A project report on

OPTIMIZING PERSONAL BUDGETS: AN ANALYSIS OF MACHINE LEARNING MODELS FOR DYNAMIC FINANCIAL FORECASTING

Submitted in partial fulfillment for the award of the degree of

Bachelor of Technology in Computer Science and Engineering with Specialization in Artificial Intelligence and Robotics

by

SAVIO SAJAN MOLOPARAMBIL

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Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)
CHENNAI

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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DECLARATION

I hereby declare that the thesis entitled "OPTIMIZING PERSONAL BUDGETS: AN ANALYSIS OF MACHINE LEARNING MODELS FOR DYNAMIC FINANCIAL FORECASTING" submitted by me, for the award of the degree of Bachelor of Technology in Computer Science and Engineering with Specialization in Artificial Intelligence and Robotics, Vellore Institute of Technology, Chennai is a record of bonafide work carried out by me under the supervision of Dr. Saleena B.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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Date: 26/04/24

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ABSTRACT

This research presents the "Personal Budget Tracker" application, a complex but user-friendly tool created to transform the way people manage their money. By leveraging the power of machine learning methods, the study strives to solve the ongoing difficulty of making educated financial choices. The fundamental purpose is to design and execute optimum models for precisely projecting individual budgets, so allowing individuals to take control of their financial destinies. At its foundation, this initiative focuses thorough data analysis and real-time insights to give users with actionable information. One of the primary goals of this study is to address scalability challenges connected with data collecting, guaranteeing that the application can efficiently manage varied financial conditions and react to users' increasing demands. Additionally, much focus is paid to improving the design of the prediction models, with the purpose of boosting their accuracy and dependability. Central to the research is the investigation of how differences in both revenue and spending affect the accuracy of budget forecasts. By investigating the delicate interaction between these aspects, the research intends to provide people a greater awareness of their financial health and allow them to make more educated choices. Moreover, the incorporation of cutting-edge technology guarantees that the application stays accessible and straightforward, appealing to users of all levels of financial literacy. Ultimately, this study tries to usher in a new era of personal money management by combining modern technologies and analytical insights. Through the creation of the "Personal Budget Tracker" application, the project seeks to educate people with the tools and information required to negotiate the complexity of contemporary finance comfortably. By encouraging financial awareness and empowerment, the study hopes to generate positive change and enhance the financial well-being of people globally.

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Place: Chennai

Date: **Savio Sajan Moloparambil**

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LIST OF ACRONYMS

ANN	ARTIFICIAL NEURAL NETWORK
LSTM	LONG SHORT-TERM MEMORY
BiLSTM	BIDIRECTIONAL LONG SHORT-TERM MEMORY
GRU	GATED RECURRENT UNIT
GAN	GENERATIVE ADVERSARIAL NETWORKS
RNN	RECURRENT NEURAL NETWORK
CNN	CONVOLUTIONAL NEURAL NETWORK
RMSE	ROOT MEAN SQUARED ERROR
MSE	MEAN SQUARED ERROR
MAE	MEAN ABSOLUTE ERROR
MAPE	MEAN ABSOLUTE PERCENTAGE ERROR
UI	USER INTERFACE
API	APPLICATION PROGRAMMING IN TERFACE

Chapter 1

INTRODUCTION

1.1 CURRENT STATE OF BUDGET TRACKING

Traditional methods of budget monitoring generally include manual procedures that are time-consuming and prone to mistakes. Many people depend on spreadsheets or pen-and-paper methods to record their income and spending, requiring them to manually enter and classify each transaction. However, this strategy may be onerous and inefficient, particularly for persons with hectic schedules or complicated financial circumstances. Additionally, manual budget monitoring systems may lack the flexibility and scalability required to respond to changing financial conditions, such as swings in revenue or unanticipated spending. To solve these issues, the "Personal Budget Tracker" application provides a contemporary and user-friendly platform for monitoring personal money. By combining technology and automation, the program streamlines the budget monitoring process, enabling users to simply enter and classify their income and spending with just a few clicks. The straightforward UI and configurable features make it easy for users to follow their financial data in real-time, helping them to make educated choices and take control of their financial destiny.

This program improves the budget monitoring process by centralizing financial data and giving users with a detailed picture of their income and spending. Instead of managing various spreadsheets or paper records, users can access all their financial information in one accessible spot, making it simpler to analyze spending trends, discover areas for improvement, and create reasonable financial goals. Moreover, the program automatically categorizes transactions and creates thorough reports, saving users time and effort and allowing them to concentrate on more important elements of financial management. By automating the budget tracking process, the "Personal Budget Tracker" application also boosts data quality and dependability. Manual budget monitoring systems are prone to human error, such as data entry problems or misclassification of transactions, which may threaten the integrity of financial records. In contrast, the program employs modern algorithms and data validation methods to assure the quality and consistency of financial data, providing users better trust in their financial information and helping them to make more educated choices. By combining the ease of digital technology with the power of automation and data analytics, the program helps users to take charge of their money and achieve better financial stability and security.

1.2 FLUCTUATING INCOME AND EXPENSES

Budget planning may be a difficult process, especially when confronted with the issue of managing shifting income and spending. Many people battle with the unpredictability of their wages, whether owing to irregular work hours, seasonal job swings, or the nature of freelance work, which may lead to considerable differences in revenue from month to month. Similarly, unexpected costs might develop suddenly, such as urgent medical problems or unplanned auto repairs, breaking even the most meticulously constructed budget plans. These uncertainties can leave people feeling overwhelmed and ill-equipped to adequately manage their money. Fortunately, our initiative intends to address these difficulties head-on by providing users with the essential tools and insights to effectively handle changing income and spending patterns. By employing modern data analysis methods and machine learning algorithms, the application is able to examine previous financial data, discover trends, and forecast future income and spending habits with a high degree of accuracy. This predictive capability helps users to anticipate changes in their financial situations and adapt their budget appropriately, ensuring that they stay aligned with their financial goals and objectives.

Moreover, the program allows users real-time access into their financial health, enabling them to track their income and spending as they occur and discover possible areas of concern before they grow. By providing users with actionable insights and alerts, such as notifications when they exceed their budget or meet unexpected costs, the application helps consumers to proactively manage their money and make educated choices about saving, investing, and spending. Furthermore, the software provides customizable budgeting tools and alerts, allowing users to establish spending restrictions and get warnings when they approach or surpass their specified budget levels. This proactive approach to budget management helps individuals to take charge of their financial destiny and make educated choices that match with their long-term financial goals. In essence, this project acts as a holistic financial management solution, delivering customers the tools, insights, and help they need to efficiently negotiate the challenges of changing income and expenditure. By integrating complex data analytics with user-friendly interfaces and tailored features, the application helps users to take charge of their money, create financial resilience, and ultimately accomplish their financial objectives.

1.3 ACCURATELY PREDICTING FUTURE INCOME AND EXPENSES

Accurately anticipating future income and spending is a cornerstone of efficient budget planning. The capacity to forecast impending sources of money and expected expenditures allows users to proactively manage their finances and make educated choices about saving, investing, and spending. This project utilizes the potential of powerful predictive modelling approaches, including machine learning algorithms and data analytics, to offer users with projections for their future income and spending. By evaluating previous financial data and finding trends and patterns within the data, the software is able to create projections for future financial trends with a high degree of accuracy. This predictive feature is crucial in helping customers plan for their financial objectives and prepare for changes in their financial situations. Whether people are saving for a significant purchase, preparing for retirement, or bracing for unanticipated financial requirements, they can depend on the software to give accurate and trustworthy estimates about their future income and spending habits. By incorporating these forecasts into their budgeting process, customers obtain vital insights that allow them to make educated choices and take proactive efforts towards attaining their financial goals.

Furthermore, the predictive features of the tool give users with a feeling of financial security and confidence in their capacity to overcome future financial issues. By having access to reliable projections, people may anticipate variations in their income and spending, enabling them to adapt their budget appropriately and reduce possible financial hazards. This proactive approach to financial management allows people to take charge of their financial destiny and make smart choices that match with their long-term financial objectives. Overall, this project serves as a great tool for those trying to enhance their budgeting process and improve their financial well-being. By employing powerful predictive modeling methods, the application gives users with the knowledge and foresight they need to make good financial choices and achieve higher financial success. Through precise forecasting and proactive planning, users may easily negotiate the complexity of personal finance and establish a firm foundation for a safe financial future.

1.3.1 ADVANTAGES AND DISADVANTAGES OF CURRENT METHODS

Traditional budget monitoring systems provide familiarity and simplicity in managing personal money, but they typically fall short in offering the information and predictive skills essential for good financial planning. Conventional approaches, such as spreadsheets or pen-and-paper systems, depend primarily on manual input and computations, leaving them subject to human mistake and requiring substantial time and effort to maintain. While these systems may work for basic budget monitoring, they lack the complexity required to adjust to changing financial situations and produce accurate long-term estimates. One of the fundamental shortcomings of manual budgeting systems is their inability to efficiently manage fluctuations in income and spending. For people with variable revenue sources, such as freelancers or seasonal workers, typical budgeting approaches fail to account swings in wages, leading to erroneous budget predictions and significant financial distress. Similarly, unanticipated costs or swings in spending habits may disrupt budgeting attempts, since manual systems generally lack the foresight to foresee and adapt for such changes.

Moreover, manual budget monitoring methods generally lack the analytical skills necessary to discover trends and patterns in financial data. Without the capacity to assess previous spending patterns and estimate future income and costs, people may find it tough to make educated financial choices and prepare for long-term financial objectives. This lack of intelligence might inhibit people from efficiently managing their money and reaching financial stability. In contrast, current budget monitoring systems employ sophisticated technology, such as machine learning algorithms and predictive analytics, to give users with intelligent insights and actionable suggestions. By automatically analyzing financial data and recognizing patterns, these programs may give individualized advice for optimizing expenditure, boosting savings, and reaching financial objectives. Additionally, automatic tools improve the budgeting process, saving customers time and effort while giving higher accuracy and predictability in financial planning.

In the end, although traditional budget monitoring systems provide simplicity and familiarity, they typically fall short in offering the intelligence and predictive abilities essential for good financial planning. By adopting current technology and automated solutions, people may transcend the constraints of manual budgeting procedures and acquire the insights and foresight required to achieve better financial stability and success.

1.3.2 ADVANTAGES AND DISADVANTAGES OF METHOD PROPOSED IN THIS PROJECT

The recommended method stated in our proposal stresses the usage and dependence on machine learning techniques, which provide a plethora of benefits including better accuracy, automation, and scalability in the field of financial forecasting. By employing machine learning algorithms to evaluate previous financial data and discover patterns and trends, these models may offer exact estimates for future revenue and expenditures. This helps consumers to make educated and smart financial choices, guided by data-driven insights rather than guesswork or intuition alone. Furthermore, machine learning models have the power to constantly improve and modify their predictions over time, exploiting fresh data inputs to boost accuracy and alignment with users' financial objectives and preferences. However, it's vital to realize that machine learning predictions also come with significant obstacles and restrictions. One key problem is the early accuracy of the models, especially when they are initially deployed and lack sufficient historical data to provide credible projections. This might offer a barrier for users who are new to the platform, since they may first find fewer accurate estimates that could undermine their faith in the system. Additionally, machine learning models may be sophisticated and opaque, making it difficult for users to grasp how the predictions are formed and how to properly integrate them into their budgeting procedures.

Another major problem of machine learning predictions is the danger of bias or mistake inherent in the algorithms themselves. Biases in the training data or the model design may lead to mistakes or biased predictions, which may compromise the dependability of the forecasts and the trustworthiness of the system as a whole. Additionally, machine learning algorithms may fail to catch some subtleties or abnormalities in financial data, especially in circumstances when there are big swings or unexpected occurrences that differ from past trends. Despite these limitations, the advantages of adding machine learning into financial forecasting exceed the downsides, especially when accompanied with comprehensive validation and transparency procedures to verify the accuracy and dependability of the projections. By addressing these issues via continuing model improvement, user education, and clear communication, we can leverage the potential of machine learning to empower users in their financial decision-making and generate better results in personal finance management.

1.4 OBJECTIVE OF THE PROJECT

The "Personal Budget Tracker" application emerges from a recognition of the critical importance of accurate financial forecasting for individual financial health. In today's dynamic economic landscape, individuals face myriad financial challenges, from managing daily expenses to planning for long-term goals. The primary objective of the project is to provide users with a robust and user-friendly tool to navigate these challenges effectively. By leveraging advanced predictive analytics and machine learning algorithms, the application empowers users to make informed decisions about their finances. Whether it's forecasting income for the coming months or anticipating upcoming expenses, the program aims to equip users with the insights they need to plan ahead and achieve their financial objectives. At the core of the project's objective is the goal of democratizing financial management. Recognizing that not everyone has a background in finance or access to sophisticated financial planning tools, the application is designed to be accessible to users of all levels of financial literacy. Through intuitive user interfaces and clear, actionable insights, the program aims to demystify budgeting and empower users to take control of their financial future. By providing personalized recommendations and alerts based on individual financial goals and spending patterns, the application helps users develop better financial habits and achieve greater financial stability. Moreover, the project aims to foster a culture of financial resilience and empowerment. By encouraging proactive financial decision-making and providing users with the tools they need to navigate financial uncertainties, the application seeks to instill confidence and self-reliance in its users. Whether it's setting savings goals, tracking expenses, or adjusting budgets in response to changing circumstances, the program enables users to adapt and thrive in an ever-changing financial landscape.

1.5 SCOPE OF THE PROJECT

The scope of the "Personal Budget Tracker" project is comprehensive, encompassing various aspects of financial management and planning. Central to the project is the development of sophisticated predictive models capable of forecasting future income and expenses with a high degree of accuracy. These models leverage historical financial data, user input, and external factors to generate forecasts tailored to each user's unique financial situation. By providing users with timely and accurate predictions, the application enables proactive financial planning and decision-making. In addition to predictive analytics, the project includes the development of a user-friendly interface that allows users to interact with their financial data easily. Through intuitive dashboards, customizable reports, and interactive tools, users can gain valuable insights into their financial health and make informed decisions about their finances. The application also incorporates features for budgeting, expense tracking, goal setting, and financial education, providing users with a comprehensive suite of tools to manage their finances effectively.

Furthermore, the project encompasses the integration of the application with external data sources and financial services. By connecting to bank accounts, investment accounts, and other financial platforms, the application can aggregate financial data from multiple sources, providing users with a holistic view of their financial landscape. This integration also enables seamless transactions, automated savings transfers, and personalized recommendations based on real-time financial data. Overall, the scope of the project is ambitious, aiming to revolutionize the way individuals manage their finances and plan for the future. By combining cutting-edge technology with user-centered design principles, the "Personal Budget Tracker" application seeks to empower users to take control of their financial destiny and achieve their long-term financial goals.

1.6 CHAPTER ORGANIZATION

This research report is structured into several chapters, each with a specific purpose in elucidating the methodology, implementation, and findings of the project. The Literature Review provides an extensive exploration of the historical context and evolution of financial management practices, focusing on budgeting and forecasting methodologies. The Methodology chapter outlines theoretical frameworks and techniques employed in predictive modeling, including algorithms and architectural design. Subsequently, the Implementation chapter details the practical execution of the project, addressing challenges and strategies employed. The Results and Observations chapter presents empirical findings and insights derived from project execution, while the Conclusion and Future Work section reflects on achievements, limitations, and proposes avenues for future research and development, highlighting ongoing commitment to innovation in financial analytics and budgeting.

Chapter 2

LITERATURE REVIEW

The area of financial time series analysis is at the junction of powerful computer approaches with the complicated dynamics of financial markets. A cornerstone in this domain is the seminal work presented in [1], which delves deep into the comparative analysis between traditional forecasting techniques, such as the Autoregressive Integrated Moving Average (ARIMA) model, and the more sophisticated Long Short-Term Memory (LSTM) model, which is a type of recurrent neural network (RNN). Through a comprehensive evaluation of predictive modeling exercises, this work provides vital insights about the relative usefulness of different techniques in capturing the complicated patterns inherent in financial time series data. Notably, the outcomes of this study underline the exceptional superiority of LSTM over ARIMA, exposing the revolutionary potential of employing deep learning methods for financial forecasting tasks.

Building upon this fundamental study, [2] goes on a thorough tour over the huge terrain of literature spanning over a decade, from 2005 to 2019, to present a panoramic picture of the progress of deep learning applications in financial time series forecasting. By rigorously classifying research attempts based on asset class and the related deep learning architectures deployed, this comprehensive assessment gives essential insights into the evolving approaches and trends defining the trajectory of financial time series analysis. Despite wrestling with the inherent obstacles of conducting such a comprehensive survey, including the heterogeneity in methodology and datasets, the research acts as a light illuminating the rising interest and acceptance of deep learning algorithms in financial forecasting.

Transitioning from theoretical frameworks to practical applications, [3] uses a pragmatic approach by concentrating on boosting stock market return prediction via the addition of unique elements collected from historical stock data. Through a rigorous comparative analysis between artificial neural network (ANN) and random forest (RF) models, the study underscores the superior predictive prowess of ANN in forecasting stock values, thus emphasizing the critical importance of integrating additional factors for heightened predictive accuracy. However, the study does not shy away from addressing the inherent limitations coming from the peculiarities of the historical dataset examined, urging for further investigations including innovative financial measures to better enhance and supplement prediction models.

In a thorough examination of prediction algorithms for stock index values and movement patterns, documented in [4], researchers methodically examined the performance of machine learning and LSTM-based deep learning models. The research gave new insights into the world of predictive analytics, highlighting the better performance of LSTM-based models in extracting features from time series data. Notably, the study recommended against the employment of multivariate analysis in LSTM-based regression, stating that such a strategy would impair both accuracy and economy. Moreover, the research astutely emphasized the untapped potential of generative adversarial networks (GANs) in further strengthening prediction skills, opening the way for creative breakthroughs in forecasting approaches.

Transitioning to the realm of real estate price forecasts, as examined in [5], researchers started on a comprehensive study incorporating the use of least squares support vector regression, attribute selection approaches, and genetic algorithms. Drawing upon real transaction data from Taichung, Taiwan, the research revealed significant insights into the parameters driving prediction accuracy. Notably, attribute selection appeared as a critical aspect, greatly strengthening the accuracy of forecasts. Furthermore, least squares support vector regression emerged as the leader among the models examined, displaying its proficiency in reducing mean absolute percentage error (MAPE). This fundamental study also underlined the necessity of continued inquiry, providing possibilities for further investigation such as the integration of varied data sources and the development of deep learning paradigms to unlock additional advances in prediction accuracy.

In a similar project reported in [6], researchers dug into the complicated domain of stock market prediction, employing a varied variety of machine learning and deep learning approaches. Focusing their attention on certain stock market groups from the Tehran stock exchange, the investigation offered fascinating insights regarding the efficiency of different forecasting models. By applying a complete suite of nine machine learning models and two deep learning methodologies, researchers obtained considerable gains in prediction accuracy, especially in situations requiring binary input. However, the study also noted the inherent limitations connected with particular stock market groups and historical data discrepancies, underlining the importance for continuing research targeted at improving prediction models and overcoming data-related impediments.

In [7], researchers work on constructing a specialized deep learning system geared exclusively for forecasting the Chinese stock market. This system uses LSTM (Long Short-Term Memory) models combined with unique feature extension methods. Through rigorous testing, the research reveals higher performance relative to leading models, underlining the benefits of introducing feature extension into LSTM designs. The paper encourages additional development of technical indices to manage irregular terms and recognizes the susceptibility of recursive feature elimination (RFE) to term lengths. By digging into the complexities of feature engineering and model architecture, the research gives useful insights into enhancing stock market forecast accuracy. Continuing the research of deep learning approaches in stock market prediction, [8] introduces a CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory) hybrid model for anticipating next-day stock closing prices. Leveraging temporal sequence aspects of stock data, the research beats different current algorithms in terms of predicting accuracy. However, the study admits difficulties associated to removing emotional aspects such as news and national policy from the prediction process. Despite these obstacles, the research indicates the possibility for strengthening sentiment analysis to further increase prediction accuracy.

In their revolutionary paper, referred as [9], researchers go deep into the convoluted realm of financial forecasting, applying the powerful Long Short-Term Memory (LSTM)-based Recurrent Neural Network (RNN) model to anticipate the opening values of NYSE shares. This ambitious project spans a varied variety of firms, including giants like GOOGL and NKE, employing a large dataset consisting of daily trade data. Through a thorough process of testing and analysis, the researchers methodically analyze the intricate interaction between epochs and data length, finding new insights regarding the influence of these elements on prediction accuracy. Their results, although insightful, also shed light on the inherent flaws of the model, notably its vulnerability to variations in the underlying data dynamics, such as heightened market volatility. Despite these obstacles, the work serves as a testimony to the strength and promise of deep learning approaches in financial forecasting, delivering useful insights and recommendations for future research attempts.

Meanwhile, in a comprehensive literature analysis mentioned as [10], researchers start on a Herculean endeavor of combining lessons from a whopping 86 publications devoted to the topic of stock and Forex price prediction applying deep learning algorithms. This extensive examination walks through a maze of models, datasets, variables, and performance measurements, presenting a panoramic perspective of the terrain of financial forecasting. However, despite the plethora of material, a conspicuous void arises — the scarcity of research concentrating on the integration of several deep learning methodologies. This key insight serves as a clarion call for academics to investigate fresh routes, such as hybrid network topologies, and diversify model approaches to boost prediction accuracy. Despite its broad reach, this study gives a nuanced view on the current state-of-the-art in deep learning-driven financial forecasting, acting as a guiding light for future research attempts in the area.

Furthermore, an insightful investigation emphasized as [11] digs into the interesting domain of deep learning algorithms and their influence on stock price prediction. Through a rigorous comparison of LSTM and Bidirectional LSTM (BI-LSTM) models, the researchers uncover surprising insights about the relative performance of both designs. Notably, BI-LSTM emerges as the leader, displaying higher performance in terms of lowering Root Mean Squared Error (RMSE) for stock price prediction tasks. While this study gives useful insights into the comparative performance of various LSTM variations, it's vital to realize its inherent limitations, especially its exclusive emphasis on LSTM and BI-LSTM architectures. This confined scope underlines the necessity for deeper experimentation embracing a diversified variety of model types to guarantee strong performance across different market conditions. Through these foundational works, the landscape of financial forecasting is revealed, laying the path for future discoveries and developments in the discipline.

In a revolutionary paper referred as [12], researchers engage on a pioneering journey into the area of financial time series data prediction by developing a unique PSR-based DNN-LSTM (Deep Neural Network - Long Short-Term Memory) model. This new strategy integrates the capability of Probabilistic Symbolic Representations (PSR) with the resilient architecture of DNN-LSTM, resulting in a prediction model that outperforms multiple other approaches in terms of prediction accuracy. Despite the significant achievements achieved in this research, the report admits several limitations, notably concerning the methodology adopted for comparison and the possible dependency of model performance on specific market circumstances. Nevertheless, the results underline the considerable potential of merging symbolic representations with deep learning frameworks to boost prediction accuracy in the dynamic and ever-evolving environment of financial markets.

Meanwhile, in an interesting examination recorded as [13], researchers dig into the delicate process of price generation in financial markets by utilizing deep learning approaches on a massive dataset containing orders and transactions for 1000 US shares. Through the use of deep neural networks for supervised training on high-frequency time series data, the research finds universal patterns, stationarity, and "long memory" phenomena in the price generation process. Despite highlighting the generalization capabilities of deep learning models, the study thoroughly addresses possible biases inherent in the dataset and the problems involved with recording severe market occurrences. By throwing light on the underlying principles driving price creation, our study adds to a better understanding of market dynamics and highlights the crucial role of deep learning approaches in decoding complicated financial phenomena.

Furthermore, in a detailed analysis presented in [14], researchers conduct a systematic assessment of the emerging subject of market prediction applying deep learning approaches, evaluating over 100 papers covering the period between 2017 and 2019. Through thorough data collecting, processing, and model evaluation, the research elucidates developing trends and issues within the area. The study argues for the discovery of innovative neural network topologies, the usage of varied data sources, and the creation of algorithmic trading methods employing reinforcement learning techniques. Despite noting limitations related to dataset biases and the realism of trading strategies, the research gives essential insights into the present state-of-the-art and future possibilities of deep learning-driven financial forecasting. Through these fundamental works, the boundary of financial prediction is pushed farther, opening the way for new approaches and tactics to traverse the intricacies of contemporary financial markets.

In [15], researchers construct a forecasting framework for stock opening prices utilizing a wavelet-transformed LSTM model with an attention mechanism. Through testing with different wavelet functions, the research illustrates the superiority of the suggested WLSTM + Attention model on certain datasets. However, the study also admits the model's susceptibility to modest price swings and advises integrating stock-related news for greater accuracy and stability during large market occurrences. By combining wavelet transformations and attention processes into LSTM architectures, the work proposes a unique way to enhancing stock price prediction accuracy under dynamic market situations.

The above literature survey offers a comprehensive examination of various research papers in the domain of financial forecasting, providing crucial insights for a project aimed at predicting a user's budget using machine learning models. One significant study, referenced as [1], delves into a comparative analysis between traditional forecasting techniques like Autoregressive Integrated Moving Average (ARIMA) and advanced deep learning models such as Long Short-Term Memory (LSTM). This comparison underscores the superior capability of deep learning methods in capturing the intricate patterns present in financial time series data, suggesting the potential revolutionary impact of employing such approaches in budget prediction tasks. Moreover, [2] provides a panoramic view of deep learning applications in financial time series forecasting, meticulously categorizing research attempts based on asset class and deep learning architectures. This classification sheds light on the evolving approaches and trends defining the trajectory of financial analysis, offering valuable insights for model selection and design. Complementing this overview, [3] focuses on enhancing stock market return prediction by incorporating unique elements from historical stock data. The study highlights the superior predictive prowess of Artificial Neural Networks (ANN) over Random Forest (RF) models, emphasizing the importance of integrating additional factors for heightened prediction accuracy.

In a related context, [4] explores prediction algorithms for stock index values and movement patterns, evaluating the performance of machine learning and LSTM-based deep learning models. This research underscores the significance of LSTM-based models in extracting features from time series data while also advocating for the exploration of Generative Adversarial Networks (GANs) to further enhance prediction skills. Furthermore, [5] investigates real estate price forecasts, emphasizing the critical role of attribute selection in improving prediction accuracy, thus offering insights into feature engineering strategies crucial for budget prediction models. Moving on, [6] delves into stock market prediction using various machine learning and deep learning approaches, achieving notable gains in prediction accuracy. However, the study acknowledges limitations associated with specific stock market groups and historical data discrepancies, underscoring the need for ongoing research to overcome these challenges. Additionally, [7] constructs a specialized deep learning system for forecasting the Chinese stock market, leveraging Long Short-Term Memory (LSTM) models combined with feature extension methods. This research showcases the benefits of integrating feature engineering into model architectures to enhance prediction accuracy, providing valuable guidance for model development in budget forecasting tasks.

In another innovative endeavor, [8] introduces a Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) hybrid model for predicting next-day stock closing prices, leveraging temporal sequence aspects of stock data. Similarly, [9] applies LSTM-based Recurrent Neural Network (RNN) models to forecast opening prices for NYSE equities, suggesting potential enhancements through the integration of stock-related news data. These studies collectively contribute to understanding the complexities of financial forecasting and offer valuable insights into model architectures and methodologies suitable for budget prediction tasks. Furthermore, [10] conducts a comprehensive literature analysis on stock and Forex price prediction using deep learning algorithms, highlighting the need for exploring hybrid network topologies and diversifying model approaches for improved prediction accuracy. Additionally, [11] compares LSTM and Bidirectional LSTM (BI-LSTM) models for stock price prediction, with BI-LSTM demonstrating superior performance in reducing Root Mean Squared Error (RMSE). This comparative analysis underscores the importance of experimenting with diverse model types to ensure robust performance across different market conditions. In [12], a Probabilistic Symbolic Representations (PSR)-based Deep Neural Network - Long Short-Term Memory (DNN-LSTM) model is introduced for predicting non-stationary financial time series data, showcasing superior prediction accuracy. Moreover, [13] explores the price generation processes in financial markets using deep learning approaches, offering insights into market dynamics and the role of deep learning in deciphering financial phenomena. Lastly, [14] conducts a systematic assessment of deep learning approaches in market prediction, highlighting emerging trends and issues, while [15] proposes a Wavelet-Transformed LSTM (WLSTM) model with an attention mechanism for predicting stock opening prices, demonstrating superior performance on certain datasets.

These research findings collectively inform the development of machine learning models for predicting budget forecasts based on income and expenses, offering insights into model selection, architecture design, and performance evaluation strategies crucial for achieving accurate and reliable predictions in financial forecasting tasks.

Chapter 3

METHODOLOGY

The methodology employed in this research is defined by a methodical approach aimed at harnessing modern machine learning methods to handle the multiple issues connected with personal money management in the digital age. It starts with the painstaking collecting and safe storage of user financial data, stressing the critical necessity of data integrity and confidentiality. The centralized database serves as the basis for subsequent data processing and normalization operations, which are methodically completed to assure the dependability and consistency of the data for future analysis and modeling. Central to the project's approach is the employment of machine learning models to anticipate future income and costs based on existing transactional data. These models, including a varied array learning approaches including 1-dimensional CNN, ANN, GAN, LSTM, BiLSTM, and GRU, undergo continual refining via user interactions and feedback loops. By iteratively updating and refining the models over time, the initiative attempts to give users with more accurate and personalized financial estimates suited to their individual circumstances.

The research strategy lays a heavy emphasis on tackling the issues inherent in data collecting and scalability as user data quantities rise over time. This is done by the adoption of a data-driven approach that promotes flexibility and adaptability to suit growing consumer demands and preferences. Moreover, considerable attention is made to architectural correctness, with model structures tailored to account for the difficulties inherent in calculating specific budgets effectively. A crucial component of the process is the full evaluation of both income and costs, allowing the creation of detailed and exact projections for the future. This comprehensive approach guarantees that consumers are supplied with the knowledge essential to make smart financial choices. Furthermore, the project focuses user experience by creating a user-friendly interface through which users may interact with their financial data smoothly. All of this is represented in the model diagram provided in Fig. 3.1. which demonstrates how the user input is then processed on conceptually to get the predictions.

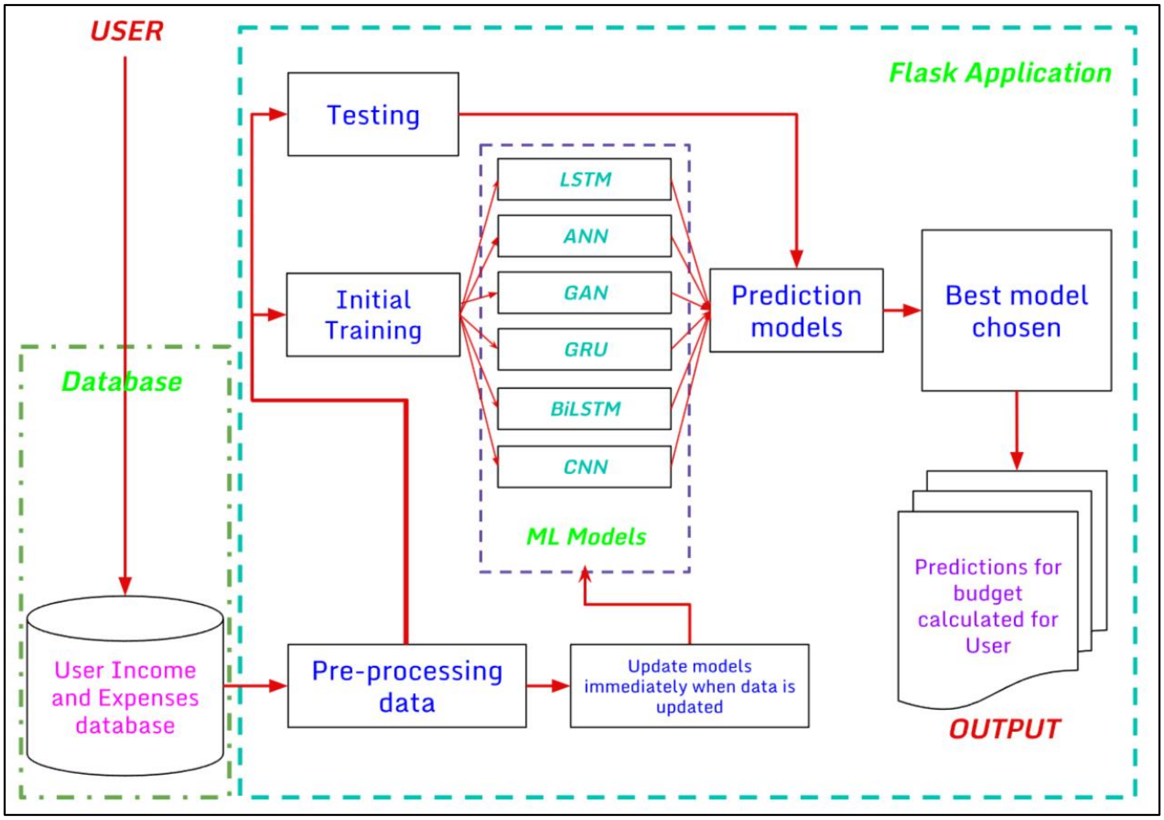

Fig. 3.1. Architecture diagram of the application process

Practical application entails the development of projections for the subsequent 12 months after the selection of the best-performing model. These projections are maintained locally for quick user access and are continually updated in real-time when new revenue or cost data is added. Through the integration of powerful machine learning models, a data-centric approach, and an unrelenting dedication to architectural correctness, the project intends to enable people to make well-informed financial choices anchored in realistic budget estimates. Ultimately, this research marks a substantial leap in customized financial planning, providing consumers a trustworthy tool to maximize their financial destiny.

3.1 MODEL BUILDING AND COMPILATION (TENSORFLOW)

In the model development and compilation step utilizing TensorFlow, the project leverages a precisely selected ensemble of machine learning models particularly suited to handle the nuances of time series forecasting in the context of personal money management. Each chosen model undergoes thorough setup to maximize its performance and assure conformity with the project's goals.

3.1.1 ARTIFICIAL NEURAL NETWORKS (ANNS)

Artificial Neural Networks (ANNs) serve as the basic component of the project's modeling architecture, selected for their adaptability and potential to identify subtle patterns within time series data. ANNs thrive in establishing obvious, linear correlations between past and future facts, providing a firm basis for early forecasting attempts. Their versatility lets them to handle many forms of data and adapt to changing situations, making them a powerful tool for studying dynamic financial facts. By employing complicated mathematical algorithms inspired by the structure and function of the human brain, ANNs can successfully gather and analyze huge volumes of data, deriving significant insights and discovering underlying trends and patterns. One of the primary characteristics of ANNs resides in their capacity to learn from past data and generate predictions based on learnt patterns. By evaluating historical transactions and financial trends, ANNs may find repeating patterns and associations that may be predictive of future behavior. This skill is especially important in financial forecasting, as historical data typically gives significant insights into future market patterns and consumer behavior. ANNs can examine enormous datasets spanning many time periods, enabling them to uncover long-term patterns and connections that may not be evident to human researchers.

However, despite their adaptability and efficacy in many applications, ANNs may have limits in some circumstances, notably in scenarios characterized by complicated temporal correlations and long-range dependencies. In multi-step forecasting situations, where successful forecasts rely on catching sequential patterns across lengthy time periods, ANNs may struggle to maintain consistency and accuracy. This is because standard ANNs are intended to evaluate data in a sequential fashion, evaluating each data point separately without considering its link to neighboring points in the sequence. As a consequence, ANNs may ignore minor subtleties and long-term patterns that are critical for effective forecasting in dynamic financial situations. Furthermore, ANNs may have issues when dealing with noisy or missing data, since they depend significantly on the quality and consistency of input data to produce correct predictions. In circumstances when data is sparse or includes outliers, ANNs may generate incorrect findings or fail to discover important patterns. Additionally, ANNs need enormous quantities of computing resources and training data to reach maximum performance, which may offer practical issues in resource-constrained contexts.

Despite these limitations, ANNs remain a significant tool in financial forecasting and data analysis, especially when used in concert with other approaches and methodologies. By integrating ANNs with complementary methodologies like as statistical modeling, time series analysis, and machine learning algorithms, analysts may harness the strengths of each method to overcome their particular limits and boost the overall accuracy and dependability of their predictions. As technology continues to progress and new methodologies emerge, ANNs are expected to remain a cornerstone of financial modeling and forecasting, providing analysts with strong tools for extracting insights and making educated choices in an increasingly complicated and dynamic financial world.

3.1.2 LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) networks play a crucial part in the project's modeling framework, recognized for its amazing potential to grasp subtle temporal patterns within financial data. LSTMs stand out for their outstanding capacity to store information over longer periods, allowing them to efficiently represent sequential data with long-range dependencies and complicated temporal interactions. Unlike traditional artificial neural networks (ANNs) which may struggle with preserving context over extended sequences, LSTMs possess the unique capability to store and utilize memory of prior states, allowing them to maintain a nuanced understanding of sequential data and make informed predictions based on historical context. The distinctive characteristic of LSTMs resides in its architecture, which features specialized memory cells intended to selectively store or delete information over time. This allows LSTMs to transcend the constraints of classic ANNs by resolving the vanishing gradient issue and capturing long-term relationships in sequential data. The architecture of an LSTM network typically consists of multiple layers of interconnected memory cells, each equipped with mechanisms such as input gates, output gates, and forget gates, which regulate the flow of information and enable the network to retain relevant information while discarding irrelevant or redundant data.

One of the primary benefits of LSTMs is their capacity to learn from prior experiences and adapt to new situations, making them extremely ideal for dynamic and developing financial datasets. By evaluating previous transaction data and recognizing repeating patterns and trends, LSTMs may generate accurate forecasts about future market behavior and consumer trends. This predictive skill is especially helpful in financial forecasting applications, where precise projections may assist firms optimize resource allocation, manage risks, and capitalize on new opportunities. Furthermore, LSTMs thrive in multi-step forecasting situations, where successful predictions require on catching sequential patterns across lengthy time periods. By maintaining memory of earlier states and utilizing this knowledge to build future projections, LSTMs may provide accurate forecasts for numerous time steps ahead, giving important insights into future market patterns and financial performance. This makes LSTMs especially well-suited for activities like as revenue forecasting, budget planning, and risk management, where precise forecasts of future events are vital for informed decision-making. Despite their success, LSTMs may encounter obstacles in some circumstances, such as when dealing with noisy or inadequate data, or when entrusted with anticipating extremely volatile or uncertain market conditions. Additionally, LSTMs need huge quantities of training data and computing resources to attain optimum performance, which may offer practical issues in resource-constrained contexts. However, with careful model calibration and optimization, LSTMs may offer very accurate and dependable forecasts, making them a useful tool in the financial analyst's toolset.

In conclusion, Long Short-Term Memory (LSTM) networks provide a strong approach for modeling complicated temporal patterns in financial data. Their capacity to capture long-range relationships and maintain memory of earlier states makes them well-suited for tasks such as multi-step forecasting and trend analysis. By exploiting the benefits of LSTM networks, analysts may acquire significant insights into future market behavior and make educated choices that drive corporate success in an increasingly dynamic and competitive financial sector.

3.1.3 BIDIRECTIONAL LSTM (BILSTM)

Bidirectional Long Short-Term Memory (BiLSTM) models provide a considerable breakthrough over typical LSTM structures, utilizing bidirectional connections to include contextual information from both past and future time steps. This unique architecture allows BiLSTM models to acquire a more thorough knowledge of temporal correlations within sequential data, leading to better computational efficiency and predictive performance. By leveraging information from preceding and succeeding time periods simultaneously, BiLSTM models can effectively analyze historical trends and anticipate future patterns, making them particularly well-suited for applications requiring accurate predictions of future transactions in the realm of personal financial management. The essential characteristic of BiLSTM models resides in their capacity to process sequential input bidirectionally, meaning they can concurrently evaluate data in both forward and backward orientations. This bidirectional processing allows BiLSTM models to collect contextual information from both previous and following time steps, helping them to better grasp the temporal connections and patterns contained in the data. This extensive examination of past data permits BiLSTM models to offer more accurate and dependable forecasts of future transactions, supporting improved financial planning and decision-making for people and companies alike.

Moreover, BiLSTM models thrive in jobs that involve capturing complex patterns over long time horizons, given to their advanced design and bidirectional processing capabilities. By evaluating input from both past and future time steps, BiLSTM models may discover subtle patterns and correlations that may be overlooked by typical unidirectional LSTM models. This greater capacity to capture temporal connections makes BiLSTM models especially useful in multi-step forecasting applications, where precise predictions of future events are critical for informed decision-making and resource allocation. In addition to their predictive potential, BiLSTM models provide benefits in terms of computational efficiency and performance. By exploiting bidirectional connections, BiLSTM models may handle sequential input more effectively, leading to quicker training durations and increased overall performance compared to typical LSTM architectures. This enhanced efficiency makes BiLSTM models well-suited for real-time applications and large-scale financial forecasting activities, where rapid and accurate forecasts are critical for effective decision-making and risk management.

Overall, Bidirectional Long Short-Term Memory (BiLSTM) models constitute a substantial improvement in the area of sequence modeling, giving increased capabilities for capturing temporal relationships and forecasting future consequences. Their bidirectional processing design, along with their capacity to evaluate data from both past and future time steps, makes them important tools for applications needing precise forecasts of future transactions in the field of personal financial management. By harnessing the benefits of BiLSTM models, people and businesses may get useful insights into their financial data, allowing them to make educated choices and enhance their financial planning strategies for long-term success.

3.1.4 GATED RECURRENT UNIT (GRU)

The Gated Recurrent Unit (GRU) stands out as a powerful rival in the domain of time series forecasting, using its computing efficiency and ability in identifying long-range relationships within sequential data. Unlike its more sophisticated predecessor, the Long Short-Term Memory (LSTM) network, GRUs provide a simplified design while keeping the capacity to dynamically alter memory cells, making them extremely ideal for tasks such as projecting future transactions in the context of this project. This flexibility is especially helpful in multi-step forecasting situations, where GRUs display endurance in tolerating different time series patterns and developing data dynamics. At the center of the GRU design lies its gated mechanism, which allows the model to selectively update and reset its internal state depending on the incoming data and previous information. This gating technique enables GRUs to successfully capture long-range relationships by limiting the flow of information across the network, supporting the preservation of essential information while eliminating unnecessary or duplicate data. As a consequence, GRUs are able to adapt to changing patterns and trends found in sequential data, making them adaptable tools for time series forecasting jobs.

One of the primary features of GRUs is in their simplicity and efficiency compared to LSTM networks. While both designs are meant to solve the problem of vanishing gradients in recurrent neural networks (RNNs), GRUs accomplish this aim with a more compact design that needs fewer parameters and calculations. This simplified design not only decreases the danger of overfitting but also speeds the training and inference processes, making GRUs an appealing solution for situations where computing resources are limited or real-time performance is required. Moreover, GRUs display resilient performance in processing extended sequences of data, due to their capacity to adaptively update and reset their memory cells. This adaptive tendency allows GRUs to capture complicated temporal patterns and relationships over numerous time steps, allowing accurate predictions in multi-step forecasting situations. By correctly modeling the underlying dynamics of sequential data, GRUs may offer trustworthy predictions of future transactions, helping users to make educated choices in financial planning and management. Furthermore, GRUs provide flexibility in parameter adjustment and optimization, enabling practitioners to fine-tune the model's architecture and hyperparameters to meet the unique needs of the forecasting job at hand. This flexibility allows researchers and practitioners to experiment with multiple configurations and settings to maximize the model's performance and adaptability to diverse datasets and contexts.

In summary, the Gated Recurrent Unit (GRU) emerges as a potent tool for time series forecasting, delivering a compelling mix of computing efficiency, versatility, and robust performance. With their simplified design and gated mechanism, GRUs excel in collecting long-range relationships within sequential data, making them well-suited for predicting future transactions in varied financial contexts. As technology continues to improve, GRUs are positioned to play an increasingly crucial role in delivering precise and trustworthy forecasts in the realm of financial forecasting and beyond.

3.1.5 1-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORKS (1D CNNS)

1-Dimensional Convolutional Neural Networks (1D CNNs) are customized to excel in collecting localized patterns within time series data, making them especially good at spotting transitory swings in both spending and income trends. Their skill resides in their capacity to recognize recurrent patterns or localized relationships between consecutive data points, which is useful in settings marked by significant temporal correlations and short-term fluctuations. By using convolutional processes, 1D CNNs may effectively extract important features from the input data, enabling them to recognize small changes and abnormalities that may suggest alterations in financial trends. The unique design of 1D CNNs allows them to perform efficiently in instances where the underlying data displays high spatial or temporal relationships. By applying a succession of convolutional layers followed by pooling operations, 1D CNNs may methodically evaluate the input sequence, discovering important patterns and features at various levels of abstraction. This hierarchical technique allows 1D CNNs to capture both low-level details and high-level patterns within the data, permitting reliable prediction of future trends and fluctuations.

However, despite their benefits in identifying localized patterns, 1D CNNs may have difficulty in handling more sophisticated forecasting jobs that contain intricate interdependencies and long-term trends. In instances where the underlying data displays nuanced temporal correlations or nonlinear dynamics, the small receptive field of 1D CNNs may hinder their capacity to capture long-range dependencies efficiently. Additionally, the fixed-size kernels utilized in convolutional processes may not be able to adapt to different patterns and trends present in the data, thus resulting to inferior performance in predicting jobs needing a richer contextual knowledge. Furthermore, the fundamental design of 1D CNNs may cause constraints in instances where the input data is characterized by irregular or sparse temporal patterns. In such instances, the convolutional layers may fail to extract significant information from the input sequence, resulting to poor predicted accuracy and dependability. Additionally, the pooling methods performed in 1D CNNs may accidentally reject vital information, further reducing their capacity to catch subtle temporal fluctuations and subtleties. Despite these limitations, 1D CNNs remain a significant weapon in the armory of time series forecasting approaches, especially in circumstances where the data reveals strong localized patterns or short-term volatility. By using its capacity to capture localized characteristics and patterns, 1D CNNs may give important insights into short-term trends and changes, assisting in decision-making and planning processes. Moreover, when coupled with other modeling techniques or incorporated into ensemble approaches, 1D CNNs may supplement current forecasting methods, boosting the overall predictive performance and resilience of the model.

In summary, although 1D CNNs provide essential skills in identifying localized patterns and short-term fluctuations within time series data, their efficiency may be restricted in predicting jobs that demand a larger contextual knowledge of long-term trends and relationships. By understanding the benefits and limits of 1D CNNs, practitioners may make educated judgments on their use in diverse forecasting scenarios, exploiting their unique capabilities to extract important insights and enhance decision-making in financial forecasting and beyond.

3.1.6 GENERATIVE ADVERSARIAL NETWORKS (GANS)

Generative Adversarial Networks (GANs), albeit unorthodox in the area of time series forecasting, claim a particular talent in creating synthetic data samples that closely mimic actual data distributions. While their direct relevance to prediction tasks may be limited, GANs play a vital role in data augmentation and synthetic data generation, which may help to strengthening model robustness and generalization. By creating synthetic data that replicates the statistical features of real-world datasets, GANs allow the development of bigger and more varied datasets, so enriching the training process and perhaps boosting the resilience of prediction models. Despite its effectiveness in specific applications, GANs may meet issues in successfully capturing the sequential character of time series data, especially in instances where temporal correlations play a large influence in prediction accuracy. The basic design of GANs, typified by the adversarial training of a generator and discriminator network, may emphasize the production of realistic data samples above effectively capturing the intricate temporal connections found in time series data. This focus on realism may lead to limits in the capacity of GANs to create coherent and trustworthy predictions over long time horizons.

In the context of the project's budget forecasting aims, extra emphasis is made to matching the output layers of GAN models with the user spending categories. This rigorous methodology provides seamless integration of GAN-generated forecasts with the broader financial forecasting framework, allowing customers to gain precise and useful insights into their spending habits. By linking the output layers to particular spending categories, the initiative seeks to give users with precise insights into their financial patterns, supporting informed decision-making and budget planning. Moreover, the project utilizes a rigorous training setting, using Mean Squared Error (MSE) as the loss function and leveraging the Adam optimizer to fine-tune model parameters. This careful approach demonstrates the project's dedication to building predictive models that give precise and trustworthy estimates suited to individual spending goals. By enhancing model performance and lowering forecast mistakes, the initiative intends to empower individuals with practical knowledge to better manage their money and accomplish their financial objectives.

Overall, although GANs may offer issues in capturing the sequential structure of time series data, their function in data augmentation and synthetic data generation may be used to boost the resilience and generalization capabilities of predictive models. Through careful alignment of output layers, rigorous training techniques, and focus on decreasing prediction errors, the project aspires to give users with actionable insights and practical tools to make educated financial choices and enhance their financial well-being.

3.2 DATA PREPROCESSING MEASURES (PANDAS, NUMPY, AND SCIKIT-LEARN)

In the arena of data preparation, the employment of modern tools such as Pandas, Numpy, and Scikit-Learn allows us to undertake a wide array of operations intended at refining and increasing the quality of our dataset. At the onset, Pandas emerges as a keystone in our data preparation pipeline, providing extensive capabilities for quick data manipulation and analysis. Leveraging Pandas' broad repertoire of functions, we go on a careful journey of data purification, where we methodically detect and fix missing values, outliers, and inconsistencies that may undermine the integrity of our dataset. Through advanced imputation algorithms and intentional elimination of erroneous values, we guarantee that our dataset stays pure and free of any abnormalities that may influence the modeling process. Simultaneously, Numpy emerges as a formidable ally, equipping us with significant capabilities for array manipulation and numerical computing. Harnessing the power of Numpy arrays, we conduct a broad array of operations ranging from molding data to executing mathematical transformations needed for model training. Additionally, NumPy's fast implementation of mathematical functions and array operations improves the preprocessing pipeline, allowing rapid and smooth data handling even with large-scale datasets. Furthermore, Scikit-Learn emerges as a cornerstone in our preprocessing arsenal, giving a full range of preprocessing methods adapted to the special needs of machine learning operations. From data scaling and normalization to feature extraction and dimensionality reduction, Scikit-Learn gives us with a broad toolset to preprocess our dataset and prepare it for efficient model training. Leveraging Scikit-Learn's standardized interfaces and strong implementation of preprocessing methods, we choreograph a harmonic symphony of preprocessing processes, ensuring that our dataset is prepped for the rigors of neural network topologies. In concert, these strong technologies synergistically merge to provide a comprehensive approach to data preparation, where each component plays a crucial role in refining and boosting the quality of our dataset. Through rigorous attention to detail and steadfast dedication to data quality, we create the groundwork for strong model training and exact budget forecasting, underlining the necessity of complete data preparation in the quest of accurate and dependable forecasts.

3.3 DATA SPLITTING (TRAINING AND TESTING)

A fundamental portion of the model construction process is the careful splitting of our dataset into different training and testing subsets, a basic step helped by the capabilities of Scikit-Learn. By separating our dataset into these distinct groups, we build the framework for rigorous model evaluation and measurement of generalization performance. Despite possible limits in the availability of significant user data, we take a pragmatic approach by employing the same dataset for both training and testing, but with tight criteria to assure fair model assessment. In this approach, the training subset acts as the crucible where our models are created and polished via iterative learning and optimization. Here, the models immerse themselves in the rich tapestry of historical data, recognizing nuanced patterns and linkages that underlying the dynamics of individual budgets. Through the lens of supervised learning, our models harvest essential insights from the training data, sharpening their prediction skills and fine-tuning their parameters to reach maximum performance.

Simultaneously, the testing subset arises as the crucible where the mettle of our models is tested and confirmed against unknown data. Here, the models are pushed to the crucible of real-world events, where their capacity to generalize and infer insights from the training data is put to the ultimate test. Through rigorous testing and validation, we try to uncover insights into the models' predictive capabilities and fine-tune their parameters to attain optimum performance, thus enhancing the accuracy and effectiveness of our budget estimates. In this continual process of model assessment and modification, we attempt to strike a careful balance between model complexity and generalization performance, ensuring that our models demonstrate robustness and resilience in varied real-world settings. Through rigorous attention to detail and persistent dedication to empirical validation, we construct a road toward accurate and dependable budget forecasting, anchored in fundamental concepts of data splitting and model assessment.

3.4 MODEL EVALUATION AND SELECTION

Once our models have crossed the furnace of training and testing, the following essential step in our technique entails a detailed review and selection of the most proficient model for budget forecasting attempts. This phase represents a vital moment when the rewards of our effort are put to the test, and the effectiveness of our prediction algorithms is thoroughly examined. Harnessing a varied variety of assessment parameters like as accuracy, loss, or other domain-specific criteria, we painstakingly evaluate the performance of the models across various dimensions to uncover their strengths and limitations. Through an intense battery of tests and analyses, each model receives rigorous inspection, with its predictive power and generalization skills exposed to painstaking analysis. During this evaluating process, we leave no stone unturned in our drive for perfection. We go deep into the details of the models, examining their predictive powers and analyzing their performance under different scenarios. Through careful testing and validation methods, we strive to draw insights into the models' predictive powers and detect detailed patterns and trends within the dataset. Armed with this empirical evidence, we engage on the laborious effort of model selection, a process that involves both experience and accuracy. Employing a prudent combination of domain expertise and statistical rigor, we carefully analyze the benefits of each model, including aspects such as accuracy, robustness, and scalability. Our aim is to select the model that not only meets but surpasses our expectations, matching effortlessly with our budget forecasting goals.

Through this continuous cycle of review and selection, we try to extract actionable insights and enhance our forecasting models to attain exceptional accuracy and dependability in predicting individual budgets. Each version puts us closer to our ultimate objective of providing customers with a tool that allows them to make educated financial choices and map a road toward financial success. By adopting a rigorous strategy anchored on empirical validation and statistical robustness, we pave the road toward accurate and trustworthy budget forecasting, helping people to manage their financial path with confidence and clarity. Through thorough study and constant improvement, we seek to provide our forecasting models with the power to give priceless insights, allowing users to manage their financial path with confidence and clarity.

3.5 APPLICATION BUILDING

The process of constructing the budget prediction application requires multiple technical processes, each critical for assuring the functionality, scalability, and dependability of the final result. At the start, we do extensive planning and architectural design, delineating the essential components and their relationships. This first phase establishes the framework for later development efforts, influencing choices about technology stack, data flow, and system design. With the architectural plan in place, our development team begins to create the backend code required to operationalize the selected machine learning models for budget prediction. This requires the integration of model APIs, data processing pipelines, and database management systems, all organized to guarantee smooth data flow and effective model inference. Through thorough testing and validation, we ensure the integrity and correctness of the backend functionality, correcting any anomalies or performance bottlenecks that may develop.

In parallel, efforts are dedicated into frontend development, where we construct an intuitive and user-friendly interface using Flask. Leveraging Flask's flexibility and extensibility, we develop a dynamic dashboard that allows users to interact with their financial data simply. From transaction input to budget presentation, every component of the user interface is methodically developed to increase usability and accessibility, catering to users of varied technological proficiencies and preferences. As development develops, we put a focus on scalability and resilience, incorporating strong error handling systems, data caching algorithms, and load balancing approaches to guarantee optimum performance under variable user demands. Through iterative refinement and continuous integration, we progressively increase the application's functionality, using user input and evolving best practices to offer a polished and feature-rich user experience.

3.6 USER INTERFACE (FLASK)

The user interface (UI) development process is a multifaceted journey that involves a series of intricate steps aimed at crafting a seamless and intuitive user experience. At the heart of this process lies the transformation of design mockups and wireframes into tangible frontend components that not only meet user expectations but also adhere to established design standards. Leveraging the robust features of Flask's templating engine and routing techniques, we meticulously architect the frontend architecture of the application, organizing content and functionality into cohesive and logically structured components. This architectural approach not only enhances the maintainability and scalability of the application but also facilitates seamless navigation and interaction for the end user. Throughout the UI development process, we place a strong emphasis on user-centric design principles, which prioritize simplicity, consistency, and intuitiveness in interface layout and interaction patterns. By adopting this approach, we aim to create an interface that is not only visually appealing but also easy to navigate and understand, thereby enhancing the overall user experience. To achieve this goal, we engage in iterative prototyping and user testing, soliciting feedback from stakeholders and conducting usability testing sessions to gather insights into user preferences and behavior. This iterative approach allows us to refine and optimize the interface design iteratively, ensuring that it aligns closely with user expectations and preferences.

An integral aspect of UI development is accessibility, which involves ensuring that the application is usable by individuals with diverse needs and abilities. To address this requirement, we adhere to online accessibility standards and guidelines, incorporating features such as keyboard navigation, screen reader compatibility, and high contrast settings. By making the application accessible to users with disabilities, we strive to create an inclusive user experience that caters to the needs of all users, regardless of their abilities. In summary, the UI development process is a comprehensive endeavor that encompasses various stages, from initial concept development to final implementation. By leveraging Flask's powerful features and adhering to user-centric design principles and accessibility standards, we aim to create a user interface that not only meets the functional requirements of the application but also provides an engaging, intuitive, and inclusive user experience for all users. Through continuous iteration, testing, and refinement, we strive to deliver a UI that exceeds user expectations and contributes to the overall success of the application.

3.7 ANALYTICS AND VISUALIZATION

Analytics and visualization serve as indispensable components in transforming raw data into actionable insights and engaging visual narratives, enabling users to make informed decisions. Leveraging the robust data processing capabilities of Flask and the versatile visualization libraries such as chart.js in JavaScript, our application excels in extracting meaningful patterns and trends from the data entered by users, presenting them in a comprehensible and interactive manner. At the core of our application's functionality lies the ability to provide users with comprehensive insights into their financial well-being through intuitive analytics dashboards. These dashboards offer a holistic view of users' financial health, encompassing everything from budget summaries to expenditure patterns. By presenting this information in visually appealing formats, such as charts, graphs, and tables, users can easily grasp the key metrics that drive their financial decisions. Whether it's monitoring spending habits, identifying areas for improvement, or tracking progress towards financial goals, our analytics dashboards empower users to take control of their finances with confidence.

In addition to traditional key performance indicators (KPIs), our application goes a step further by offering predictive analytics capabilities powered by machine learning algorithms. By training models on historical transactional data and extrapolating patterns, we provide users with personalized budget forecasts that inform their financial planning decisions and aid in goal setting. These predictive analytics features enable users to anticipate future income and expenses, allowing for proactive financial management and risk mitigation. The integration of complex analytical techniques with user-friendly visualization tools is a hallmark of our application's design philosophy. By combining sophisticated data analysis with intuitive visual representations, we strive to make financial insights accessible and actionable for users of all backgrounds. Through customizable charts, graphs, and reports, users can delve deeper into their financial data, exploring specific categories or time periods to gain deeper insights into their spending habits and financial trends.

As part of our commitment to continuous improvement, we are constantly refining and enhancing the analytics and visualization capabilities of our application. By soliciting feedback from users and staying abreast of emerging trends in data analytics and visualization technology, we aim to ensure that our application remains a valuable resource for individuals seeking to achieve financial health and well-being. Through ongoing iteration and refinement, we endeavor to provide users with the tools and insights they need to make informed financial decisions and achieve their long-term financial goals.

In this chapter, we have seen how the architecture of this project and its components pave a way for the functioning of the application and how each and every module of this project was designed with the best and most practical implementation of the application itself for effective model selection, training and display of predictions for the user. This also keeps into consideration the management and cleaning of data and its splitting and training to gain the necessary predictions for the user.

Chapter 4

IMPLEMENTATION

4.1 DATA STORAGE

The backend architecture of this project rests on the resilience and effectiveness of its data storage systems, which are entrusted with managing the flood of income and spending data from consumers. MongoDB, a premier NoSQL database technology, stands out as the cornerstone of the project's data storage architecture owing to its exceptional flexibility and scalability. Within the MongoDB ecosystem, dedicated collections are developed to store the broad variety of transactional data, precisely arranged to support smooth retrieval, modification, and analysis. The choice to employ MongoDB as the main data repository originates from its inherent capabilities in storing unstructured and semi-structured data, making it a great match for handling the dynamic nature of financial transactions. Unlike conventional relational databases, MongoDB's document-oriented design allows for the storing of data in flexible, schema-less documents, removing the requirement for predetermined table schemas and allowing seamless adaption to developing data structures.

At the core of the backend system lies the smooth interaction between the Python API application and MongoDB, supported by the mongoengine library. This connection simplifies the process of data storage, retrieval, and modification, guaranteeing that consumers have rapid access to their financial information. Through the API application, transactions are smoothly ingested into MongoDB, where they are kept in an organized way inside designated collections for revenue and spending. One of MongoDB's notable characteristics is its excellent indexing and querying capabilities, which allow lightning-fast retrieval of data even from enormous databases. By carefully indexing critical fields within the transactional data, the backend system may instantly discover and retrieve essential information, allowing real-time analysis and reporting. Moreover, MongoDB's capability for complicated queries and aggregations allows the backend system to do advanced analytics and provide important insights into users' financial actions.

In this module of the project, the backbone of data storage and management is established through the powerful MongoDB database, seamlessly integrated into the program's architecture. The first step in this process involves the creation of distinct collections within MongoDB, meticulously structured to organize the wealth of financial data generated by the application. These collections serve as repositories for two fundamental categories: incomes and expenses, mirroring the essential components of financial transactions. Each entry within these collections encapsulates vital information pertaining to a specific transaction, capturing essential attributes essential for comprehensive financial tracking and analysis. Among these attributes are the title of the transaction, providing a succinct descriptor of its purpose or origin, the precise amount involved in the transaction, enabling accurate financial calculations and insights, and the date of the transaction, crucial for chronological organization and trend analysis. The functioning of this model can also be summarized from the given figure Fig. 4.1.

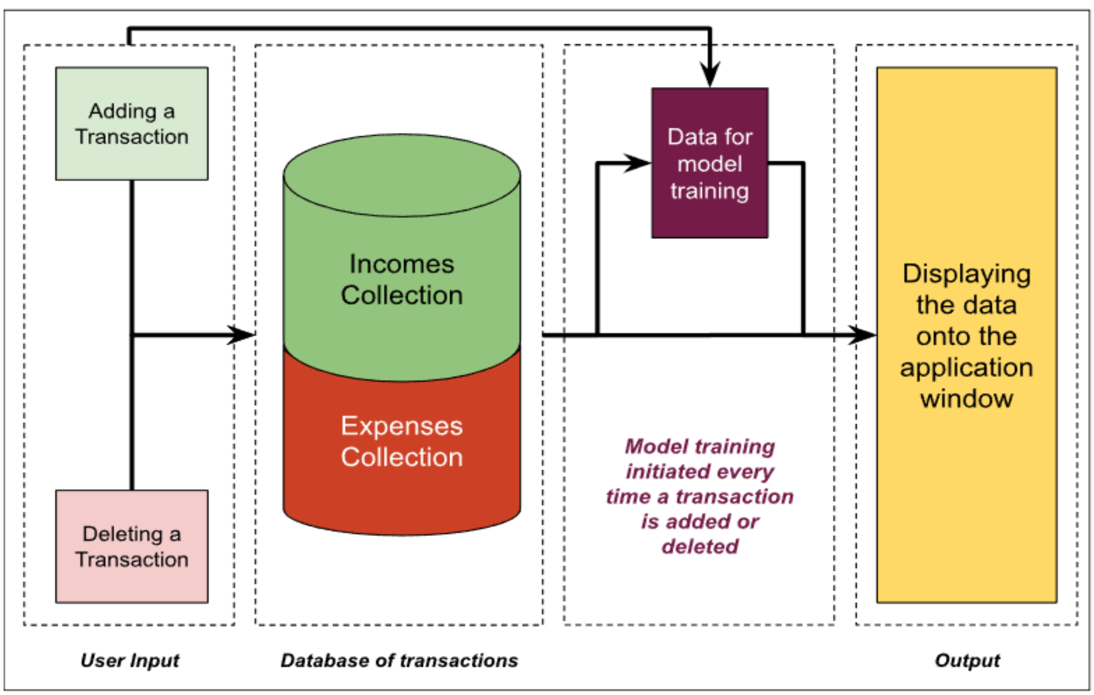

Fig. 4.1. Basic functioning of the data storage module

Furthermore, each transaction entry includes categorical information delineating its nature as either an income or an expense, facilitating intuitive classification and segmentation of financial data. Additionally, a description field is included, offering users the flexibility to provide contextual details or additional notes pertaining to the transaction, enhancing clarity and comprehension. Automated parameters such as "createdAt" and "updatedAt" timestamps are embedded within each transaction entry, meticulously tracking the creation and modification times of the transaction data. These timestamps provide valuable metadata for auditing, versioning, and historical analysis, ensuring data integrity and accountability. In addition, a unique identifier (ID) is assigned to each transaction entry, serving as a primary key for efficient retrieval, referencing, and manipulation of data. This ID ensures the integrity and uniqueness of each transaction record within the database, preventing duplication and facilitating seamless data operations. Examples of this can be seen in Fig. 4.2.


```
_id: ObjectId('652246f5d136a0e78ab32fee')
title: "adfa"
amount: 534
type: "expense"
date: 2023-10-03T18:30:00.000+00:00
category: "groceries"
description: "afabb"
createdAt: 2023-10-08T06:06:45.816+00:00
updatedAt: 2023-10-08T06:06:45.816+00:00
__v: 0
```

```
_id: ObjectId('6520fdb7a962b47f1d0e2442')
title: "asdf"
amount: 984
type: "income"
date: 2023-09-30T18:30:00.000+00:00
category: "stocks"
description: "afdasfa"
createdAt: 2023-10-07T06:41:59.935+00:00
updatedAt: 2023-10-07T06:41:59.935+00:00
__v: 0
```


Fig. 4.2. Examples of transaction entries

Within the application's dynamic ecosystem, the frontend interacts seamlessly with the backend, orchestrating a seamless flow of data between the user interface and the MongoDB database. Whenever a transaction is added or deleted through user actions within the application, the frontend triggers corresponding requests to the backend, which in turn interfaces with MongoDB to execute these operations within the database. This real-time synchronization ensures that any modifications to the financial data, whether additions or deletions, are promptly reflected within the application's interface, providing users with up-to-date and accurate insights into their financial activities. Through this module, the program empowers users with robust data storage, efficient retrieval, and seamless synchronization, laying the foundation for comprehensive financial management and analysis.

4.2 MODEL DESIGNING AND TRAINING

Model development and training represent the foundation of the backend system, where machine learning techniques are employed to estimate future revenue and costs based on prior transactional data. The process begins with the selection and configuration of various deep learning architectures, including Artificial Neural Networks (ANN), Generative Adversarial Networks (GAN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Unit (GRU), and 1-Dimensional Convolutional Neural Network (1D CNN), all implemented using TensorFlow. Each model architecture is constructed to represent distinct features of the temporal dynamics inherent in financial time series data. Architectural factors, such as the number of layers, neuron topologies, and activation functions, are customized to enhance performance and accuracy for the particular forecasting job at hand as seen in Fig. 4.3.

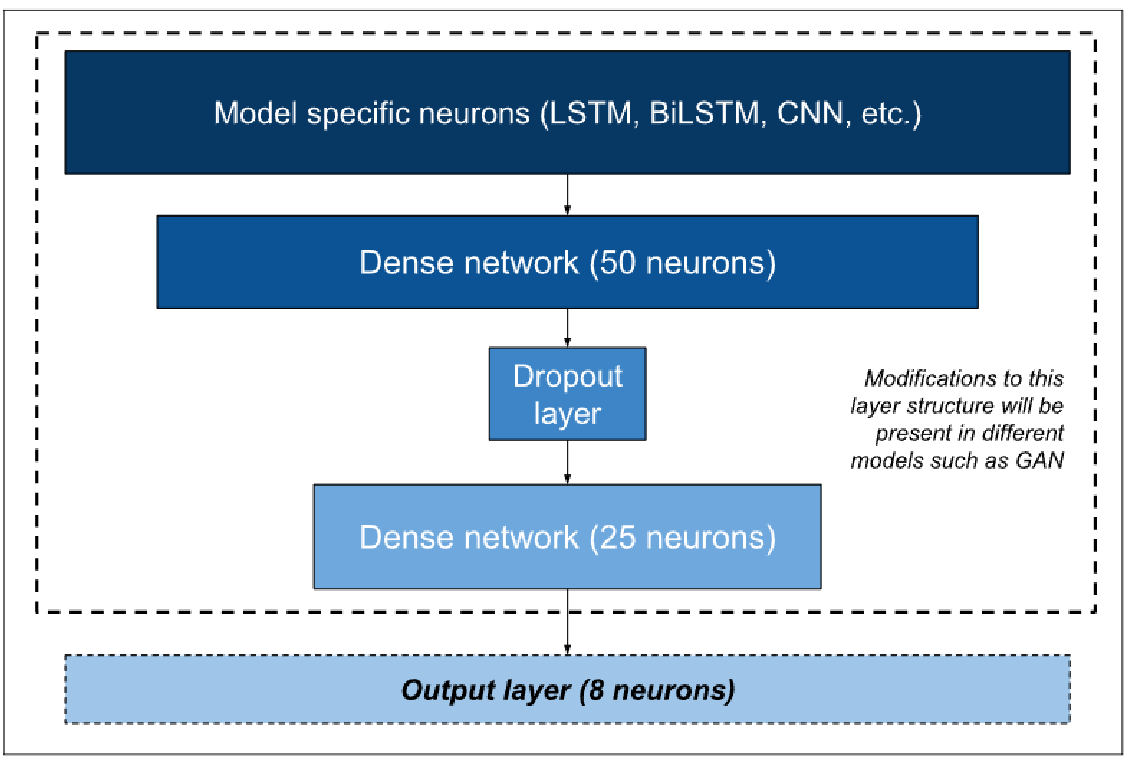

Fig. 4.3. Layer structure of models used

The reason why there are 8 neurons in the output layer of all these models is because the expenses and incomes both have 8 different categories namely "education", "groceries", "health", "subscriptions", "takeaways", "clothing", "travelling" and "other" for expenses and "salary", "freelancing", "investments", "stocks", "bitcoin", "bank", "youtube", "other" for incomes. Thus, each neuron corresponds to each category of either incomes or expenses, depending on which data the models are used on. The training process is activated dynamically in response to user interactions, especially when new transactions are created or removed inside the program. This on-demand training guarantees that the models stay up-to-date with the latest user data, allowing for adaptive forecasting based on changing financial behaviors. During training, the data undergoes preprocessing processes to guarantee consistency and dependability. This comprises cleaning, normalization utilizing methods like min-max scaling, and feature engineering to extract important information from raw transactional data. Hyperparameter tuning approaches are applied to increase model performance, altering parameters like as dropout rates and neuron counts to maximize prediction accuracy.

Once trained, the models are capable of giving multi-step time series projections for the future 12 months beyond the latest recorded transaction. This iterative forecasting technique includes estimating transactions for each succeeding month based on the prior month's projection, thus projecting future financial patterns over an extended horizon. To expedite prediction retrieval and boost application responsiveness, the projected data is serialized and saved in a pickle file. This offers immediate access to forecasts without the need for recurrent model training, guaranteeing that customers may receive accurate and up-to-date financial estimates with little delay.

4.3 MODEL COMPARISON

In the model comparison phase, a dedicated file is applied to analyze the performance of the six machine learning models: ANN, GAN, LSTM, BiLSTM, GRU, and 1D CNN. The aim is to discover the model that displays higher predictive ability for estimating future costs based on previous data. To imitate real-world circumstances, a synthetic dataset including 10,000 entries is constructed, reflecting the structure of a user's costs. Each expenditure category, including "education," "groceries," "health," "subscriptions," "takeaways," "clothing," "traveling," and "other," is represented by a specific curve (e.g., linear, sine wave, cosine wave) with values ranging from 0 to 10,000. To create unpredictability and imitate real-world noise, random noise is introduced to each point in the curve, with values randomly sampled from the range (-1000, 1000). Any negative data points arising from the noise addition are immediately transformed to 0 to protect data integrity. This curated dataset is then treated to each of the six machine learning models, followed by hyperparameter adjustment to maximize model performance. The tuning procedure comprises modifying parameters such as the number of neurons, activation functions, dropout amounts, and learning rates.

The dataset is divided into training and testing subsets with an 80:20 ratio before the training phase begins. This is done in order to evaluate the models' capacity to generalize when applied to new data. After being reshaped to conform to the input criteria of each model, the data is then normalized with the help of the Min-Max Scaler. Model performance measures such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are recorded using the test data. The training is carried out for a total of five epochs, with a batch size of one hundred twenty. In order to get a full picture of the models' average performance across a variety of circumstances, this rigorous testing procedure is repeated for a total of three hundred tests. The resultant MSE, RMSE, and MAE scores are pooled to compute the mean and median values, offering insights into the average prediction accuracy of each model across the 300 tests. This systematic review allows for an educated selection of the most effective machine learning model for predicting future costs, leading to the refining and improvement of the budget forecasting system.

4.4 FRONTEND AND VISUALIZATION

The frontend development of the application is a methodically planned process, harnessing the power of React.js to give users with a smooth and engaging experience in managing their financial accounts. With an emphasis on user-centric design concepts, the frontend interface is meant to be straightforward, efficient, and visually attractive. Users may quickly add information about their income and spending, including specifics such as transaction names, quantities, and categories like bitcoin profits or petrol and food prices. This data entry procedure is simplified and user-friendly, guaranteeing that users can quickly and properly submit their financial information without any problem. The frontend interface is meticulously built to help users through the data entering process, delivering clear instructions and prompts to provide a pleasant user experience. Once the user submits their financial data, it is instantly transferred to the backend API and saved in the MongoDB database. This seamless interface between the frontend and backend systems enables for quick data transmission and storage, ensuring that users' financial information is safely saved and conveniently accessible. One of the notable aspects of the frontend interface is the depiction of expected income and spending for the following 12 months. Leveraging pre-trained machine learning models kept in a pickle file, consumers obtain important insights into their financial future. They may pick individual months to obtain precise predictions of their income and expenditures, enabling them to make educated choices regarding their financial planning and budgeting techniques. In addition to predictive analytics, the frontend interface also contains a judgment component where users may specify a target balance for a future month. This tool allows users to declare their financial goals and objectives, such as attaining a particular savings target or lowering costs to a specified level. The system then analyzes income and expenditure data for the chosen month to compute the expected balance and offer alterations to cost categories to attain the desired balance. Users have the freedom to exclude particular expense categories from alteration, providing them better control over their budget management process.

4.5 VERDICT CREATION COMPONENT

Embedded inside the same file as the model training and result-saving operations, the expenditure reduction algorithm plays a crucial role in directing financial management choices within the application's architecture. Unlike traditional algorithms with well-established names and functions, this unique algorithm is deliberately created to answer the special needs of financial management intrinsic to the application's aims. Fundamentally, the algorithm conducts a number of sophisticated operations aimed at completely assessing the user's financial condition, devising a strategic reduction strategy, and optimizing spending to satisfy preset criteria. Initially, the algorithm tackles the duty of determining the total income and expenditure based on the user's transaction history and the data held inside the MongoDB database. This first computation acts as the cornerstone, giving crucial insights into the user's financial inputs and outflows, so establishing the framework for later computations and analysis. Subsequent to identifying the entire revenue and expenditure, the algorithm continues to discover the user's financial balance by subtracting the total spending from the total income. This ensuing balance acquires enormous significance, acting as a crucial indication of the user's overall financial health and playing a pivotal part in influencing future decision-making processes. Should the computed balance fall below a specified level, signifying the demand for corrective actions to restrict expenditure, the algorithm launches a thorough reduction plan targeted at optimizing spending habits and improving the user's financial situation. This reduction technique comprises a range of operations, ranging from identifying particular expenditure areas ripe for reduction to effecting changes in spending patterns or applying customized cost-cutting tactics adapted to the user's unique circumstances.

Algorithm 1 acts as a blueprint, describing the logical sequence of operations and activities conducted by this tailored expenditure reduction algorithm, so building a sturdy basis for the deployment of cost minimization functions inside the program. By seamlessly incorporating this algorithm into the broader system design, the program encourages users to take proactive actions in managing their money and eventually attaining higher financial stability and resilience in the face of shifting circumstances.

Algorithm 1 Algorithm for Expense Reduction with Priority and Proportionality

Input:

x: Floating-point value representing the desired minimum balance.

y: Array of binary integers (0 or 1) indicating reduction eligibility for each category.

income: Array of floating-point values representing income for each category.

expenses: Array of floating-point values representing expenses for each category.

getCategoryName(index): Function that returns the category name for a given index.

Output:

reduction_statement: String, describing the planned expense reduction or indicating eligibility/impossibility.

Calculate Total Income and Expenses:

```
1.  total_income = reduce(income, (acc, curr) => acc + curr, 0)
2.  total_expenses = reduce(expenses, (acc, curr) => acc + curr, 0)
```

Calculate Balance:

```
3.  balance = total_income - total_expenses
```

Check Balance:

```
4.  IF balance >= x:
5.      RETURN: "No action required"
6.  ELSE:
7.      shortfall = x - balance
```

Identify Categories for Reduction:

```
8.  categoriesToReduce = []
9.  FOR i in range(len(expenses)):
10.     IF y[i] == 1 && expenses[i] > 0:
11.         categoriesToReduce.push({ index: i, amount: expenses[i] })
```

Prioritize Categories by Expense:

```
12. categoriesToReduce.sort((a, b) => b.amount - a.amount)
```

Initialize Reduction Plan:

13. reductionPlan = new Array(expenses.length).fill(0)

Calculate Remaining Reduction:

14. reductionRemaining = shortfall

Check Categories for Reduction:

15. IF categoriesToReduce.length > 0:
16. totalExpenseToReduce = reduce(categoriesToReduce, (acc, curr) => acc + curr.amount, 0)

Calculate Proportional Reduction:

17. FOR ({ index, amount }) in categoriesToReduce:
18. reduction = (amount / totalExpenseToReduce) * shortfall
19. reductionPlan[index] = Math.min(reduction, expenses[index])
20. reductionRemaining -= reductionPlan[index]

Distribute Remaining Reduction:

21. WHILE reductionRemaining > 0:
22. remainingCategories = filter(categoriesToReduce, ({ index }) => reductionPlan[index] < expenses[index])
23. IF remainingCategories.length == 0:
24. RETURN: "Cannot reduce expenses to reach the desired balance"
25. equalReductionPerCategory = reductionRemaining / remainingCategories.length
26. FOR ({ index }) in remainingCategories:
27. reductionAmount = Math.min(equalReductionPerCategory, expenses[index] - reductionPlan[index])
28. reductionPlan[index] += reductionAmount
29. reductionRemaining -= reductionAmount

Generate Reduction Statement:

30. filtered_categories = categoriesToReduce.filter(({ index }) => reductionPlan[index] > 0).map(({ index, amount }) =>${reductionPlan[index].toFixed(2)} in ${getCategoryName(index)})
31. reduction_statement = join(", ", filtered_categories)

Return Reduction Statement:

32. IF reduction_statement:

```
    RETURN: "Reduce " + reduction_statement
ELSE:
    IF y.count(1) == 0:
        RETURN: "No categories eligible for reduction"
    ELSE:
        RETURN: "Cannot reduce expenses to reach the desired balance"
```

The aforementioned algorithm is a precisely built framework targeted at assisting efficient spending management to attain a predetermined minimum balance. This algorithmic technique functions via a succession of painstakingly planned processes, each contributing to the ultimate aim of optimal cost reduction while preserving balance and financial stability. At its heart, the algorithm starts by obtaining many critical inputs vital for steering the expenditure reduction process. These inputs contain the intended minimum balance ('x'), an array signaling the eligibility for reduction in each expenditure category ('y'), and arrays reflecting both revenue and expenses for each relevant category. These inputs serve as the core aspects upon which subsequent computations and judgments are formed. Following the input collection step, the algorithm commences the process of determining the overall revenue and costs. By aggregating the data from the given arrays, the algorithm builds a thorough overview of the present financial environment, establishing the framework for later analysis and actions. Once the overall revenue and costs are calculated, the algorithm continues to compare the current balance against the targeted minimum balance. In circumstances when the current balance reaches or exceeds the stated threshold, the algorithm decides that no further action is required, therefore saving resources and reducing unwanted modifications. However, if the present balance falls short of the required minimum, the algorithm immediately shifts into action, identifying spending categories suitable for reduction. This essential stage entails a comprehensive review of each expenditure category, evaluating both the reduction eligibility indication ('y') and the existence of positive expenses within each category. With qualifying expenditure categories identified, the algorithm applies a strategic prioritizing approach to decide the order in which reductions will be applied. By prioritizing categories based on their relative spending amounts, the algorithm guarantees that reductions are assigned in a way that maximizes the possible influence on total balance improvement. Following the prioritizing step, the algorithm initializes a reduction plan, distributing reduction amounts to each qualifying expenditure category. This reduction plan serves as a blueprint for delivering targeted reductions, directing decision-making and resource allocation throughout the expenditure management process. To further improve the reduction plan, the algorithm determines the remaining reduction required to bridge the gap between the present balance and the planned minimum. This remaining reduction shows the deficit that must be addressed via smart allocation and optimization of reduction amounts across eligible expenditure categories. In order to divide the remaining reduction across qualifying categories, the algorithm utilizes a proportionate reduction strategy. This strategy guarantees that reduction amounts are assigned to each category in proportion to their individual expenditure amounts, hence ensuring justice and equality in the reduction process. In circumstances when the remaining reduction cannot be entirely distributed across eligible categories, the algorithm applies an iterative strategy to thoroughly assign reduction amounts until the necessary minimum balance is attained. This iterative procedure guarantees that reduction efforts are maximized, exploiting every possible opportunity to optimize balance improvement. Finally, the algorithm creates a detailed reduction statement, detailing the anticipated decrease for each qualifying expenditure category. This reduction statement offers users with clear insights into the recommended changes, helping them to make educated choices and take proactive efforts to meet their financial goals. In conclusion, the "Algorithm for Expense Reduction with Priority and Proportionality" is a smart and systematic approach to cost management, utilizing strategic prioritizing and proportionate allocation to maximize balance improvement. Through its precise calculations and intelligent decision-making, this algorithm offers users with a strong tool for navigating the complexity of financial management, helping them to reach their financial objectives with confidence and clarity. In this project, user requests such as collecting the verdict, building graphs for future transactions, and other functionality are implemented effortlessly using API interactions. This API acts as the primary interface for accessing and changing the underlying machine learning models, as well as retrieving stored results from pickle files created during earlier training sessions. Users may easily begin numerous activities via the API, eliminating the requirement for direct contact with the underlying model architecture.

The project's basic functionality is to pick the best machine learning algorithm for forecasting future transactions over the following 12 months. The study discovers the ideal model through thorough examination and comparison, demonstrating greater performance in accurately and reliably projecting user transactions. This careful screening procedure guarantees that consumers receive accurate and practical insights into their financial expectations. Once the best-performing model has been identified, the project will train it using the user-provided transaction data. This training process allows the model to learn and adapt to the user's specific financial patterns and habits, hence improving its prediction skills. The trained model creates and maintains the outcomes of expected transactions for the following 12 months, which are then used to deliver useful insights and suggestions to the user. Furthermore, the project includes a unique algorithm that generates a verdict defining particular spending categories that must be decreased and by how much to meet the user's desired balance level. This algorithm examines the user's financial data, finds possible areas for improvement, and generates actionable recommendations based on the user's financial objectives and preferences. By seamlessly combining machine learning algorithms, bespoke algorithms, and API-driven interactions, the project provides users with full financial management tools and insights. Users may make educated decisions, optimize their spending habits, and achieve better financial stability and success by adopting a user-centric strategy and leveraging innovative technology.

This chapter has thus shown how this project application has been meticulously built from the decision and implementation of the data storage meant for the user transaction data to the implementation of models for learning, comparison, training and predictions to building the backend and frontend of the application in the necessity of facilitating the predictions and their visualizations for the user.

Chapter 5

RESULTS AND OBSERVATION

This project gives 3 results parallel to each other and yet instrumental to each other. These 3 results include

COMPARISON AND MODEL SELECTION:

The comparison and selection of the best machine learning model is an essential component of the project. This phase entails a thorough assessment of numerous models, each with its own set of strengths and drawbacks. For example, Artificial Neural Networks (ANNs) are well-known for their flexibility and ability to detect patterns in time series data. Long Short-Term Memory (LSTM) networks are excellent at collecting long-range relationships and sequential patterns, making them perfect for anticipating future transactions. Gated Recurrent Unit (GRU) networks, while less sophisticated than LSTMs, are effective in identifying long-term associations in data, providing a good mix of performance and computational resources. The project examines each model's performance using criteria like as accuracy, loss, and generalization ability. This meticulous evaluation ensures that the selected model is well-suited to the unique characteristics of the user's financial data and the objectives of the project.

TRAINING AND PREDICTION GENERATION:

After determining the best machine learning model, the project moves on to the training phase, during which the model is trained using historical transaction data. This procedure entails providing the model with a huge dataset of previous transactions, which allows it to learn and discover underlying trends and patterns. Using modern algorithms and approaches, the model modifies its parameters to reduce forecast mistakes and improve accuracy. The trained model is then used to make predictions about the user's future income and spending. Importantly, these forecasts continue up to 12 months beyond the user's most recent recorded transaction, giving useful information about their long-term financial prospects. By continually improving and updating the model based on fresh data inputs, the initiative ensures that forecasts stay accurate and relevant over time, empowering users to make informed financial decisions with confidence.

VERDICT GENERATION:

In addition to anticipating future transactions, the project includes a complex verdict generating process that makes actionable suggestions to the user. This algorithm examines the user's financial information, including income, spending, and planned financial objectives. Based on this study, the algorithm generates individualized suggestions for which areas of costs the user should consider cutting in order to attain a defined balance within a specific future month. The judgment generating component helps individuals to make educated decisions according to their own financial situation and aspirations. Furthermore, by giving clear and practical advice, the project enables users to manage their money proactively, optimize their budgeting practices, and work confidently and clearly toward their long-term financial objectives.

These three pillars work together to offer consumers with a complete picture of their financial status, allowing them to make educated decisions. The project intends to alter how consumers manage their finances and achieve their financial goals by utilizing powerful machine learning techniques, rigorous model selection, and tailored recommendation algorithms.

5.1 MODEL COMPARISON FOR TRAINING

In the implementation phase, a unique Python program was constructed inside the backend architecture, working independently from the main backend activities. However, it plays a significant role by simplifying the assessment and comparison of multiple machine learning models. This distinct software is responsible for undertaking rigorous testing scenarios, allowing for the thorough evaluation of model performance under varied settings. Notably, the chosen best-performing model is effortlessly incorporated into the core backend structure, acting as the default model for further training operations. For the assessment procedure, a complete test suite was built, containing 300 distinct tests to extensively analyze the effectiveness and robustness of the six approved machine learning models. These models include Artificial Neural Networks (ANN), Generative Adversarial Networks (GAN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Unit (GRU), and 1-Dimensional Convolutional Neural Network (1D CNN). Each model underwent extensive testing methods, spanning hyperparameter tweaking and training stages.

The testing technique comprised the production of a pseudo-random dataset including 10,000 items, replicating the features of user spending across multiple categories. Each category, such as "education," "groceries," and "health," was represented by a separate curve, including linear, sine wave, and cosine wave patterns. Moreover, random noise was injected to the dataset, replicating real-world fluctuations and uncertainty associated with financial transactions. Subsequently, the dataset was partitioned into training and testing subsets, guaranteeing rigorous assessment measures. Throughout the testing process, each model was subjected to hyperparameter adjustment to maximize its performance. Parameters such as the number of neurons, activation functions, dropout rates, and learning rates were rigorously changed to boost model accuracy and generalization capabilities. Following parameter tuning, the models were trained for five epochs using a batch size of 120, providing thorough learning from the dataset.

The performance of each model was assessed based on important measures, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These measures give vital insights into the models' predicted accuracy, error distribution, and overall performance across the varied test situations. The findings of the testing phase were painstakingly documented and reported, offering important insights into the comparative performance of each model. To simplify data analysis and interpretation, the mean and median scores of MSE, RMSE, and MAE were obtained for each model over all 300 tests. These aggregated findings were structured and presented in Tables 5.1, 5.2, and 5.3, offering a full summary of the models' performance characteristics. The tables serve as essential reference points for model selection and optimization, guiding further stages in the creation and refining of the budget forecast system.

Table 5.1. Mean and Median of MSE for each model

Models	Mean Squared Error (MSE)	
	Mean	***Median***
ANN	0.060888	0.060523
LSTM	0.101054	0.099527
BiLSTM	0.083325	0.072938
GRU	0.057919	0.057839
CNN	0.059502	0.059158
GAN	0.193552	0.193552

Table 5.2. Mean and Median of RMSE for each model

Models	Root Mean Squared Error (MSE)	
	Mean	***Median***
ANN	0.246699	0.246014
LSTM	0.313341	0.315479
BiLSTM	0.284271	0.270063
GRU	0.240646	0.240497
CNN	0.243881	0.243225
GAN	0.437912	0.443922

Table 5.3. Mean and Median of MAE for each model

Models	Mean Absolute Error (MSE)	
	Mean	***Median***
ANN	0.208880	0.208539
LSTM	0.254545	0.252129
BiLSTM	0.234149	0.221471
GRU	0.205422	0.205225
CNN	0.207309	0.206933
GAN	0.364127	0.367847

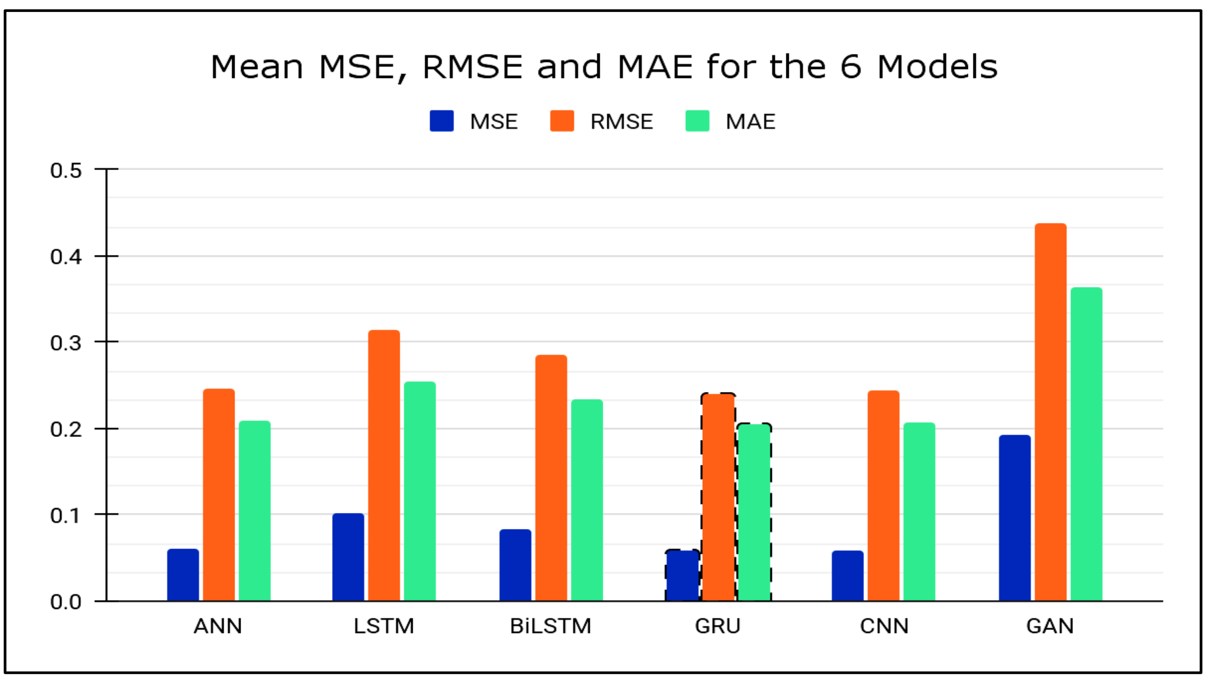

Fig. 5.1. Column chart of the mean MSE, RMSE and MAE

Upon analysis of the results presented in Tables 5.1, 5.2, and 5.3, alongside Fig. 5.1, it becomes evident that the GRU model consistently outperforms its counterparts across the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) scores attained as they are consistently the lowest among all models considered. This demonstrates the greater predictive accuracy and dependability of the GRU model in projecting future transactions.

In comparison, the Generative Adversarial Network (GAN) model demonstrates the least favorable performance across all three error measures, suggesting its considerably weaker predictive skills. The GAN model regularly returns greater error scores in MSE, RMSE, and MAE, underlining its limitations in effectively capturing the complex patterns and connections inherent in financial time series data. A deeper inspection of the findings also exposes the competitive performance of the 1D CNN model, which emerges as a close challenger to the GRU model. While the 1D CNN model falls somewhat short of the GRU model in terms of predicting accuracy, it nonetheless exhibits impressive performance, especially when compared to other models such as the GAN.

To offer a full perspective of the relative performance of each model, the findings are further synthesized and presented in Table 5.4. This table ranks the models based on their overall performance across all assessment measures, taking into consideration the cumulative error scores. Through this ranking, it becomes obvious that the GRU model emerges as the top-performing model, followed closely by the 1D CNN model. Conversely, the GAN model holds the lowest place in the ranking, showing its inferior performance in contrast to other models.

Table 5.4. Ranking each model by error measure

Ranking	***Model***
1	GRU
2	1D CNN
3	ANN
4	BiLSTM
5	LSTM
6	GAN

Overall, our results underline the vital role of model selection in producing accurate and dependable forecasts in financial forecasting activities. The higher performance of the GRU model, along with the competitive performance of the 1D CNN model, illustrates the usefulness of recurrent neural network architectures in capturing the complicated dynamics of financial time series data. These findings serve as significant assistance for directing future model selection and optimization efforts in the development of the budget forecast system. The greater performance of the GRU (Gated Recurrent Unit) model in this scenario may be ascribed to its intrinsic traits and capabilities. GRUs are notable for their computational efficiency and adeptness in capturing long-range relationships in time series data. Unlike standard recurrent neural networks, GRUs include gating mechanisms that enable them to selectively store and update information over time, allowing them to successfully encode sequential patterns over lengthy durations. This makes them especially well-suited for jobs such as transaction forecasting, where knowing historical patterns is vital for predicting future results.

Additionally, GRUs display the ability to adapt to shifting trends and patterns in the data, because to their capability to learn over lengthy periods. This flexibility allows them to change their projections in response to developing income and expenditure trends, hence boosting their forecasting accuracy. By using prior knowledge and constantly changing their memory, GRUs may successfully capture the complex temporal correlations inherent in financial time series data. In contrast, Generative Adversarial Networks (GANs) may have fared less well in this project owing to various intrinsic restrictions. Unlike GRUs, GANs are not often utilized for time series forecasting applications, since their major concentration rests in creating realistic data samples rather than predicting future sequences. GANs may fail to effectively capture the sequential character of time series data, since their training goals favor the formation of realistic data distributions rather than the precise forecasting of future trends.

Moreover, the application of GANs in time series forecasting frequently demands large computing resources and sophisticated training data, which may not correspond with the aims of this research. The focus on computational economy and accurate forecasting in the context of budget prediction involves the employment of models like GRUs that achieve a compromise between performance and efficiency. Furthermore, GANs are prone to difficulties such as mode collapse and training instability, which might impede their performance in time series forecasting applications. These issues may further restrict the usefulness of GANs for applications requiring dependable and robust predictions over long time periods.

5.2 MODEL TRAINING AND PREDICTIONS

The act of integrating income and spending data into the budget monitoring application is crucial to its functioning and value for users. Initially, the revenue and cost data are collected from the servers, providing a dual goal of showing this information inside the application interface (Fig. 5.2) and simplifying its usage in the model training process for forecast creation. This seamless connectivity guarantees that users have real-time access to their financial data while also allowing the application to exploit this data for predictive analysis.

Fig. 5.2. Display of user transaction history

Given its better performance in making correct predictions, as indicated by the evaluation results discussed in the previous sections, the GRU model emerges as the ideal option for model training inside our budget monitoring application. The choice to pick the GRU model is driven by its powerful financial trend prediction skills, making it well-suited for projecting future income and spending with a high degree of accuracy. By harnessing the predictive potential of the GRU model, users may receive useful insights into their financial trajectory, helping them to make educated choices and prepare efficiently for the future. The forecasts given by the GRU model contain three key categories: income, spending, and a thorough review of both. These predictions serve as useful tools for consumers, delivering a glance into their financial environment by providing insights into anticipated sources of income, planned expenditures, or a holistic perspective of both elements concurrently. By delivering precise estimates across six major categories, the budget monitoring tool helps users to proactively manage their money, uncover possible areas for improvement, and make educated choices to meet their financial objectives.

Furthermore, the integration of the GRU model into the budget monitoring application marks a substantial leap in personal money management. By exploiting the predictive potential of modern machine learning methods, such as the GRU model, the program allows users to go beyond reactive financial management and embrace a proactive approach to budgeting and planning. This proactive approach helps people to anticipate changes in their financial situations, alter their spending and saving practices appropriately, and ultimately take control of their financial destiny.

The adoption of a dynamic updating approach is central to ensuring the timeliness and relevance of the financial forecasts provided by our budget tracking application. This approach enables the application to respond promptly to any changes made by the user, ensuring that the forecasts accurately reflect the most current financial data. For instance, when a user makes modifications to their income or spending information, the corresponding income or expenditure forecasts are immediately updated to reflect these changes. Similarly, adjustments to spending trigger revisions to the expenditure estimates, ensuring that the forecasts remain accurate and reflective of the user's financial situation. Furthermore, the application employs a sophisticated updating mechanism for the "both" category, which encompasses changes in both income and spending occurring simultaneously. This ensures that the forecasts for this category accurately capture the overall financial picture, taking into account all relevant changes in income and expenditure. By dynamically updating the forecasts in response to user actions, the application provides users with real-time insights into their financial trajectory, enabling them to make informed decisions and adjust their financial plans as needed.

Once the predictions are generated, they are seamlessly transmitted to the application's frontend for user accessibility. The application interface plays a crucial role in presenting these predictions in a visually intuitive manner, enhancing user comprehension and engagement. Leveraging the features of the chart.js library, the application visualizes the prediction findings through interactive graphs and charts, making it easier for users to interpret and analyze their financial projections. By presenting the forecasts in a clear and visually appealing format, the application empowers users to gain a comprehensive understanding of their financial situation and take proactive measures to achieve their financial goals. The seamless integration of prediction visualization into the application interface is evident in Figures 5.3, 5.4, and 5.5, which showcase the application's ability to provide users with detailed financial projections. These visualizations serve as powerful tools for empowering users to take charge of their financial future, enabling them to make informed decisions and take proactive steps towards achieving their financial objectives. Through clear visualization and real-time updates, our budget monitoring tool equips users with the insights they need to navigate their financial journey with confidence and clarity.

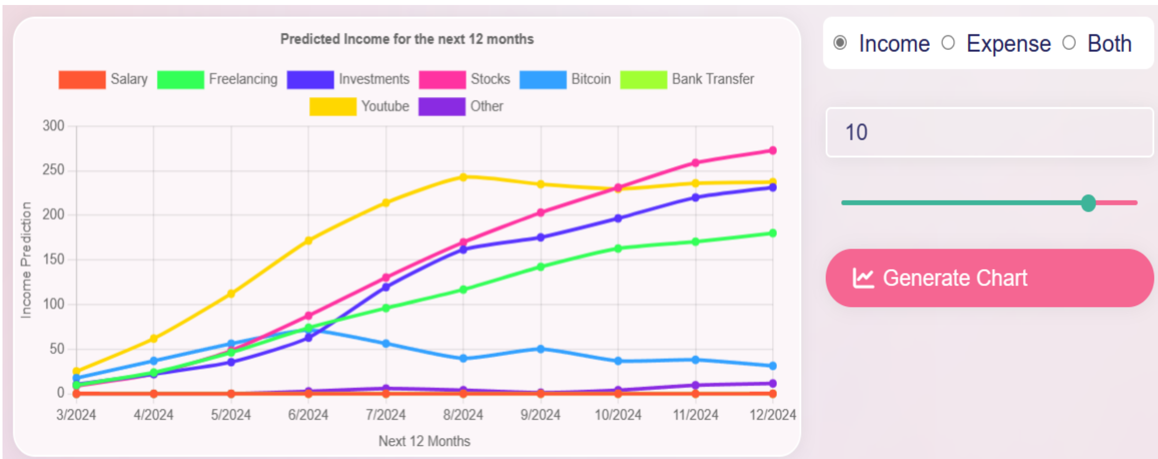

Fig. 5.3. Income prediction of the user for the next 10 months

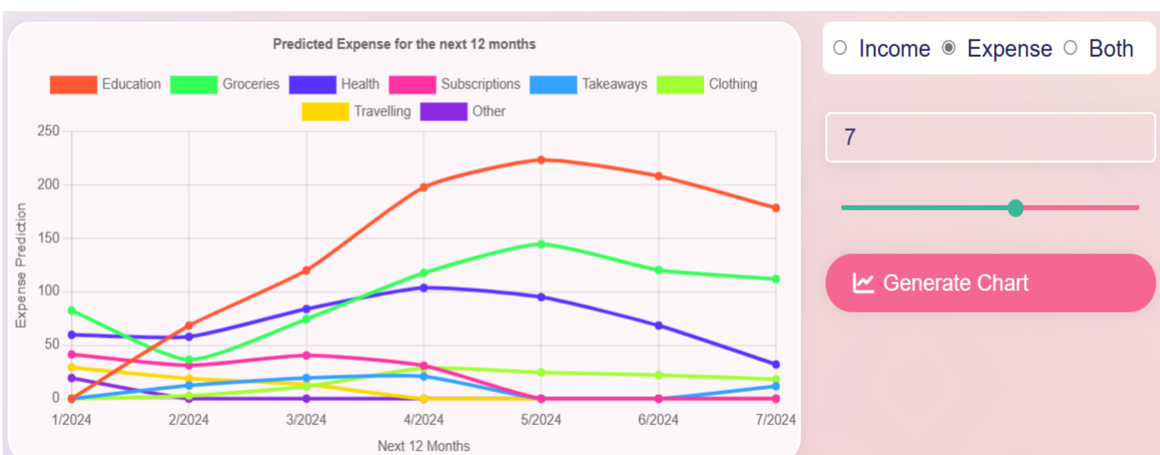

Fig. 5.4. Expense prediction of the user for the next 7 months

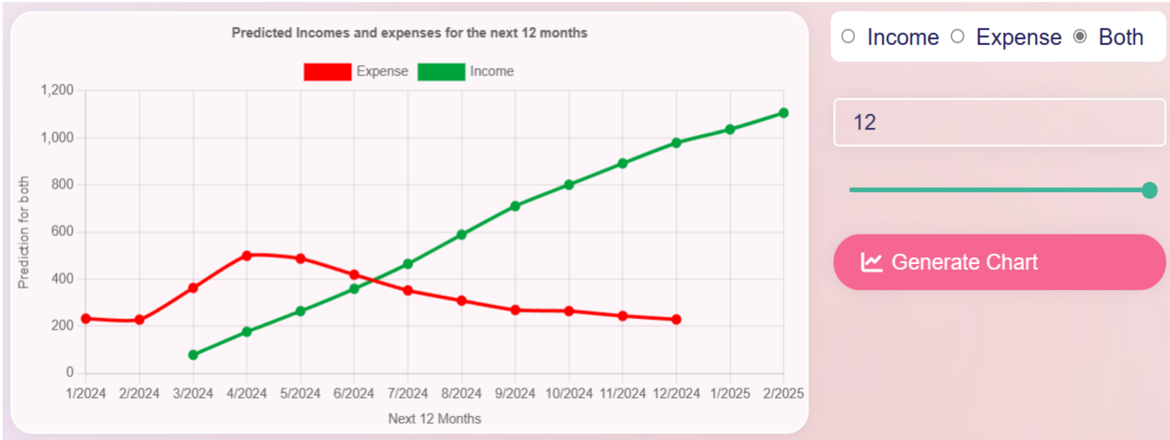

Fig. 5.5. Prediction of both income and expense of the user

5.3 VERDICT GENERATION

Following the production of income and cost estimates, the final phase entails the recovery of this crucial financial data from a defined location inside the model construction program. This retrieval procedure is crucial as it permits the supply of expected income and spending numbers for a certain month, often within the forthcoming 12-month period after the user's last recorded transaction. These projections serve as essential pieces for further analysis and decision-making processes, establishing the basis upon which users may plan and strategy their financial actions. Once collected, these income and spending estimations are subject to a unique proprietary algorithm implemented inside the frontend interface. This algorithm does a detailed examination of the projected income and costs, pitted against the user-defined goal balance for the selected month. In doing so, it considers in several elements, including predicted surpluses or deficits and the distribution of costs across different spending categories. By assessing both user input needs and predicted financial data, the algorithm creates a nuanced judgment that gives actionable insights to the user.

The judgment offered by the algorithm surpasses basic numerical outputs; rather, it incorporates smart advice customized to the user's financial situation and aims. These suggestions are methodically created to aid users in making educated financial choices, whether it includes altering spending habits, reallocating resources, or making smart financial investments. By exploiting the comprehensive insights supplied by the algorithm, users may manage their financial path with clarity and confidence, eventually steering towards their intended financial results. In essence, the integration of this powerful algorithm into the frontend interface marks a paradigm leap in personal money management, allowing customers unrivaled access to actionable financial knowledge. Through this unique method, users are encouraged to make proactive choices that correspond with their financial objectives and ambitions, providing a route towards greater financial well-being and stability.

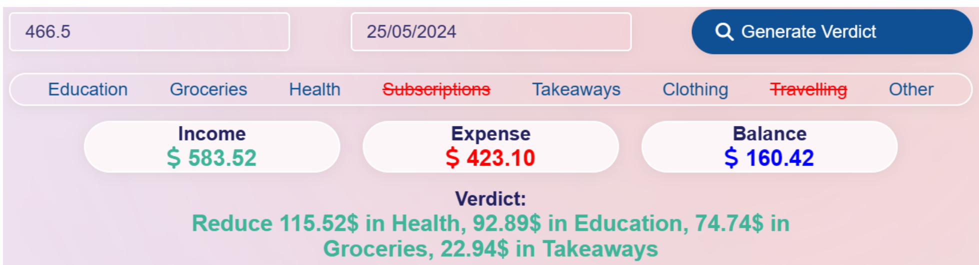

Fig. 5.6. Verdict generated (except subscriptions and travelling)

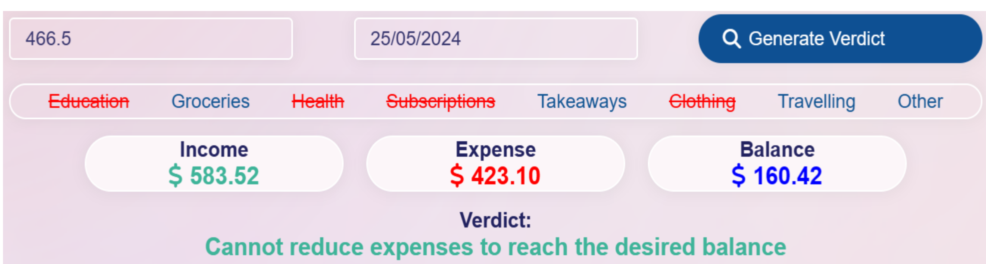

Fig. 5.7. Verdict generated (except education, health, subscriptions and clothing)

As seen in Fig. 5.6 and Fig. 5.7, the judgment provided by the system acts as a vital component in directing users towards reaching their financial goals. This decision summarizes the conclusion of a complex study that examines the possibility of decreasing expenditures to achieve the user-defined balance criterion. Upon careful examination, the verdict may indicate that mere expense reduction might not suffice to attain the desired balance, or alternatively, it may offer specific recommendations regarding the categories of expenses that can be trimmed by varying amounts to align with the user's financial goals. The relevance of this conclusion resides in its capacity to present consumers with actionable information and a clear financial perspective. By employing a comprehensive method that incorporates algorithmic analysis, human input, and predictive modeling, the system allows users to take proactive actions towards managing their money successfully. Through this method, users receive a thorough picture of their financial environment, allowing them to make well-informed choices that are in accordance with their aims and objectives.

Furthermore, the system's focus on user empowerment emphasizes its dedication to supporting financial liberty and control. By giving individualized suggestions and insights, consumers are empowered with the skills and resources required to manage difficult financial issues with confidence and clarity. Whether it entails modifying spending patterns, reallocating resources, or establishing strategic financial plans, users can depend on the system to give them with the assistance and support required to accomplish their financial objectives. Ultimately, the judgment provided by the system acts as a light of direction, illuminating the route towards financial well-being and stability. Through its extensive analysis and intelligent suggestions, the system helps users to make educated choices that correspond with their beliefs and goals. By embracing the power of technology and data-driven insights, consumers may begin on a path towards financial success and satisfaction, confident in the knowledge that they have a trusted friend by their side.

In this chapter, we have seen how the application as effectively been able to choose the best model for the prediction of transactions for the user using measuring parameters such as error and then show how the user interface functions and facilitates for the user to be able to see their predictions and transaction in both their past, present and future.

Chapter 6

CONCLUSION AND FUTURE WORK

Our research adventure launched upon a mission to reimagine financial forecasting for individual customers, motivated by an insatiable hunger for innovation and a dedication to leveraging the potential of machine learning. Through painstaking testing and thorough research, we traveled the terrain of many machine-learning models, finally unearthing the Gated Recurrent Unit (GRU) model as the beacon of predictive brilliance and computational efficiency among a sea of challengers. The GRU's dominance is built on its amazing aptitude for recognizing and recording the complicated temporal dependencies inherent in sequential financial data. By virtue of its advanced gating mechanism, the GRU model adeptly stores important information while eliminating unnecessary data, permitting the accurate modeling of complicated transaction patterns with exceptional accuracy and fidelity. Conversely, the Generative Adversarial Network (GAN) model, albeit showing promise in its capacity to produce synthetic data, crumbled under inspection, afflicted by problems coming from adversarial training and a bias towards preferring data variety above prediction accuracy. These constraints left the GAN model ill-suited for the complex nuances of financial transactions, underlining the vital necessity of picking a model matched with the particular needs of the job at hand.

In our constant quest of perfection, we arranged the construction of a complex system intended to store prediction results in a simplified pickle file format, therefore changing the prediction process and elevating the user experience to unparalleled heights. This strategic approach not only obviates the need for recurrent model training but also expedites the retrieval of predictions upon user request, imbuing our system with a novel degree of agility and responsiveness that boosts overall efficiency and customer pleasure. However, our adventure was not free of hurdles, as we struggled with the first inconsistencies coming from the restricted availability of transaction data during the fledgling phases of our research. Nevertheless, bolstered by an unrelenting dedication to quality, we remain resolute in our quest to transcend these challenges and chart a route towards ever-greater heights of predicted accuracy and customer happiness. With each new transaction added to our database, we inch closer to a future when our models stand as paragons of accuracy and dependability, giving users with unique insights into their financial trajectories and helping them to make educated choices with confidence and clarity.

Looking forward, our eyes is firmly placed on the horizon of possibilities, as we investigate options for greater refinement and optimization. By adopting modern methodologies such as incremental learning and diligent model weight optimization, we seek to uncover new horizons of prediction accuracy and efficiency, driving our budget monitoring system to unparalleled levels of performance and value. Moreover, we are dedicated to studying alternative machine learning models and algorithms, striving to optimize our expenditure reduction suggestion process and present customers with individualized suggestions that correspond with their specific financial objectives and circumstances. In conclusion, although our path so far has been distinguished by victories and obstacles alike, our dedication to innovation and quality remains unshakable. With each passing day, we inch closer to our vision of a future when financial forecasting is not only a tool, but a trusted friend in the quest of financial well-being and success. Through research, creativity, and a persistent attention to our users' requirements, we are set to alter the landscape of personal finance and enable people to take charge of their financial destinies with confidence and clarity.

REFERENCES

[1]. Rhanoui, M., Yousfi, S., Mikram, M., & Merizak, H. (2019). Forecasting financial budget time series: ARIMA random walk vs LSTM neural network. IAES International Journal of Artificial Intelligence, 8(4), 317.

[2]. Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. Applied soft computing, 90, 106181.

[3]. Vijh, M., Chandola, D., Tikkiwal, V. A., & Kumar, A. (2020). Stock closing price prediction using machine learning techniques. Procedia computer science, 167, 599-606.

[4]. Mehtab, S., Sen, J., & Dutta, A. (2021). Stock price prediction using machine learning and LSTM-based deep learning models. In Machine Learning and Metaheuristics Algorithms, and Applications: Second Symposium, SoMMA 2020, Chennai, India, October 14–17, 2020, Revised Selected Papers 2 (pp. 88-106). Springer Singapore.

[5]. Pai, P. F., & Wang, W. C. (2020). Using machine learning models and actual transaction data for predicting real estate prices. Applied Sciences, 10(17), 5832.

[6]. Nabipour, M., Nayyeri, P., Jabani, H., Shahab, S., & Mosavi, A. (2020). Predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data; a comparative analysis. IEEE Access, 8, 150199-150212.

[7]. Shen, J., & Shafiq, M. O. (2020). Short-term stock market price trend prediction using a comprehensive deep learning system. Journal of big Data, 7(1), 1-33.

[8]. Lu, W., Li, J., Li, Y., Sun, A., & Wang, J. (2020). A CNN-LSTM-based model to

forecast stock prices. Complexity, 2020, 1-10.

[9]. Moghar, A., & Hamiche, M. (2020). Stock market prediction using LSTM recurrent neural network. Procedia Computer Science, 170, 1168-1173.

[10]. Hu, Z., Zhao, Y., & Khushi, M. (2021). A survey of forex and stock price prediction using deep learning. Applied System Innovation, 4(1), 9.

[11]. Sunny, M. A. I., Maswood, M. M. S., & Alharbi, A. G. (2020, October). Deep learning-based stock price prediction using LSTM and bi-directional LSTM model. In 2020 2nd novel intelligent and leading emerging sciences conference (NILES) (pp. 87-92). IEEE.

[12]. Yu, P., & Yan, X. (2020). Stock price prediction based on deep neural networks. Neural Computing and Applications, 32, 1609-1628.

[13]. Sirignano, J., & Cont, R. (2021). Universal features of price formation in financial markets: perspectives from deep learning. In Machine Learning and AI in Finance (pp. 5-15). Routledge.

[14]. Jiang, W. (2021). Applications of deep learning in stock market prediction: recent progress. Expert Systems with Applications, 184, 115537.

[15]. Qiu, J., Wang, B., & Zhou, C. (2020). Forecasting stock prices with long-short term memory neural network based on attention mechanism. PloS one, 15(1), e0227222.