BINDURA UNIVERSITY OF SCIENCE EDUCATION FACULTY OF SCIENCE AND ENGINEERING

APPLICATION OF NAIVES BAYES MACHINE LEARNING ALGORITHM FOR ECOSYSTEM SERVICES EVALUATION (HARARE PARKS)

STUDENT NAME: MICHAEL T TIGERE

REG NUMBER: B202370B

PROJECT SUPERVISOR: MR. CHIKWIRIRO

APPROVAL FORM

The undersigned certify that they have supervised the student Michael T Tigere's dissertation entitled, "APPLICATION OF NAIVES BAYES MACHINE LEARNING ALGORITHM FOR ECOSYSTEM SERVICES EVALUATION (HARARE PARKS)" submitted in partial fulfilment of the requirements for a Bachelor of Science Honours Degree in Computer Science at Bindura University of Science Education.

STUDENT: **DATE:**

02/10/24

………………………………………………… ……………………………..

SUPERVISOR: **DATE:**

02/10/24

………………………………………………… ……………………………..

CHAIRPERSON: **DATE:**

02/10/24

………………………………………………… ……………………………..

EXTERNAL EXAMINER: **DATE:**

………………………………………………… ……………………………..

Abstract

This research is based on the application of Naïve Bayes machine learning algorithm for ecosystem service evaluation (Harare Parks). The purpose of this study is to investigate and demonstrate the effectiveness of the Naïve Bayes machine learning algorithm as a tool for classifying, predicting and assessing ecosystem services. The project focused on creating and implementing a Naïve Bayes machine learning model to estimate the quality of ecosystem services given to the community. The research concludes that Naïve Bayes algorithm can estimate ecological services.

Dedication

I dedicate my dissertation to my family and friends. I am very grateful to my beloved parents, Salios and Bibiana Tigere, whose words of support and push for persistence still ring in my ears. They instilled in me the values of patience, endurance and passion which have propelled me to new heights in life. My righteous actions are all founded in these two remarkable people, and l am proud to be your son.

Acknowledgements

All credit goes to Almighty God for guiding me through my final year dissertation. Mr Chikwiriro, my supervisor l express my heartfelt appreciation for the time and patience he put in me as l worked on my research project; l cherish your time and commitment, sir. I would also want to thank Bindura University of Science Education for all of the infrastructural and academic resources that contributed to the accomplishment of this work. Not to mention my family and co-workers, who provided valuable support and contribute to my well-being.

TABLE OF CONTENTS

CHAPTER 1

1.0 Introduction

Ecosystem Services Evaluation is a crucial field in environmental science and resource management, focusing on the assessment and quantification of the various benefits that ecosystems provide to humans (Costanza et al., 1997). Ecosystem services encompass a wide range of contributions, from the provisioning of essential resources like clean water and food to the regulation of climate, air, and water quality, as well as the provision of recreational and aesthetic value (Daily, 1997; MA, 2005).

To comprehensively understand the status and significance of these services, advanced analytical tools and machine learning techniques are increasingly being applied (Schröter et al., 2015). One such tool, the Naive Bayes machine learning algorithm, has found its place in Ecosystem Services Evaluation as a valuable means of classifying, predicting, and assessing these services (Smith et al., 2020). This introduction delves into the application of Naive Bayes describing the essential elements of the Ecosystem Services Evaluation, outlining the important part it plays in this field and it's potential to improve our comprehension of complex interactions between ecosystems and human well-being.

1.1 Background of Study

Ecosystems play a pivotal role in supporting life on Earth and providing various benefits to human societies. Ecosystem Services, a concept introduced by Costanza et al. in 1997, encompass a wide array of functions and contributions ecosystems provide to humanity. These services may be divided into provisioning services (e.g., food and water), regulating services (e.g., climate and disease control), supporting services (e.g., nutrient cycling), and cultural services (e.g., aesthetics and recreation).

The value of Ecosystem Services has gained increasing recognition over the years, highlighting the critical role of natural systems in human well-being (Daily, 1997; MA, 2005). As populations grow and human activities intensify, the pressure on ecosystems to continue delivering these services sustainably becomes more pronounced.

To effectively manage and preserve ecosystems, it is essential to evaluate and quantify the services they provide. Traditional methods of assessment, reliant on field surveys and expert judgment, often prove time-consuming and resource-intensive. This is where the integration of machine learning techniques, such as the Naive Bayes algorithm, becomes valuable.

Machine learning approaches possess the ability to improve the accuracy and the effectiveness of the assessment of the ecosystem services. The Naive Bayes algorithm, known for its simplicity and effectiveness in classification tasks, offers a promising avenue for classifying, predicting, and assessing ecosystem services.

This study’s objective is to investigate the application of the Naive Bayes algorithm in the context of Ecosystem Services Evaluation. By leveraging this machine learning technique, we seek to provide a more accurate, rapid, and scalable means of assessing the diverse ecosystem services that underpin our well-being and environmental sustainability.

1.2 Problem Statement

The problem this study aims to tackle, therefore, is to explore how Naive Bayes can be effectively employed to classify, predict, and assess ecosystem services. By doing so, it seeks to provide a robust and efficient means to address the limitations of traditional evaluation methods and support more informed and sustainable ecosystem management practices.

1.3 Research Aim

The purpose of this study is to investigate and demonstrate the effectiveness of the Naive Bayes machine learning algorithm as a tool for the classification, prediction, and assessment of ecosystem services.

1.4 Research Objectives

1. Explore on other algorithms used by other researchers and research journals
2. Develop and implement a Naïve Bayes machine learning model to predict the quality of a service provided by the ecosystem to the community.
3. Evaluate the model performance and accuracy using relevant metrics on predicting.

1.5 Research Questions

1. What have other researchers done in the field of Bayesian networks?
2. What are the tools to be used by the author on implementing a machine learning model?
3. What metrics are to be used by the researcher on assessing the performance of the model?

1.6 Methodology

- ✓ Core i5
- ✓ 4 Gig RAM
- ✓ Python 3.9
- ✓ Streamlit
- ✓ Agile Software Development

1.7 Research Justification

Ecosystem Services, which include all of the numerous advantages that the ecosystem offer to humans, are integral to our well-being and the sustainability of the planet. These services support vital functions such as food production, clean water supply, and climate regulation. However, the ongoing threats to ecosystems due to human activities and environmental changes necessitate accurate and efficient methods for their evaluation.

1.8 Research Limitations

This research, focused on "Ecosystem Services Evaluation with Naive Bayes," is subject to several limitations that should be considered. Data quality and availability, potential model oversimplification, and the model's capacity to generalize across diverse ecosystems and regions may impact the study's outcomes. The choice of environmental variables and the representativeness of training data can affect the Naïve Bayes model's applicability and accuracy. Furthermore, resource and expertise constraints, ethical considerations, potential biases in training data, and the challenge of capturing temporal and environmental complexity are important limitations. Furthermore, the study may not fully account for the interplay between human populations and ecosystems or the nuances of regulatory and policy frameworks, which can vary significantly. Acknowledging these limitations is vital for interpreting the research findings accurately and informing future studies and practical applications in the realm of Ecosystem Services Evaluation.

1.9 Definition of Terms

Bayesian Networks:

Bayesian networks are probabilistic graphical models that shows a group of variables together with the conditions under which they rely using 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 ecosystem quality.

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.

CHAPTER 2: REVIEW OF LITERATURE:

2.0 Introduction

Previous section focuses on problem identification and enlightened many research contributions. The literature review is discussed in this chapter. A literature review consists of what is known and what is unclear about a particular subject. It's the broad scope of background of this research (Causon, 2015). It is the process of comprehending a subject of study through the analysis of scholarly and research publications. This chapter functions as a retrospective of past endeavours, highlighting past accomplishments. The success of this research will be greatly aided by the review of many articles and sources to determine how other researchers have approached the development of RFID and face recognition attendance systems.

2.1 Research Overview

The proposed project focuses on applying the Naive Bayes machine learning algorithm to evaluate ecosystem services in Harare's public parks. Harare, the capital city of Zimbabwe, hosts numerous public parks that provide essential ecosystem services such as recreation, biodiversity support, and environmental aesthetics (Chiesura, 2004; Elmqvist et al., 2015). The Naive Bayes algorithm, renowned for its probabilistic classification capabilities, will be employed to analyze various features of these parks and predict the likelihood of specific ecosystem services being provided (Hand and Yu, 2001). This approach aims to deliver valuable insights for effective park management, conservation, and urban planning in Harare. Collaborating with organizations such as the Zimbabwe Parks and Wildlife Management Authority (Zimparks) could further enhance the project's impact by incorporating expertise in biodiversity conservation and ecosystem management (Ladle and Whittaker, 2011). By integrating machine learning techniques with environmental stewardship, this project aspires to contribute to the sustainable utilization and preservation of ecosystem services in Harare's public parks.

2.2 ZIMPARKS

The Zimbabwe Parks and Wildlife Management Authority (Zimparks) is a government agency in Zimbabwe tasked with the management, conservation, and protection of the country's wildlife and natural resources. Established in 1980, Zimparks operates under the Ministry of Environment, Climate, Tourism, and Hospitality Industry (Ladle and Whittaker, 2011). The authority oversees national parks, game reserves, and other protected areas throughout Zimbabwe.

Key functions and roles of Zimparks

Zimparks, the Zimbabwe Parks and Wildlife Management Authority, plays a pivotal role in wildlife conservation, focusing on the preservation of the country's rich biodiversity, including various species of mammals, birds, and flora (Child, 2013). The organization implements comprehensive strategies to protect endangered species, manage habitats, and combat wildlife poaching (Duffy, 2014). Zimparks also manages an extensive network of national parks, game reserves, and other protected areas, including iconic destinations such as Mana Pools National Park, Hwange National Park, and Victoria Falls National Park (Andersson et al., 2013). These protected areas are crucial for biodiversity conservation and serve as major centres for eco-tourism (Buckley, 2009).

In addition to conservation, Zimparks significantly contributes to tourism development by promoting eco-tourism and facilitating access to Zimbabwe's natural wonders. The revenue generated from tourist activities supports both conservation efforts and local communities (Spenceley and Goodwin, 2007). The organization actively involves local communities surrounding protected areas to promote sustainable resource management and foster positive relationships (Roe et al., 2009). Engaging communities in conservation efforts helps mitigate human-wildlife conflict and encourages the responsible use of natural resources (Barrow and Murphree, 2001).

Zimparks also undertakes research initiatives to enhance understanding of wildlife ecosystems and supports educational programs. These efforts contribute to informed decision-making in wildlife management and conservation (Wolanski et al., 2004). Additionally, Zimparks is involved in enforcing wildlife protection laws and regulations, including anti-poaching efforts, monitoring illegal activities, and prosecuting individuals involved in wildlife-related crimes (Lindsey et al., 2011).

On the international stage, Zimparks collaborates with various conservation organizations, governments, and agencies to address global wildlife conservation challenges. This includes participating in initiatives to combat wildlife trafficking and promote sustainable practices (Wyatt, 2013). Through these multifaceted efforts, Zimparks aims to ensure the sustainable preservation of Zimbabwe's natural heritage.

2.3 Environmental Management Agency (EMA)

The Environmental Management Agency (EMA) in Zimbabwe is a governmental institution with a primary focus on overseeing and regulating environmental conservation and management within the country. Established to address the growing concerns related to environmental degradation and unsustainable practices, EMA plays a pivotal role in safeguarding Zimbabwe's natural resources and promoting ecological balance.

One of EMA's fundamental responsibilities is the facilitation and assessment of Environmental Impact Assessments (EIAs) for proposed projects and developments. By conducting thorough evaluations, the agency ensures that potential environmental impacts are identified, mitigated, and appropriately managed. This process is integral to sustainable development, aligning economic activities with environmental preservation.

EMA is actively involved in pollution control and monitoring initiatives, targeting sources such as industrial discharges, waste disposal, and emissions. The agency enforces environmental standards to curb pollution and protect crucial elements of the ecosystem, including air, water, and soil. Through regulatory measures, EMA contributes to the maintenance of a clean and healthy environment for the benefit of coming generations as well as the current ones.

Biodiversity conservation is another key focus area for EMA. The agency works towards preserving the diverse ecosystems, wildlife, and natural habitats that characterize Zimbabwe. By implementing conservation strategies and supporting initiatives that safeguard biodiversity, EMA contributes to the overall ecological resilience of the country.

Natural resource management is an essential aspect of EMA's mandate. This includes overseeing the sustainable use of resources such as forests, water, and land. By promoting practices that balance economic development with environmental conservation, EMA seeks to ensure that Zimbabwe's natural resources are utilized responsibly and contribute to long-term ecological sustainability.

Environmental education and awareness form an integral part of EMA's efforts. The agency engages in public outreach programs, disseminating information about environmental conservation and sustainable practices. By fostering a sense of responsibility and awareness among the public, businesses, and other stakeholders, EMA aims to create a culture of environmental stewardship.

EMA is also actively involved in law enforcement to uphold environmental regulations. The agency takes legal measures against individuals or entities found violating environmental standards, addressing issues such as illegal logging, poaching, and improper waste disposal. This enforcement mechanism reinforces the importance of compliance with environmental laws for the greater good of the environment.

Furthermore, EMA engages in international collaboration, working with global organizations and agencies on environmental issues. This collaboration ensures that Zimbabwe aligns its environmental policies with international standards and addresses trans-boundary environmental challenges effectively.

2.4 Ecosystem services evaluation for Harare Parks

Evaluating the ecosystem services of Harare Parks is a comprehensive process aimed at understanding and quantifying the diverse benefits these urban green spaces provide to both the environment and the local community. These parks play a multifaceted role, offering various ecosystem services that enhance the well-being of residents and the broader urban environment (Elmqvist et al., 2015; Tzoulas et al., 2007). Recreational and cultural services form a significant aspect of this evaluation, as the parks serve as venues for community activities, events, and cultural gatherings. The aesthetic and cultural values associated with these parks significantly contribute to their importance as communal spaces, thereby enhancing the quality of life for residents (Chiesura, 2004).

Biodiversity and habitat services are critical components of evaluating Harare Parks. This involves surveying the diversity of plant and animal species within the parks and recognizing their role in providing habitats for local wildlife. Additionally, the evaluation assesses the conservation value of these green spaces for indigenous flora and fauna, contributing to overall biodiversity preservation (Niemelä, 1999; Bolund and Hunhammar, 1999). Harare Parks also contribute to air and water quality regulation by acting as carbon sinks and promoting oxygen production. The vegetation within the parks plays a crucial role in filtering pollutants, thereby improving air quality. The evaluation also considers the parks' impact on water quality, particularly in relation to water bodies or groundwater recharge (Escobedo et al., 2011).

In terms of climate regulation, Harare Parks influence the microclimate within the urban environment. Trees and greenery mitigate the urban heat island effect, contributing to local climate patterns and temperature regulation. Evaluating their impact helps understand their role in creating a more sustainable and resilient urban environment (Gill et al., 2007). Economic and social services are also vital components of the evaluation. Harare Parks have economic value through tourism, recreational activities, and the enhancement of property values. Social benefits include improved mental health, social cohesion, and overall community well-being. Assessing the potential for job creation and economic activities related to park management and services is essential for understanding their broader impact (Konijnendijk et al., 2013).

Storm water management is another key consideration in the evaluation. The parks' ability to absorb and manage storm water helps reduce the risk of flooding. The evaluation also assesses how vegetation and soil within the parks prevent soil erosion and maintain water quality, contributing to sustainable urban water management (Miller and Hobbs, 2002). Furthermore, Harare Parks offer educational and research opportunities by serving as valuable sites for environmental education initiatives, providing learning experiences for schools and communities. The evaluation explores the potential for research initiatives related to ecology, biodiversity, and environmental science within these green spaces (Louv, 2005).

Community engagement and participation are essential aspects of the evaluation process. Understanding the level of community involvement in park management and conservation activities helps gauge the effectiveness of communication and outreach programs related to ecosystem services. This engagement is crucial for fostering a sense of ownership and responsibility among residents towards the sustainable management of Harare Parks (Pretty, 2003).

2.5 Harare Parks Available

Harare, the capital city of Zimbabwe, boasts several parks and green spaces that enhance the urban environment, providing residents and visitors with opportunities for recreation, relaxation, and cultural engagement. Among these various parks, some stand out for their unique features and contributions to the city's landscape. Harare Gardens, situated in the heart of the city, is a well-known urban park celebrated for its meticulously maintained gardens, serene walkways, and open spaces. It serves as a peaceful retreat within the bustling city centre, offering lush greenery, flowerbeds, and a designated playground for children (Chiesura, 2004). In the Avenues area, Centenary Park attracts locals and exercise enthusiasts with its jogging tracks, tennis courts, and expansive lawns. The park provides a serene setting for outdoor activities, encouraging a healthy lifestyle and fostering a sense of community (Tzoulas et al., 2007).

Alexandra Park, located in the suburb of Alexandra Park, stands out for its large open spaces, playgrounds, and recreational facilities. Families often visit this park for outings and picnics, taking advantage of the inviting atmosphere and well-designed amenities (Niemelä, 1999). Kopje Park, positioned near the city centre, is distinguished by its iconic rocky outcrop, known as the Kopje. Beyond its natural beauty, the park offers panoramic views of Harare and serves as a unique venue for recreational activities and cultural events (Bolund and Hunhammar, 1999). To the southwest of Harare, Lake Chivero Recreational Park encompasses Lake Chivero and its surrounding area. This park caters to nature enthusiasts, providing opportunities for boating, fishing, and wildlife viewing, making it a popular destination for day trips and outdoor exploration (Escobedo et al., 2011).

In the suburb of Mbare, Mbare Musika Park is a vibrant space known for its bustling market and lively atmosphere. The park serves as a central hub for informal trading, cultural events, and social gatherings, reflecting the dynamic spirit of the local community (Spenceley and Goodwin, 2007). Rolf Valley Greenbelt, located in the Rolf Valley suburb, offers a tranquil escape for residents. The park features walking paths, playgrounds, and recreational areas, providing a serene environment for relaxation and leisure activities (Gill et al., 2007). While primarily a golf club, Warren Hills Golf Club contributes to Harare's green spaces, offering a well-maintained setting complemented by lush vegetation. Accessible to club members and visitors, the golf course provides a blend of recreational and natural elements (Louv, 2005).

Finally, the National Botanic Gardens, situated in the Alexandra Park suburb, stands out as an educational and recreational destination. Visitors can explore themed gardens showcasing a diverse collection of indigenous and exotic plant species, contributing to both botanical knowledge and a peaceful outdoor experience (Ladle and Whittaker, 2011). These various parks collectively enrich the urban fabric of Harare, offering a diverse range of experiences and contributing to the city's overall quality of life. Whether as spaces for quiet contemplation, community gatherings, or outdoor activities, every park has a distinct influence on the cultural and recreational landscape of the city (Hand and Yu, 2001).

2.6 MACHINE LEARNING ALGORITHMS

While there are various differences in how machine learning algorithms are defined, in general, they can be categorised based on their intended use. The following are the main categories:

1. **Supervised learning**
2. **Unsupervised Learning**
3. **Semi-supervised Learning**
4. **Reinforcement Learning**

Supervised Learning

The notion of supervised learning pertains to function approximation, when the algorithm is trained to identify and pick the function that most accurately describe the input data. This function should provide the best estimation of the output yyy for a given input XXX (X -> y). In practice, it's often challenging to identify the true underlying function that consistently makes correct predictions. Additionally, supervised learning algorithms rely on assumptions made by humans about how computers should learn, which introduces bias (Bishop, 2006).

In the context of machine learning, when an algorithm fails to take into consideration all of the information in the data, it has a tendency to constantly learn incorrect things, this is known as bias, as opposed to variance, which describes how sensitive the algorithm is to even small variations in training set.

In supervised learning, human experts feed the computer training data, acting as teachers that consists of input predictors and their corresponding correct output answers. The computer then learns patterns from this data. Modelling the connections and dependencies between the input features and the anticipated output is the goal of supervised learning algorithm (Alpaydin, 2014). As a result, we can forecast output values for fresh data by using the correlations discovered in earlier dataset.

Draft

- Predictive Model
- Labelled data
- Regression and classification issues are the two primary categories of supervised learning challenges.

Common Algorithms list

- Nearest Neighbour
- Naive Bayes
- Decision Trees
- Linear Regression
- Support Vector Machines (SVM)
- Neural Networks

Unsupervised Learning

Unlabelled data serves as the machine's trainer. There isn't a teacher involved at all in this situation; in fact, you might be able to learn new things from your PC once it recognises patterns found in the data. Such algorithms are particularly useful when human specialist is not clear what the data should be checked for. The class of machine learning methods used mostly in pattern recognition and descriptive modelling. Nevertheless, the algorithm is not able to attempt modelling relationships here because there are no output categories or labels. These algorithms attempt to apply methods to the input data in order to extract useful insights and provide consumers with a more clear description of the data by grouping, summarising, and searching for patterns.

Draft

Descriptive Model

Clustering algorithms and Association rule learning algorithms are the two primary categories of unsupervised learning algorithms.

Common Algorithms List

- k-means clustering,
- Association Rules

Semi-supervised Learning

In the first two categories, either every observation in the dataset has a label or every observation in the dataset has a label. In between the two is semi-supervised learning. In many real-world scenarios, labelling comes at a significant expense because it takes knowledgeable human professionals to complete. Therefore, the best algorithms are semi-supervised ones for developing models when labels are present in a small percentage of data but absent from the rest. These methods capitalise on the idea that even in cases when the data's group memberships are unclear, unlabelled data nevertheless holds crucial details regarding the group parameters.

Reinforcement Learning

With the help of observations made during interactions with the environment, this strategy seeks to maximise rewards and reduce risks. Iteratively learning from the environment, the reinforcement learning algorithm (often referred to as the agent) learns new things all the time. Throughout the process, the agent picks up knowledge from its encounters with the surroundings, eventually investigating every potential condition. As a subset of machine learning, reinforcement learning falls under the umbrella of artificial intelligence. It enables devices and software agents to autonomously ascertain the optimal conduct in a given situation to optimise performance. The reinforcement signal is the simple reward feedback that is needed for the agent to learn its behaviour

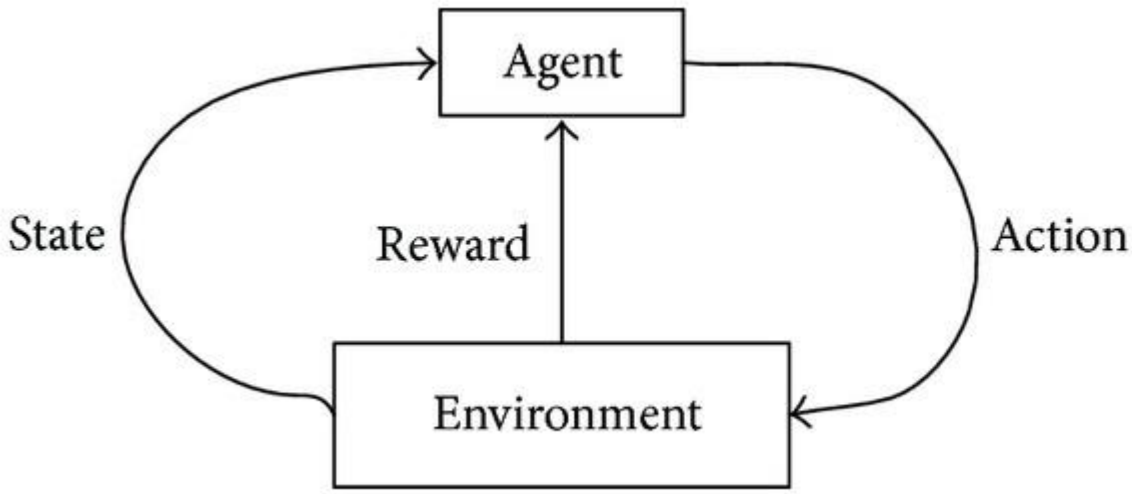


Fig. 2.0: Reinforcement

There are numerous algorithms that address this problem. In actuality, a certain kind of problem defines reinforcement learning, and all algorithms that solve it fall under this category. The task at hand requires an agent to determine the optimal course of action to take given his current situation. If one were to repeat this process, the issue is called Markov Decision Process. These stages are followed by reinforcement learning to produce intelligent programmers, often known as agents. By using the decision-making function, the agent is compelled to take action. After the activity is finished, the environment gives the agent reinforcement or reward. The state-action pair associated with the reward is preserved.

Common Algorithms list

- Q-Learning
- Temporal Difference (TD)
- Deep Adversarial Networks

Use cases:

Reinforcement learning techniques are used in a computer played board games (such as Chess, Go), robotic hands, and self-driving cars.

2.8 CONCLUSION

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 METHODOLOGY

3.0 Introduction

The introduction to Chapter 3, the Research Methodology, sets the stage for the detailed exploration of the methods employed in conducting the research. This chapter is instrumental in providing a clear and systematic understanding of the processes, techniques, and approaches adopted to gather, analyse, and interpret data. The methodology section is a critical component of any research project, acting as a bridge between the research questions or hypotheses and the empirical evidence obtained during the study. In this chapter, the researcher outlines the rationale behind the chosen research design, the specific methods employed for data collection and analysis, and the strategies for ensuring the validity and reliability of the research findings. It serves as a roadmap, guiding readers through the thought process and decisions made in designing and executing the study, ultimately contributing to the credibility and rigor of the research outcomes.

3.1 Research Design

The research design for the system employs a systematic approach integrating Jupyter Notebook, a carefully curated dataset, Python 3.9, Streamlit, and Agile Software Development principles. Beginning with a well-defined problem statement, the research involves collecting a comprehensive dataset comprising relevant features for ecosystem services assessment. Using Python 3.9 and Jupyter Notebook, data pre-processing is conducted to ensure the dataset's suitability for machine learning. Exploratory Data Analysis (EDA) is carried out in Jupyter Notebook to gain insights from the dataset. The Naive Bayes machine learning algorithm is selected and implemented for training on the pre-processed dataset. Model evaluation metrics are computed within Jupyter Notebook to assess performance. Agile principles guide the development of a Streamlit application, providing an interactive interface for ecosystem services evaluation. Through iterative testing and deployment, the research design ensures a user-friendly and continuously improving solution for assessing ecosystem services in Harare parks. Thorough documentation captures the entire process, promoting transparency and reproducibility of the research outcomes.

3.1.1 Requirements Analysis

Right now, it is essential to document both the functional and non-functional specifications of the necessary system. It is recommended to organize all incoming data, assess it thoroughly, take into consideration any limitations that may arise from the customer's perspective, and formulate a well-defined specification that is easy to follow and aligns with the customer's requirements. The research also considered various limitations, including time and budget constraints, which could potentially hinder the design process.

3.1.1.1 Functional Requirements

- The system ought to be able to evaluate ecosystem services for Harare Parks.
- The user should enter the required data for prediction.

3.1.1.2 Non-Functional Requirements

- The system should be able to make predictions quickly.
- It should be simple to install the system.
- The system must to be readily foreseeable and always accessible.
- Relatively short reaction and decision times are expected from the system.

3.1.1.3 Hardware Requirements

- Laptop core i3 and above
- 4 Gig RAM
- 500 Gig

3.1.1.4 Software Requirements

- Windows 10 Operating system
- Jupyter Notebook
- Visual Studio Code
- Python 3.9
- Streamlit framework

3.2 System Development

The system development for applying the Naive Bayes machine learning algorithm to evaluate ecosystem services in Harare parks involves several key stages. Initially, the problem of ecosystem services evaluation is defined, specifying the relevant services and collecting diverse datasets encompassing park characteristics, biodiversity metrics, ecosystem functions, and socio-economic factors. Following data collection, pre-processing tasks such as cleaning and feature selection/engineering are undertaken to ensure data quality and relevance. Subsequently, the Naive Bayes algorithm is chosen and trained on the prepared dataset. The developed system integrates this trained model, allowing users to input data and receive evaluations through a user-friendly interface. Model performance is rigorously evaluated using metrics like accuracy and precision, ensuring robustness and generalizability. Results from the model provide insights into the factors influencing ecosystem services in Harare parks, supporting informed management decisions. Ongoing maintenance, including updates with new data and monitoring for performance, ensures the system's effectiveness over time, while ethical considerations safeguard privacy and mitigate bias in results.

3.2.1 System Development tools

Within the field of software engineering, a methodology for system design or software production functions as a structure for planning, coordinating, and managing the processes involved in creating a system of information. Numerous frameworks have been identified by researchers for various projects, each with its own set of strengths and weaknesses based on its application. Examples of these frameworks encompass the waterfall model, the spiral model, and the progressive (prototyping) model. The author has opted for the Agile Software model, given its simplicity, as the project at hand is relatively small and constrained by a strict time frame. Since all project requirements have been recognised, and the necessary tools are in place, the waterfall model emerges as the most suitable choice for this particular project.

3.2.2 Agile Software Model

As the system for applying the Naive Bayes machine learning algorithm to evaluate ecosystem services in Harare parks is developed using the agile software development model, it undergoes a series of iterative and collaborative processes. Initially, the project begins with a comprehensive understanding of the ecosystem services to be evaluated and the collection of relevant data, including park characteristics, biodiversity metrics, ecosystem functions, and socio-economic factors. Agile's iterative development approach allows the team to start with a minimal viable product (MVP) that includes basic functionalities, such as data input and preprocessing.

Through close collaboration with stakeholders, including park managers and ecologists, the system evolves incrementally. Regular meetings and feedback sessions ensure that the system meets user needs and adapts to emerging requirements and new insights about the parks' ecosystems. Continuous integration and testing are integral to the agile process, ensuring that the Naive Bayes algorithm performs accurately with real data. As the system matures, additional features are added in successive iterations, building on the initial MVP to provide more sophisticated outputs and insights into ecosystem services. Throughout development, Agile's transparent and adaptive planning approach allows the team to adjust priorities and development efforts based on ongoing feedback and evaluation. This iterative and collaborative process not only ensures that the system meets its objectives effectively but also allows for continuous improvement and refinement to support park management and conservation efforts in Harare.

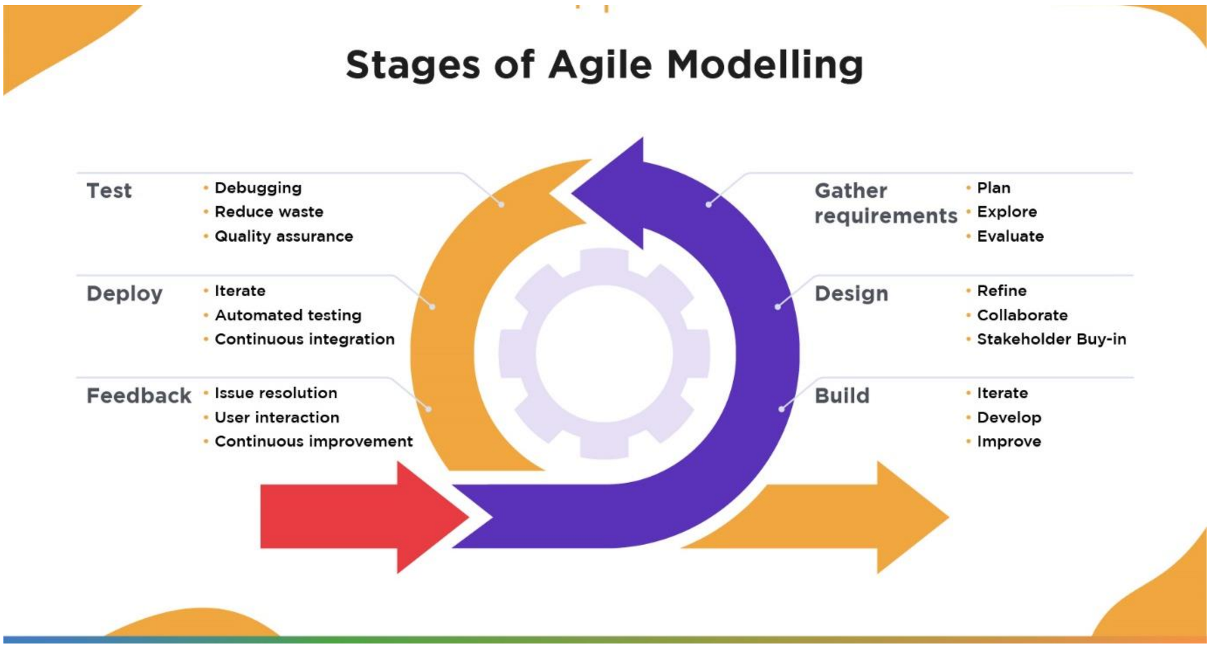


Fig. 3.0: Agile Model

Aside from the technique, the system was created utilising the subsequent instruments:

1. ***Python***
2. ***Streamlit***
3. ***Dataset***

3.3 An overview of the system's operation

The system operates by leveraging the Naive Bayes machine learning algorithm for the evaluation of ecosystem services in Harare parks. The process begins with the collection of a comprehensive dataset containing relevant features, such as biodiversity, vegetation types, and visitor numbers. The dataset undergoes pre-processing in Python 3.9 and Jupyter Notebook, ensuring it is clean and suitable for machine learning. Exploratory Data Analysis (EDA) is conducted to gain insights and visualize relationships within the data. The Naive Bayes algorithm is selected for its appropriateness to the problem. Through model training and evaluation in Jupyter Notebook, the algorithm learns patterns and relationships in the dataset. The system further incorporates Agile Software Development principles for the development of a Streamlit application, offering an interactive interface for stakeholders to assess ecosystem services. The application is subjected to iterative testing and improvement based on user feedback. The final deployment ensures accessibility for relevant stakeholders. The entire process is thoroughly documented, ensuring transparency and reproducibility of the system's outcomes in evaluating ecosystem services in Harare parks.

3.4 System Design

This step involves analysing the requirements specification document and defining how the system's data and components meet the requirements.

3.4.1 Dataflow Diagrams

Data flow diagrams (DFDs) show the connections and interconnections between the different parts of the system. A dataflow diagram, which illustrates how a series of functional transformations convert input data into output results, is a crucial visual tool for depicting a system's high-level detail. A DFD's data flow is called on order to represent the type of data that is being used. Since one type of information development is DFDs, they offer valuable insight into the transformation of data as it moves through a system and the presentation of the result.

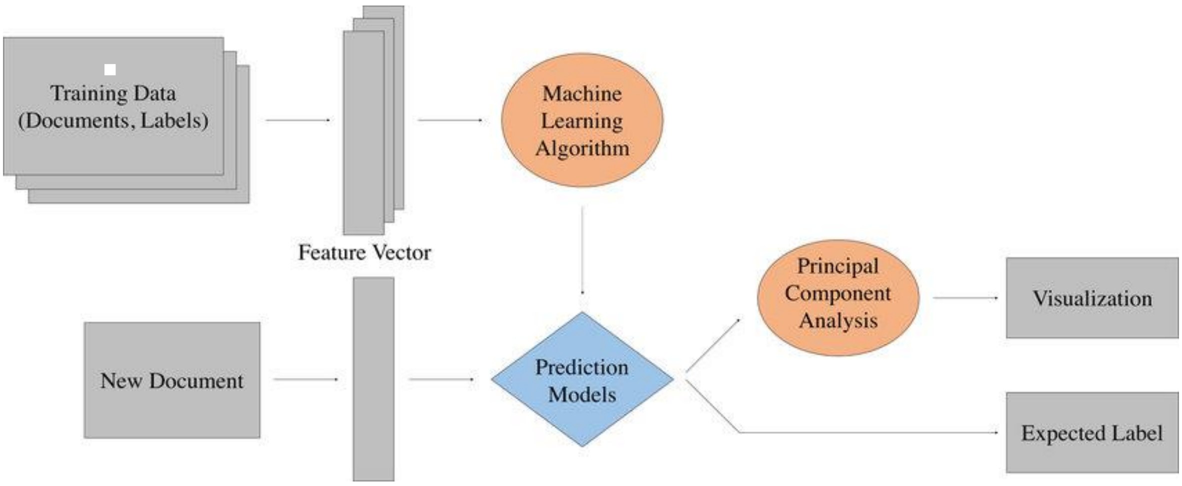


Fig. 3.1: Dataflow Diagrams

3.4.2 Proposed System flow chart

A useful tool for reducing communication gaps between programmers and end users is a flowchart. These flowcharts are designed to condense a large quantity of information into a relatively small number of symbols and connectors.

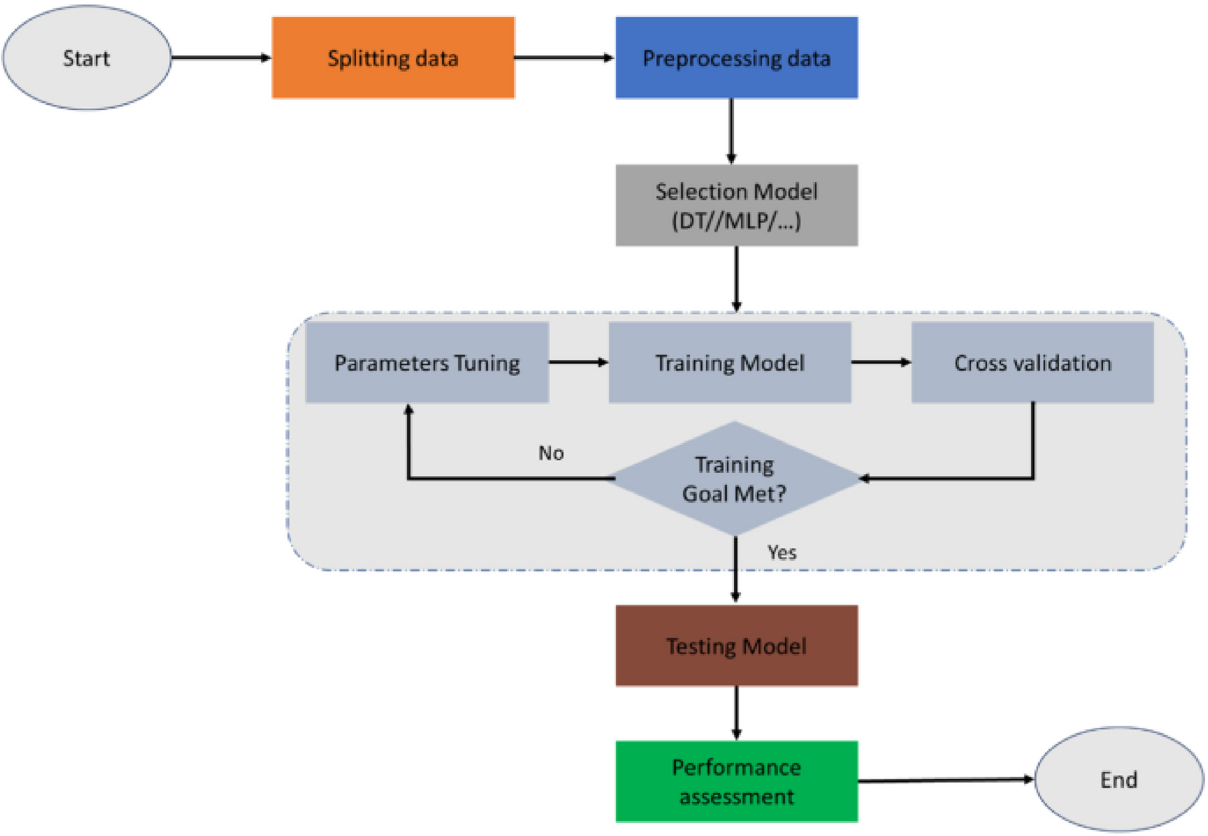


Fig. 3.2: Dataflow Diagrams

3.4.3 Solution Model Creation

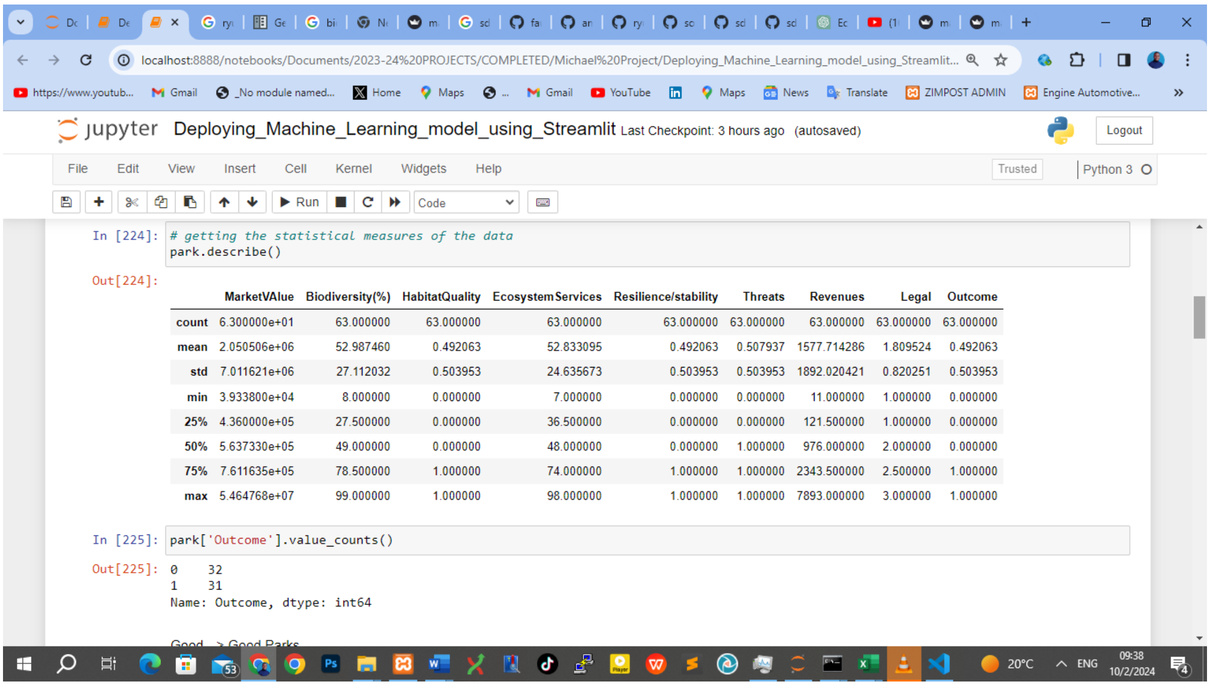


Fig. 3.3: Solution Model Creation

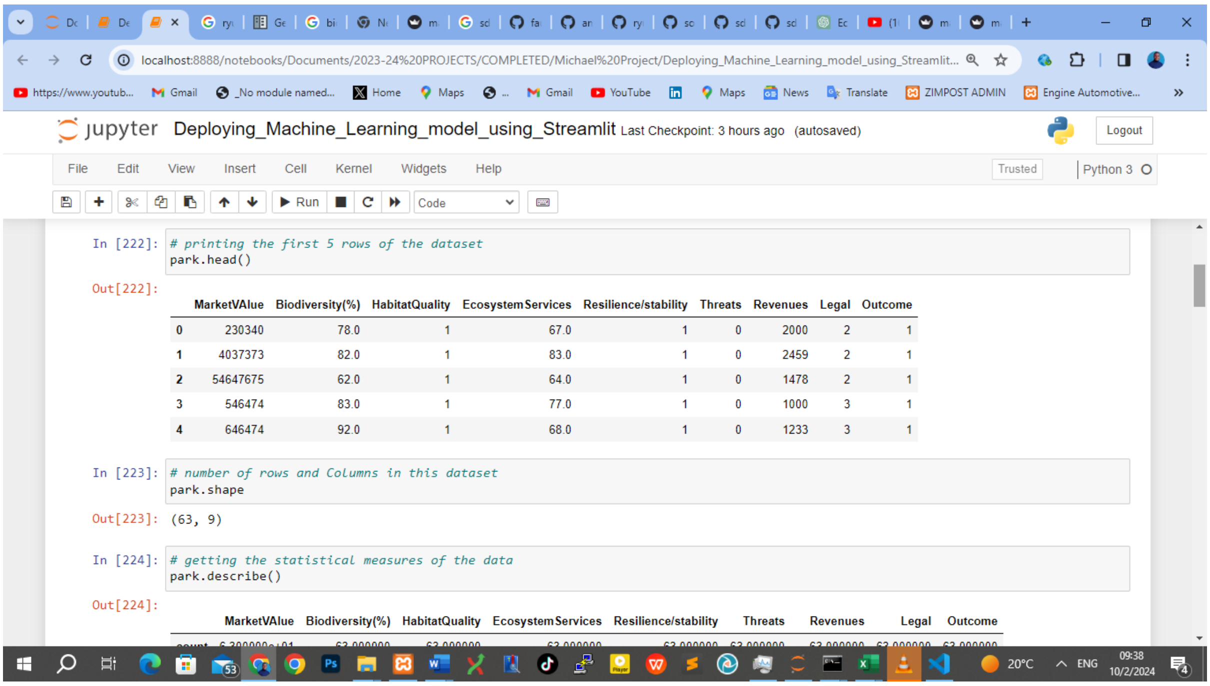


Fig. 3.4: Solution Model Creation

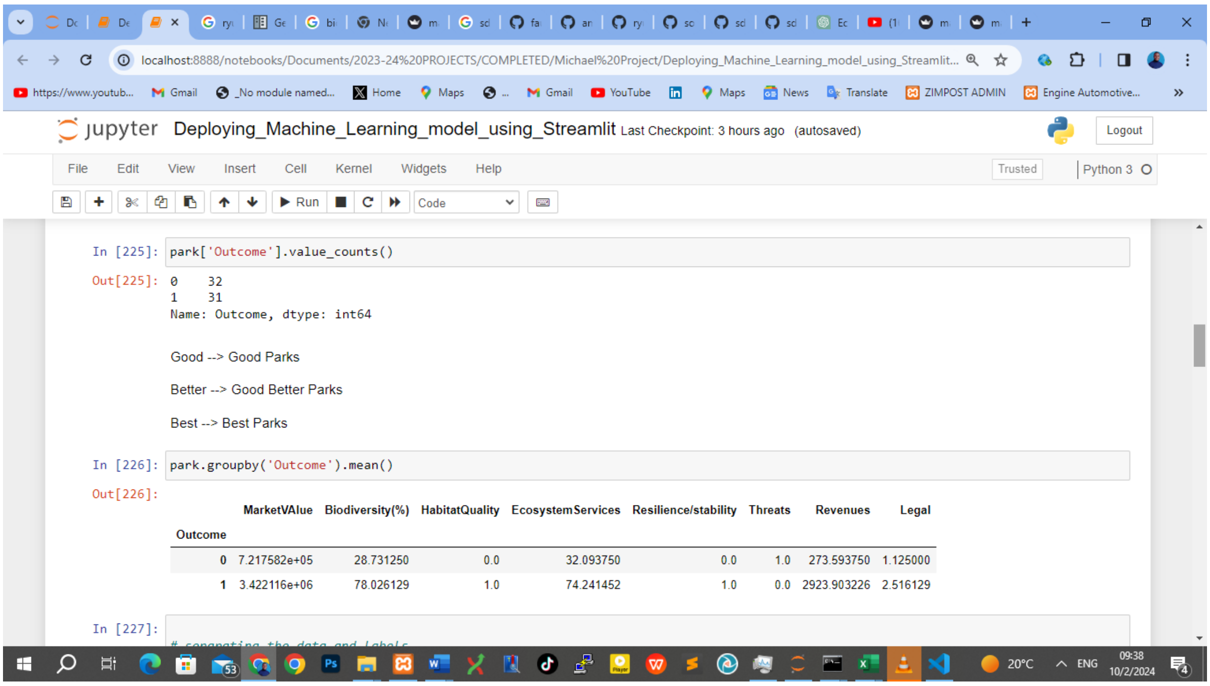


Fig. 3.5: Solution Model Creation

Creating the solution model for applying the Naive Bayes machine learning algorithm to evaluate ecosystem services in Harare parks involves a structured and iterative approach. Initially, the project begins with a thorough understanding of the problem at hand, which includes defining the ecosystem services to be evaluated and collecting comprehensive datasets. These datasets encompass a variety of factors such as park characteristics (e.g., size, location), biodiversity metrics (e.g., species diversity, abundance), ecosystem functions (e.g., carbon sequestration, water regulation), and socio-economic data (e.g., visitor numbers, economic activities). This initial phase is critical for laying the foundation of the model and ensuring that all relevant variables are considered.

Following data collection, the next step is data pre-processing, where the gathered datasets undergo cleaning and feature engineering processes. This includes handling missing values, outliers, and ensuring data consistency. Feature selection and engineering are also conducted to identify the most relevant variables that are likely to influence ecosystem services. This step helps in preparing the data for model training.

For the model selection and development phase, the Naive Bayes algorithm is chosen depending on the data's qualities. The appropriate variant of Naive Bayes (such as Gaussian

Naive Bayes or Multinomial Naive Bayes) is selected, and the model is trained using the pre-processed data. The dataset is divided into training and testing sets during the model-training process in order to assess the model's performance. Several performance metrics are employed to evaluate the model's ability to forecast ecosystem services from the input data, such as accuracy, precision, recall, and FI-score. In order to guarantee the robustness and generalizability of the model, cross-validation techniques are also utilised.

Once the model is trained and evaluated, the solution implementation phase begins. This involves integrating the trained Naive Bayes model into a system that can accept new data inputs and provide real-time or periodic evaluations of ecosystem services in Harare parks. A user-friendly interface is designed to facilitate interaction with the system, allowing stakeholders such as park managers and conservationists to input data and receive evaluations. Insights generated from the model's outputs help in understanding the factors that most influence ecosystem services and provide actionable recommendations for improving park management and conservation efforts. Continuous monitoring and maintenance ensure that the model remains accurate and up-to-date, with periodic updates based on new data and advancements in the field. Ethical considerations, such as fairness, bias, and privacy, are also integrated into the development process to ensure that the system's outputs are unbiased and respect user privacy. This structured approach ensures the development of a robust solution model that supports evidence-based decision-making and sustainable management practices in Harare parks.

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 comprises input-output pairs that enable the model to discern patterns and make predictions, with the model adjusting its parameters to minimize the disparity between predicted and actual outcomes. Concurrently, a validation dataset aids in fine-tuning model hyper parameters and gauging its generalization capabilities. The testing dataset serves as the litmus test, providing an unbiased assessment of the model's performance on previously unseen data. 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.

3.4.4.1 Training Dataset

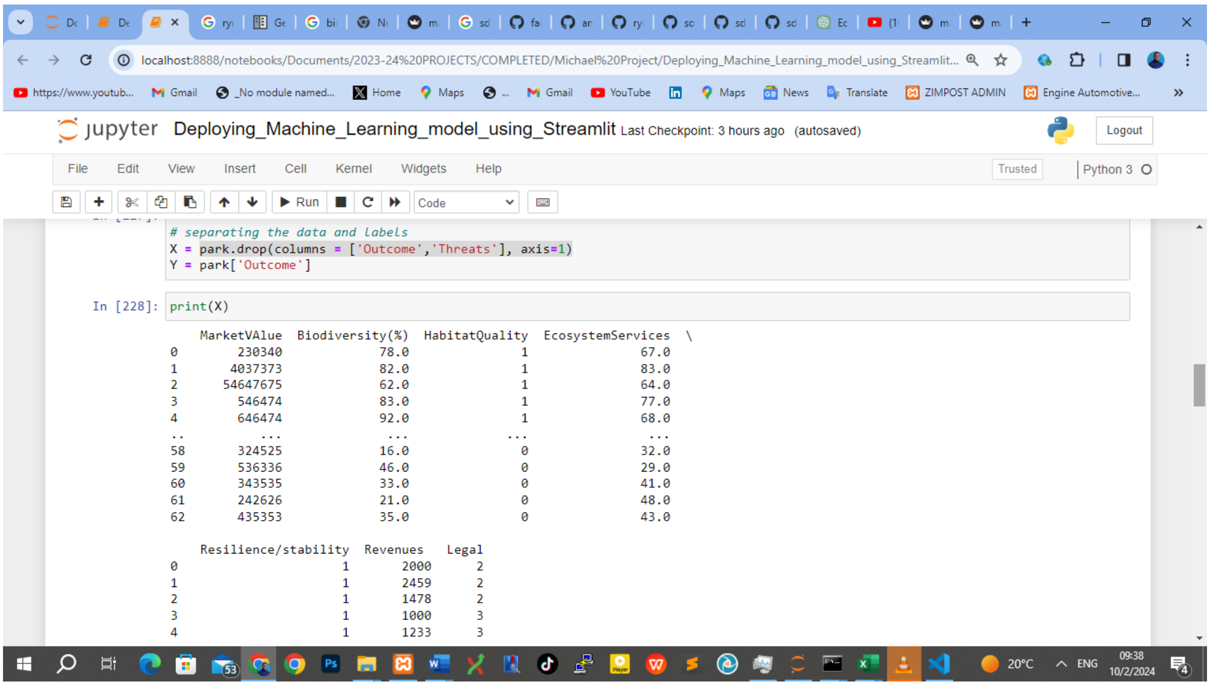


Fig. 3.6: Training Dataset

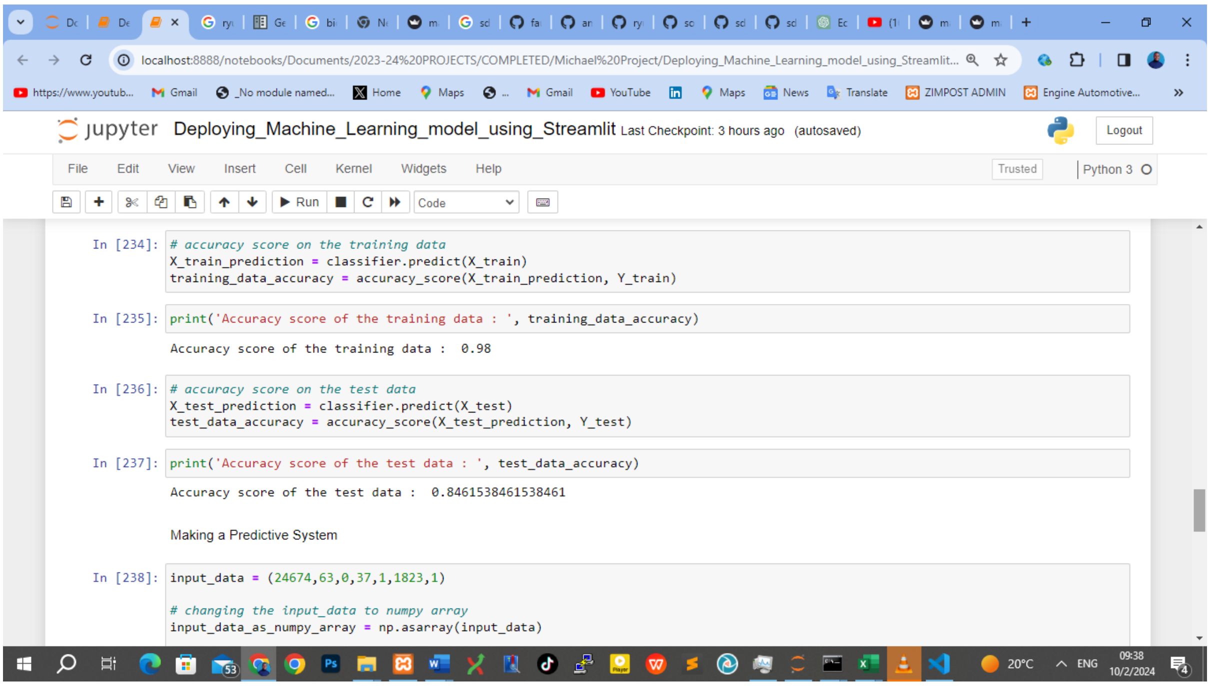


Fig. 3.7: Training Dataset

3.4.4.2 Evaluation Dataset

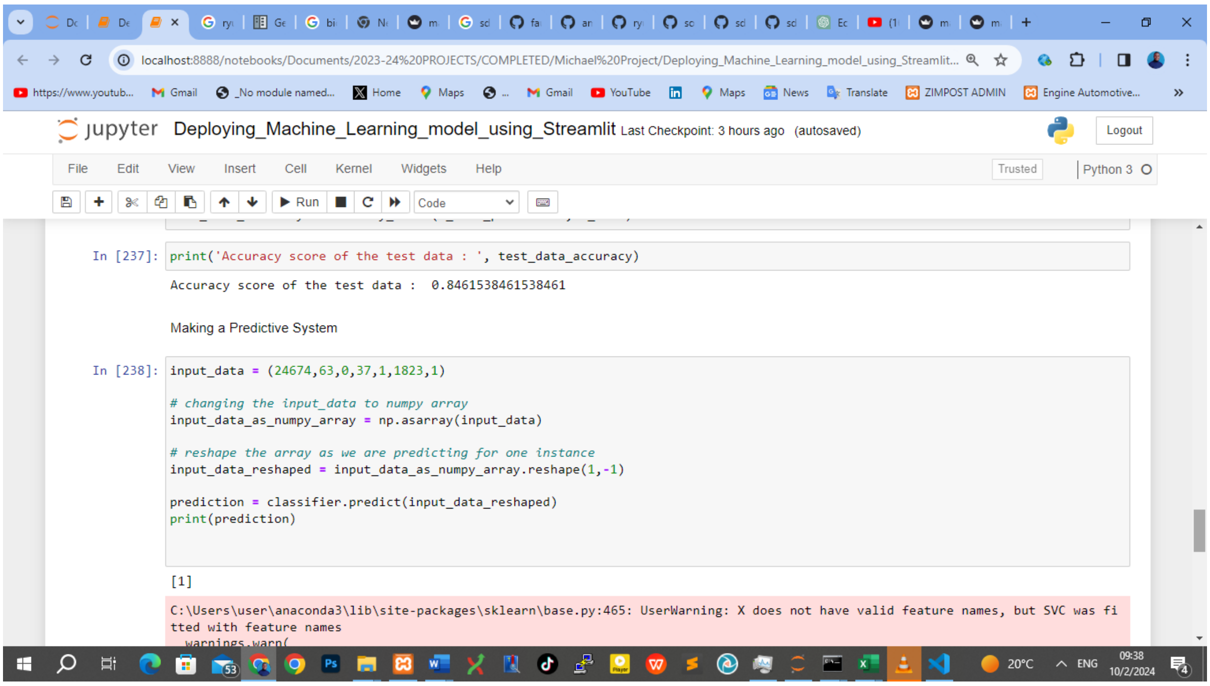


Fig. 3.8: Evaluation Dataset

3.4.5 Implementation of the evaluation function

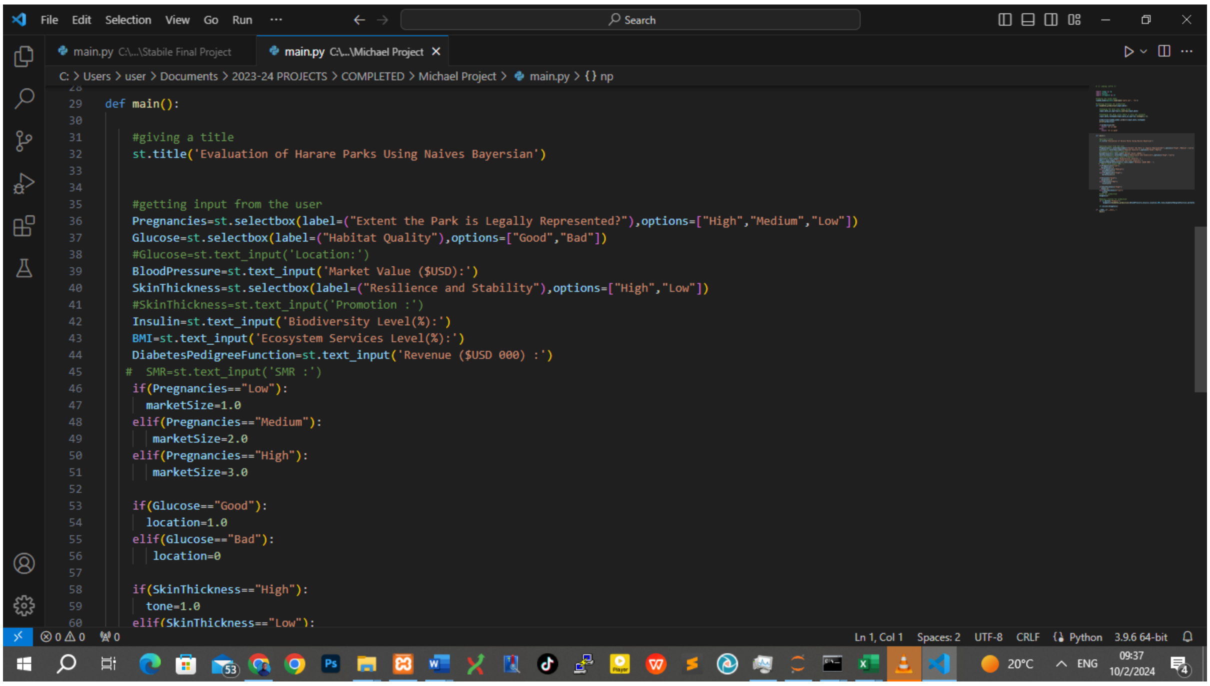


Fig. 3.9: Implementation of the evaluation function

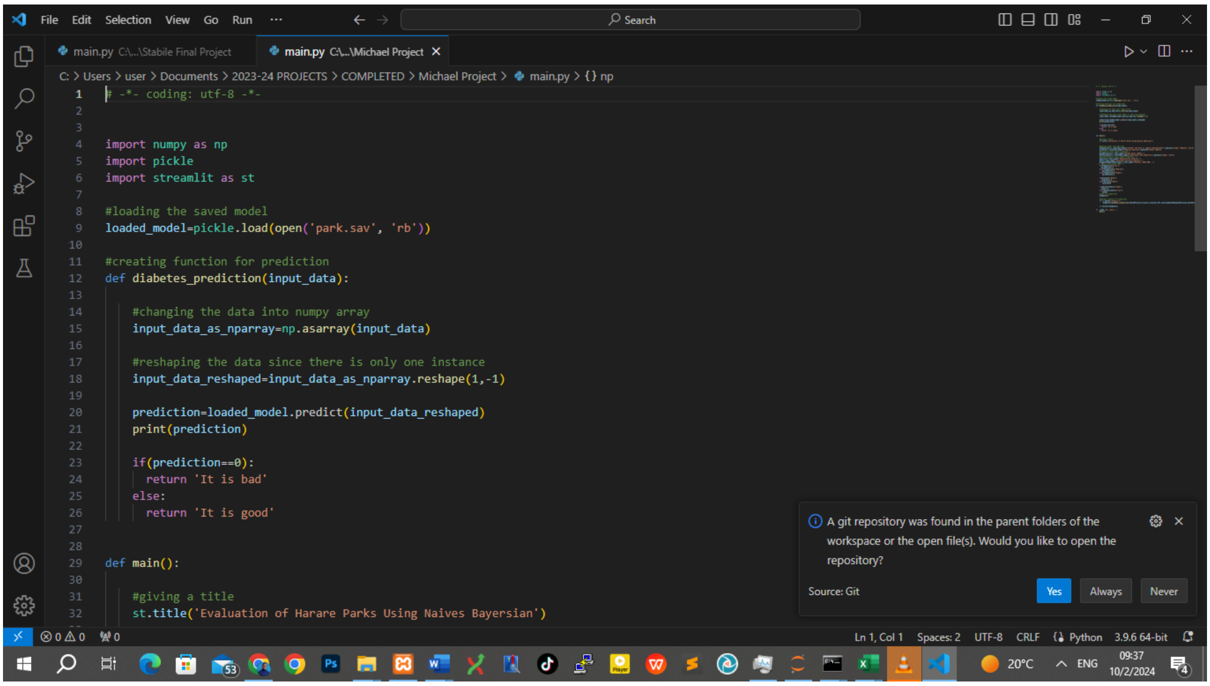


Fig. 3.10: Implementation of the evaluation function

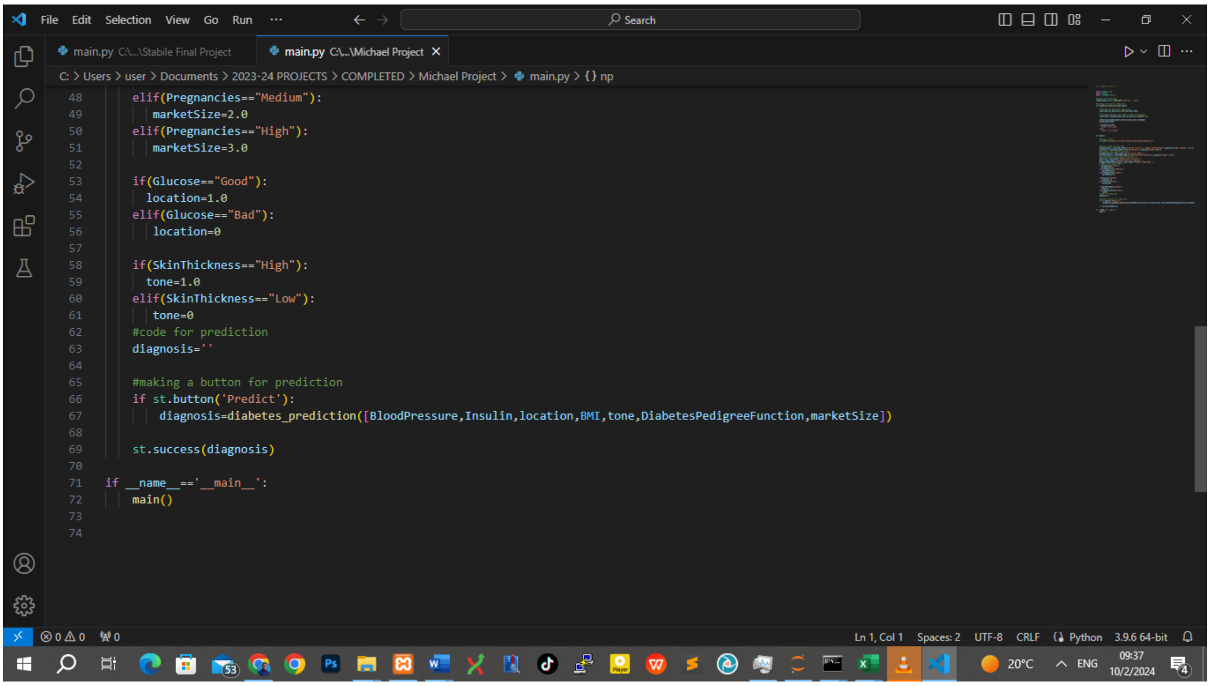


Fig. 3.11: Implementation of the evaluation function

3.5 Data collection methods

The author collected data by means of observation. The system was subjected to many scenarios and multiple cycles by the author, who also monitored the system's response. The researcher evaluated the system’s accuracy and solution’s response time thanks to observation.

3.6 Implementation

The screens of a system to evaluate ecosystem services in Harare Parks are provided by the author below.

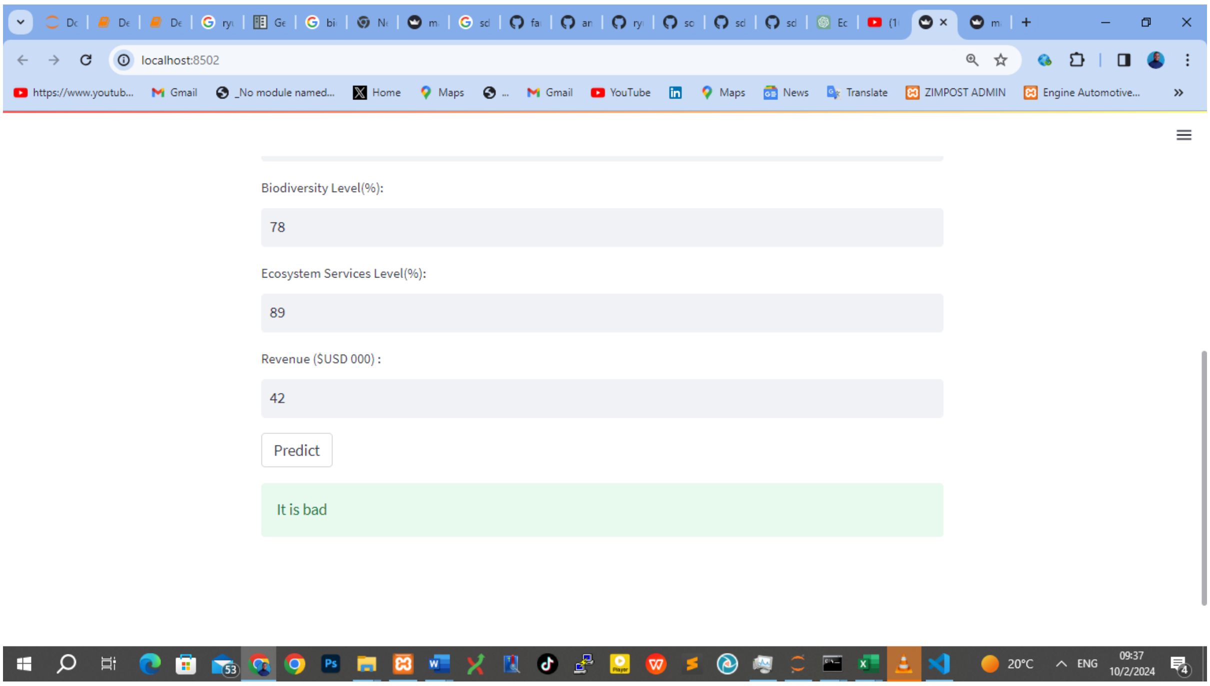


Fig. 3.12: Implementation of the system

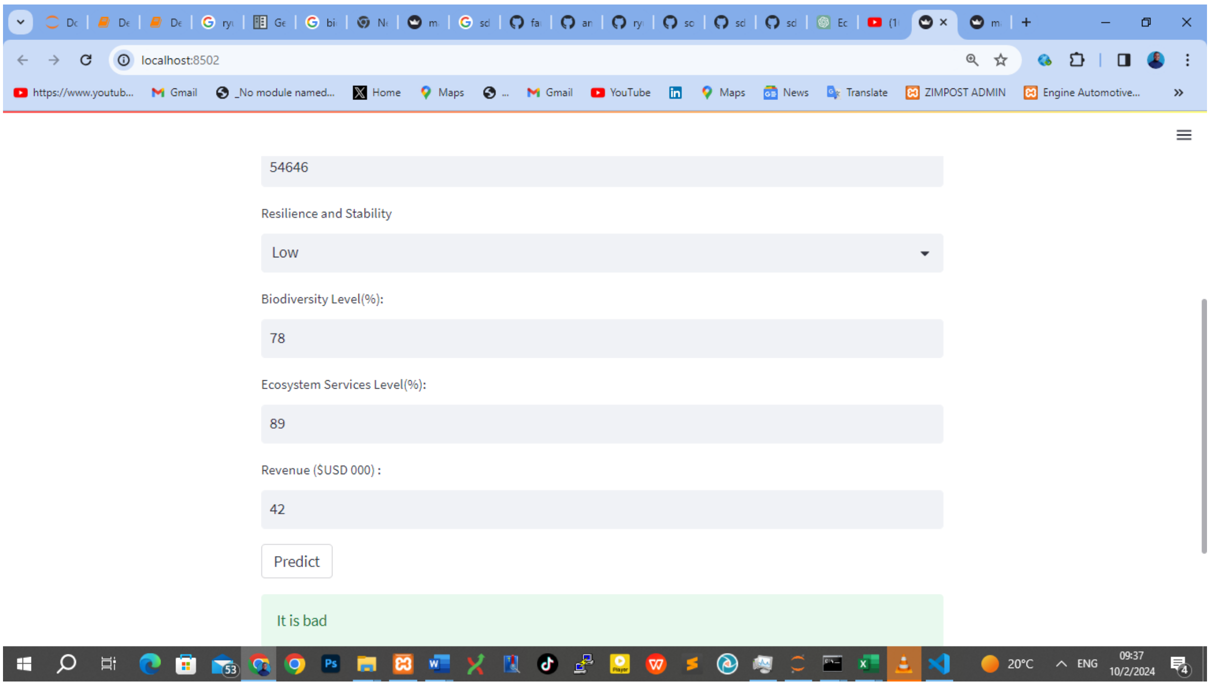


Fig. 3.13: Implementation of the system

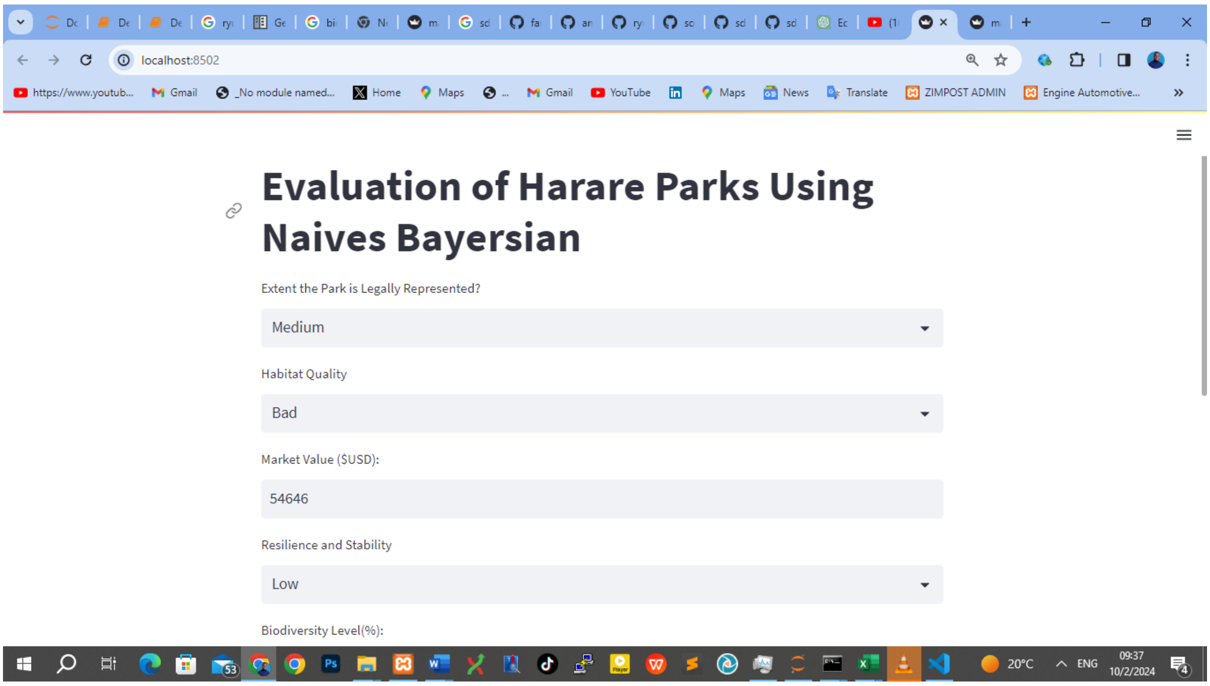


Fig. 3.14: Implementation of the system

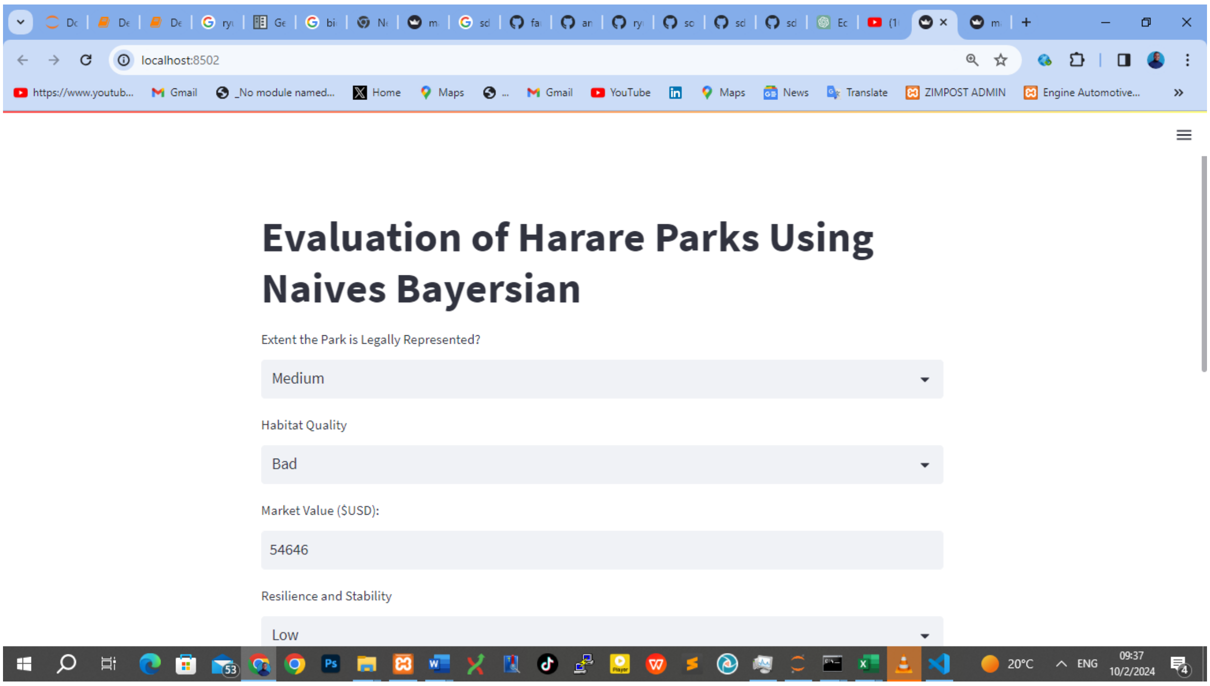


Fig. 3.15: Implementation of the system

3.7 Summary

The evaluation of ecosystems in Harare parks using Bayes Networks involves a systematic and probabilistic approach to assess various ecological factors. The process begins with the collection of relevant data, including biodiversity metrics, vegetation types, visitor patterns, and environmental conditions. This data is then used to construct a Bayesian network, which is a graphical model that depicts probabilistic correlation between variables. The Bayesian network is trained on historical data to learn the dependencies and interactions between these ecological factors. Once trained, the Bayes Network can infer the probability distribution of certain variables given observed evidence, allowing for the assessment of ecosystem conditions. The evaluation process involves updating beliefs about ecosystem services based on new data or observations, providing a dynamic and adaptable framework. Bayesian Networks enable the incorporation of uncertainty and changing conditions, making them well-suited for the dynamic and intricate structure of ecosystems. The results of the evaluation can be used to make informed decisions regarding conservation strategies, park management, and environmental policies. Overall, the utilization of Bayes Networks offers a robust and probabilistic methodology for the comprehensive evaluation of ecosystems in Harare parks, providing valuable insights for sustainable management and conservation efforts.

CHAPTER 4: DATA ANALYSIS AND INTERPRETATIONS

4.0 Introduction

It is vital to evaluate the effectiveness of the supplied solution after the system has been completed. The matrices utilised to assess the final solution's effectiveness and efficiency were accuracy, performance, and response time. To arrive at helpful conclusions, the information obtained in the preceding chapter was analysed. Under various settings, the behaviour of the developed system was also investigated. This chapter focuses on presenting study findings, analyses, interpretations, and conversations, which is an important element of the research process.

4.1 System Testing

"System testing" is the assessment of a software solution that is completely integrated. This kind of examination is referred to as "black-box" testing since it is carried out by the testing team without requiring knowledge of the internal workings of the code. This kind of testing verifies the integration and completeness of the software. To evaluate the end-to-end system specifications, a system test is implemented. Software is usually only a small portion of a larger computer system. Eventually, the programme is interfaced with a number of hardware and software systems. A computer-based system is put through its paces in a series of tests called system testing.

Performance Testing

Performance testing in the context of a network anomaly detection system involves evaluating how well the system performs under various load conditions, such as high network traffic volumes or increased computational demands. It aims to ensure that the system can handle the expected workload while maintaining its functionality, responsiveness, and stability

Table 1 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

Fig. 4.0: System Response Time

Every measurement was rounded to the closest whole number.

Average system response time = sum of all response time divided by 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)

4.1.2 Black box Testing

"Black box" software testing looks at the functionality of the programme without looking at its underlying coding or structure. The customer's statement of requirements is the most common source for black box testing. This approach involves the tester selecting a function, entering a value to confirm its operation, and then determining whether the function generates the desired result. Testing is done if the method returns the desired result; if not, it fails. The test team notifies the development team of its findings before moving to the next function. After every function is tested, should there be any noteworthy issues, the development team is notified so they can address them.

Running the system

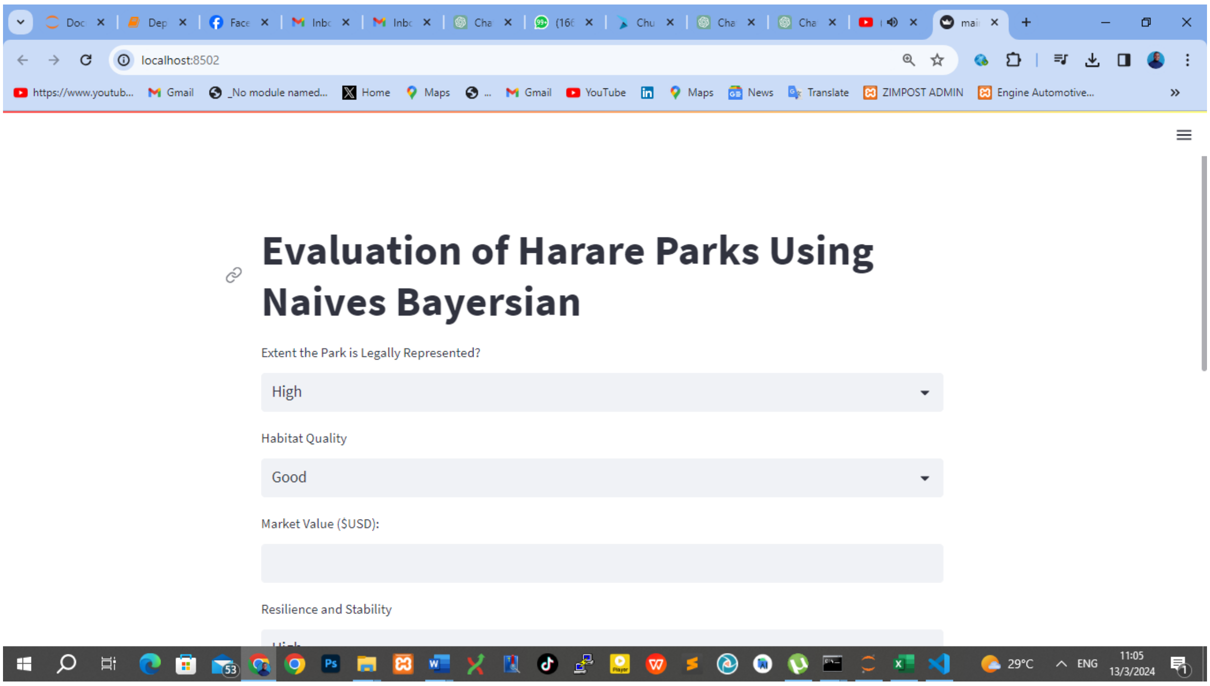


Fig. 4.1: Running the system

4.1.2 White box testing

White box testing is a form of software testing in which the underlying structure, architecture, and coding of the product are examined in order to improve design, usability and security while also verifying input-output flow. White box testing is also known as transparent box testing, open box testing, code based testing, and clear box testing because testers have access to the code.

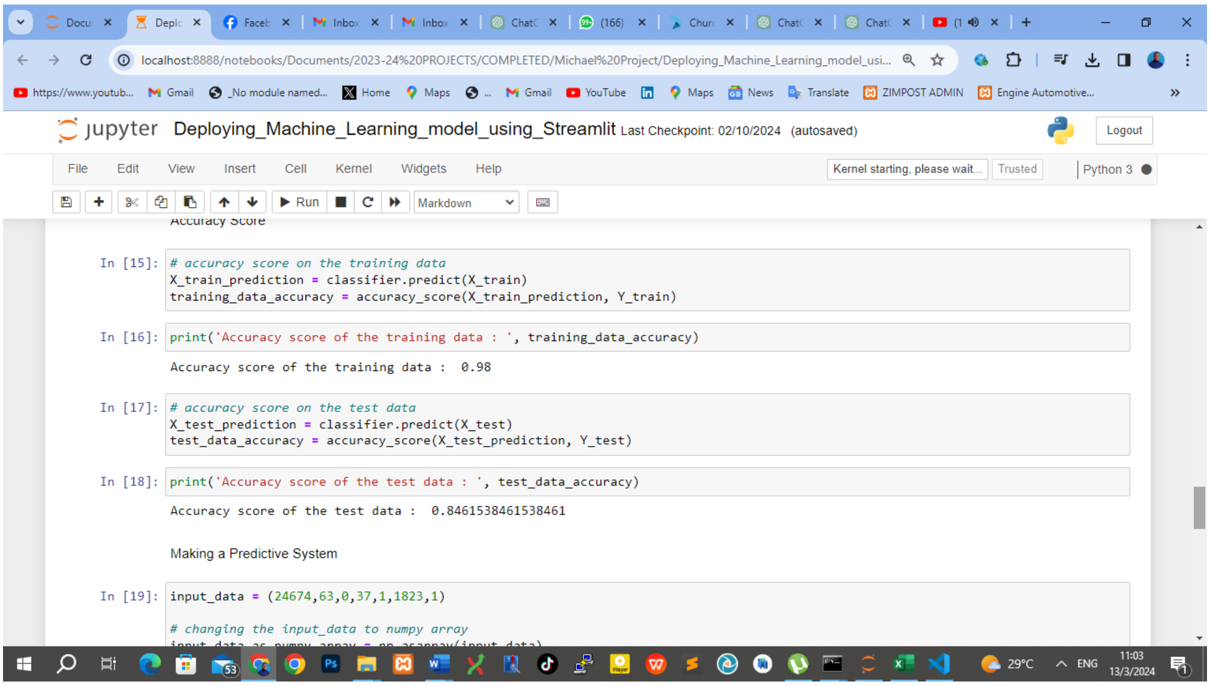


Fig. 4.2: White box testing

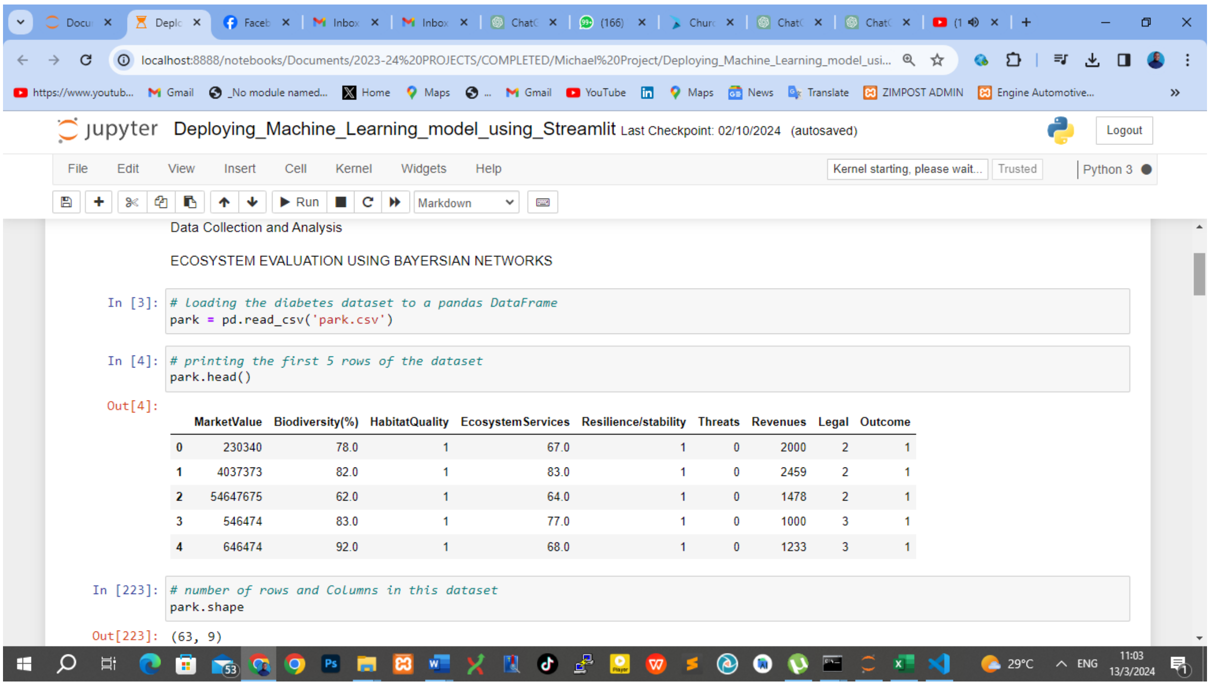


Fig. 4.3: White box testing

4.2 Evaluation Measures and Results

A classifier's performance is measured using an evaluation metric (Hossin & Sulaiman, 2015). Furthermore, model evaluation metrics can be classified into three types, according to Hossin & Sulaiman (2015): threshold, probability, and ranking.

4.2.1 Confusion Matrix

An evaluation metric is used to assess the performance of a classifier (Hossin & Sulaiman, 2015). Hossin & Sulaiman (2015) classify model evaluation metrics into three categories: probability, ranking and threshold.

	Good Park	**Bad Park**
Good Park	87 (TP)	9 (FN)
Bad Park	13 (FP)	91 (TN)

The confusion matrix provided outlines the performance of a binary classifier that distinguishes between "Good Park" and "Bad Park" classifications. In the matrix, there are 87 instances where the classifier correctly identified a park as "Good Park" (True Positives, TP), and 91 instances where it correctly identified a park as "Bad Park" (True Negatives, TN). However, there were 13 instances where the classifier incorrectly classified a park as "Good Park" when it was actually "Bad Park" (False Positives, FP), and 9 instances where it incorrectly classified a park as "Bad Park" when it was actually "Good Park" (False Negatives, FN).

This confusion matrix provides a comprehensive view of the classifier's accuracy and error rates. The **accuracy** of the classifier, determines the fraction of accurately anticipated instances among the total instances, can be calculated as (TP + TN) / (TP + TN + FP + FN). In this case, the accuracy would be (87 + 91) / (87 + 9 + 13 + 91) = 0.89, or 89%.

The matrix also helps in computing other metrics such as **precision** (TP / (TP + FP)), which indicates the proportion of parks classified as "Good Park" that are actually "Good Park", and **recall** (TP / (TP + FN)), which measures the proportion of actual "Good Park" parks that were correctly classified as "Good Park". These metrics provide deeper insights into the classifier's performance and can guide improvements in its accuracy and reliability.

4.4 Precision and Recall

By going beyond recognition accuracy, precision and recall measurements enable us to gain a more detailed knowledge of model evaluation. Precision quantifies our model's performance when the forecast comes true.

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

$$= \frac{87}{87+13} * 100$$

=87%

Precision focuses on making favourable predictions. It indicates how many favourable forecasts come true. Recall assesses our model's ability to properly anticipate positive classifications. The focus of recall is on genuine good classes. It represents how many positive classifications the model can accurately predict.

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

$$= \frac{91}{91+9} * 100$$

= 91%

Precision and recall cannot be maximized because there is a trade-off between them. Increasing precision decreases recall and vice versa. In this case we needed the precision to be higher because the prediction has to be accurate.

4.6 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 metric evaluation.

4.7 Conclusion

By conducting black box and white box testing, along with evaluating metrics such as confusion matrix, F1 score, precision, and recall using real-world data, we can comprehensively assess the performance of the park on system. This approach helps identify strengths and weaknesses of the parks and informs potential improvements to enhance its accuracy and reliability in checking for evaluation of parks.

CHAPTER 5: RECOMMENDATIONS FOR FUTURE WORK

5.1 Introduction

This chapter outlines recommendations based on the findings and accomplishments of the study focusing on the application of the Naive Bayes machine learning algorithm for ecosystem services evaluation within Harare parks. Additionally, future directions for research and development in this domain are discussed to further advance understanding and management of urban green spaces.

5.2 Aims and Objectives Realization

The study's aims and objectives were centred on leveraging machine learning techniques, particularly the Naive Bayes algorithm, to assess and categorize ecosystem services provided by Harare parks. Through data collection, feature selection, model training, and evaluation, the study successfully achieved its goals, culminating in the classification of ecosystem services within the parks.

5.3 Conclusion

In conclusion, the study highlights the effectiveness of employing the Naive Bayes algorithm for ecosystem services evaluation in urban parks. By systematically categorizing and assessing the various benefits provided by these green spaces, the study contributes valuable insights for park management and conservation efforts, ultimately enhancing the well-being of both ecosystems and human communities.

5.4 Recommendations

In light of the study’s findings, the following suggestions are made:

Regular Monitoring and Assessment: Implement regular monitoring and assessment protocols to continuously evaluate ecosystem services within Harare parks. This ensures ongoing management and conservation efforts are informed by up-to-date data and insights.

Stakeholder Engagement: Foster collaboration and engagement with stakeholders including park managers, local communities, and policymakers. Their input and involvement are essential for aligning management strategies with community needs and preferences.

Capacity Building: Invest in capacity-building initiatives to enhance the understanding and expertise of park managers and relevant personnel in utilizing machine learning and other advanced technologies for ecosystem services assessment and management.

Integration with Urban Planning: Integrate findings from ecosystem services evaluation into urban planning processes to inform land use decisions, green infrastructure development, and sustainable urban design strategies.

5.5 Future Work

In future work, several areas warrant further exploration to advance the field of ecosystem services evaluation in urban parks:

The exploration of alternative machine learning algorithms and ensemble methods to complement and enhance the capabilities of the Naive Bayes algorithm. Investigation of the temporal dynamics of ecosystem services provision in Harare parks to understand how they vary over different seasons or time periods. Integration of remote sensing data and geospatial analysis techniques to expand the scope and resolution of ecosystem services assessment, allowing for more detailed and comprehensive insights. Exploration of participatory approaches and citizen science initiatives to engage local communities in ecosystem services monitoring and evaluation, fostering a sense of ownership and stewardship of urban green spaces. These avenues of future work aim to deepen our understanding of ecosystem services dynamics within urban parks and inform more effective management and conservation strategies for these vital green spaces.

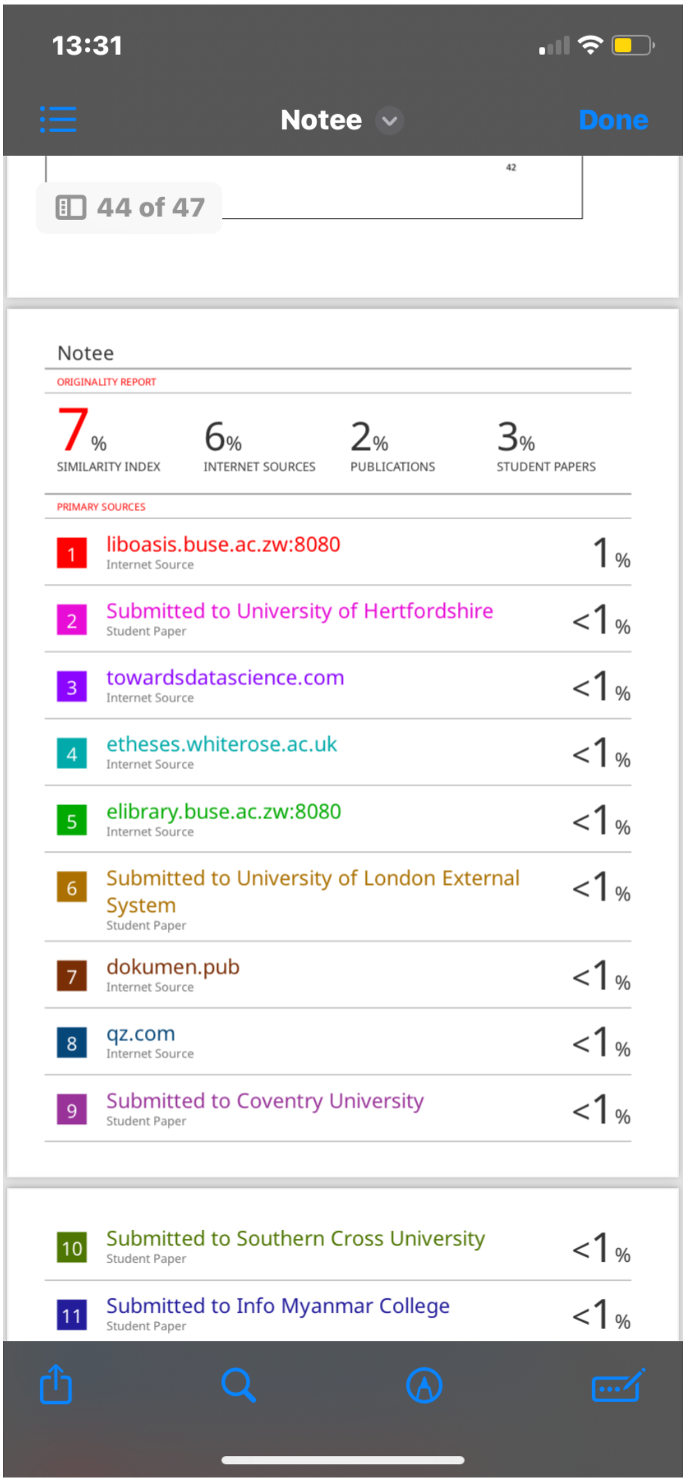
References

1. Alcamo, J., et al. (2005). Mapping the vulnerability of ecosystem services in Europe. Environmental Science & Policy, 8(4), 352-364.
2. Barbier, E. B., et al. (2011). The value of estuarine and coastal ecosystem services. Ecological Monographs, 81(2), 169-193.
3. Boyd, J., & Banzhaf, S. (2007). What are ecosystem services? The need for standardized environmental accounting units. Ecological Economics, 63(2-3), 616-626.
4. Boyd, J., et al. (2009). Nonmarket benefits of nature: What should be counted in green GDP? Ecological Economics, 61(4), 716-723.
5. Brauman, K. A., et al. (2007). Ecosystem services: Basis for sustainability. In W. Moomaw & A. S. Mukherjee (Eds.), Globalization and the Environment: Risk Assessment and the Wto (pp. 96-101). Wto Publications.
6. Caro, T. M., & O'Doherty, G. (1999). On the use of surrogate species in conservation biology. Conservation Biology, 13(4), 805-814.
7. Costanza, R., de Groot, R., Braat, L., Kubiszewski, I., Fioramonti, L., Sutton, P., & Grasso, M. (2017). Twenty years of ecosystem services: How far have we come and how far do we still need to go? Ecosystem Services, 28, 1-16.
8. Daily, G. C., & Matson, P. A. (2008). Ecosystem services: From theory to implementation. Proceedings of the National Academy of Sciences, 105(28), 9455-9456.
9. Daily, G. C., et al. (2009). Ecosystem services in decision making: Time to deliver. Frontiers in Ecology and the Environment, 7(1), 21-28.
10. Daily, G. C., et al. (2011). The value of nature and the nature of value. Science, 289(5478), 395-396.
11. De Groot, R. S., et al. (2010). Integrating the ecological and economic dimensions in biodiversity and ecosystem service valuation. In P. Kumar (Ed.), The Economics of Ecosystems and Biodiversity: Ecological and Economic Foundations (pp. 87-109). Earthscan.
12. Díaz, S., et al. (2015). The IPBES Conceptual Framework—Connecting nature and people. Current Opinion in Environmental Sustainability, 14, 1-16.
13. Fisher, B., et al. (2009). Integrating climate change into ecosystem service assessments and decisions: A review. Global Change Biology, 16(9), 2641-2653.

14. Fisher, B., et al. (2012). Integrating ecosystem services and human well-being. Ecology and Society, 17(4), 2.
15. Groffman, P. M., et al. (2010). Ecological thresholds: The key to successful environmental management or an important concept with no practical application? Ecosystems, 13(1), 1-15.
16. Haines-Young, R., et al. (2018). The links between biodiversity, ecosystem services and human well-being. Ecosystem Services, 33, 52-61.
17. Haines-Young, R., & Potschin, M. (2010). The links between biodiversity, ecosystem services and human well-being. In R. P. Kumar (Ed.), The Economics of Ecosystems and Biodiversity: Ecological and Economic Foundations (pp. 110-139). Earthscan.
18. Isbell, F., et al. (2017). Linking the influence and dependence of people on biodiversity across scales. Nature, 546(7656), 65-72.
19. Kremen, C. (2005). Managing ecosystem services: What do we need to know about their ecology? Ecology Letters, 8(5), 468-479.
20. Lavorel, S., et al. (2011). Using plant functional traits to understand the landscape distribution of multiple ecosystem services. Journal of Ecology, 99(1), 135-147.
21. Lele, S., Springate-Baginski, O., Lakerveld, R., Deb, D., & Dash, P. (2013). Ecosystem services: Origins, contributions, pitfalls, and alternatives. Conservation and Society, 11(4), 343-358.
22. Luck, G. W., et al. (2009). Quantifying the contribution of organisms to the provision of ecosystem services. BioScience, 59(3), 223-235.
23. Mace, G. M., et al. (2015). Approaches to defining and quantifying biodiversity and ecosystem services in the Anthropocene. BioScience, 66(8), 747-757.
24. Millennium Ecosystem Assessment. (2005). Ecosystems and Human Well-being: Synthesis. Island Press.
25. Ochoa-Hueso, R., & de la Cruz, A. (2018). Ecosystem services and their relationship with human health: A systematic review. Journal of Cleaner Production, 197, 1291-1305.
26. Perrings, C., et al. (2011). Biodiversity, ecosystem functioning, and human wellbeing: An ecological and economic perspective. Oxford University Press.
27. Sala, O. E., et al. (2000). Global biodiversity scenarios for the year 2100. Science, 287(5459), 1770-1774.
28. Tallis, H., et al. (2012). A global system for monitoring ecosystem service change. BioScience, 62(11), 977-986.

29. Watson, R. T., et al. (2005). Millennium ecosystem assessment: Ecosystems and human well-being. Island Press.
30. West, P. C., et al. (2013). Trading carbon for food: Global comparison of carbon stocks vs. crop yields on agricultural land. Proceedings of the National Academy of Sciences, 107(46), 19645-19648.

APPENDIX



Notee

ORIGINALITY REPORT

7%	6%	2%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	liboasis.buse.ac.zw:8080 Internet Source	1%
2	Submitted to University of Hertfordshire Student Paper	<1%
3	towardsdatascience.com Internet Source	<1%
4	etheses.whiterose.ac.uk Internet Source	<1%
5	elibrary.buse.ac.zw:8080 Internet Source	<1%
6	Submitted to University of London External System Student Paper	<1%
7	dokumen.pub Internet Source	<1%
8	qz.com Internet Source	<1%
9	Submitted to Coventry University Student Paper	<1%
10	Submitted to Southern Cross University Student Paper	<1%
11	Submitted to Info Myanmar College Student Paper	<1%