SMART BUDGET ASSISTANT USING MACHINE LEARNING

A MINOR PROJECT REPORT

Submitted by

Sathyapriya SB (RA2011008020021)

Agnel Joshua Raj D (RA2011008020037)

Tarun M (RA2011008020111)

Under the Guidance of

Dr. R.M. Rani

(Assistant Professor, Department of Information Technology)

in partial fulfillment of the requirements for the degree

of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY

DEPARTMENT OF INFORMATION TECHNOLOGY

FACULTY OF ENGINEERING AND TECHNOLOGY

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

RAMAPURAM, CHENNAI - 600089

NOVEMBER 2023

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY
RAMAPURAM – 600 089

BONAFIDE CERTIFICATE

Certified that this Bachelor of Technology project report titled **"SMART BUDGET ASSISTANT USING MACHINE LEARNING"** is the bonafide work of **Sathyapriya SB (RA2011008020021), Agnel Joshua Raj D (RA2011008020037), Tarun M (RA2011008020111)** who carried out the project work under my/our supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion for this or any other candidate.

16.11.23

SIGNATURE

DR. R.M. Rani

Supervisor

SRM Institute of Science &Technology

Ramapuram, Chennai – 600089

Rajeswari

SIGNATURE

Dr. Rajeswari Mukesh

Head of the Department

SRM Institute of Science & Technology

Ramapuram, Chennai – 600089

Head of the Department
Department of Information Technology
Faculty of Engineering & Technology
S.R.M. UNIVERSITY
Ramapuram Campus, Chennai-600 089

SUBMISSION OF **18CSP107L MINOR PROJECT** REPORT FOR VIVA-VOICE HELD ON 17/11/23

17/11/2023

INTERNAL EXAMINER – 1

17.11.2023

INTERNAL EXAMINER – 2

ACKNOWLEDGEMENT

To the grace and generous blessing of God Almighty, I attribute the successful completion of the Minor Project. It is my duty to respectfully offer our sincere gratitude to all the people who have kindly offer their valuable support, guidance. I would like to extend my heartiest thanks to the Management of our college, who provided me with necessities for the completion of the seminar.

I want to express my sincere gratitude to **Dr. M. MURALI KRISHNA (DEAN, CET)** for his invaluable support and cooperation, which I consider a true privilege. Furthermore, I extend my appreciation to **Dr. RAJESWARI MUKESH (HOD / IT)** for her continuous guidance and unwavering encouragement, which have been instrumental in my journey. Their mentorship and dedication have been a cornerstone of my success, and I'm truly grateful for their contributions to my academic and personal growth.

I thank my project coordinator **Dr. R. DEEPTHA,** Associate Professor for her consistent guidance and mentoring throughout the project phase. It would be a great honour to thank my guide **Dr. R.M. Rani,** Assistant Professor whose constant persistence and support helped me in the completion of the Minor project. Last but not the least, we thank all others and especially our classmates who in some-way or other helped us in successful completion of this work.

RAMAPURAM SRM

Annexure II

Department of Information Technology

SRM Institute of Science &Technology Own Work* Declaration Form

To be completed by the student for all assessments

Degree/ Course : **Bachelor of Technology/ Information Technology**

Student Name : **Sathyapriya SB, Agnel Joshua Raj D, Tarun M**

Registration Number : **RA2011008020021, RA2011008020037,RA2011008020111**

Title of Work : **A visual cryptographic scheme for colour QR codes in defence**

I / We hereby certify that this assessment compiles with the University's Rules and Regulations relating to Academic misconduct and plagiarism**, as listed in the University Website, Regulations, and the Education Committee guidelines.

I / We confirm that all the work contained in this assessment is my / our own except where indicated, and that I / We have met the following conditions:

- Clearly references / listed all sources as appropriate.
- Referenced and put in inverted commas all quoted text (from books, web, etc)
- Given the sources of all pictures, data etc. that are not my own.
- Not made any use of the report(s) or essay(s) of any other student(s) either past or present.
- Acknowledged in appropriate places any help that I have received from others. (e.g., fellow students, technicians, statisticians, external sources)
- Compiled with any other plagiarism criteria specified in the Course handbook / University website.

I understand that any false claim for this work will be penalized in accordance with the University policies and regulations.

DECLARATION:
I am aware of and understand the University's policy on Academic misconduct and plagiarism and I certify that this assessment is my / our own work, except were indicated by referring, and that I have followed the good academic practices noted above.
If you are working in a group, please write your registration numbers and sign with the date for every student in your group.

Sathyapriya S.B

Sathyapriya SB | **Agnel Joshua Raj D** | **Tarun M**

TABLE OF CONTENTS

CHAPTER NO	CONTENTS	PAGE NO.
1.	**INTRODUCTION**	1
2.	**LITERATURE SURVEY** 2.1 OVERVIEW 2.2 LITERATURE REVIEW 2.3 INFERENCE OF LITERATURE REVIEW	2
3.	**SYSTEM ANALYSIS** 3.1 OVERVIEW 3.2 EXISTING SYSTEMS 3.3 DRAWBACKS OF EXISTING SYSTEM 3.4 ADVANTAGES OF PROPOSED SYSTEM 3.5 SUMMARY	7
4.	**SYSTEM REQUIREMENTS** 4.1 OVERVIEW 4.2 REQUIREMENTS 4.2.1 HARDWARE REQUIREMENTS 4.2.2 SOFTWARE REQUIREMENTS 4.2.2.1 PYTHON 4.2.2.2 IDE 4.2.2.3 PANDAS 4.2.2.4 STREAMLIT 4.2.2.5 VS CODE 4.2.2.6 VERSION CONTROL 4.2.2.7 LIBRARIES AND DEPENDENCIES 4.3 SUMMARY	10
5.	**ARCHITECTURE OF SMART BUDGET ASSISTANT** 5.1 OVERVIEW 5.2 SYSTEM ARCHITECTURE 5.3 SUMMARY	13

6.	**MODULES OF SMART BUDGET ASSISTANT** 6.1 OVERVIEW 6.2 MODULES 6.2.1 DATA COLLECTION AND PREPROCESSING 6.2.2 MODEL TRAINING AND EVALUATION 6.2.3 INPUT AND OUTPUT 6.3 SUMMARY	**15**
7.	**SYSTEM IMPLEMENTATION** 7.1 SUMMARY 7.2 DATA COLLECTION 7.3 DATA PREPROCESSING 7.4 TRAIN DATA & TEST DATA 7.5 MODEL TRAINING USING DECISION TREE 7.6 MODEL EVALUATION 7.7 INPUT DATA 7.8 OUTPUT PREDICTION 7.9 SUMMARY	**17**
8.	**RESULT & DISCUSSION** 8.1 OVERVIEW 8.2 DECISION TREE 8.3 ACCURACY GRAPH 8.3.1 R-SQUARED 8.4 SUMMARY	**22**
9.	**CONCLUSION**	**30**
10.	**FUTURE ENHANCEMENTS**	**31**
	REFERENCES	**32**
	APPENDIX 1. SAMPLE SOURCE CODE 2. SAMPLE OUTPUT SCREENSHOT	**33**

LIST OF FIGURES

FIGURE NO.	NAME OF THE FIGURES	PAGE NO.
5.1	ARCHITECTURE DIAGRAM	13
7.1	SAMPLE CODE 1	19
7.2	SAMPLE CODE 2	19
7.3	SAMPLE CODE 3	20
7.4	SAMPLE CODE 4	20
7.5	SAMPLE OUTPUT	21
8.1	GRAPH CODE 1	24
8.2	GRAPH CODE 2	24
8.3	ACCURACY GRAPH FOR FOOD	25

8.4	ACCURACY GRAPH FOR TRANSPORT	25
8.5	ACCURACY GRAPH FOR ENTERTAINMENT	26
8.6	ACCURACY GRAPH FOR UTILITIES	26
8.7	ACCURACY GRAPH FOR HEALTHCARE	27
8.8	ACCURACY GRAPH FOR GROOMING	27
8.9	ACCURACY GRAPH FOR SAVINGS	28
8.10	ACCURACY GRAPH FOR OTHERS	28

LIST OF ABBREVIATIONS

S.NO	ACRONYM	FULL FORM
1	ML	MACHINE LEARNING
2	IDE	INTEGRATED DEVELOPMENT ENVIRONMENT
2	R^2	R SQUARED OR SQUARE OF CORRELATION COEFFICIENT

ABSTRACT

This system addresses the pressing issue of personal financial management in an increasingly dynamic and challenging economic landscape. The motivation behind the development of this solution stems from the inadequacies of existing financial models that predominantly cater to industries, alongside basic money trackers for individuals. To bridge this gap, "The Smart Budget Assistant" project introduces a novel approach that leverages machine learning techniques to provide personalized financial guidance to individuals, enabling them to optimize their budgets and foster a robust financial life. By employing decision trees, this system tailors financial advice to individual circumstances, taking into account income, expenses, and financial goals, ultimately ensuring efficient resource allocation. The primary goal is to empower users to make informed and prudent financial decisions, enhancing their financial literacy and promoting self-reliance. In contrast to existing solutions, this project's data-driven approach offers a more comprehensive, user-centric, and personalized financial management system, promoting better decision-making, greater financial stability, and an improved quality of life for individuals. In essence, "The Smart Budget Assistant" project aspires to democratize financial wisdom, making it accessible to a broader community, regardless of their financial expertise or background, thus contributing to a more financially resilient society.

Keywords:

Budget Optimization, Financial literacy, Machine Learning, Decision tree, Resource Allocation

CHAPTER – 1
INTRODUCTION

In today's fast-paced and ever-changing world, achieving financial stability and optimizing budgets have become essential skills for individuals seeking to secure their financial future. Yet, navigating the complexities of personal finance can often prove daunting, leaving many individuals uncertain about how to manage their hard-earned money best. While there are existing models designed for industries and money trackers for individuals, we believe in the power of personalized financial guidance. With this vision in mind, we present the "Smart Budget Assistant," a transformative project aimed at helping individuals unlock the potential of their finances and maintain a healthy financial life.

At its core, the Smart Budget Assistant seeks to empower individuals to make informed and efficient spending decisions, tailored to their unique needs and circumstances. By utilizing the powerful tool of decision tree, we have designed an innovative approach that harnesses the potential of data-driven insights to create personalized financial guidelines. Taking into account an individual's salary and rent and financial aspirations, our project offers a comprehensive set of strategies to manage budgets, maximize savings, and make sound investments.

The underlying objective of this project is clear: to enable users to allocate their resources wisely, ultimately leading to greater financial independence and security. By promoting financial literacy and empowering individuals to make better financial choices, we aim to uplift the lives of countless individuals and foster a more resilient society. Throughout this journey, the Smart Budget Assistant strives to instill confidence in individuals as they take control of their finances. Our focus extends beyond immediate budgeting decisions, encompassing long-term financial planning and cultivating a sense of self-reliance. Armed with the knowledge and tools to manage their own financial destiny, users are equipped to navigate life's financial challenges with ease and confidence.

We envision a world where financial well-being is accessible to all, irrespective of their background or financial standing. Through Smart Budget Assistant, we aim to democratize financial wisdom, making it attainable for everyone, regardless of their level of financial expertise.

CHAPTER – 2

LITERATURE SURVEY

2.1 OVERVIEW

Smart Budget Assistant using Machine Learning is designed to tackle the complex challenges of personal finance in today's fast-paced world. What sets our project apart is its focus on delivering personalized financial guidance through data-driven insights, achieved through the application of Decision tree techniques to customize financial strategies according to the unique circumstances of individuals. The overarching objective of our project is to empower users, enabling them to make well-informed spending decisions, enhance their financial independence, and foster financial literacy. Real-time data collected from a diverse pool of users is used to train and test our models, ultimately providing personalized expenditure recommendations. Our vision for Smart Budget Assistant extends towards a future where financial well-being becomes universally accessible, irrespective of one's financial expertise, thereby democratizing financial wisdom and fostering a more resilient society.

In this chapter, we delve into the existing body of literature relevant to the Smart Budget Assistant using machine learning, aiming to provide a comprehensive overview of the research landscape in this domain. The literature survey serves as a foundational exploration of the existing research, setting the stage for our project's contribution to this evolving field. Additionally, our project places significant emphasis on data privacy and security, ensuring that users' financial information is handled with the utmost care and compliance with industry standards. By maintaining robust data protection protocols, we not only deliver personalized financial guidance but also prioritize the confidentiality and security of our users' sensitive information, thereby further enhancing the trust and reliability of our system.

2.2 LITERATURE REVIEW

"The Personal Budget Project: A practical introduction to financial literacy", Cynthia P. Guthrie, Curtis M. Nicholls [1], In "Personal Budget Project" the aim is to equip individuals, with essential financial skills and knowledge to navigate their financial futures successfully. The target of this project underscores the importance of teaching individuals, especially students about to enter the workforce, about the practical aspects of budgeting and financial planning. In addition, the project emphasizes the financial principle of living within one's means. In conclusion, the "Personal Budget Project" described in the passage represents a valuable educational initiative.

“Predictive Model Building for Driver-Based Budgeting Using Machine Learning”, N Kunnathuvalappil Hariharan [2], This project shifts from traditional budgeting to more dynamic and data-driven approaches, particularly driver-based planning, with the help of machine learning for enhanced predictive capabilities. Driver-based planning approach focuses on identifying key business drivers that significantly influence financial outcomes. By centering on predictions and aligning budgets with these drivers, an individual can create more flexible and responsive financial plans. Machine learning algorithms excel at analyzing vast datasets and identifying complex patterns, making them valuable tools for identifying key business drivers and predicting their effects on budgets. Hence, this project represents a promising approach to achieving more adaptive and data-driven budgeting strategies, particularly in complex and uncertain business environments.

“Machine learning for financial forecasting, planning, and analysis: recent developments and pitfalls”, Helmut Wasserbacher and Martin Spindler [3], represents the application of machine learning within the domain of Financial Forecasting, Planning, and Analysis. It emphasizes the potential benefits of imposing machine learning for data-driven decision-making in finance to warn against the inherent challenges associated with applying traditional machine learning techniques to planning and resource allocation. The financial sector has progressively turned to machine learning due to its ability to efficiently extract meaningful outcomes from vast datasets. This project introduces the "double machine learning framework," which is to address causal questions in the context of FP&A. In conclusion, this project offers a comprehensive overview of the role of machine learning in FP&A, emphasizing its strengths in data-driven decision-making.

“Using Machine Learning to Predict Personal Expenditure”, Pez Cuckow (author), Dr. Gavin Brown (supervisor) [4], The project's goal is to create an app that makes it easier to manage personal finances in light of the average person's diminishing discretionary income. The project is divided into two main parts: first, the development of a user-friendly interface for gaining access to previous financial data, and second, the application of machine learning methods to forecast upcoming financial transactions. The report also discusses security issues related to the storage of private financial data. Following the application's development, the report evaluates the effectiveness of selected methodologies and identifies potential areas for additional study that could increase the predicted accuracy of the application. Through the use of machine learning and user-friendly interfaces for financial data analysis and prediction, this research makes a contribution to the developing field of personal finance management.

“WONGA: The Future of Personal Finance Management – A Machine Learning-Driven Approach for Predictive Analysis and Efficient Expense Tracking” Uyanahewa M.I.R, Jayawardana G.V.H.D, Bandara M.B.D.N, Hapugala H.A.V.V, Buddhima Attanayaka and Dasuni Nawinna [5], This research introduces an innovative approach to address the challenges associated with personal finance management, particularly in regions like Sri Lanka, where financial literacy is relatively low. Their "WONGA" system utilizes machine learning techniques to simplify the process of money management for individuals, providing an efficient and user-friendly solution that doesn't demand extensive financial knowledge from users. By automating data collection through SMS messages and expense receipts, categorizing expenditures, and creating personalized budget plans based on spending habits, the system empowers users to maintain financial discipline and prevent excessive spending. Additionally, its predictive features, linked to calendar events, enable users to proactively plan for future expenses, enhancing their overall financial readiness.

“Machine Learning and Financial Planning”, John M. Mulvey [6], The combination of machine learning technology and the field of finance are examined in this project, which highlights a traditional reliance on formal decision models in financial decision making. Machine learning has seen efficient applications in specific financial domains like high-frequency trading and credit scoring for loans, the financial sector has generally been cautious in adopting machine learning for significant decision processes. The project raises a significant challenge the difficulty in assessing the quality of ML recommendations in the context of strategic financial decisions due to uncertainties and time lags, emphasizing the need for robust correctness measurements in supervised learning models.

“Can Interpretable Reinforcement Learning Manage Prosperity Your Way?”, Charl Maree and Christian W. Omlin [7], the authors address the growing importance of personalization in banking and commerce. They highlight the potential of machine learning, particularly reinforcement learning, to enhance customer modeling and decision-making in complex financial environments without relying heavily on conventional methods such as model assumptions. The paper emphasizes the regulatory challenges of model explainability and interpretability while underscoring their potential to provide deeper customer insights. The authors propose an inherently interpretable reinforcement learning algorithm that aligns investment advice with prototype financial personality traits, demonstrating that trained agents adhere to intended characteristics, grasp the value of compound growth, and implicitly consider risk, thus improving policy convergence. This research contributes to the evolving field of interpretable AI in personalized financial management.

“Using a business simulator with elements of machine learning to develop personal finance management skills”, Dmytro S. Antoniuk, Tetiana A. Vakaliuk, Vladyskav V. Didkivskyi, Oleksandr Yu. Vizghalov, Oksana V. Oliinyk, and Valentyn M. Yanchuk [8], In this paper, the authors address the critical need for individuals, including school children and students, to acquire proficiency in personal finance management. Recognizing the importance of both personal finance knowledge and the effectiveness of pedagogy in this domain, the authors introduce a web-based business simulator designed to enhance personal finance management skills. This simulator not only offers valuable insights into financial management but also incorporates elements of machine learning to improve its functionality. With its potential application in both secondary and higher education institutions in Ukraine, this innovative tool holds promise for fostering financial literacy among a wide range of learners, including those with limited prior knowledge in the field of personal finance.

“Personal Financial Intelligence - AI and the Future of Money Management” Catherine Flax [9], highlights the unexplored potential of artificial intelligence (AI) in revolutionizing personal finance management. Despite the transformative impact of AI in various aspects of life, the field of personal finance has seen limited innovation. The key challenge of financial illiteracy can be effectively addressed by leveraging AI's capabilities. The paper discusses various AI methodologies, including feedforward neural networks, reinforcement learning, collaborative filtering, and speech and language interfaces. The integration of these interfaces with AI financial advisors represents a groundbreaking advancement, allowing individuals to receive financial guidance in a natural and human-like manner, revolutionizing the way people interact with their finances.

2.3 INFERENCE OF LITERATURE REVIEW

The field of Smart Budget Assistant using machine learning is poised to revolutionize personal finance management by providing tailored solutions to individuals' unique financial circumstances. The projects and research discussed, demonstrate the increasing importance of data-driven decision-making in financial planning, offering innovative approaches to budgeting, forecasting, and expense tracking. These initiatives aim to empower individuals with the knowledge and tools needed to navigate their financial futures successfully, regardless of their level of financial expertise.

From educational initiatives like the "Personal Budget Project" to dynamic driver-based budgeting in "Predictive Model Building for Driver-Based Budgeting Using Machine Learning," and user-friendly applications like "WONGA," each project contributes to the democratization of financial wisdom. Machine learning's ability to analyze vast datasets and extract meaningful insights is harnessed to create more adaptive and data-driven budgeting strategies. Furthermore, the projects discussed also shed light on the challenges and considerations associated with integrating machine learning into financial decision-making, such as model explainability, correctness measurements, and addressing uncertainties. As the financial sector continues to explore the possibilities of machine learning, it becomes essential to strike a balance between innovation and accountability. Finally, the potential of AI and machine learning in personalized financial management, as highlighted in "Can Interpretable Reinforcement Learning Manage Prosperity Your Way?" and "Personal Financial Intelligence," offers a glimpse into the future of money management. These technologies hold the promise of providing individuals with personalized financial guidance in a natural and human-like manner, potentially transforming the way people interact with and manage their finances.

In summary, the research and projects discussed in this overview underscore the growing importance of machine learning in Smart Budget Assistant and its potential to empower individuals, foster financial literacy, and create more resilient and informed financial decision-makers. The intersection of technology and finance is an exciting frontier, offering the prospect of a more financially secure and prosperous future for all.

CHAPTER – 3
SYSTEM ANALYSIS

3.1 OVERVIEW

System analysis for Smart Budget Assistant involves a comprehensive examination of the components and processes that contribute to effective financial planning and expenditure management. In this, the existing system utilizes different methods to calculate expenditure. It employs data analysis, accurate prediction, and implementation of algorithms. However, it has limitations, including low prediction efficiency and outdated datasets. The proposed Smart Budget Assistant helps to overcome the following issues. It uses machine learning techniques to implement the process and provides more accurate output.

3.2 EXISTING SYSTEMS

Before implementing the Smart Budget Assistant system, it's essential to understand the existing landscape. Currently, individuals often rely on manual budgeting, which can be time-consuming and error-prone. Some may use spreadsheet-based tools or apps that require manual data entry and categorization. While these tools can provide insights, they lack the predictive power of machine learning. Traditional financial software may offer budgeting features, but they often rely on user-set parameters rather than data-driven predictions. The existing system is largely dependent on user expertise and effort, and it may not adapt well to changes in income and financial goals. As such, there is a need for a more data-driven and predictive approach to budget optimization.

Some projects shift towards more dynamic budgeting through machine learning, focusing on predictive capabilities and aligning budgets with key business drivers. Others introduce user-friendly apps and automated methods for personal expenditure prediction, contributing to better financial discipline. Additionally, there are projects addressing financial management in regions with low financial literacy, using machine learning to automate data collection, categorize expenses, and create personalized budget plans. Furthermore, the integration of machine learning, reinforcement learning, and artificial intelligence are explored to enhance customer modeling and decision-making, addressing the need for personalization in finance and emphasizing the importance of interpretability. These projects collectively represent a comprehensive landscape of diverse strategies for predictive personal finance management.

3.3 DRAWBACKS OF EXISTING SYSTEMS

- **Manual and Time-Consuming:** The existing system relies on manual budgeting, which is time-consuming and labor-intensive. Users need to input and categorize their expenses and income, which can be a tedious process.
- **Error-Prone:** Manual budgeting is prone to human error. Users may make mistakes in data entry or categorization, leading to inaccurate budget calculations.
- **Data Privacy:** Machine learning systems may raise concerns about data privacy and the security of personal financial information.
- **Accuracy:** Machine learning algorithms are not infallible, and errors in prediction or budgeting could lead to financial issues.
- **Maintenance:** Systems may require continuous updates and maintenance, adding to the time and effort needed for effective use.
- **Lack of Predictive Power:** Traditional financial tools, even if they offer budgeting features, often lack predictive capabilities. They depend on user-set parameters, which may not adapt well to changing income or financial goals.
- **Personalization Challenges:** While machine learning can tailor recommendations, it might not fully understand an individual's unique financial situation and preferences.
- **Lack of User-centric Approach:** Many existing budgeting tools follow a generic, one-size-fits-all approach, which does not consider the substantial variations in financial needs between different user demographics. For instance, the financial requirements of a family vastly differ from those of a university student.
- **Learning Curve:** Users may need time to adapt to the features and functions of these systems, which could be a barrier to their immediate utility.
- **Cost:** Certain advanced systems might come with subscription fees or costs, making them less accessible to many users who require budgeting.

3.4 ADVANTAGES OF PROPOSED SYSTEM

- **Personalization:** Our project focuses on providing personalized financial guidance. It takes into account an individual's specific income, financial goals, and aspirations. This ensures that the budget recommendations are tailored to each user's unique circumstances, making it more effective.

- **Data-Driven Insights:** By using decision tree and real-time data collection, our project offers data-driven insights and recommendations. It leverages historical and real-time financial data to provide accurate and informed budgeting suggestions. This is in contrast to manual budgeting and spreadsheet-based tools that cannot analyze large datasets effectively.
- **Automation:** The project automates the process of financial guidance, reducing the manual effort required for budget optimization and financial planning.
- **Customization:** Users receive tailored financial strategies based on their unique financial circumstances, ensuring recommendations are highly relevant.
- **Scalability:** The system can accommodate a large number of users simultaneously, making it suitable for widespread adoption.
- **Real-Time Updates:** The Smart Budget Assistant can provide real-time updates and recommendations, allowing users to adapt quickly to changing financial situations.
- **Security:** Robust security measures are in place to protect users' financial data, ensuring privacy and data integrity.
- **Accessibility:** The project is designed with user-friendly interfaces, making it accessible to individuals with varying levels of technical expertise.
- **Machine Learning:** Machine learning algorithms continuously improve the accuracy of financial recommendations as they learn from user data.

3.5 SUMMARY

In this system analysis, the existing expenditure calculation system employs various methods, including data analysis, prediction, and algorithm implementation. However, it suffers from limitations such as low prediction efficiency and reliance on outdated datasets. To address these issues, the proposed Smart Budget Assistant system utilizes machine learning techniques to enhance the process and deliver more accurate and efficient results.

CHAPTER – 4

SYSTEM REQUIREMENTS

4.1 OVERVIEW

The structure of the Smart Budget Assistant system unfolds through a well-organized framework comprised of interconnected modules, each tailored to contribute to the ultimate goal of suggesting the expenditure of an individual. These modules encapsulate essential stages, from initial data collection to final conversion, underscoring the systematic approach employed to help the users by advocating a good expenditure system. This overview delves into the intricate interplay of modules, demonstrating how they collectively pave the way for accurate recommendations.

4.2 REQUIREMENTS

4.2.1 HARDWARE REQUIREMENTS

- **RAM**: Minimum 4 GB RAM
- **Disk Space:** At least 10 GB of free space
- **Processor:** Intel Core i3 processor or equivalent, or higher
- **Graphics Card (Optional, for GPU Acceleration):** NVIDIA GeForce GTX 1050 or equivalent
- **Monitor:** Standard display for visualization and coding
- **Input Devices:** Keyboard and mouse for interaction with the system
- **Internet Connection:** Required for downloading datasets, libraries, and updates.

Meeting these hardware specifications ensures smooth execution of the project, efficient training of neural networks, and effective handling of image processing tasks.

4.2.2 SOFTWARE REQUIREMENTS

- Python
- IDE (Integrated Development Environment)
- Pandas
- Streamlit

- Visual Studio Code (VS Code)
- Version Control
- Libraries and Dependencies

4.2.2.1 PYTHON

Python is a versatile high-level programming language known for its simplicity and readability. Python is widely used across various domains like machine learning, data analysis, and web development. It also provides an extensive standard library and a vast ecosystem of third-party libraries and tools.

4.2.2.2 IDE (INTEGRATED DEVELOPMENT ENVIRONMENT):

An Integrated Development Environment (IDE) provides a comprehensive environment for writing, debugging, and managing the project code. IDEs offer features such as code completion, syntax highlighting, and version control integration, enhancing productivity. Visual Studio Code, in particular, is a popular choice among developers for its lightweight yet powerful features.

4.2.2.3 PANDAS

Pandas is a Python library designed for data manipulation and analysis. It provides data structures like DataFrames and Series that make it easy to work with structured data. Pandas is particularly useful for tasks like data cleaning, transformation, and exploration. Pandas can assist in handling and organizing data, which is often a crucial step in machine learning and data analysis workflows.

4.2.2.4 STREAMLIT

Streamlit is an open-source Python library for rapidly creating web applications. It simplifies converting data scripts into shareable web apps, widely used in data science and machine learning. With Streamlit, developers can easily build interactive web applications by writing Python scripts, including data dashboards and visualizations. It streamlines web development tasks, handling UI, widgets, and data rendering. Streamlit apps can be executed from the command line, facilitating easy sharing and serving.

4.2.2.5 VISUAL STUDIO CODE (VS CODE):

Visual Studio Code (VS Code) is a widely used code editor in machine learning projects. It offers a robust environment for coding, debugging, and collaboration. VS Code's integrated terminal and Git integration simplify version control and project management. Its versatility, rich extension library, and cross-platform support make it a top choice for data scientists and machine learning engineers.

4.2.2.6 VERSION CONTROL:

Version control systems, such as Git, are essential for managing code changes and collaborating with a team. They enable us to track revisions, merge contributions, and maintain a history of the project's development. Git, in combination with platforms like GitHub or GitLab, facilitates efficient code sharing and collaboration among team members, ensuring a smooth development process.

4.2.2.7 LIBRARIES AND DEPENDENCIES:

Libraries and dependencies refer to the various additional packages and modules the application may rely on. These can include specialized libraries for specific tasks or external components that extend the functionality of the project. Managing these libraries and dependencies is crucial to ensure that the application functions correctly and efficiently. Tools like package managers (e.g., pip for Python) help in installing and managing these dependencies.

4.3 SUMMARY

The project's structure is designed with interconnected modules aimed at recommending individual expenditure systematically. These modules cover initial data collection to final conversion, ensuring accurate recommendations. Hardware requirements include a minimum of 4 GB RAM, 10 GB disk space, an Intel Core i3 processor or equivalent, optional NVIDIA GeForce GTX 1050 for GPU acceleration, standard display, keyboard, mouse, and an internet connection. Software requirements encompass Python, IDE (Integrated Development Environment), Streamlit, Pandas for data manipulation, an integrated development environment like Visual Studio Code, version control (e.g., Git), and various libraries and dependencies. These specifications ensure efficient neural network training and image processing for the project's success.

CHAPTER – 5

ARCHITECTURE OF SMART BUDGET ASSISTANT

5.1 OVERVIEW

Smart Budget Assistant using Machine Learning is designed to tackle the complex challenges of personal finance in today's fast-paced world. What sets our project apart is its focus on delivering personalized financial guidance through data-driven insights, achieved through the application of Decision tree techniques to customize financial strategies according to the unique circumstances of individuals. The overarching objective of our project is to empower users, enabling them to make well-informed spending decisions, enhance their financial independence, and foster financial literacy. Real-time data collected from a diverse pool of users is used to train and test our models, ultimately providing personalized expenditure recommendations.

5.2 SYSTEM ARCHITECTURE

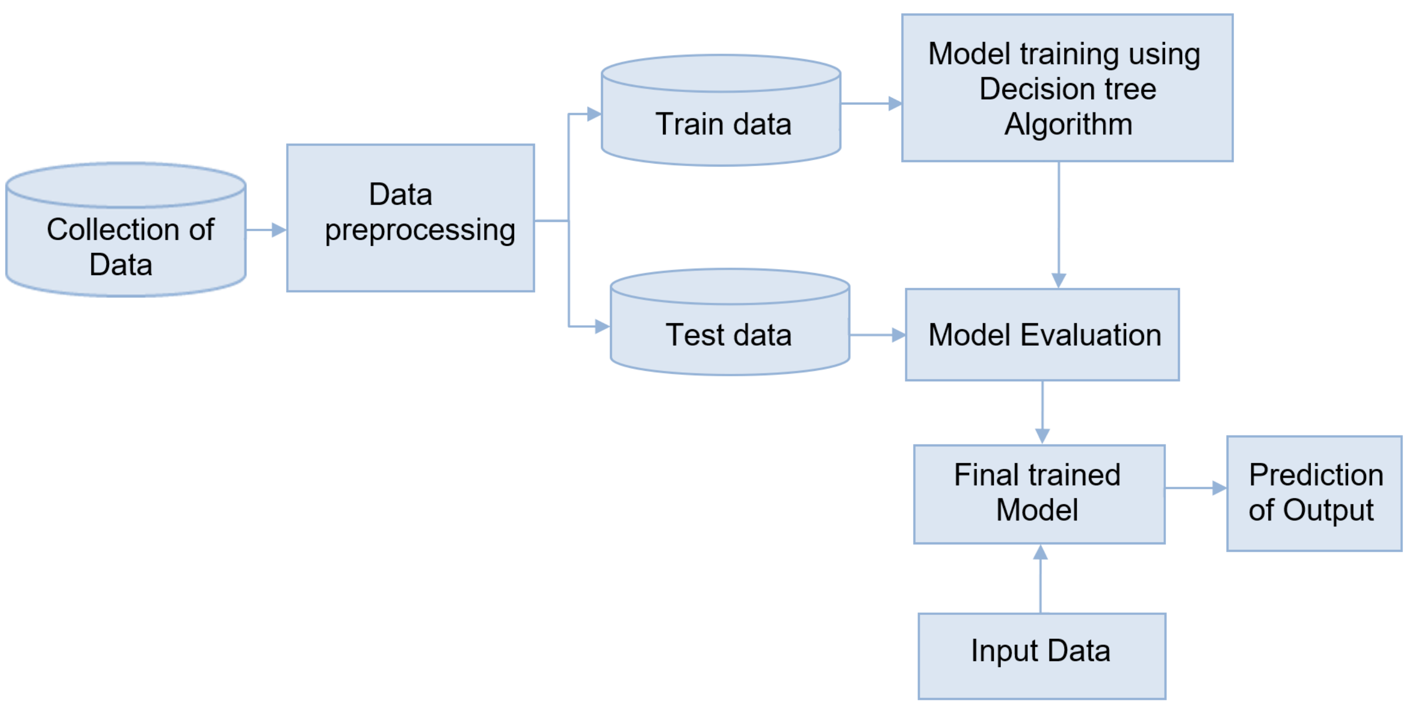


Fig 5.1 Architecture Diagram

5.3 SUMMARY

The project architecture of this project involves several key steps. It all begins with the collection of real-time monthly expenditure data from users, which is crucial for predicting outcomes. Following data collection, the information is subjected to data preprocessing, ensuring it is in numerical format and free of missing values, and then converted into a CSV format. The dataset, consisting of 202 data points, is divided into Training (80%) and Testing (20%) data. The core of the project lies in Model Training using Decision tree, which involves creating a robust model that correlates independent variables with the dependent ones, specifically, salary and rent as the target value. The trained model is then employed for making predictions. Model evaluation is conducted using R-squared (R^2) as a performance metric, and for input data, numerical values for salary and rent is taken to produce predictions as the final output. This comprehensive process ensures the accurate prediction of monthly expenditures based on user inputs.

CHAPTER – 6
MODULES OF SMART BUDGET ASSISTANT

6.1 OVERVIEW

The Smart Budget Assistant system is a transformative initiative aimed at empowering individuals to make informed and efficient spending decisions, thereby enhancing their financial well-being. It consists of several key modules to achieve this goal. It follows a structured workflow, commencing with collecting and preprocessing real-time expenditure data. It then proceeds to the model training phase, where the Decision tree is utilized to establish relationships between salary and rent, and other independent variables. Model evaluation is performed using R Squared Error. The Input and Output module handles user interactions, taking numerical input and providing predictions as the final output.

6.2 MODULES

- Data collection and preprocessing
- Model training and evaluation
- Input and output

6.2.1 DATA COLLECTION AND PREPROCESSING

The data collection process gathers real-time monthly expenditure data from users, ensuring all information is in numerical form and free from missing values. This data is then preprocessed to enhance its quality and converted into CSV format for further analysis. Data integrity is crucial to provide accurate financial guidance to users, making this module a fundamental step in the project.

6.2.2 MODEL TRAINING AND EVALUATION

The core of the project centers on the "Model Training and Evaluation" module, which employs a decision tree approach to establish relationships between the user's salary, rent, financial aspirations, and other financial. It aims to create a personalized financial guideline by creating a decision tree that effectively predicts values. The effectiveness of the model is evaluated using the R-squared (R2) score to ensure that the financial recommendations are reliable and trustworthy.

6.2.3 INPUT AND OUTPUT

The "Input and Output" module allows users to provide their financial information, particularly their salary and rent, in numerical form. The system processes this input through the trained model to generate personalized financial predictions. These predictions offer tailored recommendations for managing budgets, maximizing savings, and making sound investments. The output is considered as the final financial guidance that users can use to make informed financial decisions.

6.3 SUMMARY

In summary, the project is structured around three main system modules. The project starts by gathering and preparing real-time expenditure data, ensuring its numerical format and cleanliness. The core of the project involves training a Decision tree model, utilizing the majority of the data for training and a portion for testing. The model's performance is evaluated using the R-squared value. Users provide numerical inputs for salary and rent, and the trained model processes these inputs to make predictions, ultimately delivering the anticipated outcome. This structured approach ensures that the project successfully predicts outcomes based on user-provided data.

CHAPTER – 7
SYSTEM IMPLEMENTATION

7.1 OVERVIEW

In this procedure, machine learning, specifically decision tree, is employed to create a personalized budget optimization system. Real-time monthly expenditure data is collected from users and preprocessed to ensure data quality. The dataset is then divided into training and testing data. The primary focus is on model training using decision tree, where the goal is to establish a relationship between an individual's salary and rent and financial aspirations as the target variable and other financial variables as independent variables. The trained model aims to assist users in making informed financial decisions.

7.2 DATA COLLECTION

This process begins with the collection of real-time monthly expenditure data from the users. The following data will be used to predict the outcome.

7.3 DATA PREPROCESSING

Data preprocessing is one of the most important steps for this project. In this process, the data are verified that all information received from the user is in numerical form and ensures that there's no missing value in every cell. Then the collected data is been converted to CSV format.

7.4 TRAIN DATA & TEST DATA

The total number of data we got is 202. Out of which 20 percent of data was allocated for Testing data and 80 percent of data was allocated for Training data.

7.5 MODEL TRAINING USING DECISION TREE

Model training using decision tree involves constructing a tree structure by recursively partitioning the data based on selected features, making decisions at each node to split the data into subsets, and optimizing the tree to minimize impurity or error until a stopping criterion is met. This process results in a decision tree model that can be used for predictions and classifications. For this system, salary and rent is taken as the target value. And the remaining is taken as the independent value. The trained model can then be used to make the desired prediction.

7.6 MODEL EVALUATION

Model evaluation for a project using decision trees typically involves assessing the tree's performance by measuring its accuracy, precision, recall, F1 score, R-squared, and possibly other relevant metrics. R-squared helps assess the goodness of fit of the model, with higher R-squared values indicating a better fit to the data and stronger predictive capabilities.

7.7 INPUT DATA

The system initiates by requesting the user's name to establish a personalized connection. Following the introduction, the project prompts the user to input their salary and rent data. according to which the prediction is done. It must be given only in numerical form.

7.8 OUTPUT PREDICTION

Once the user's input data, including their name, salary, and rent, is collected, the system efficiently processes this information. The input is processed into the model and according to the value, prediction is done. This output encompasses a breakdown of estimated monthly expenses, touching on crucial spending categories like food, transport, entertainment, utilities, healthcare, grooming, savings, and other miscellaneous expenditures. The prediction will be considered as the final output.

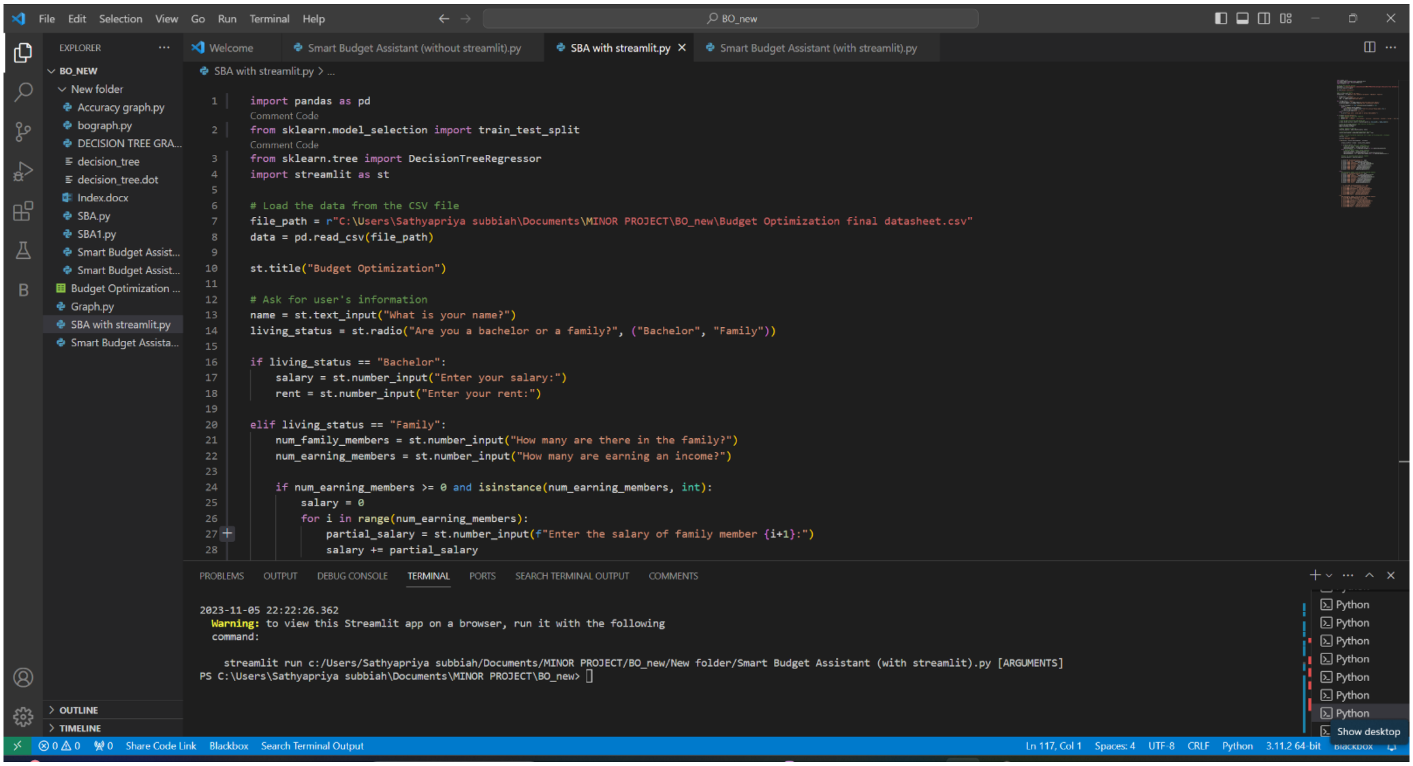


Fig 7.1 Sample Code 1

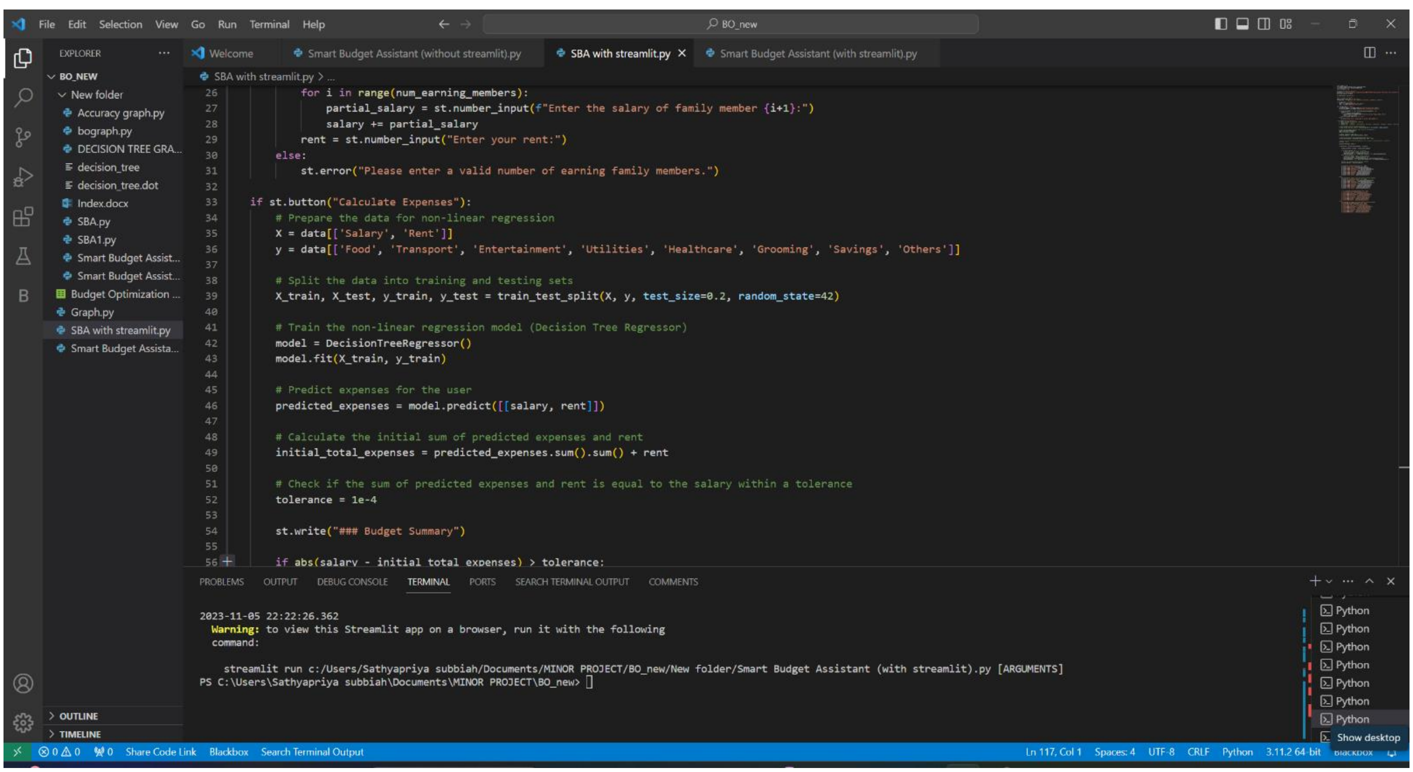


Fig 7.2 Sample Code 2

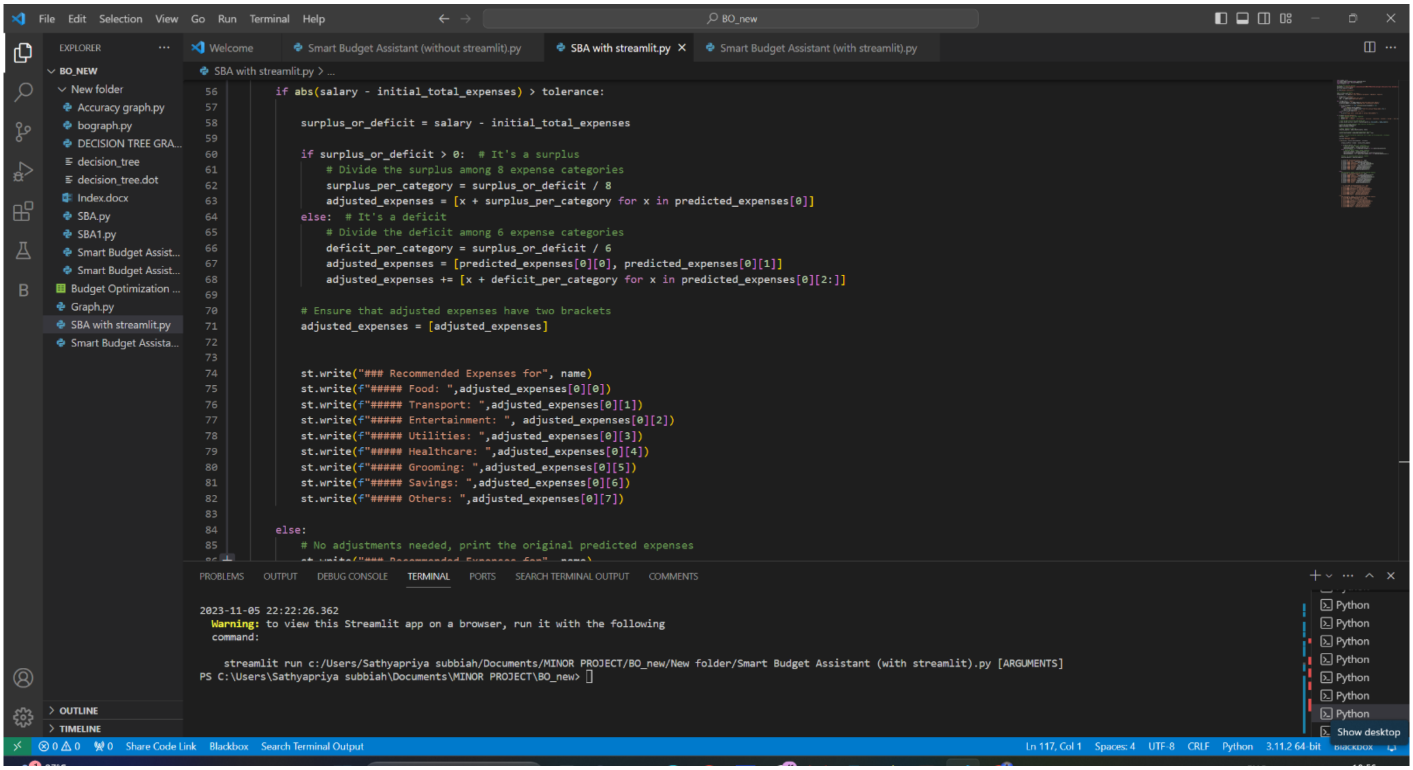


Fig 7.3 Sample Code 3

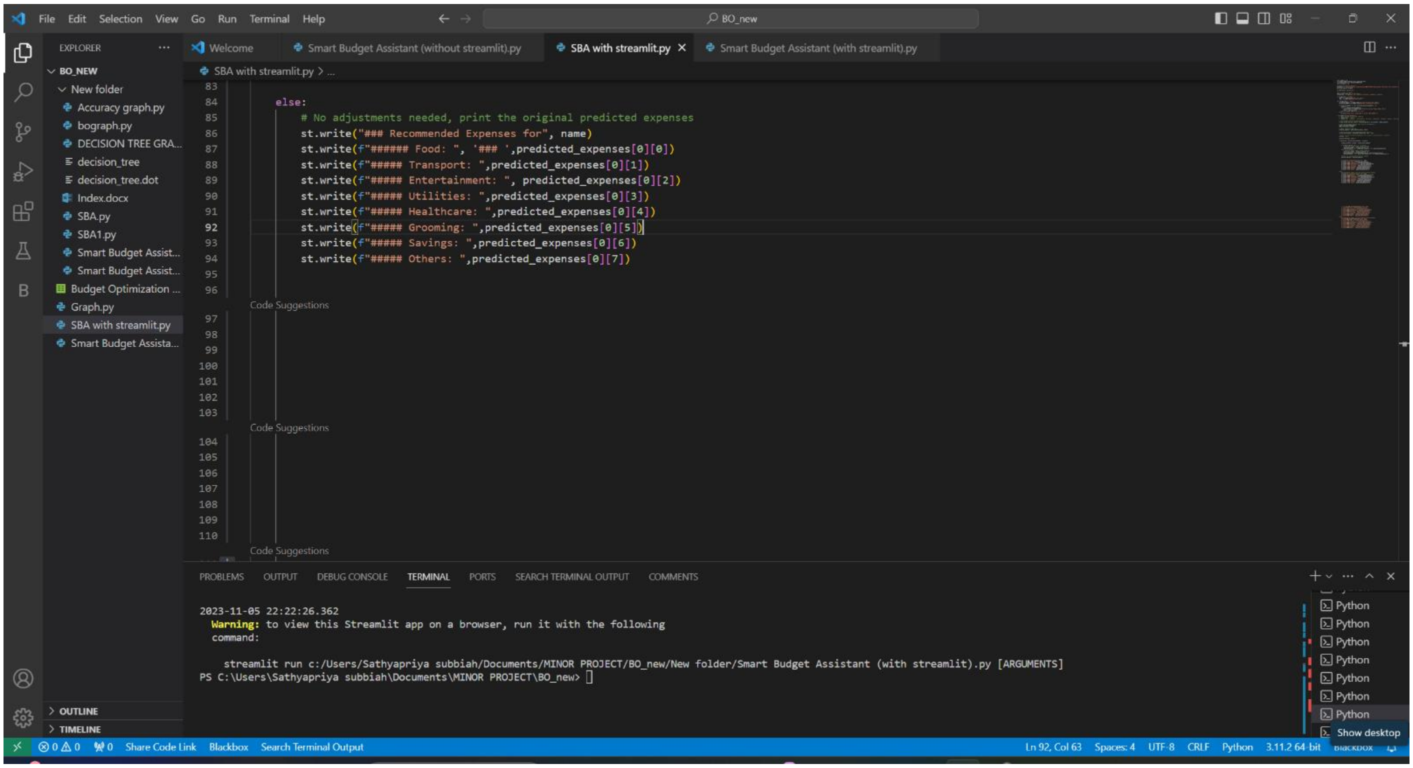


Fig 7.4 Sample Code 4

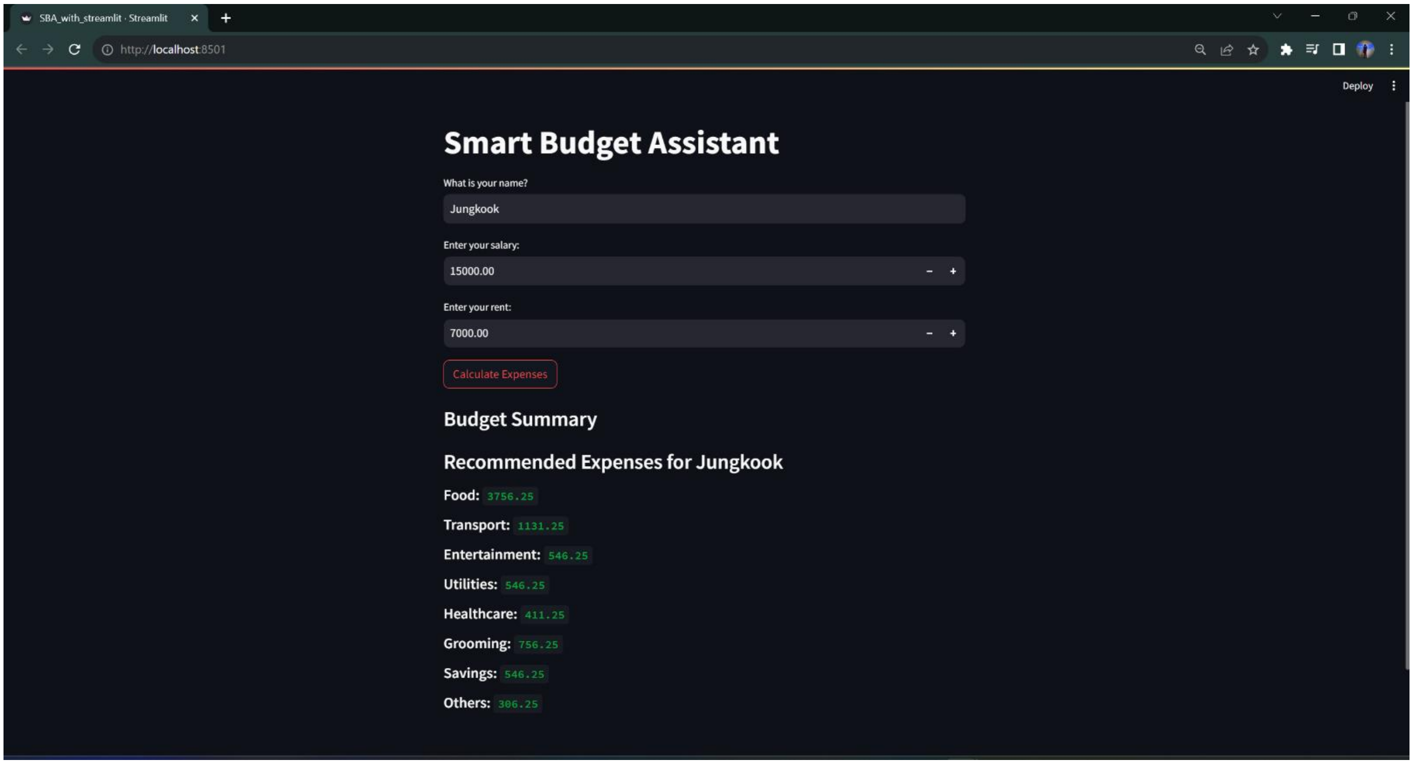


Fig 7.5 Sample Output

7.9 SUMMARY

The implementation of the Smart Budget Assistant system is harnessed to create a personalized financial planning tool. Real-time monthly expenditure data from users is collected and meticulously preprocessed to ensure data quality, followed by the division of the dataset into training and testing data. The core of the system lies in the training of a decision tree model, which establishes a relationship between an individual's income and financial goals, with salary and rent as the primary focus. Model evaluation is performed using R-squared (R^2) as a key metric to assess the goodness of fit of the decision tree model. Users provide their numerical salary and rent data, and the trained model processes this information to deliver precise predictions. This structured and data-driven approach empowers users to make informed financial decisions, making the system a valuable resource for budget optimization and analysis.

CHAPTER – 8
RESULT & DISCUSSIONS

8.1 OVERVIEW

The "Smart Budget Assistant" serves as a personalized guide, enabling individuals to make informed financial decisions that align with their unique financial situations. It utilizes a Decision Tree Regressor model to predict and recommend monthly expenses based on user input regarding salary, living situation, and other factors. It first loads a dataset from a CSV file and collects user information. Using the Decision Tree model, the code predicts expenses and adjusts them if there's a budget deficit or surplus, ultimately providing recommended expenses. The analysis delves into essential aspects, including data preprocessing, the decision tree model's performance, and the use of the R-squared metric for evaluation. To enhance its accuracy and user-friendliness, further improvements can be made, including feature expansion and a more polished user interface via Streamlit.

8.2 DECISION TREE

Decision trees, a fundamental concept in machine learning and data analysis, provide an intuitive way to make decisions and solve complex problems. It is a popular machine-learning algorithm that is used for both classification and regression tasks. The decision tree model is a simple and interpretable model that recursively splits the dataset into subsets based on the most important features to make decisions. Decision trees are often used for decision support, especially when the goal is to understand and explain the decision-making process.

In the context of machine learning, decision trees are often used for classification and regression tasks. Classification trees assign data points to specific categories, while regression trees predict numerical values. The power of decision trees lies in their simplicity and interpretability. Their visual representation makes it easy to understand how a decision is reached, which is invaluable for making informed choices. At their core, decision trees are flowchart-like structures used for decision-making. They break down a decision into a sequence of questions and choices, much like the game "Twenty Questions." Each node in the tree represents a question or decision, and the branches from each node lead to possible answers or further decisions. These branches eventually lead to "leaves," which hold the final decisions or classifications.

8.3 ACCURACY GRAPH

An "accuracy graph" is a graphical representation of the performance of a machine learning model concerning its accuracy score across different scenarios or conditions. In most cases, it's used to visualize how the accuracy of a model changes as you modify specific parameters or settings. Accuracy is a common performance metric in classification tasks, indicating the proportion of correctly predicted instances. It helps in tasks like hyperparameter tuning and assessing the impact of dataset size on model performance.

Decision tree models are known for their interpretability. R-squared is an interpretable metric that allows you to communicate how well the model captures the relationships within your data to non-technical stakeholders.

8.3.1 R-SQUARED (R^2 OR SQUARE OF CORRELATION COEFFICIENT)

In decision tree models, R-squared, or the coefficient of determination, plays a vital role in assessing the accuracy and goodness of fit. It tells us how effectively the chosen independent variables explain the variability in the dependent variable, helping to evaluate the quality of the model. When working with decision trees, a higher R-squared value indicates a more accurate model because it signifies that a greater portion of the dependent variable's variation is explained by the independent variables.

R-squared provides a clear measure of how well the decision tree model fits the data. It quantifies the percentage of variance in the target variable that the model can explain using the independent variables. R-squared is more commonly associated with regression models that predict numerical values, where it's used as a measure of accuracy.

Formula

$$R^2 = 1 - \frac{SSE}{SST}$$

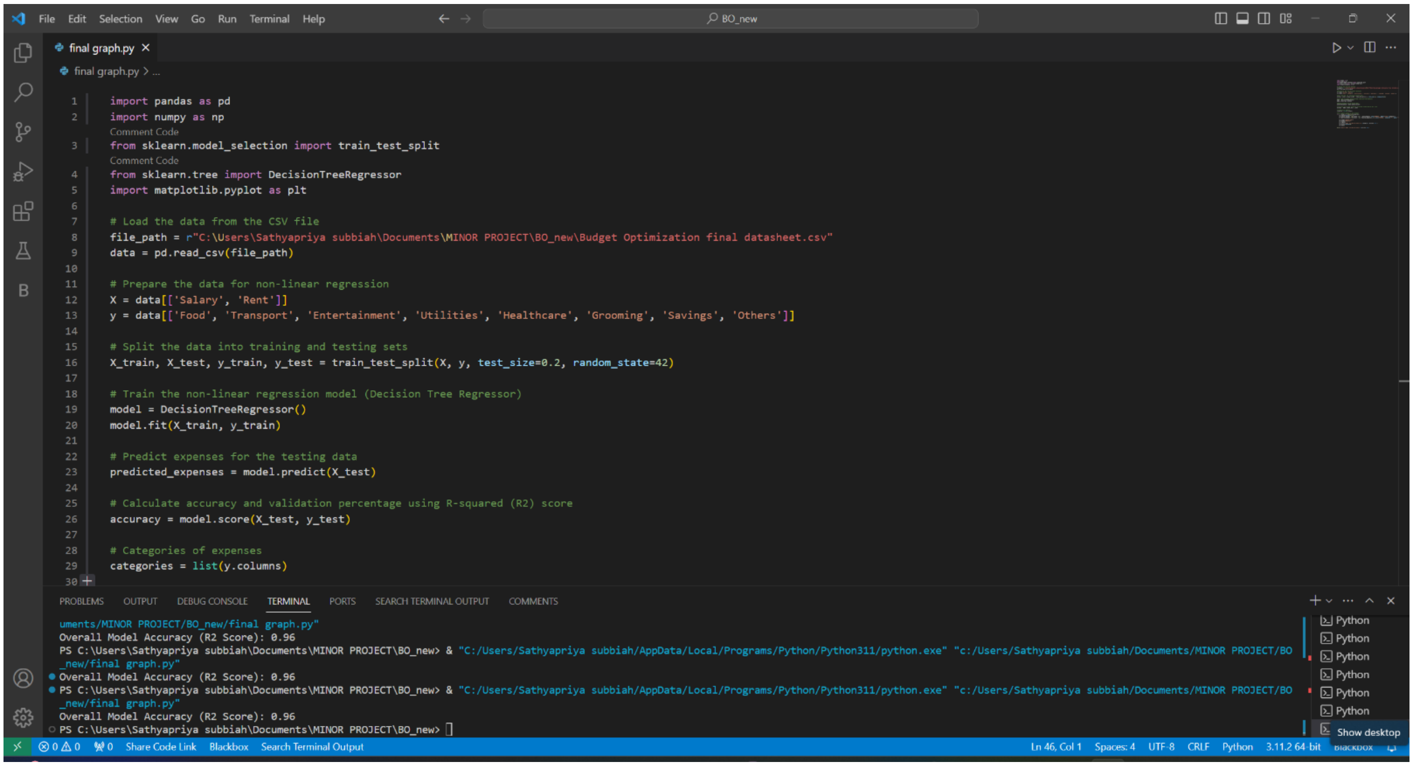


Fig 8.1 Graph Code 1

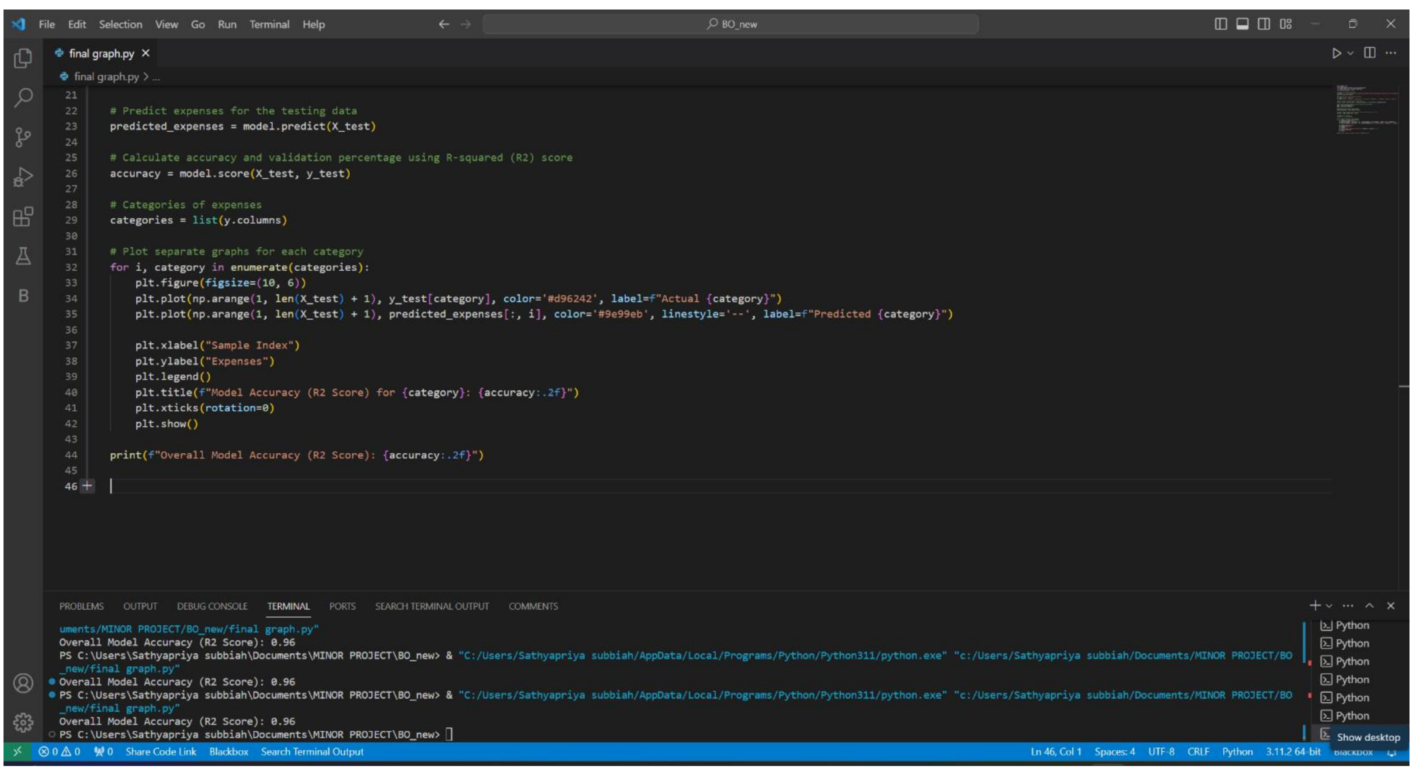


Fig 8.2 Graph Code 2

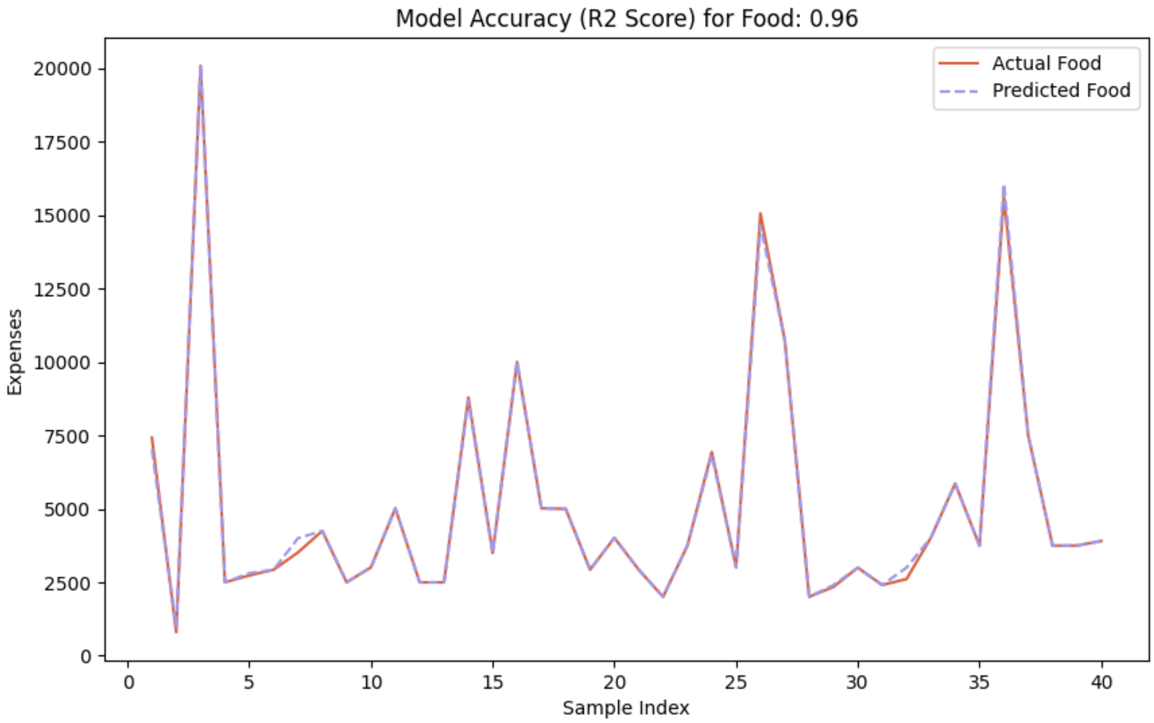


Fig 8.3 Accuracy Graph for Food

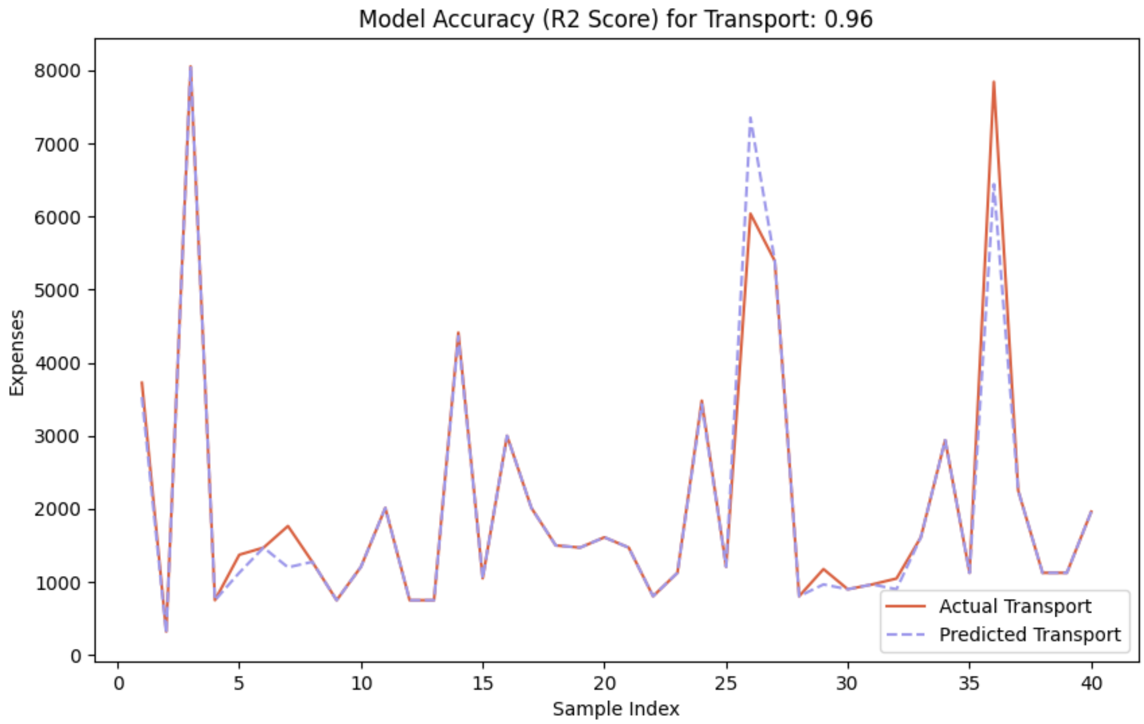


Fig 8.4 Accuracy Graph for Transport

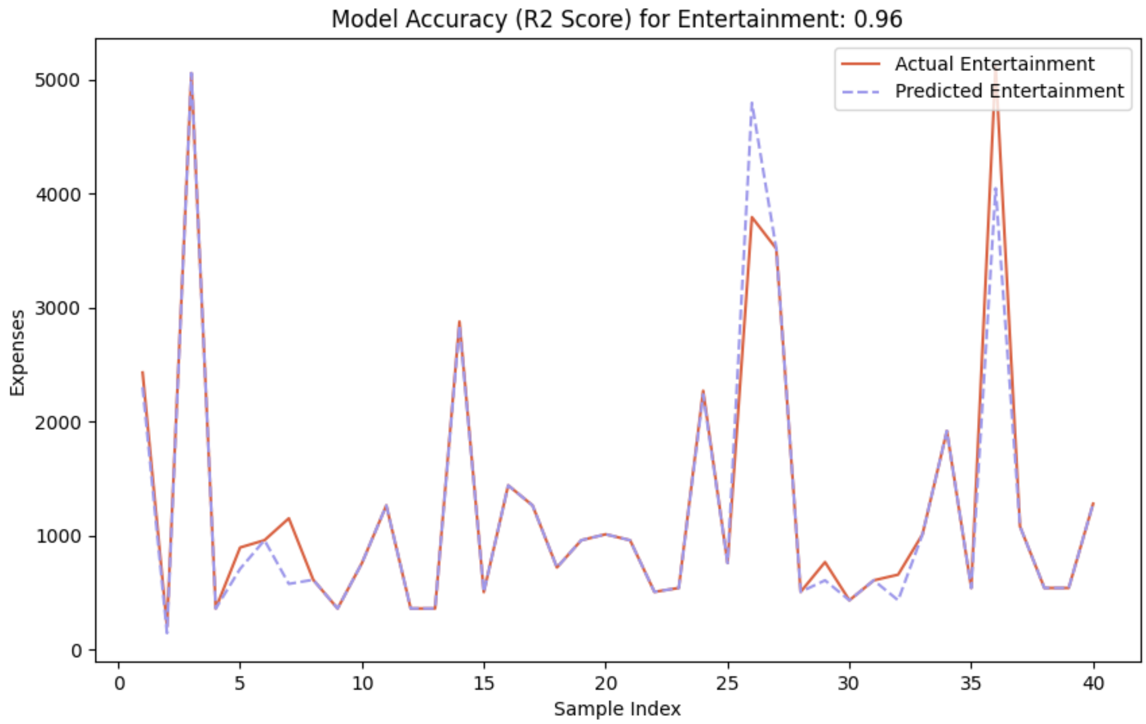


Fig 8.5 Accuracy Graph for Entertainment

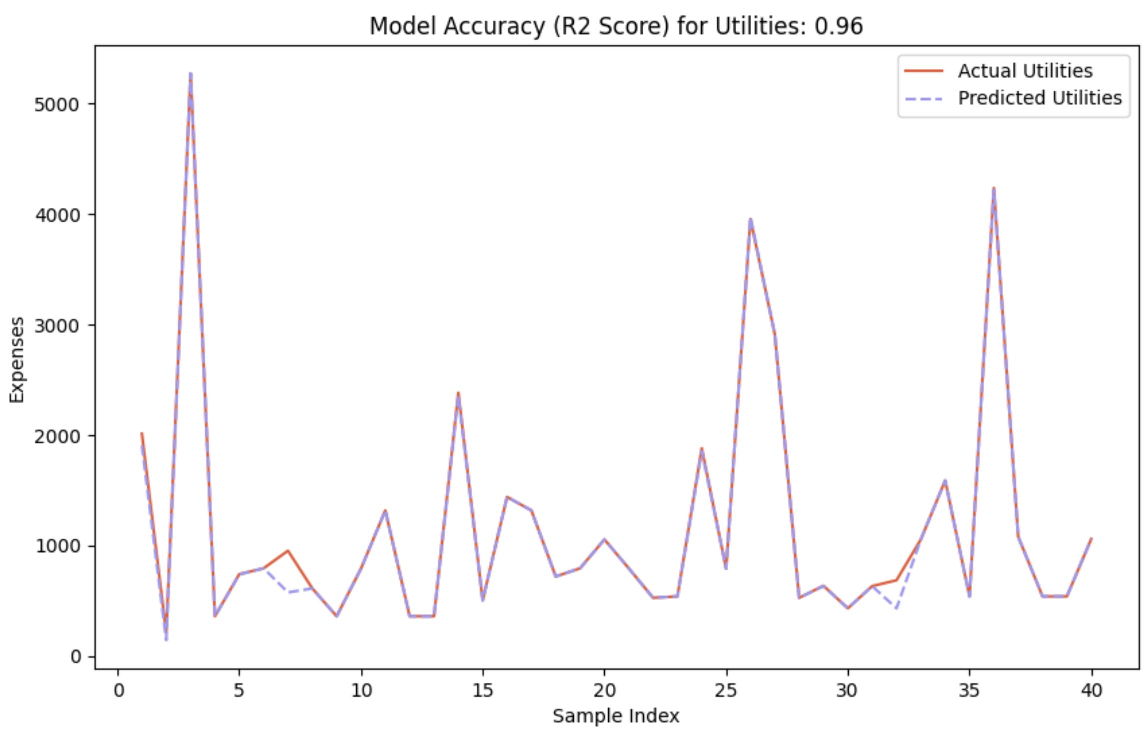


Fig 8.6 Accuracy Graph for Utilities

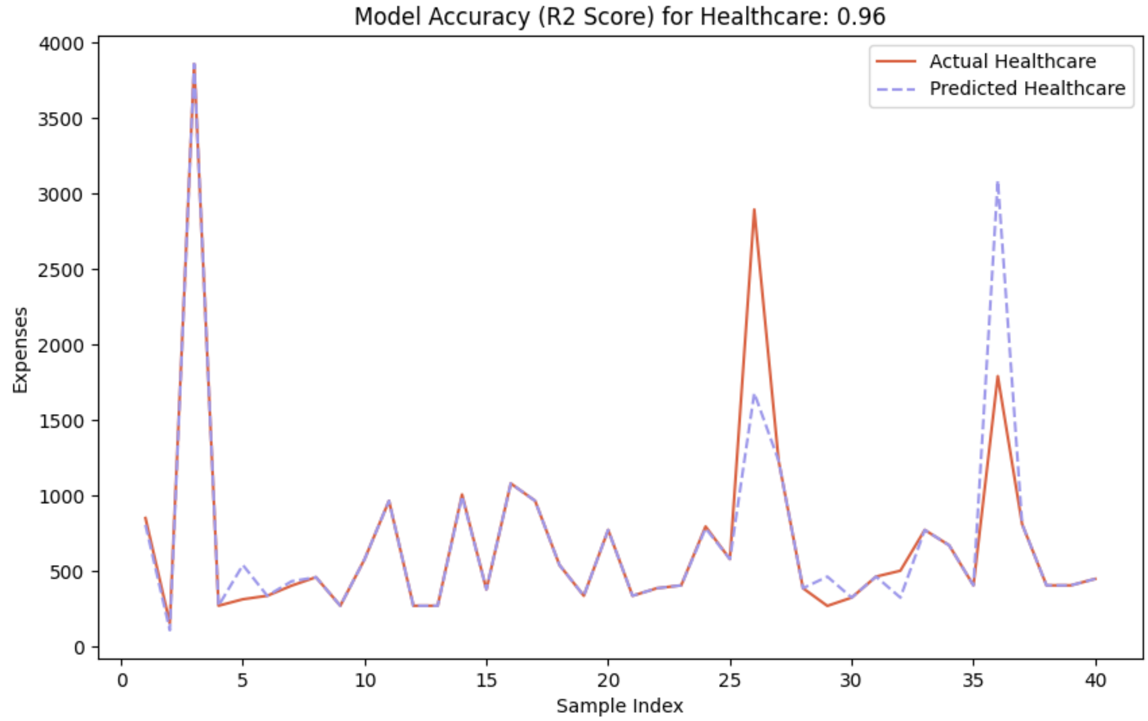


Fig 8.7 Accuracy Graph for Healthcare

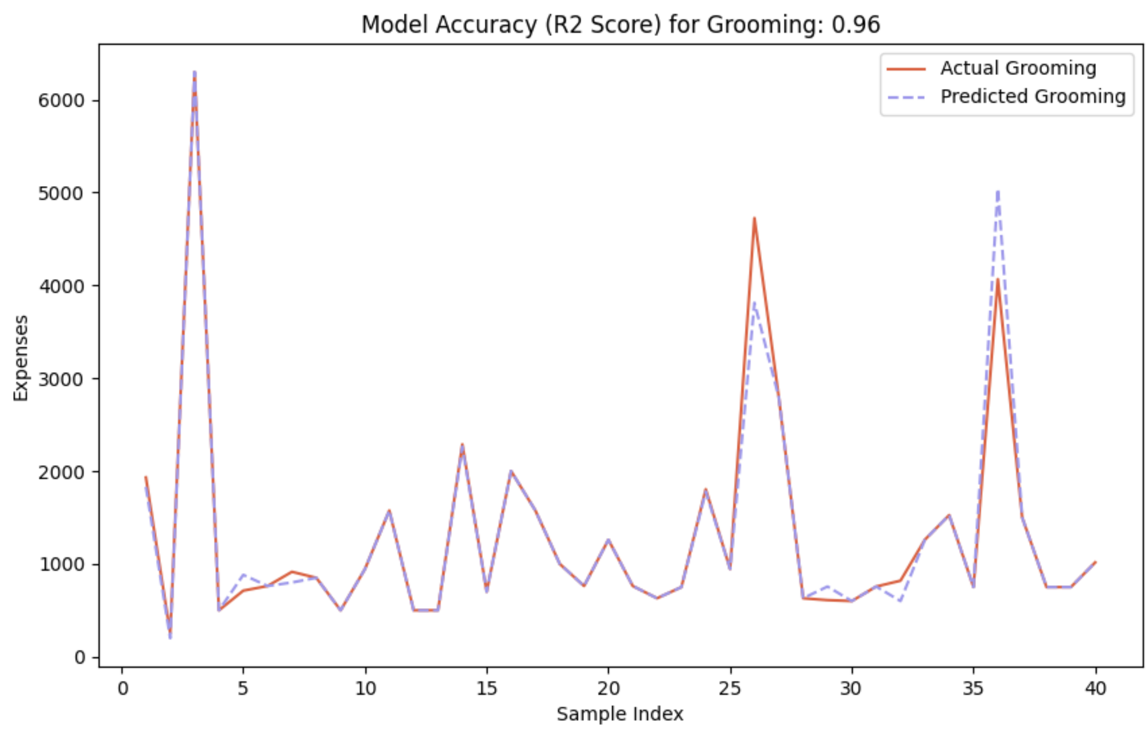


Fig 8.8 Accuracy Graph for Grooming

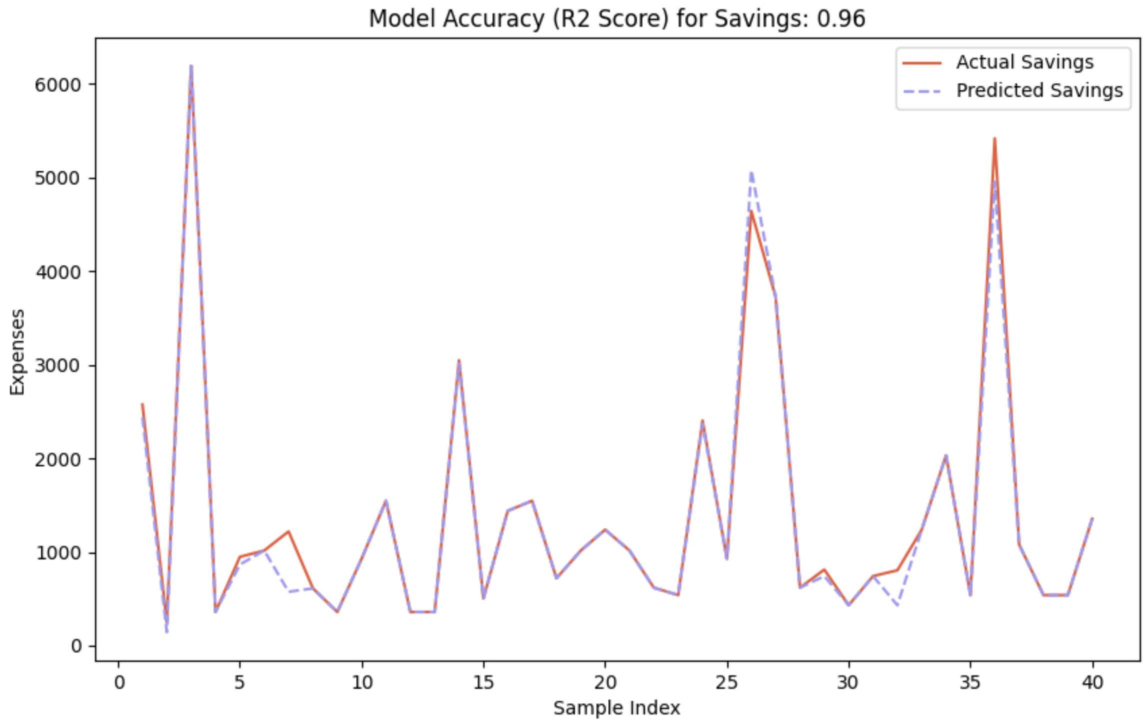


Fig 8.9 Accuracy Graph for Savings

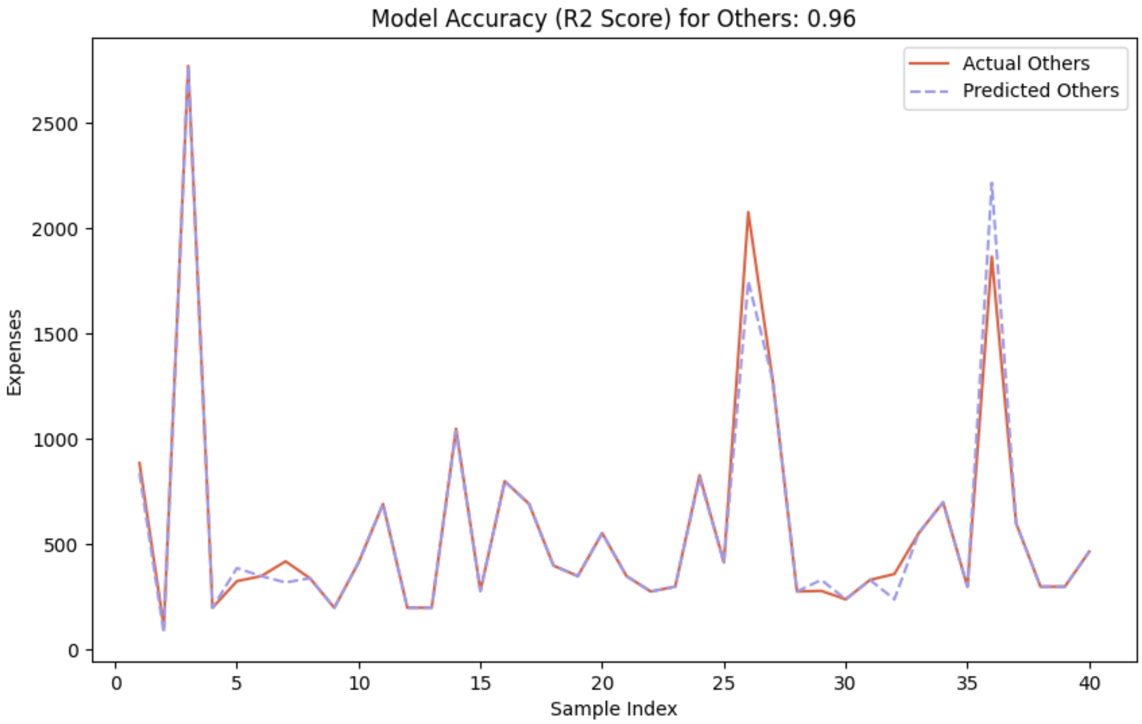


Fig 8.10 Accuracy Graph for Others

8.1 SUMMARY

In conclusion, the provided Python code showcases an application of Decision Tree Regressor modeling in the domain of budget optimization. It effectively bridges user input with data-driven predictions, accommodating both individuals and families. The model's flexibility in handling budget deficits and surpluses ensures practicality in real-life scenarios. However, it's essential to remember that this code represents a foundational framework. To enhance its utility, further refinements such as additional features, a user-friendly interface via tools like Streamlit, and expanded datasets can be implemented. These enhancements will contribute to more accurate and user-centric financial recommendations, making it a valuable tool for budget management and financial planning.

CHAPTER – 9

CONCLUSION

In conclusion, "Smart Budget Assistant" represents a significant leap forward in the realm of personal finance management. In today's dynamic and ever-evolving financial landscape, the need for personalized, data-driven financial guidance is more critical than ever. The existing systems, often reliant on manual input and limited predictive capabilities, are fraught with drawbacks, from time-consuming processes to the potential for human error. Our project, however, stands out as a transformative force in financial planning and expenditure management. We prioritize personalization, recognizing that everyone's financial situation is unique, and we tailor our recommendations to suit individual needs and aspirations.

The three key modules of data collection and preprocessing, model training and evaluation, and input and output form a well-structured framework, ensuring the accuracy and reliability of the financial recommendations provided. Real-time data collection, careful preprocessing, and rigorous model training enable us to deliver data-driven insights that can guide individuals toward better financial decisions.

Our vision extends beyond immediate budgeting concerns; it aims to instill financial literacy and cultivate self-reliance. We are committed to democratizing financial wisdom, making it accessible to all, regardless of their financial expertise or background. With Smart Budget Assistant, we aspire to create a world where financial well-being is attainable for everyone.

To achieve this, we have ensured that our project is user-friendly, scalable, and equipped with robust security measures to safeguard personal financial data. It not only automates the budget optimization process but also provides real-time updates, allowing users to adapt swiftly to changing financial circumstances.

In essence, Smart Budget Assistant is more than just a financial tool; it's a means to transform lives and foster a more resilient society. We believe that by offering personalized, data-driven financial guidance, we can enable individuals to achieve greater financial independence and security. We invite you to join us on this journey towards a brighter financial future, one where financial wisdom is within reach for all.

CHAPTER – 10

FUTURE ENHANCEMENTS

In considering the future enhancements of our Smart Budget Assistant project, there are several avenues we could explore to further refine and expand the system's capabilities. One crucial aspect to focus on is the incorporation of additional financial variables beyond just salary and rent. We should aim to provide a more comprehensive financial analysis for users, taking into account variables such as expenses, savings, investments, and debt. This will enable users to receive a holistic view of their financial situation and make more well-rounded decisions.

Furthermore, we could consider implementing more advanced machine-learning techniques beyond the decision tree. Exploring algorithms like decision trees, random forests, or neural networks could potentially yield more accurate predictions and allow for more complex financial modeling. This would require a larger and more diverse dataset, so efforts to collect and preprocess data from a broader user base would be beneficial.

Another area of improvement lies in user experience. We should work on creating a more intuitive and user-friendly interface, possibly with visualization tools that help users better understand the financial insights and predictions generated by the system. Moreover, incorporating real-time data updates and providing users with notifications and insights about potential financial opportunities or risks would enhance the system's utility. To ensure the project's long-term sustainability, we should also consider data security and privacy measures. Implementing robust data encryption, user consent mechanisms, and compliance with relevant data protection regulations will build trust with our users.

Lastly, conducting user feedback surveys and analysis can help us gain insights into the system's performance and areas that require improvement. Listening to user feedback and iterating on the system based on their needs and suggestions will be essential for the continued success of our Smart Budget Assistant project. Overall, these future enhancements will enable us to create a more powerful and user-centric financial planning tool, helping individuals make even more informed and effective financial decisions.

REFERENCES

[1] The Personal Budget Project: A practical introduction to financial literacy", Cynthia P. Guthrie, Curtis M. Nicholls.

[2] Predictive Model Building for Driver-Based Budgeting Using Machine Learning", N Kunnathuvalappil Hariharan.

[3] Machine learning for financial forecasting, planning, and analysis: recent developments and pitfalls", Helmut Wasserbacher and Martin Spindler.

[4] Using Machine Learning to Predict Personal Expenditure", Pez Cuckow (author), Dr. Gavin Brown (supervisor).

[5] WONGA: The Future of Personal Finance Management – A Machine Learning-Driven Approach for Predictive Analysis and Efficient Expense Tracking" Uyanahewa M.I.R, Jayawardana G.V.H.D, Bandara M.B.D.N, Hapugala H.A.V.V, Buddhima Attanayaka and Dasuni Nawinna.

[6] Machine Learning and Financial Planning", John M. Mulvey.

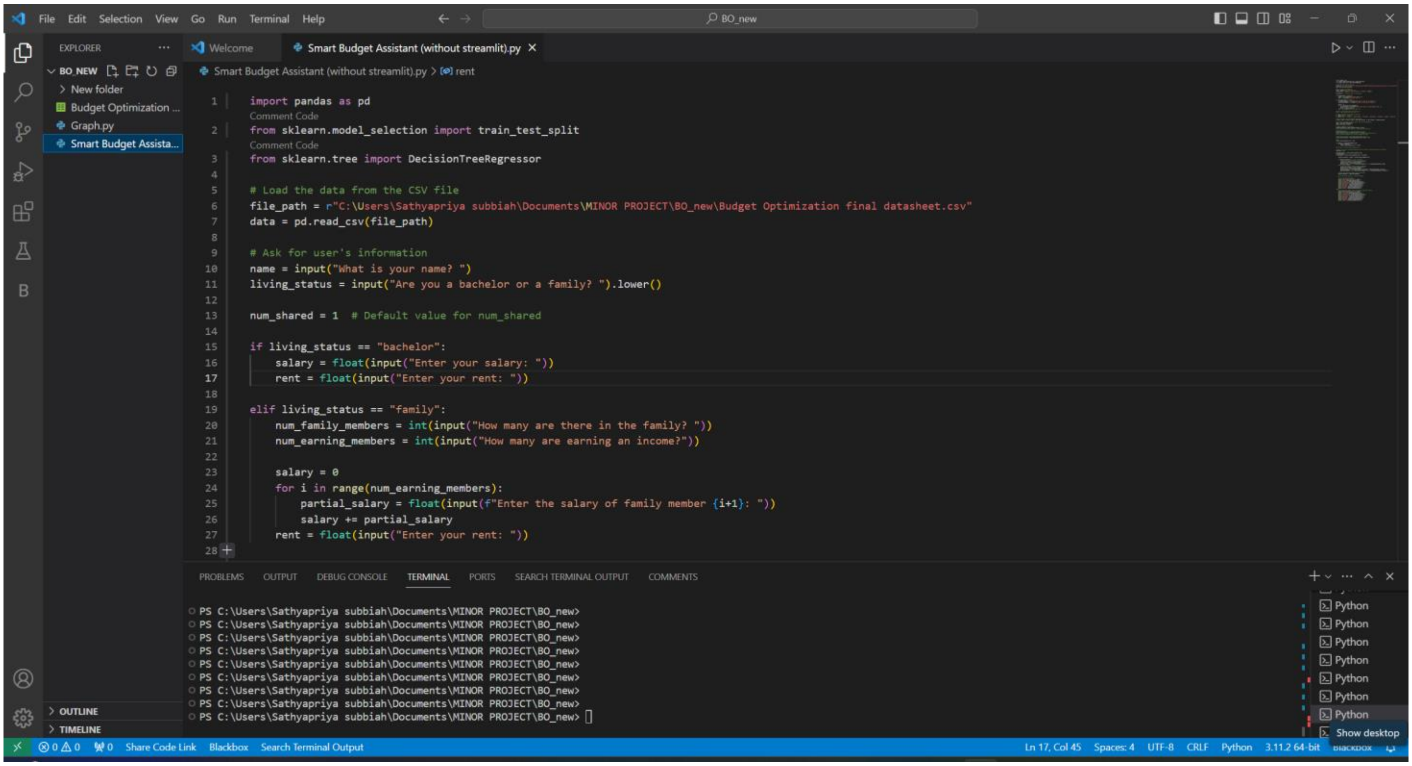
[7] Can Interpretable Reinforcement Learning Manage Prosperity Your Way?", Charl Maree and Christian W. Omlin.

[8] Using a business simulator with elements of machine learning to develop personal finance management skills", Dmytro S. Antoniuk, Tetiana A. Vakaliuk, Vladyskav V. Didkivskyi, Oleksandr Yu. Vizghalov, Oksana V. Oliinyk, and Valentyn M. Yanchuk.

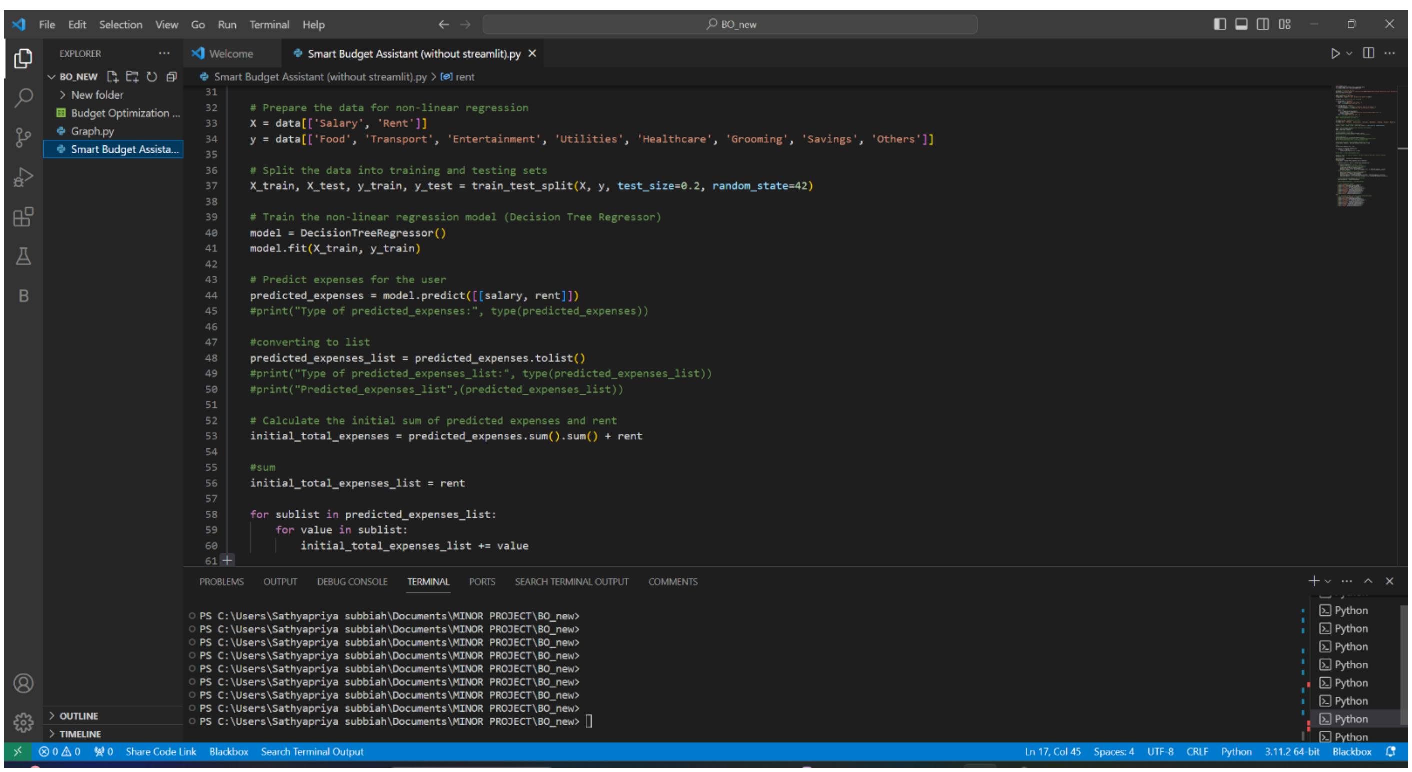
[9] Personal Financial Intelligence - AI and the Future of Money Management" Catherine Flax.

APPENDIX 1

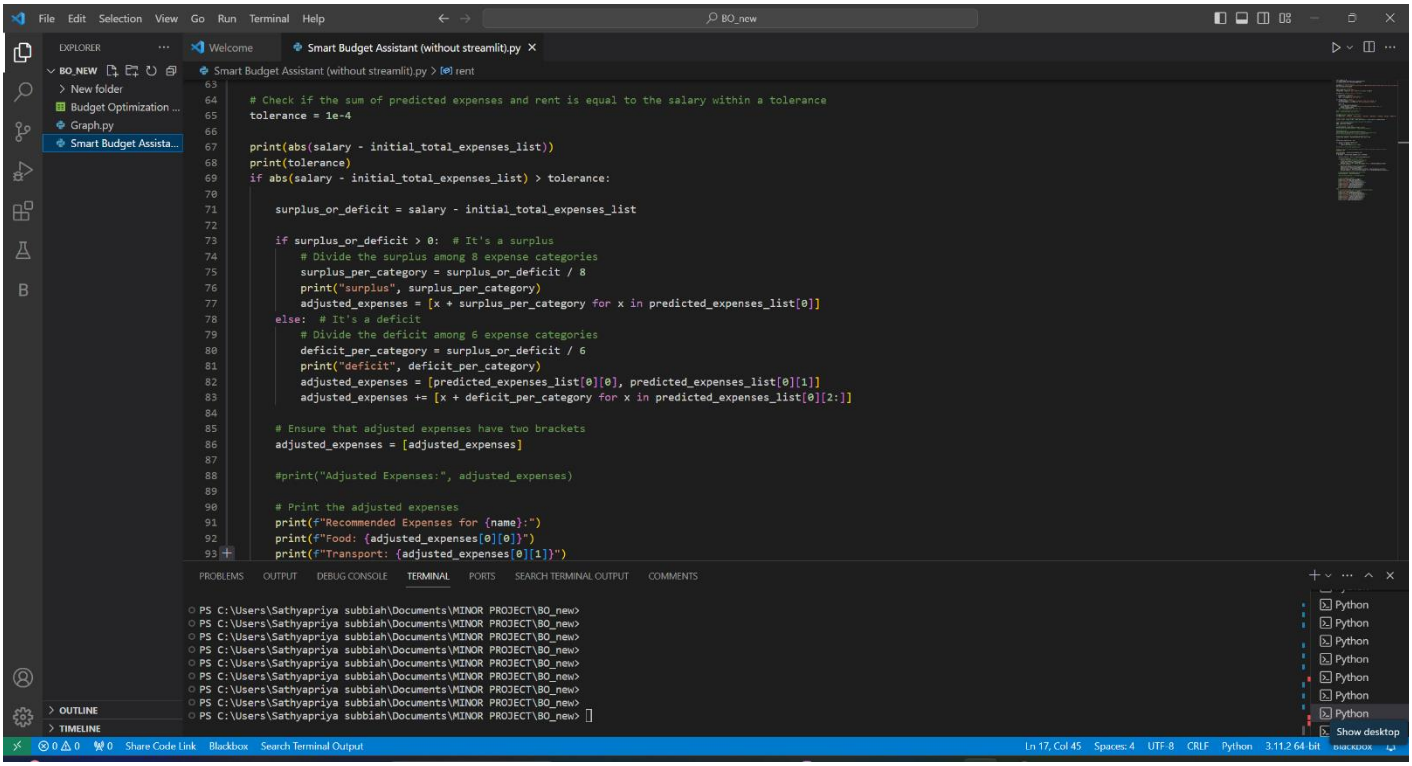
SAMPLE CODING



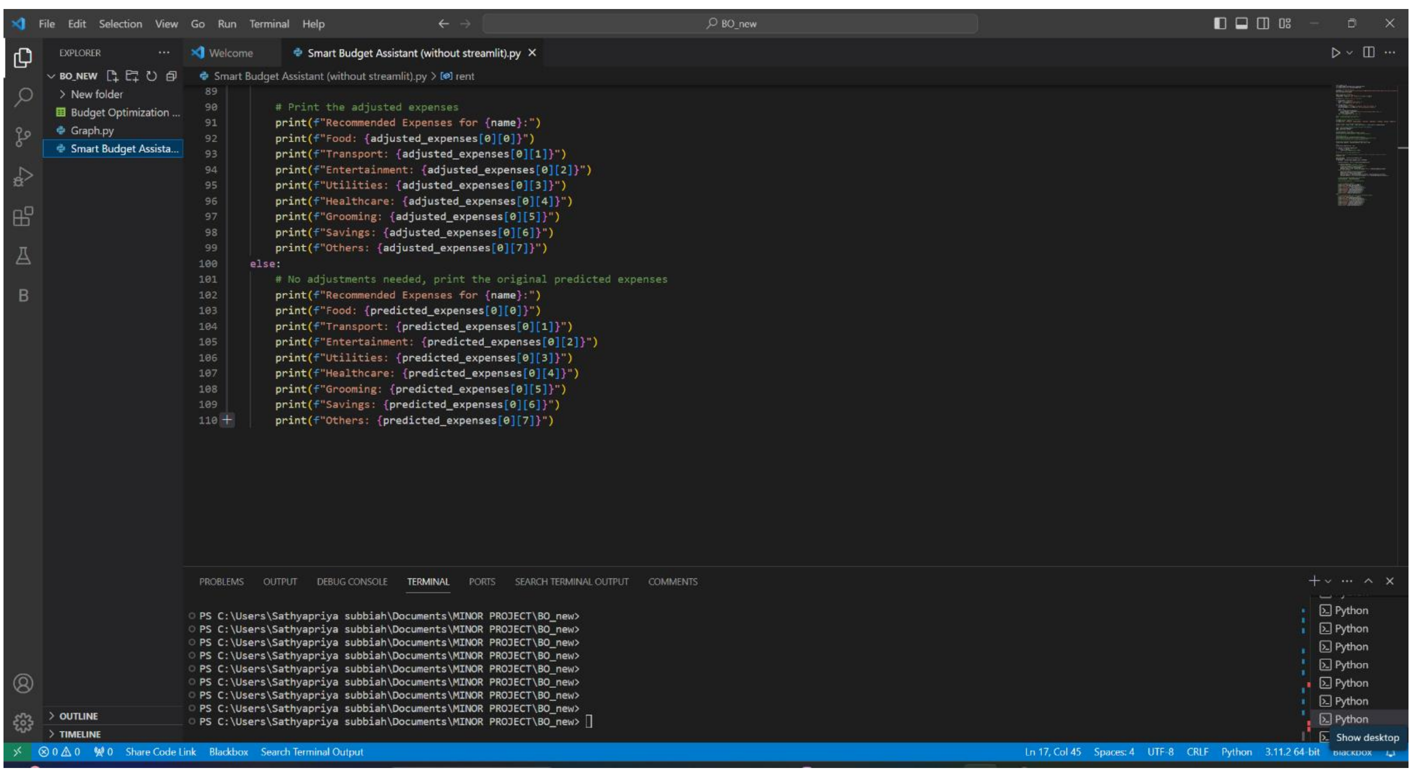
```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor

# Load the data from the CSV file
file_path = r"C:\Users\Sathyapriya subbiah\Documents\MINOR PROJECT\BO_new\Budget Optimization final datasheet.csv"
data = pd.read_csv(file_path)

# Ask for user's information
name = input("What is your name? ")
living_status = input("Are you a bachelor or a family? ").lower()

num_shared = 1  # Default value for num_shared

if living_status == "bachelor":
    salary = float(input("Enter your salary: "))
    rent = float(input("Enter your rent: "))

elif living_status == "family":
    num_family_members = int(input("How many are there in the family? "))
    num_earning_members = int(input("How many are earning an income?"))

    salary = 0
    for i in range(num_earning_members):
        partial_salary = float(input(f"Enter the salary of family member {i+1}: "))
        salary += partial_salary
    rent = float(input("Enter your rent: "))
```



```python
# Prepare the data for non-linear regression
X = data[['Salary', 'Rent']]
y = data[['Food', 'Transport', 'Entertainment', 'Utilities', 'Healthcare', 'Grooming', 'Savings', 'Others']]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train the non-linear regression model (Decision Tree Regressor)
model = DecisionTreeRegressor()
model.fit(X_train, y_train)

# Predict expenses for the user
predicted_expenses = model.predict([[salary, rent]])
#print("Type of predicted_expenses:", type(predicted_expenses))

#converting to list
predicted_expenses_list = predicted_expenses.tolist()
#print("Type of predicted_expenses_list:", type(predicted_expenses_list))
#print("Predicted_expenses_list",(predicted_expenses_list))

# Calculate the initial sum of predicted expenses and rent
initial_total_expenses = predicted_expenses.sum().sum() + rent

#sum
initial_total_expenses_list = rent

for sublist in predicted_expenses_list:
    for value in sublist:
        initial_total_expenses_list += value
```



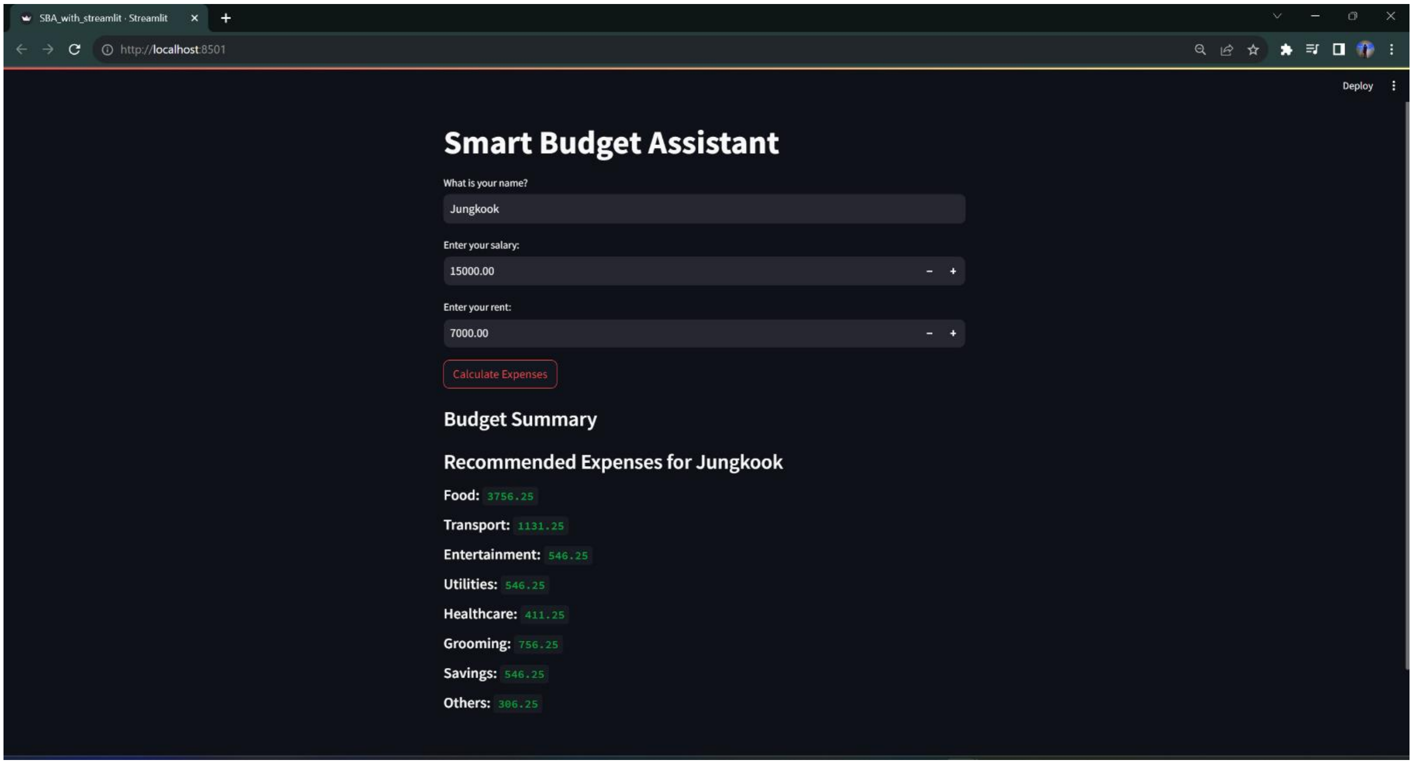
Smart Budget Assistant (without streamlit).py
# Check if the sum of predicted expenses and rent is equal to the salary within a tolerance
tolerance = 1e-4
print(abs(salary - initial_total_expenses_list))
print(tolerance)
if abs(salary - initial_total_expenses_list) > tolerance:
surplus_or_deficit = salary - initial_total_expenses_list
if surplus_or_deficit > 0: # It's a surplus
# Divide the surplus among 8 expense categories
surplus_per_category = surplus_or_deficit / 8
print("surplus", surplus_per_category)
adjusted_expenses = [x + surplus_per_category for x in predicted_expenses_list[0]]
else: # It's a deficit
# Divide the deficit among 6 expense categories
deficit_per_category = surplus_or_deficit / 6
print("deficit", deficit_per_category)
adjusted_expenses = [predicted_expenses_list[0][0], predicted_expenses_list[0][1]]
adjusted_expenses += [x + deficit_per_category for x in predicted_expenses_list[0][2:]]
# Ensure that adjusted expenses have two brackets
adjusted_expenses = [adjusted_expenses]
#print("Adjusted Expenses:", adjusted_expenses)
# Print the adjusted expenses
print(f"Recommended Expenses for {name}:")
print(f"Food: {adjusted_expenses[0][0]}")
print(f"Transport: {adjusted_expenses[0][1]}")



Smart Budget Assistant (without streamlit).py
# Print the adjusted expenses
print(f"Recommended Expenses for {name}:")
print(f"Food: {adjusted_expenses[0][0]}")
print(f"Transport: {adjusted_expenses[0][1]}")
print(f"Entertainment: {adjusted_expenses[0][2]}")
print(f"Utilities: {adjusted_expenses[0][3]}")
print(f"Healthcare: {adjusted_expenses[0][4]}")
print(f"Grooming: {adjusted_expenses[0][5]}")
print(f"Savings: {adjusted_expenses[0][6]}")
print(f"Others: {adjusted_expenses[0][7]}")
else:
# No adjustments needed, print the original predicted expenses
print(f"Recommended Expenses for {name}:")
print(f"Food: {predicted_expenses[0][0]}")
print(f"Transport: {predicted_expenses[0][1]}")
print(f"Entertainment: {predicted_expenses[0][2]}")
print(f"Utilities: {predicted_expenses[0][3]}")
print(f"Healthcare: {predicted_expenses[0][4]}")
print(f"Grooming: {predicted_expenses[0][5]}")
print(f"Savings: {predicted_expenses[0][6]}")
print(f"Others: {predicted_expenses[0][7]}")

APPENDIX 2

SAMPLE SCREENSHOTS



6% Overall Similarity

Top sources found in the following databases:

- 5% Internet database
- 3% Publications database
- Crossref database
- Crossref Posted Content database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	tib.eu Internet	<1%
2	ceur-ws.org Internet	<1%
3	Catherine Flax. "Personal Financial Intelligence- AI and the Futureof M... Crossref	<1%
4	mpra.ub.uni-muenchen.de Internet	<1%
5	safespot-eu.org Internet	<1%
6	mdpi.com Internet	<1%
7	dspace.univ-adrar.edu.dz Internet	<1%
8	serpdotai.gitbook.io Internet	<1%
9	econpapers.repec.org Internet	<1%

10	journals.elsevier.com Internet	<1%
11	Kishore S, Rekha R Nair, Vishal Mehra, Tina Babu. "A Generalized Fram... Crossref	<1%
12	sportold.ubbcluj.ro Internet	<1%
13	Jie Sun, Xiao-feng Hui. "An Application of Decision Tree and Genetic Al... Crossref	<1%
14	R. Kirubahari, S. Miruna Joe Amali. "An improved restricted Boltzmann ... Crossref	<1%
15	vulners.com Internet	<1%
16	gamesradar.com Internet	<1%
17	dailyprogress.com Internet	<1%
18	pt.scribd.com Internet	<1%
19	sunscrapers.com Internet	<1%
20	Semra Sungur. "Modeling the Relationships among Students' Motivatio... Crossref	<1%
21	cheatography.com Internet	<1%

22	first.org Internet	<1%
23	Marcellino Bonamutial, Simeon Yuda Prasetyo. "Exploring the Impact o... Crossref	<1%
24	link.springer.com Internet	<1%
25	zenodo.org Internet	<1%
26	"The WealthTech Book", Wiley, 2018 Crossref	<1%
27	hdl.handle.net Internet	<1%
28	Gizem Topaloğlu, Tolga Ahmet Kalaycı, Kaan Pekel, Mehmet Fatih Aka... Crossref	<1%
29	Helmut Wasserbacher, Martin Spindler. "Machine learning for financial ... Crossref	<1%

SMART BUDGET ASSISTANT USING MACHINE LEARNING

[1] RM. Rani, [2] Sathyapriya SB , [3] Agnel Joshua Raj D , [4] Tarun M

[1, 2, 3, 4] Department of Information technology, SRM Institute of Science & Technology, Ramapuram Campus, Chennai,

Email-id: [1]ranir@srmist.edu.in, [2]ss4131@srmist.edu.in, [3]ad1971@srmist.edu.in, [4]tm9692@srmist.edu.in

ABSTRACT

This system addresses the pressing issue of personal financial management in an increasingly dynamic and challenging economic landscape. The motivation behind the development of this solution stems from the inadequacies of existing financial models that predominantly cater to industries, alongside basic money trackers for individuals. To bridge this gap, "The Smart Budget Assistant" project introduces a novel approach that leverages machine learning techniques to provide personalized financial guidance to individuals, enabling them to optimize their budgets and foster a robust financial life. By employing decision trees, this system tailors financial advice to individual circumstances, taking into account income, expenses, and financial goals, ultimately ensuring efficient resource allocation. The primary goal is to empower users to make informed and prudent financial decisions, enhancing their financial literacy and promoting self-reliance. In contrast to existing solutions, this project's data-driven approach offers a more comprehensive, user-centric, and personalized financial management system, promoting better decision-making, greater financial stability, and an improved quality of life for individuals. In essence, "The Smart Budget Assistant" project aspires to democratize financial wisdom, making it accessible to a broader community, regardless of their financial expertise or background, thus contributing to a more financially resilient society.

Keywords: Budget Optimization, Financial literacy, Machine Learning, Decision tree, Resource Allocation **.**

1. INTRODUCTION

In today's fast-paced and ever-changing world, achieving financial stability and optimizing budgets have become essential skills for individuals seeking to secure their financial future. Yet, navigating the complexities of personal finance can often prove daunting, leaving many individuals uncertain about how to best manage their hard-earned money. While there are existing models designed for industries and money trackers for individuals, we believe in the power of personalized financial guidance. With this vision in mind, we present the "Smart Budget Assistant," a transformative project aimed at helping individuals unlock the potential of their finances and maintain a healthy financial life.

At its core, the Smart Budget Assistant seeks to empower individuals to make informed and efficient spending decisions, tailored to their unique needs and circumstances. By utilizing the powerful tool of decision tree, we have designed an innovative approach that harnesses the potential of data-driven insights to create personalized financial guidelines. Taking into account an individual's salary and rent and financial aspirations, our project offers a comprehensive set of strategies to manage budgets, maximize savings, and make sound investments.

The underlying objective of this project is clear: to enable users to allocate their resources wisely, ultimately leading to greater financial independence and security. By promoting financial literacy and empowering individuals to make better financial choices, we aim to uplift the lives of countless individuals and foster a more resilient society. Throughout this journey, the Smart Budget Assistant strives to instill confidence in individuals as they take control of their finances. Our focus extends beyond immediate budgeting decisions, encompassing long-term financial planning and cultivating a sense of self-reliance. Armed with the knowledge and tools to manage their own financial destiny, users are equipped to navigate life's financial challenges with ease and confidence.

We envision a world where financial well-being is accessible to all, irrespective of their background or financial standing. Through Smart Budget Assistant, we aim to democratize financial wisdom, making it attainable for everyone, regardless of their level of financial expertise.

2. RELATED SURVEYS

“The Personal Budget Project: A practical introduction to financial literacy”, Cynthia P. Guthrie, Curtis M. Nicholls [1], In "Personal Budget Project" the aim is to equip individuals, with essential financial skills and knowledge to navigate their financial futures successfully. The target of this project underscores the importance of teaching individuals, especially students about to enter the workforce, about the practical aspects of budgeting and financial planning. In addition, the project emphasizes the financial principle of living within one's means. In conclusion, the "Personal Budget Project" described in the passage represents a valuable educational initiative.

“Predictive Model Building for Driver-Based Budgeting Using Machine Learning”, N Kunnathuvalappil Hariharan [2], This project shifts from traditional budgeting to more dynamic and data-driven approaches, particularly driver-based planning, with the help of machine learning for enhanced predictive capabilities. Driver-based planning approach focuses on identifying key business drivers that significantly influence financial outcomes. By centering on predictions and aligning budgets with these drivers, an individual can create more flexible and responsive financial plans. Machine learning algorithms excel at analyzing vast datasets and identifying complex patterns, making them valuable tools for identifying key business drivers and predicting their effects on budgets. Hence, this project represents a promising approach to achieving more adaptive and data-driven budgeting strategies, particularly in complex and uncertain business environments.

“Machine learning for financial forecasting, planning, and analysis: recent developments and pitfalls”, Helmut Wasserbacher and Martin Spindler [3], represents the application of machine learning within the domain of Financial Forecasting, Planning, and Analysis. It emphasizes the potential benefits of imposing machine learning for data-driven decision-making in finance to warn against the inherent challenges associated with applying traditional machine learning techniques to planning and resource allocation. The financial sector has progressively turned to machine learning due to its ability to efficiently extract meaningful outcomes from vast datasets. This project introduces the "double machine learning framework," which is to address causal questions in the context of FP&A. In conclusion, this project offers a comprehensive overview of the role of machine learning in FP&A, emphasizing its strengths in data-driven decision-making.

“Using Machine Learning to Predict Personal Expenditure”, Pez Cuckow (author), Dr. Gavin Brown (supervisor) [4], The project's goal is to create an app that makes it easier to manage personal finances in light of the average person's diminishing discretionary income. The project is divided into two main parts: first, the development of a user-friendly interface for gaining access to previous financial data, and second, the application of machine learning methods to forecast upcoming financial transactions. The report also discusses security issues related to the storage of private financial data. Following the application's development, the report evaluates the effectiveness of selected methodologies and identifies potential areas for additional study that could increase the predicted accuracy of the application. Through the use of machine learning and user-friendly interfaces for financial data analysis and prediction, this research makes a contribution to the developing field of personal finance management.

"WONGA: The Future of Personal Finance Management – A Machine Learning-Driven Approach for Predictive Analysis and Efficient Expense Tracking" Uyanahewa M.I.R, Jayawardana G.V.H.D, Bandara M.B.D.N, Hapugala H.A.V.V, Buddhima Attanayaka and Dasuni Nawinna [5], This research introduces an innovative approach to address the challenges associated with personal finance management, particularly in regions like Sri Lanka, where financial literacy is relatively low. Their "WONGA" system utilizes machine learning techniques to simplify the process of money management for individuals, providing an efficient and user-friendly solution that doesn't demand extensive financial knowledge from users. By automating data collection through SMS messages and expense receipts, categorizing expenditures, and creating personalized budget plans based on spending habits, the system empowers users to maintain financial discipline and prevent excessive spending. Additionally, its predictive features, linked to calendar events, enable users to proactively plan for future expenses, enhancing their overall financial readiness.

"Machine Learning and Financial Planning", John M. Mulvey [6], The combination of machine learning technology and the field of finance are examined in this project, which highlights a traditional reliance on formal decision models in financial decision making. Machine learning has seen efficient applications in specific financial domains like high-frequency trading and credit scoring for loans, the financial sector has generally been cautious in adopting machine learning for significant decision processes. The project raises a significant challenge the difficulty in assessing the quality of ML recommendations in the context of strategic financial decisions due to uncertainties and time lags, emphasizing the need for robust correctness measurements in supervised learning models.

"Can Interpretable Reinforcement Learning Manage Prosperity Your Way?", Charl Maree and Christian W. Omlin [7], In this, the authors address the growing importance of personalization in banking and commerce. They highlight the potential of machine learning, particularly reinforcement learning, to enhance customer modeling and decision-making in complex financial environments without relying heavily on conventional methods such as model assumptions. The paper emphasizes the regulatory challenges of model explainability and interpretability while underscoring their potential to provide deeper customer insights. The authors propose an inherently interpretable reinforcement learning algorithm that aligns investment advice with prototype financial personality traits, demonstrating that trained agents adhere to intended characteristics, grasp the value of compound growth, and implicitly consider risk, thus improving policy convergence. This research contributes to the evolving field of interpretable AI in personalized financial management.

"Using a business simulator with elements of machine learning to develop personal finance management skills", Dmytro S. Antoniuk, Tetiana A. Vakaliuk, Vladyskav V. Didkivskyi, Oleksandr Yu. Vizghalov, Oksana V. Oliinyk, and Valentyn M. Yanchuk [8], In this paper, the authors address the critical need for individuals, including school children and students, to acquire proficiency in personal finance management. Recognizing the importance of both personal finance knowledge and the effectiveness of pedagogy in this domain, the authors introduce a web-based business simulator designed to enhance personal finance management skills. This simulator not only offers valuable insights into financial management but also incorporates elements of machine learning to improve its functionality. With its potential application in both secondary and higher education institutions in Ukraine, this innovative tool holds promise for fostering financial literacy among a wide range of learners, including those with limited prior knowledge in the field of personal finance.

"Personal Financial Intelligence - AI and the Future of Money Management" Catherine Flax [9], highlights the unexplored potential of artificial intelligence (AI) in revolutionizing personal finance management. Despite the transformative impact of AI in various aspects of life, the field of personal finance has seen limited innovation. The key challenge of financial illiteracy can be effectively addressed by leveraging AI's capabilities. The paper discusses various AI methodologies, including feedforward neural networks, reinforcement learning, collaborative filtering, and speech and language interfaces. The integration of these interfaces with AI financial advisors represents a groundbreaking advancement, allowing individuals to receive financial guidance in a natural and human-like manner, revolutionizing the way people interact with their finances.

3. SYSTEM MODULES

The Smart Budget Assistant system is a transformative initiative aimed at empowering individuals to make informed and efficient spending decisions, thereby enhancing their financial well-being. It consists of several key modules to achieve this goal. It follows a structured workflow, starting with collecting and preprocessing real-time expenditure data.

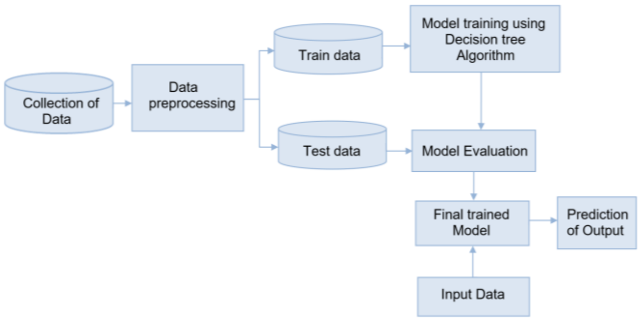


Fig 3.1 Architecture Diagram

The following are the system modules in our project:

1. Data collection and preprocessing
2. Model training and evaluation
3. Input and output

i. DATA COLLECTION AND PREPROCESSING

The data collection process gathers real-time monthly expenditure data from users, ensuring all information is in numerical form and free from missing values. This data is then preprocessed to enhance its quality and converted into CSV format for further analysis. Data integrity is crucial to provide accurate financial guidance to users, making this module a fundamental step in the project.

ii. MODEL TRAINING AND EVALUATION

The core of the project centers on the "Model Training and Evaluation" module, which employs a decision tree approach to establish relationships between the user's salary, rent, financial aspirations, and other financial. It aims to create a personalized financial guideline by creating a decision tree that effectively predicts values. The effectiveness of the model is evaluated using the R-squared (R2) score to ensure that the financial recommendations are reliable and trustworthy.

iii. INPUT AND OUTPUT

The "Input and Output" module allows users to provide their financial information, particularly their salary and rent, in numerical form. The system processes this input through the trained model to generate personalized financial predictions. These predictions offer tailored recommendations for managing budgets, maximizing savings, and making sound investments. The output is considered as the final financial guidance that users can use to make informed financial decisions.

4. RESULT & DISCUSSION

4.1 DECISION TREE

Decision trees, a fundamental concept in machine learning and data analysis, provide an intuitive way to make decisions and solve complex problems. . It is a popular machine-learning algorithm that is used for both classification and regression tasks. Decision tree model is a simple and interpretable model that recursively splits the dataset into subsets based on the most important features to make decisions. Decision trees are often used for decision support, especially when the goal is to understand and explain the decision-making process.

In the context of machine learning, decision trees are often used for classification and regression tasks. Classification trees assign data points to specific categories, while regression trees predict numerical values. The power of decision trees lies in their simplicity and interpretability. Their visual representation makes it easy to understand how a decision is reached, which is invaluable for making informed choices. At their core, decision trees are flowchart-like structures used for decision-making. They break down a decision into a sequence of questions and choices, much like the game "Twenty Questions." Each node in the tree represents a question or decision, and the branches from each node lead to possible answers or further decisions. These branches eventually lead to "leaves," which hold the final decisions or classifications.

4.2 ACCURACY GRAPH

An "accuracy graph" is a graphical representation of the performance of a machine learning model concerning its accuracy score across different scenarios or conditions. In most cases, it's used to visualize how the accuracy of a model changes as you modify specific parameters or settings. Accuracy is a common performance metric in classification tasks, indicating the proportion of correctly predicted instances. It helps in tasks like hyperparameter tuning and assessing the impact of dataset size on model performance.

Decision tree models are known for their interpretability. R-squared is an interpretable metric that allows you to communicate how well the model captures the relationships within your data to non-technical stakeholders.

4.2.1 R-SQUARED (R2 OR SQUARE OF CORRELATION COEFFICIENT)

In decision tree models, R-squared, or the coefficient of determination, plays a vital role in assessing the accuracy and goodness of fit. It tells us how effectively the chosen independent variables explain the variability in the dependent variable, helping to evaluate the quality of the model. When working with decision trees, a higher R-squared value indicates a more accurate model because it signifies that a greater portion of the dependent variable's variation is explained by the independent variables.

R-squared provides a clear measure of how well the decision tree model fits the data. It quantifies the percentage of variance in the target variable that the model can explain using the independent variables. R-squared is more commonly associated with regression models that predict numerical values, where it's used as a measure of accuracy.

Formula

$$R^2 = 1 - \frac{SSE}{SST}$$

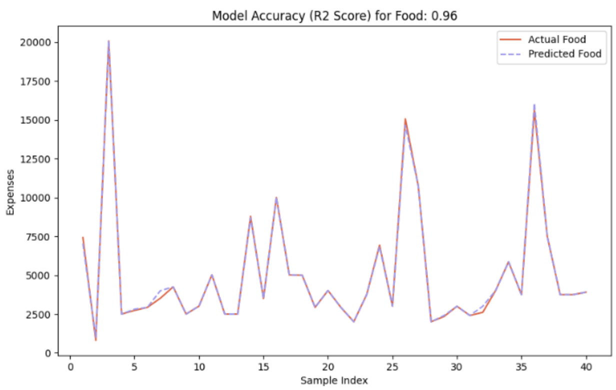


Fig 4.1 Accuracy Graph for Food

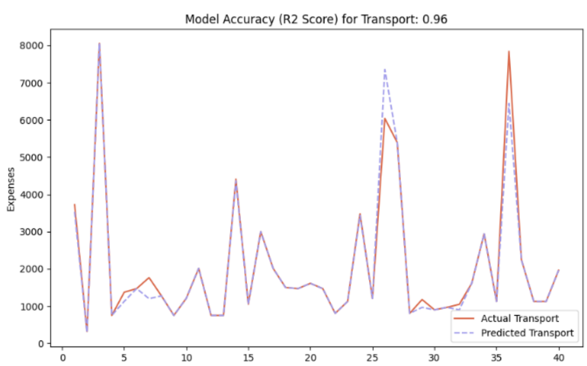


Fig 4.2 Accuracy Graph for Transport

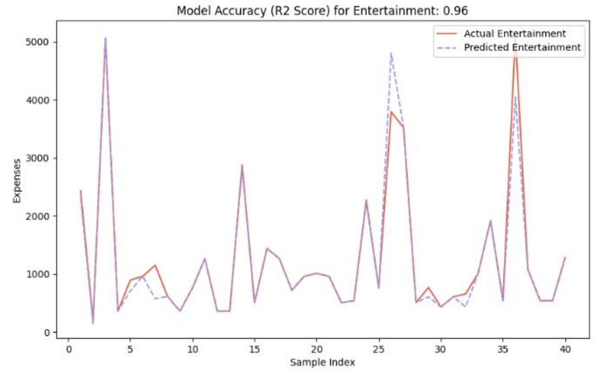


Fig 4.3 Accuracy Graph for Entertainment

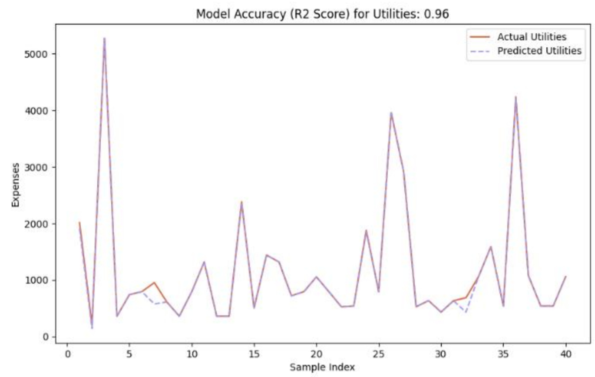


Fig 4.4 Accuracy Graph for Utilities

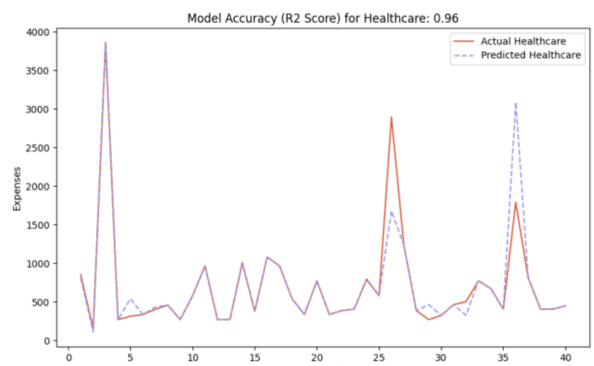


Fig 4.5 Accuracy Graph for Healthcare

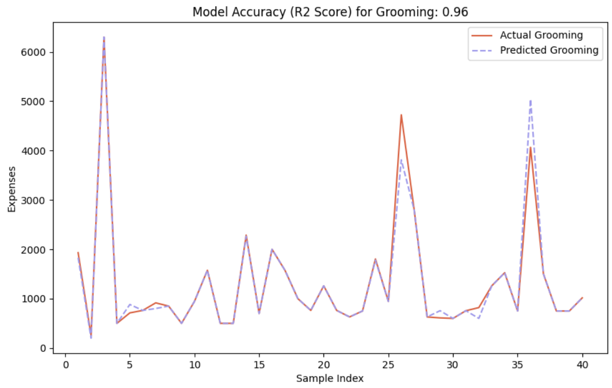


Fig 4.6 Accuracy Graph for Grooming

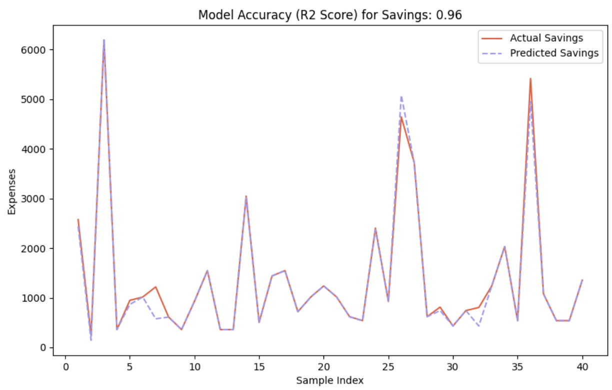


Fig 4.7 Accuracy Graph for Savings

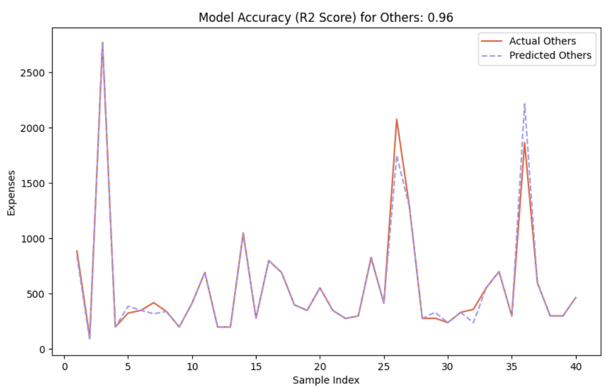


Fig 4.8 Accuracy Graph for Others

5. CONCLUSION

In conclusion, "Smart Budget Assistant" represents a significant leap forward in the realm of personal finance management. In today's dynamic and ever-evolving financial landscape, the need for personalized, data-driven financial guidance is more critical than ever. The existing systems, often reliant on manual input and limited predictive capabilities, are fraught with drawbacks, from time-consuming processes to the potential for human error. Our project, however, stands out as a transformative force in financial planning and expenditure management. We prioritize personalization, recognizing that everyone's financial situation is unique, and we tailor our recommendations to suit individual needs and aspirations.

The three key modules of data collection and preprocessing, model training and evaluation, and input and output form a well-structured framework, ensuring the accuracy and reliability of the financial recommendations provided. Real-time data collection, careful preprocessing, and rigorous model training enable us to deliver data-driven insights that can guide individuals towards better financial decisions.

Our vision extends beyond immediate budgeting concerns; it aims to instill financial literacy and cultivate self-reliance. We are committed to democratizing financial wisdom, making it accessible to all, regardless of their financial expertise or background. With Smart Budget Assistant, we aspire to create a world where financial well-being is attainable.

To achieve this, we have ensured that our project is user-friendly, scalable, and equipped with robust security measures to safeguard personal financial data. It not only automates the budget optimization process but also provides real-time updates, allowing users to adapt swiftly to changing financial circumstances.

In essence, Smart Budget Assistant is more than just a financial tool; it's a means to transform lives and foster a more resilient society. We believe that by offering personalized, data-driven financial guidance, we can enable individuals to achieve greater financial independence and security. We invite you to join us on this journey towards a brighter financial future, one where financial wisdom is within reach for all.

6. REFERENCES

[1] The Personal Budget Project: A practical introduction to financial literacy", Cynthia P. Guthrie, Curtis M. Nicholls.

[2] Predictive Model Building for Driver-Based Budgeting Using Machine Learning", N Kunnathuvalappil Hariharan.

[3] Machine learning for financial forecasting, planning, and analysis: recent developments and pitfalls", Helmut Wasserbacher and Martin Spindler.

[4] Using Machine Learning to Predict Personal Expenditure", Pez Cuckow (author), Dr. Gavin Brown (supervisor).

[5] WONGA: The Future of Personal Finance Management – A Machine Learning-Driven Approach for Predictive Analysis and Efficient Expense Tracking" Uyanahewa M.I.R, Jayawardana G.V.H.D, Bandara M.B.D.N, Hapugala H.A.V.V, Buddhima Attanayaka and Dasuni Nawinna.

[6] Machine Learning and Financial Planning", John M. Mulvey.

[7] Can Interpretable Reinforcement Learning Manage Prosperity Your Way?", Charl Maree and Christian W. Omlin.

[8] Using a business simulator with elements of machine learning to develop personal finance management skills", Dmytro S. Antoniuk, Tetiana A. Vakaliuk, Vladyskav V. Didkivskyi, Oleksandr Yu. Vizghalov, Oksana V. Oliinyk, and Valentyn M. Yanchuk.

[9] Personal Financial Intelligence - AI and the Future of Money Management" Catherine Flax.

8% Overall Similarity

Top sources found in the following databases:

- 7% Internet database
- 4% Publications database
- Crossref database
- Crossref Posted Content database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	tib.eu Internet	1%
2	ceur-ws.org Internet	1%
3	Catherine Flax. "Personal Financial Intelligence- AI and the Futureof M... Crossref	<1%
4	mail.easychair.org Internet	<1%
5	serpdotai.gitbook.io Internet	<1%
6	econpapers.repec.org Internet	<1%
7	journals.elsevier.com Internet	<1%
8	mdpi.com Internet	<1%
9	mpra.ub.uni-muenchen.de Internet	<1%

10	cheatography.com Internet	<1%
11	link.springer.com Internet	<1%
12	hdl.handle.net Internet	<1%
13	Gizem Topaloğlu, Tolga Ahmet Kalaycı, Kaan Pekel, Mehmet Fatih Aka... Crossref	<1%
14	Helmut Wasserbacher, Martin Spindler. "Machine learning for financial ... Crossref	<1%

SRM INSTITUTE OF SCIENCE & TECHNOLOGY (Deemed to be University u/s 3 of UGC Act, 1956)

AGNEL JOSHUA D (RA2011008020037) <ad1971@srmist.edu.in>

Dr. R. Deeptha mam students

AGNEL JOSHUA D (RA2011008020037) <ad1971@srmist.edu.in> Tue, Nov 14, 2023 at 12:58 PM
To: "iccetconference@gmail.com" <iccetconference@gmail.com>

Dear ICCET Committee,

I hope this email finds you well. We are final year B.Tech IT students from SRM University Ramapuram, and we are excited to submit our paper for consideration for presentation at your esteemed conference.

Attached to this email, you will find our paper, which represents our collective efforts and innovative insights in the field. We believe that our research aligns well with the themes and objectives of your conference.

We are enthusiastic about the opportunity to share our findings and engage with fellow researchers and professionals during the conference. Your consideration of our submission is highly appreciated.

Thank you for your time, and we look forward to the possibility of presenting our work at your conference.

Smart Budget Assitant (Journal).pdf
240K