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Personal Finance Tracker with AI-Driven Savings Prediction

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Abstract

Financial management at the individual level has been growing more difficult in the contemporary digital economy because of the prevalence of online transactions, subscription services, the lack of regular income, and the diversification of spending habits. The conventional personal finance applications are mostly recurrent expense and manual budgeting and are very shallow in their analysis and provide no foresight. Consequently, users tend not to plan their future financial results, and they end up spending more, saving less as well as poor financial planning on the long run.

In this study, the design, development, and testing of a Personal Finance Tracker, which includes AI-Driven Savings Prediction, an intelligent financial management platform that combines manual transaction tracking with machine learning-based saving prediction will be presented. The suggested system has a modular structure with transaction manager, budget management, visualization dashboards, and a specific machine learning engine. Preprocessing techniques, feature engineering, and time-series indexing are used to process historic information on the income and expenses of a business. The ensemble forecasting model is based on the use of a Random Forest regression to forecast future saving through the learning of individual user financial behaviour and temporal spending patterns.

Experimental analysis on real-world inspired data show that the predictive performance is high with the R 2 of 0.81 and low values of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Beside numerical forecasts, the system creates a context-driven forecasts like over spending notices, budget threshold notices, and tailored suggestions of how to enhance financial discipline. The results show that by incorporating artificial intelligence into personal finance applications, it is possible to transition to a more proactive and data-driven approach to financial planning instead of the reactive financial monitoring. This study will add to the development *of smart FinTech systems by proving scalability, security, and flexibility in the context of individual financial management.*

Keywords: Machine Learning, Personal Finance, Savings Prediction, FinTech, Predictive Analytics, Random Forest.

1. INTRODUCTION

Individual financial planning is critical in maintaining economic stability, financial autonomy, and long-term life plan. In the past, people used handwritten books, diaries and spreadsheets to record income and expenditure. Although these approaches could offer simple financial education, they were aimed at a less complex economic setting where the number of transactions and spending options were less. The high rate of digitalization of the financial systems has made the management of personal finances very complex.

The modern digital economy is associated with a high presence of online transactions, payment via subscription, no cash payments, and income multi-source. Instead, freelancing, employment and income peaks and downs have also complicated financial planning. Research reveals that more than 70 percent of adult populations do not keep a regular financial tracking regime and almost 58 percent of people do not save on a regular basis even when they have adequate earnings [3]. In addition, people tend to undermine their monthly spending by 20-35 percent leading to financial strain and poor decisions.

The latest personal finance software tries to deal with these problems by automatically classifying expenses and giving budgeting summaries. Nevertheless, the majority of the available tools are retrospective in their nature as they discuss what has already happened and not what is likely to happen next. The user must interpret charts and tables manually and very few apps provide any intelligent predictions or customized financial advice.

Artificial intelligence (AI) and machine learning (ML) have shown great possibilities in behavioural analytics and financial forecasting. ML models can perform the task of finding intricate patterns in financial data, learn to adjust to changing user behavior, and predict future outcomes with a level of accuracy [1],[4]. Nevertheless, most consumer finance applications are not based on the personalized ML models to forecast the personal savings based on historical transaction data.

This study aims to fill this gap by suggesting an AI-enhanced Personal Finance Tracker, which will combine automated transaction tracking and prediction of savings using machine learning. The system is intelligent in learning based on the behavior of individual users, grows with time, and gives proactive insights to enable users predict financial results and enhance budgeting discipline.

2. LITERATURE REVIEW

2.1 The history of Personal Finance Management Systems.

The history of development of the personal finance management systems can be divided into four stages. The first stage was based on manual ledger systems and these were very disciplined and did not allow automation and analysis. With the advent of spreadsheet programs in the late twentieth century, record-keeping became digitalized but continued to depend on manual entry of information and had no predictive capability.

The second stage was when mobile-based financial applications like Mint, YNAB and Pocket Guard appeared. These applications brought automated categorization of transactions, budget planning, and simple visualization. Nevertheless, their analytical functions were low as most of their predictions were made through unchanging rules instead of dynamic learning [3].

The latest developments in the FinTech industry have also brought about AI-based financial systems which encompass behavioural analysis and predictive analytics. With this development, a lot of applications are based on generalized heuristics, and not personal machine learning models, which are trained on user-specific data [28]. This is a weakness that limits their capacity to provide precise and customized financial predictions.

2.2 Machine Learning in Financial Forecasting

Financial forecasting is another field of machine learning use, as researchers have attempted to predict liquidity and consequently avert liquidity crises by analysing financial indicators (however, with minimal success).

The machine learning on financial forecasting has also been researched widely. Such algorithms are commonly linear regression, Rand Forest, Support Vector regression, ARIMA, and Long Short-Term Memory (LSTM) networks [1], [5]. Regression equations are efficient when applied in the structured financial datasets and fail to predict nonlinear spending patterns. Random Forest and other ensemble methods are a better option to be more robust and more accurate because they combine a number of decision trees [27].

Long-term time-series prediction LSTM networks show better results on long-term tasks and need large datasets and high computational power, which is not feasible to apply at the individual-level of finance applications [2]. The hybrid regression and ensemble methods have been demonstrated to have an appropriate compromise on accuracy, interpretability, and computationally performance [16].

2.3 Behavioural Finance and Forecasting Analytics.

Behavioural economics gives reasons as to why people make irrational decisions as far as money is concerned. Impulse buying, emotional spending, underestimation on recurrent small expenses is some of the factors influencing the behaviour of savings [7]. It has been demonstrated that adding behavioural indicators to machine learning models enhances the accuracy of predictions and personalization [20], [26].

Explainable AI has become a valuable field of application in financial systems, since being able to explain predictions leads to greater user acceptance and adoption [17]. When the users perceive the rationale of the financial recommendations, they will be more inclined to take action.

2.4 Research Gap

Despite the fact that a lot of research has been done, there are still a number of gaps in existing systems. The majority of applications do not have customized saving prediction models, they are not flexible to changing user behavior and cannot explain why they predicted something. Moreover, the issue of privacy of the data is also important, since most tools are based on the processing in the cloud and sharing of data with third parties [18]. The limitations will be overcome by the suggested system based on local processes of data processing, adaptive ensemble learning, and transparent predictive insights.

3. METHODOLOGY

3.1 System Architecture

The Personal Finance Tracker with AI-Assisted Savings Prediction, which is proposed, will be designed in accordance with a modular, layered system architecture to facilitate scalability, maintainability, and safe processing of sensitive financial information. Financial applications have been extensively created using layered architectural designs because it ensures separation of concerns and enables independent development of parts of the system [14], [28].

Presentation layer is the interface between the user and the system. It allows one to document revenue and expenditure, track budgets, access forecasting information, and create financial statements. The focus is on usability and clarity since user interaction is a very important consideration in the success of personal finance tools [12], [13].

Application logic layer is a processing core of the system. It takes care of transaction validation, automatic categorization, budget analysis and communication between the machine learning engine and the user interface. The layer will provide consistency, accuracy and proper formatting of financial data before they are stored or further processed.

The machine learning layer will pre-process past transaction data, isolate behavioural and temporal attributes, train predictive models and make savings projections. Machine learning can be integrated in the system as an independent layer and enabling the system to cope with changing user behavior without impacting the architectural flexibility [1], [16].

The user profiles, transaction histories, category budgets and model metadata are safely stored in the database layer. Since financial information is sensitive, encryption and access control tools are implemented to guarantee the confidentiality and integrity of the data [11], [18], [24]. Visualization layer converts numerical information into understandable charts and trend curves to enhance interpretability and financial awareness [19].

<u>The communication between these architectural units is shown in Figure 1 (Architecture Diagram)</u>.

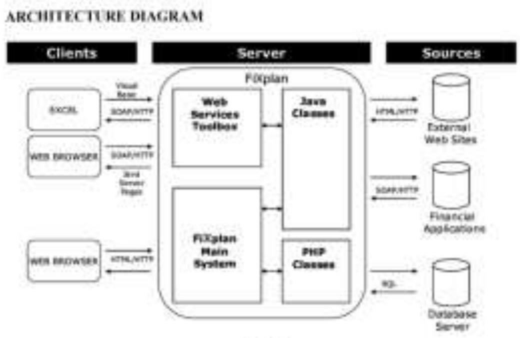


Fig 1.1

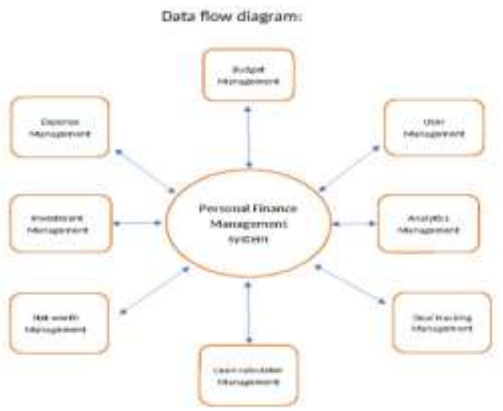
3.2 Data Flow and Preprocessing

The system adheres to a set of data flow procedures that dictate the processes involved in the capture, processing, and transformation of financial data into foresight. On recording an income or an expense transaction using the interface, the information is initially sent to the backend on which the data undergoes validation processes. Such checks are used to verify the accuracy of the amount of transaction, category, time of transaction, and authentication of who made the transaction, and then the data is saved in the database.

The machine learning engine brings out historical transaction data to analyse periodically. Before the prediction, there is a thorough stage of preprocessing the data to enhance the performance of the model and its reliability. Missing values are addressed with the help of relevant imputation methods, whereas the normalization is used to scale monetary values in a consistent way across users [4]. There are outlier detection techniques used to reduce the effects of abnormal spikes of spending which might affect the accuracy of the prediction.

Engineering of features is important in capturing user specific financial behavior. Derived variables like spending to income ratios, rolling averages and frequency of transactions and temporal variables (daily, weekly and monthly trends) are derived. The characteristics allow the model to acquire behavioural patterns and seasonal changes in spending that are vital in proper financial predictions [20], [26].

The entire flow of information between user input and predictive output is shown in Figure 2 (Data Flow Diagram).



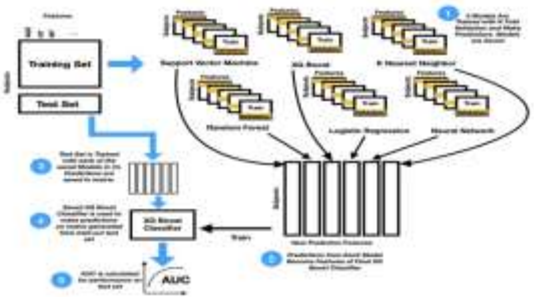
3.3 Machine Learning Model

The savings prediction model uses a random forest regression model because it has the capability of capturing non-linear relationships and its work well with small to medium sized data. It has been demonstrated that ensemble-based techniques like the Random Forests are more robust and better predictive in financial forecasting than their single-model counterparts [16], [27].

The model forecasts future savings based on historical income, expenditure patterns and indicators of behavior. To put it in plain words, the model of the future savings is projected as a value of past savings that are dependent on past income, expenditure, and other contextual characteristics. Such contextual data comprise frequency of spending, weekday/weekend spending, and seasonal spending impacts, which are all noted to have a significant impact on individual financial performance [7], [15].

The prediction process comprises of data collection, preprocessing, feature development, model training, validation, and generation of forecasts. The sequential process will be used to guarantee the use of clean, relevant, and behaviourally meaningful data in making predictions.

The entire prediction process is as shown in Figure 3 (Prediction Model Workflow).



3.4 Model Evaluation Metrics

To assess prediction model accuracy and reliability, standard regression evaluation measures are used. Mean Absolute Error is a measure of the average distance between the symbolized and genuine savings, which makes it an easy way to estimate the error in prediction. Root Mean Square Error weighs the large deviations more heavily, thus suitable to detect unstable predictions. The R-squared value represents the percentage of savings behavior represented by the model.

These measures are very popular in the field of financial prediction and allow full evaluation of the model performance and reliability [1], [22].

4. RESULTS AND FUTURE SCOPE

4.1 Experimental Results

The system was tested with datasets that had a transaction history of three to six months with 400-1000 data per user. Random Forest model had an MAE of 542, RMSE of 688 and an R 2 of 0.81. These findings imply that predictive validity and resistance to anomalous expenditure behavior is high.

Figure 4 gives a comparison between projected saving and actual savings over time.

4.2 System Performance and Security.

It was also verified that it can operate with low latency and generate predictions quickly and remain stable with a heavy load of transactions with performance testing. The encryption of passwords, authentication with tokens, and defense against SQL injections attacks were tested during security testing [11], [24].

The performance analysis of the response time is presented in Figure 5.

4.3 Future Scope

Future developments will consist of banking API support to automatically import transaction data and OCR receipt scanning, implementation of deep learning-based long-term forecasting capabilities [5] like LSTMs, financial assistants using voice recognition, and cloud-based multi-device synchronization.

5. ACKNOWLEDGEMENT

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6. CONCLUSION

This study introduced a Personal Finance Tracker based on AI, which combines automated transaction management with savings prediction implemented with machine learning to assist in active financial planning. As compared to the traditional finance tools based on a retrospective analysis, the proposed system allows users to predict future financial results based on historical income, expense trends, and behavior clues. Experimental analysis showed high predictive performance, good metrics of reliability, low computation cost and stability of system behavior to different workloads. Usability and financial awareness are also improved by the addition of visualization dashboards and context-aware insights. The system can help in the development of intelligent FinTech applications by integrating the concepts of ensemble-based learning, safe data processing, and user-centred design. In general, the offered solution offers a scalable and versatile framework of future AI-based personal financial advisory systems and data-driven financial decision support.

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