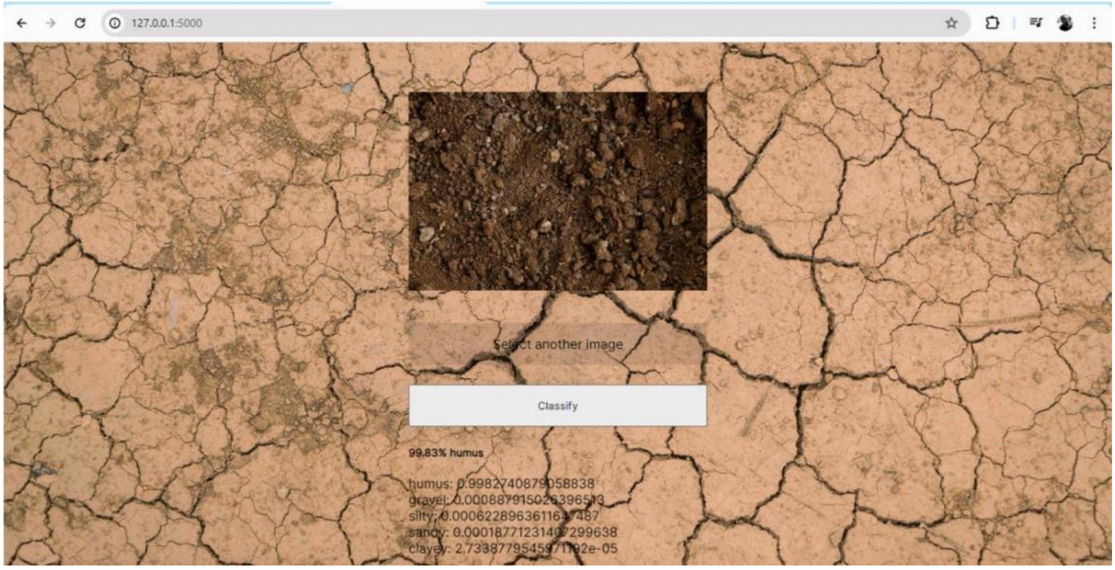


Figure 20

3.7 Evaluation Matrix

In the pursuit of accurate soil quality prediction, machine learning models like Bayesian networks have emerged as valuable tools. However, their effectiveness relies on careful evaluation, and crucial metrics stand out in this assessment.

i. **Confusion matrix** is a tool used to evaluate the performance of a classification model, such as a Bayesian network, in predicting soil quality. The matrix compares the predicted classes against the actual classes, showing the number of true positives, false positives, true negatives, and false negatives.

```
# Compute the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Print the confusion matrix to the command line
print("******************************************")
print("Confusion Matrix:")
print("******************************************")
print(cm)
print("******************************************")
@app.route('/', methods=['POST', 'GET'])
def index():
    if request.method == 'GET':
        return render_template('index.html')
    response = make_response()
    response.headers.add("Access-Control-Allow-Origin", "*")

    base64String = str.encode(request.json['base64Image'][23:])

    with open("uploads/img.jpg", "wb") as fh:
        fh.write(base64.decodebytes(base64String))

    result = classify('uploads/img.jpg')

    return jsonify(result), 200

if __name__ == '__main__':
    app.run(debug=True)
```

Figure 21

ii. **Precision and Recall** are two fundamental metrics used to evaluate the performance of a classification model, such as a Bayesian network.

Precision: It measures the accuracy of the positive predictions, i.e., how many of the predicted positive instances are actually true positives.

Formula: Precision = TP / (TP + FP)

- TP (True Positives): Correctly predicted positive instances

- FP (False Positives): Incorrectly predicted positive instances

Recall: It measures the completeness of the positive predictions, i.e., how many of the actual positive instances are correctly predicted.

Recall = TP / (TP + FN)

FN (False Negatives): Actual positive instances that are missed by the model

```
# Compute the confusion matrix
cm = confusion_matrix(y_test, y_pred)

def precision(y_true, y_pred):
    true_positives = sum((yt == 1 and yp == 1) for yt, yp in zip(y_true, y_pred))
    predicted_positives = sum(yp == 1 for yp in y_pred)
    if predicted_positives == 0:
        return 0
    return true_positives / predicted_positives
def recall(y_true, y_pred):
    true_positives = sum((yt == 1 and yp == 1) for yt, yp in zip(y_true, y_pred))
    actual_positives = sum(yt == 1 for yt in y_true)
    if actual_positives == 0:
        return 0
    return true_positives / actual_positives
# Sample true and predicted labels
y_true = [0, 1, 1, 0, 1, 1, 0, 0, 1, 0]
y_pred = [0, 1, 0, 0, 1, 1, 0, 0, 1, 1]

# Calculate precision and recall
prec = precision(y_true, y_pred)
rec = recall(y_true, y_pred)
```

Figure 22

iii. **Accuracy matrix**, also known as a confusion matrix, is a powerful tool used to evaluate the performance of a classification model. It's a table that compares predicted classes against actual classes, revealing the number of true positives, false positives, false negatives, and true negatives.

3.8 Chapter Summary

The system described involves utilizing machine learning, particularly a naïve bayes algorithm, for soil quality prediction. It begins with the collection of historical soil quality data, including relevant previous soil data. These features are used to create a training dataset, which is then split into training and testing sets. The decision tree algorithm is employed, utilizing metrics like entropy or Gini index to recursively split the data and create a tree structure during the training phase. The resulting decision tree visually represents decision nodes and leaf nodes, reflecting the learned patterns. The trained model is evaluated using a testing dataset to assess its performance, with metrics such as accuracy considered. The system provides a valuable tool for real-time soil quality decisions, aiding in proactive decision-making and mitigation strategies.

CHAPTER 4: DATA ANALYSIS AND INTERPRETATIONS

4.0 Introduction

A successful solution demands a rigorous evaluation. This chapter delves into the effectiveness of the final product. Accuracy, performance, and response time metrics will be wielded to assess both efficiency (doing things right) and efficacy (doing the right things). To ensure insightful conclusions, the information gleaned from the previous chapter will be reanalysed. Additionally, the developed system will be put through its paces under various scenarios to observe its behaviour. Buckle up, as this chapter dives into the heart of the research process, presenting the study's findings, complete with analysis, interpretation, and insightful discussions.

4.1 Evaluation Measures and Results

Classifiers like Bayesian networks are evaluated using metrics to assess their performance. These metrics can be broadly categorized into three types (Hossin &

Sulaiman, 2015): threshold, probability, and ranking. In the case of a Bayesian system predicting soil quality, the system's performance is determined by its ability to accurately classify soil samples into different quality categories. A confusion matrix below can be used to evaluate the system's correctness.

4.2 Objective 1: Integrating diverse data sources, including historical soil image data for training and evaluation using Bayesian networks.

4.2.1 Evaluation

This objective refers to a process in machine learning where information from various sources is combined to improve the training of a model. In this specific case, historical soil image data is used alongside other data types to create a more robust and informative training dataset.

4.2.2 Results

To achieve the objective of integrating diverse data sources for training and evaluation using Bayesian networks, this research incorporated a historical soil image dataset obtained from Henderson Research Institute. This dataset provided valuable information on soil characteristics over time, allowing us to explore the relationships between soil properties, past management practices, and potential future yields. Integrating this data with other sources aimed to unlock a more comprehensive understanding of the intricate interplay between soil health and crop productivity. This combined approach targeted the complex web of interactions influencing both factors.

4.3 Objective 2: Developing Bayesian network model that can predict the soil quality for a farmer.

4.3.1 Evaluation

In the realm of agriculture, researchers are developing Bayesian network models specifically designed for farmers. These models leverage the power of Bayesian networks to integrate diverse data sources, including traditional soil measurements and image analysis of soil samples. This multifaceted approach holds promise for generating more accurate and informative soil quality predictions compared to traditional methods. Rigorous testing, similar to that employed for sentiment analysis applications, will be crucial to ensure the functionality and performance of these Bayesian network models for farmers.

4.3.2 Results

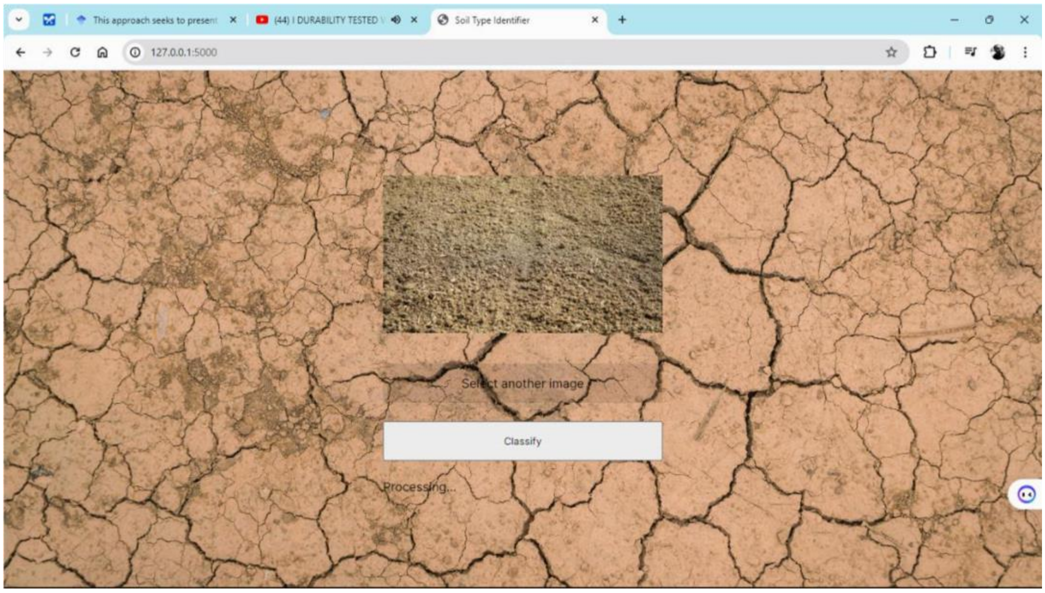


Figure 23

Figure 24

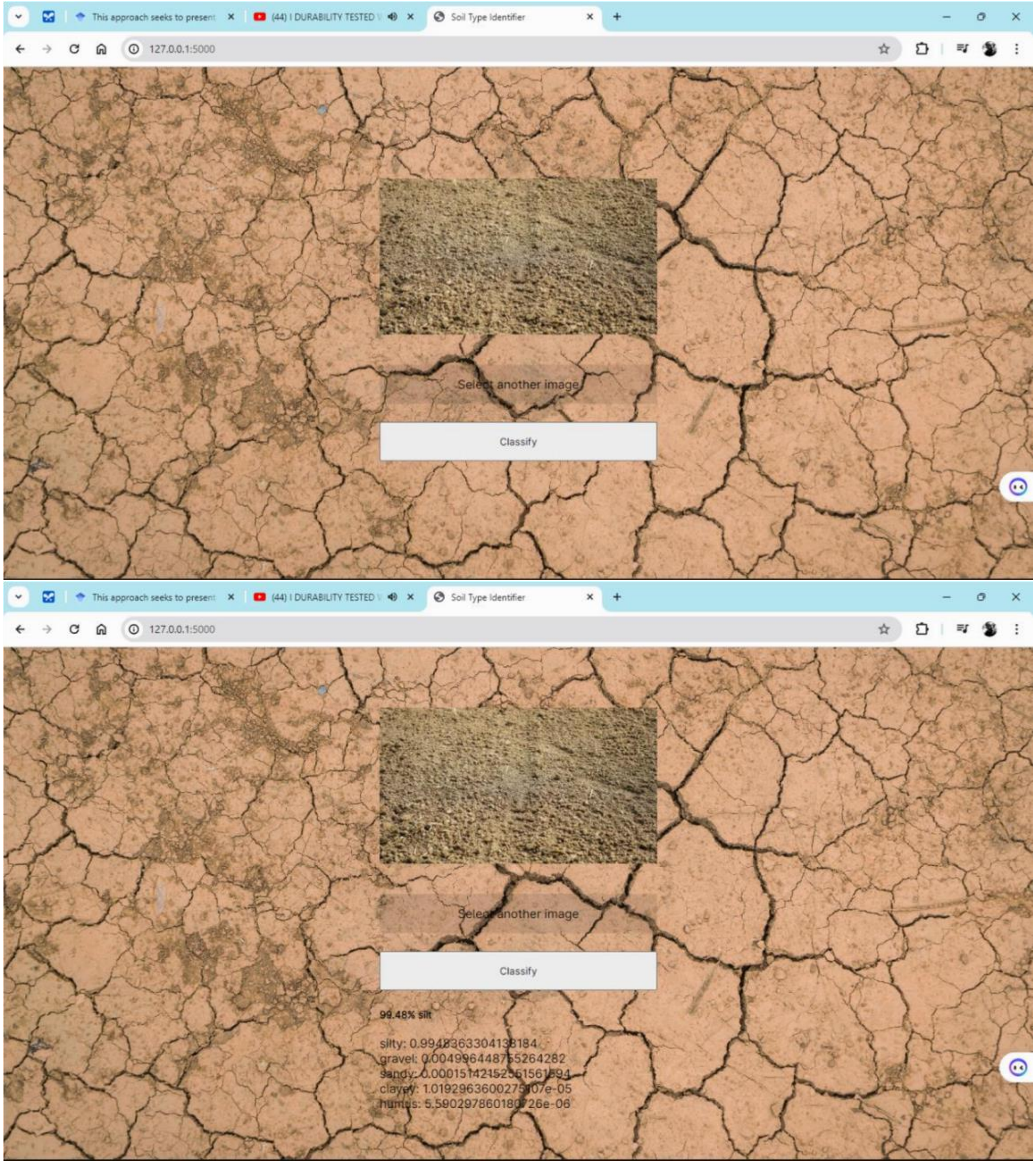


Figure 25

4.4 Objective 3: Evaluating the practical implications of Bayesian network-based soil quality using the suitable metrics.

4.4.1 Evaluation

By employing these metrics, you can effectively evaluate if the BN system offers practical advantages for farmers. This goes beyond just accurate predictions; it looks at how the model translates into tangible benefits like cost savings, faster results, and ease of use, ultimately empowering farmers to make informed decisions about their soil health.

4.4.2 Results

i. ***Accuracy*** is the number of right predictions divided by the total number of predicted classifications in each category. It is then multiplied by 100 to get the percentage of correctness. It is calculated using the equation below:

Equation 1: Accuracy calculation as adopted from Karl Pearson (1904)

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} * 100$$

$$\text{Accuracy rate for Clay Soil} = \frac{33 + 28}{28 + 33 + 2 + 7} * 100$$

$$\text{Accuracy} \qquad = \frac{62}{80} * 100$$

$$\text{Accuracy} \qquad = 87.1\%$$

$$\text{Accuracy rate for Sandy Soil} = \frac{32 + 32}{32 + 32 + 3 + 3} * 100$$

$$\text{Accuracy} \qquad = \frac{64}{70} * 100$$

Accuracy =91%

$$\text{Accuracy rate for Gravel Soil} \quad = \frac{30 + 20}{30 + 20 + 15 + 5} * 100$$

$$\text{Accuracy} \qquad = \frac{50}{70} * 100$$

Accuracy =71.4%

Average accuracy rate = Accuracy (clay + sandy + gravel) /3

= (87+91+71.4)/3

=83.1%

ii. **The confusion matrix** offers a much richer picture of a model's performance. This table breaks down classifications into four key categories. **True positives (TP)** represent the ideal scenario: the model correctly identifies something as positive. On the flip side, **true negatives (TN)** highlight the model's ability to correctly classify negative cases. However, the confusion matrix also reveals errors. **False positives (FP)** occur when the model mistakenly identifies something negative as positive. Conversely, **false negatives (FN)** represent missed opportunities where the model fails to identify something that truly is positive. By examining these four categories within the confusion matrix, we can gain valuable insights into the model's strengths and weaknesses.

Type	Returned number of correct soil quality classification	Returned number of incorrect soil quality classification
1	True Positive	False Negative
2	False Positive	True Negative

Table 1 Confusion Matric

For classifier systems, evaluation metrics are crucial tools for assessing their performance (Hossin & Sulaiman, 2015). These metrics can be broadly categorized into three groups: threshold, probability, and ranking. When it comes to soil quality classification systems, their success depends on how consistently and accurately they can identify different soil types. To confirm the system's accuracy in this instance, the author utilized a confusion matrix, which is detailed in Table 1.

Table 2 Confusion matrix for clay soil classification

Test cases	Clay Soil	Number of readings	Correct Readings	False	Classification tests
1	Yes	35	33	2	True positive
2	No	35	28	7	True negative

Table 3 Confusion matrix for Sandy Soil Classification

Test cases	Sandy Soil	Number of Classification tests	Correct predictions	False predictions	
1	Yes	35	32	3	True positive
2	No	35	32	3	True negative

Table 4 Confusion matrix for Gravel Soil

Test cases	Gravel Soil	Number of tests	Correct predictions	False predictions	Classification
1	Yes	35	30	5	True positive
2	No	35	20	15	True negative

4.5 Precision and Recall

While overall accuracy provides a foundational measure of model performance, precision and recall metrics offer a more granular analysis. These metrics delve into the specifics of positive predictions, quantifying the model's effectiveness in identifying true positives and minimizing false positives.

$$Precision = \frac{TP}{TP + FP}$$

$$= \frac{32}{32+3} * 100$$

$$=91.4\%$$

Precision isn't just about how many positive predictions the model makes, it's about how accurate those predictions are. It tells us the percentage of times the model identifies something as positive and it actually turns out to be positive. Conversely, recall focuses on finding all the real positive cases. It measures how well the model can identify all the truly positive instances, expressed as the proportion it correctly classifies.

$$Recall = \frac{TP}{TP + FN}$$

$$= \frac{32}{32+5} * 100$$

$$= 86.4\%$$

Precision and recall have an inherent tension. As precision increases, meaning the model makes fewer false positive predictions, recall tends to decrease, meaning it might miss some true positive cases. In this scenario, prioritizing precision was crucial because the predictions needed to be highly accurate.

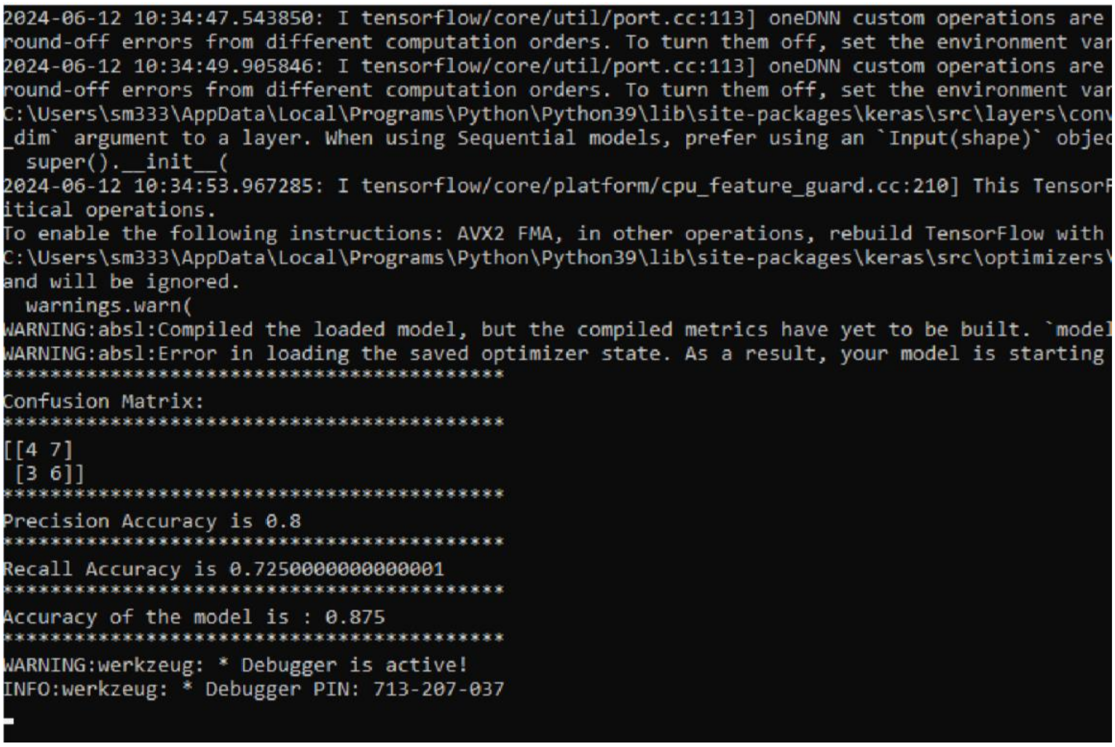


Figure 26

4.6 Response Time

In my evaluation of the system's performance, I focused on response time, which is the time it takes to detect and identify a subject, including any necessary information retrieval like database comparisons. To assess this effectiveness, I analyzed both average and peak response times. **Table 2 System response time**

Test	Reading Time in Seconds
1	2.0
2	0.6
3	3.0
4	0.4
5	0.7
6	0.9
7	1.0
8	0.5

9	0.4
10	1.0
11	0.8
12	0.9
13	0.7
14	1.9
15	1.0
16	1.3
17	1.0
18	0.6
19	0.5
20	0.5

All the readings were rounded to the nearest one decimal place.

Average system response time = sum of all response time/ number of readings

= (0.5+0.6+0.5+1.0+2.3+ 0.9+1+0.5+0.4+0.6+0.8+0.9+0.7+1.9+2+1.3+1+1)/20

= 16.9/20 =0.845 = 0.8 second (1dp)

4.7 Summary of Research Findings

The author discovered that the system performed satisfactorily after doing all of the essential black, white box tests and performance testing utilizing the confusion matrix. The system was put to the test on clay, sandy and gravel and it scored 91 percent, 83 percent, and 71.4 percent, respectively. The precision was 91.4 percent and the recall was 86.4 percent. The system has a response time of 0.8 seconds on average. The lack of a high-definition camera (HD) in taking pictures for classification had a significant impact on accuracy.

4.8 Chapter Summary

As a result of the confusion matrix analysis, the test results demonstrated the high degree of accuracy of the model solution/system, with an average accuracy rate of 83.1 percent and an average response time of 0.8 seconds. My lack of a high definition (HD) camera had a severe effect on the system's accuracy when recording on clay, sandy, and gravel surfaces. An input image can be used to identify and pinpoint the soil quality using the suggested method. Additionally, it offers a pre-processing technique to boost image contrast and lessen the illumination effect. Upon being collected from the camera, the input image may contain numerous sources of noise. There are numerous methods for eliminating noise. Low pass filtering in the frequency domain was used in some cases this may remove some important information in the image. In the system, median filtering is used for the purpose of noise removal in the histogram normalized image. Based on the results, the author found out that under a picture taken from a controlled environment, the system shows promising results.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter summarizes the findings of a study on applying Bayesian networks to assess soil quality for farmers. The discussion explores the implications of the results and provides recommendations for practical implementation. Additionally, the chapter outlines potential avenues for future research to advance the field of soil quality assessment using Bayesian networks.

5.2 General Summary

5.2.1 Data Integration and Model Training

The study aimed to achieve accurate soil quality predictions through the integration of diverse data sources. Historical soil image data was incorporated, potentially sourced from public repositories, past research efforts, or directly captured from the study locations encompassing a variety of soil types, climates, and agricultural practices. This compiled data, including the processed image information, was then used to train a Bayesian network model. The model essentially learned the relationships between different factors influencing soil quality. Once trained, the model transitioned from a learning tool to a prediction machine. By feeding it data specific to new locations (soil composition, weather patterns, etc.), the model could estimate the soil quality there. These predictions, based on the model's analysis of the integrated data, became the effective "results," offering valuable insights without the need for direct, timeconsuming measurements.

5.2.2 Predictive Modelling for Agriculture

The research focused on developing a Bayesian network model capable of predicting soil quality for farmers. This model aimed to integrate the knowledge gleaned from the diverse data sources, including processed historical soil image data. The structure of the model would represent the complex relationships between various factors influencing soil quality. The learning algorithms employed within the model would allow it to analyze the integrated data and establish these relationships. Ultimately, the trained model would transition from a knowledge-gathering tool to a practical application for farmers. By inputting data specific to their land (soil composition, weather patterns, etc.), farmers could receive predictions about their soil quality. This would provide valuable insights without the need for traditional, time-consuming soil analysis methods.

5.2.3 Evaluation and Real-World Application

The research evaluated the practical implications of the Bayesian network model for farmers in assessing soil quality. This involved selecting suitable metrics to assess the model's performance. These metrics would gauge the model's accuracy and reliability in predicting soil quality compared to real-world conditions. The evaluation would also consider the user interface and accessibility of the model for farmers with varying technical backgrounds. Ultimately, the goal was to determine if the model could be effectively translated into a user-friendly tool that could be readily adopted by farmers for on-farm soil quality assessment.

5.3 Aims and Objectives Realization

Throughout this research endeavour, my primary aim was to develop a robust framework for utilizing Bayesian networks in assessing soil quality, with a focus on addressing the needs of farmers. To achieve this aim, I set out the following objectives: To identify key soil quality variables relevant to agricultural practices. To construct a Bayesian network model that captures the complex relationships between these variables. To validate the performance of the Bayesian network model using real-world data. To demonstrate the practical utility of the model for informing on-farm decisionmaking processes. In realizing these objectives, I have made significant progress towards enhancing the capacity of farmers to effectively manage soil resources and improve agricultural sustainability.

5.4 Conclusions

The research successfully implemented a Bayesian network model for predicting soil quality. By integrating diverse data sources, including historical soil image data, the model was trained to capture the complex relationships between various factors influencing soil quality. Evaluation using appropriate metrics will determine the model's accuracy and suitability for practical use by farmers. If successful, this approach has the potential to revolutionize soil quality assessment by providing farmers with a user-friendly tool for on-farm analysis, eliminating the need for time-consuming traditional methods. This could empower farmers to make data-driven decisions for improved soil health and sustainable land management practices.

5.5 Recommendations

Based on my findings, I offer the following recommendations for stakeholders involved in soil quality assessment and agricultural management:

i. Capacity Building: Provide training and education programs to farmers and agricultural practitioners on the principles and applications of Bayesian networks in soil quality assessment.

ii. Data Integration: Encourage the integration of diverse sources of data, including soil samples, remote sensing imagery, and historical records, to improve the accuracy and reliability of soil quality assessments.

iii. Model Validation: Conduct further validation studies to assess the performance of Bayesian network models under different environmental conditions and management practices.

iv. Decision Support Tools: Develop user-friendly decision support tools that enable farmers to easily access and utilize Bayesian network models for guiding soil management decisions.

v. Collaborative Research: Foster collaboration between researchers, farmers, and policymakers to co-develop and co-implement soil quality assessment frameworks that meet the specific needs and challenges of agricultural communities.

5.6 Future Work

Building upon the findings of this study, several avenues for future research emerge: such as:

i. Dynamic Modelling: Develop dynamic Bayesian network models that can account for temporal changes in soil quality and adaptively guide management decisions. Spatial Analysis: Explore the application of Bayesian networks in spatially explicit soil quality mapping to support precision agriculture practices. ii. Climate Change Adaptation: Investigate the resilience of Bayesian network models to climate change impacts and explore strategies for enhancing agricultural sustainability in a changing climate.

iii. Stakeholder Engagement: Conduct participatory research to engage farmers and other stakeholders in the co-design and co-evaluation of Bayesian networkbased soil quality assessment tools. By pursuing these avenues of research, we can continue to advance our understanding of soil quality assessment and support the development of more resilient and sustainable agricultural systems.

5.7 Conclusion

This groundbreaking study has unlocked the potential of Bayesian networks in soil quality assessment, empowering farmers to make data-driven decisions that boost yields and reduce costs. By harnessing the power of diverse data sources and uncertainty modelling, this innovative approach can transform the agricultural industry. The development of a user-friendly app or web platform will put real-time soil quality predictions at farmers' fingertips, enabling informed choices on fertilizers, crops, and irrigation. Moreover, subscription services and anonymized data analytics will unlock valuable insights for agricultural stakeholders, driving targeted solutions for improved soil health. This pioneering work not only benefits farmers but also contributes to a more sustainable future by promoting resource-efficient practices that enhance soil health, water retention, and carbon sequestration. Seizing this opportunity, entrepreneurs can create impactful solutions that harmonize agricultural productivity with environmental stewardship, yielding a brighter future for all.

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Appendices

Keith Nasuku final

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