EXPENSE TRACKER USING AI AND ML

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ABSTRACT

Managing personal costs can be difficult in today's fast-paced environment. This article introduces an AI and machine learning-based cost tracker that automates expense categorization based on bank transaction data. The technology also allows users to manually enter their spending using a simple web interface. The user can also set limitations for particular categories and create their own categories, such as food, clothing, rent, and bills. The user will see visual data on expenditures by transaction date or category. Anyone who wants to track their costs can use this software; it is not designed for a specific user or age group. Thus, the primary objective of this article is to help customers monitor and analyze their overall spending habits by developing a mobile application that, by just scanning the receipts, analyzes all of the user's transactions. By safely connecting with bank accounts to automate spending classification and offer tailored insights, the AI- and ML-powered expense tracker streamlines financial management. It is based on the MERN stack and has a user-friendly chatbot with natural language processing for tracking, goal-setting, and budgeting. By examining expenditure trends, forecasting future costs, and providing practical guidance, machine learning improves functionality. This tool enables users to effectively manage their funds and attain financial stability with cross-device accessibility, real-time visualizations, and comprehensive reports.

Keywords: Expense Tracker, Suggestion using Chatbot, Machine Learning Algorithms, Financial Prediction, Personal Finance Management, Predictive Analytics.

I. INTRODUCTION

In the ever-evolving real of personal finance management, the ability to navigate the complex terrain of income, expenses, and financial planning is more crucial than ever. In a time of economic instability, growing financial responsibilities, and a plethora of investment and insurance possibilities, people today require powerful tools that empower them to make informed decisions about their financial futures. The current study investigates the root causes of this financial dilemma and presents a novel solution that forecasts future expenses based on the user's wage using machine learning and provides tailored recommendations for life insurance plans.

More Given the erratic nature of the financial markets and the increasingly complicated lifestyles that people lead, more proactive and data-driven personal finance methods are needed. Unquestionably, the advancement of digital technology has made budgeting and spending tracking simpler, but the question of "What lies ahead?" remains largely unresolved. The research of advanced tools and systems that can not only preserve historical financial data but also look into the financial future and accurately and skillfully article expenses are motivated by this unpredictability.

In particular, Random Forest integration and Support Vector Machines (SVM) show promise as solutions to this challenging issue. These algorithms, which are well known for their capacity to predict the future and offer customers a simple, real-time expenditure tracker that can adapt to their unique financial situation, form the foundation of our recommended solution. Using these algorithms, our service leverages the user's income data to generate estimates that serve as a beacon amidst the financial planning tangle.

But our objectives are not limited to cost projections. By providing a revolutionary feature—an algorithmically generated list of life insurance plans—our solution goes above and beyond. This function recognizes how financial decisions are interconnected. This application aims to provide users with insurance recommendations that enhance their present and future financial stability by utilizing user-specific financial profiles and preferences.

This work has wide-ranging effects on personal finance, machine learning, and their dynamic interactions. Our work contributes by creating a sound technique that transforms the impersonal idea of financial planning into a tangible, useful experience. By giving people a thorough and customized financial companion that not only documents their previous financial stories but also creates the next ones, our study supports the ideas of financial empowerment.

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By navigating through the methodology, findings, and conversations that support our research, we will discover the complexities of our system as we set out on this exploratory voyage. The pages that follow provide a thorough roadmap to a financial future characterized by prudent choices, with a vision of personal financial management as dynamic and active as the financial lives it aims to enlighten.

II. LITERATURE OVERVIEW

A. Personal Finance Management:

The number of digital tools and software available for managing personal finances has significantly expanded. The literature has extensively discussed the various applications and tools designed to help consumers manage their budgets and keep tabs on their expenditures. Despite offering useful data regarding previous spending patterns, these apps usually can't predict future expenses based on a user's unique financial situation.

B. Machine Learning in Finance:

Financial applications have seen a rise in the use of machine learning, particularly with regard to algorithms like Support Vector Machines (SVM) and Random Forest. These algorithms have been investigated by researchers for applications like stock market forecasting, fraud detection, and credit scoring. Machine learning's ability to adapt to jobs involving financial forecasting paves the way for its use in personal finance.

C. Predictive Analytics in personal Finance:

The difficulties of predicting personal spending have begun to be studied in the field of predictive analytics. Time-series analysis and regression models are frequently used in this research. But they frequently lack real-time capabilities, and they might not take into account a user's wage as a crucial input for forecasting.

D. Income-Expense Modeling:

However, other research has not fully tapped into the capabilities of machine learning algorithms and have instead concentrated on estimating revenue and expenses. These works frequently use statistical techniques and fundamental heuristics. SVM and Random Forest algorithm integration for income- expense modeling is yet largely researched.

E. Financial planning and life Insurance:

The literature is clear on the value of financial preparation, including insurance. Research has examined the value of life insurance plans in ensuring financial stability and has underlined the significance of selecting plans that are compatible with a person's financial objectives and circumstances. On automating the recommendation of insurance plans based on a person's financial information, there is, however, little research.

III. PROPOSED METHODOLOGY

A. Data Collection:

Approach:

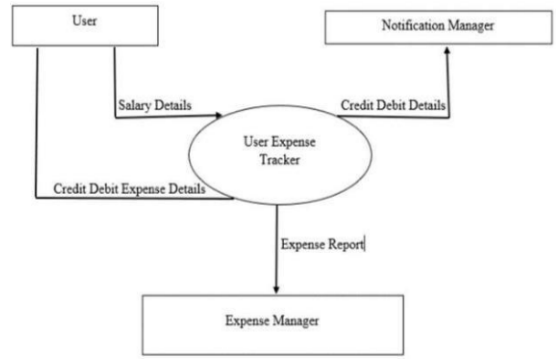

Fig.1: System of Expense Tracker

User submit:

The main data that users submit into the system is their pay information. Sensitive information is protected by privacy and data security safeguards that are put in place when this data is acquired through the user interface.

Expense Data:

The training dataset for machine learning models is the historical expense data collected from users. This data can be entered by the user or imported from other financial sources (such bank statements and receipts).

Insurance Information:

Data on life insurance plans is collected from different insurance firms or databases in order to create an exhaustive list of available policies.

B. Data Preprocessing

Data cleaning:

Because raw spending data may contain errors or inconsistencies, it has been standardized and cleaned. Missing values and outliers are appropriately handled.

Engineering Features:

Relevant attributes, like the categories of expenses, the timing of expenses, and the salary-to-expense ratio, are extracted from the data. These characteristics are input variables for the machine learning models.

C. Machine Learning Model Selection:

Support Vector Machines (SVM):

SVM is selected due to its ability to efficiently handle both regression and classification tasks. In order to forecast future expenses, it is trained using historical spending data.

Random Forest:

Random Forest was chosen because of its potent ensemble learning methodology and resistance to overfitting. Additionally, it is trained to forecast future costs, and the outcomes are contrasted with SVM's.

D. Model Training and Evaluation:

The dataset is divided into training and testing sets in order to train and evaluate the machine learning models.

Model Training:

The SVM and Random Forest models are trained using the user wage data and historical spending data. Hyperparameters are adjusted to enhance the model's performance.

Model Evaluation:

Using pertinent metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), the models' accuracy in projecting future expenses is evaluated.

Model Training: The SVM and Random Forest models are trained using the user wage data and historical spending data. Hyperparameters are adjusted to enhance the model's performance.

Model Evaluation:

Using pertinent metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), the models' accuracy in projecting future expenses is evaluated.

E. Real-Time cost Prediction:

The trained models are incorporated into the real-time cost tracker system, which anticipates future spending based on the user's current salary.

F. Implementation of the System:

A user-friendly interface allows users to enter their income, view estimated expenses, and access a list of recommended life insurance products. The entire system has been built and implemented.

G. Testing and User Feedback:

The system is extensively tested to ensure that it is accurate and functional.

IV. REALTIME EXPENSE PREDICTION

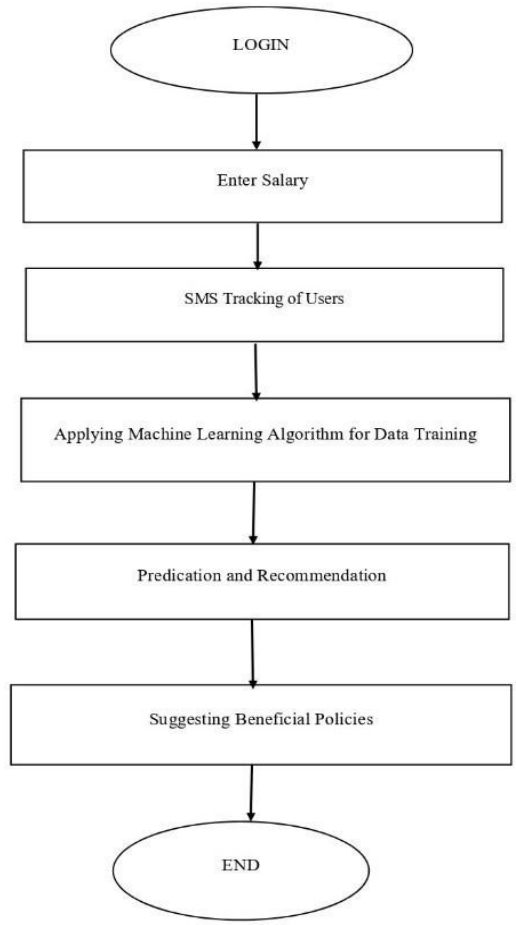

Fig.2 : Architecture Diagram

A. Expense Tracker Prediction:

One of the primary objectives of the program is to provide users with the resources they require to actively manage their own finances. Through the seamless integration of user pay data, historical expense datasets, and machine learning algorithms, the system offers real-time forecasts of future spending. This section outlines the primary functions of the Expense Tracker Prediction module.

B. Data Integration and Preparation:

The integration of user input-their present salary- begins the process of spending projection. This is a crucial sign of the user's financial resources for the following month. In parallel, historical expense data gathered from the user or from outside

financial sources serves as the basis for training machine learning models. Accurate cost projections are made possible through feature engineering and the harmonization of various datasets.

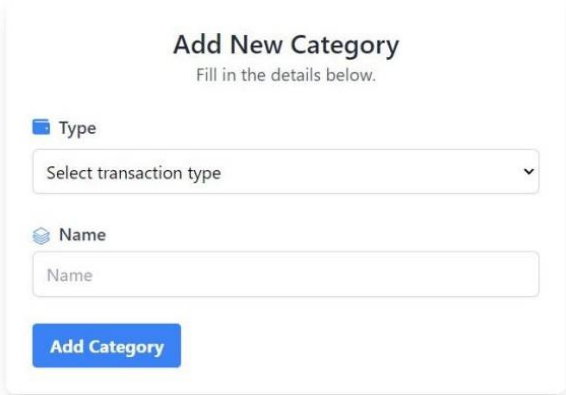

Fig.3 : Category Diagram

C. Machine Learning Models:

Support Vector Machines (SVM) and Random Forest, two reliable machine learning techniques, are used to estimate expenses.

Support Vector Machines (SVM):

SVM is used to anticipate costs because of its applicability to both classification and regression applications. The SVM model uses its prediction abilities and is trained on historical expense data and the user's salary to produce insights into upcoming expenses.

Random Forest:

The Random Forest model is introduced for ensemble learning as a complement to SVM. It excels in providing stability in forecasting and resistance to overfitting. Similar to SVM, Random Forest uses salary input and previous spending data to produce expense predictions.

D. Real-Time Expense Predictions:

Users activate the machine learning models by entering their income information into the system. By taking into account the user's income and previous spending habits, these models estimate their financial condition. The algorithm quickly creates real-time estimates of spending for the following month by looking at pertinent features and insights obtained from the training data.

E. User Empowerment and Financial Planning:

Real-time spending forecasts are a powerful tool that consumers may utilize to improve their financial planning. These insights enable people to allocate resources wisely, make wise financial choices, and manage their spending in a proactive manner. In this way, the app serves as a user's financial ally, assisting them in reaching their goals and maintaining their financial well-being.

F. Society Benefits:

Financial Awareness: As a result of increased awareness of their own spending patterns and financial well-being, users' financial literacy improves.

Budget Management: People are able to successfully create and oversee budgets, which discourages excessive spending and encourages prudent financial practices.

Early Problem Detection: Machine learning algorithms have the ability to recognize anomalous expenditure patterns, which may indicate fraud or financial difficulty.

Tailored Financial Guidance: Utilizing data from individual spending habits, the system can offer customers tailored financial guidance to assist in making wise selections. Better Saving Practices: Users who have a better grasp of their expenses are better able to pinpoint areas where they may make savings.

This real-time spending tracker combines the power of machine learning with personal finance to improve individual financial well-being and offer insightful data that can benefit society as a whole.

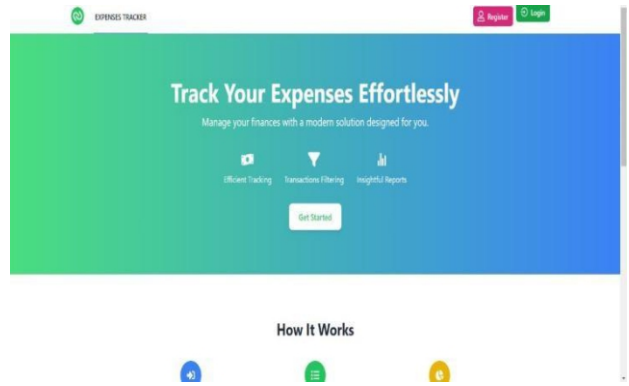

Fig. 4 : Home Diagram

V. RESULT

The evaluation of the implemented system, created to improve personal financial management through individualized insurance policy suggestions and real- time spending estimates, has produced insightful and encouraging results. the summary of the results and performance metrics seen throughout the system's rigorous testing and actual use are provided in this section.

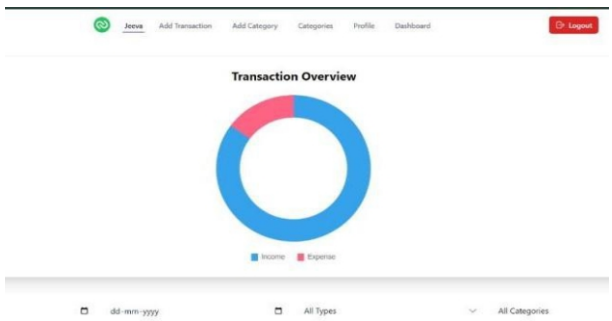

Fig. 5 : Result Diagram

A. Model Performance:

Support Vector Machines (SVM) and Random Forestage two machine learning techniques that the system uses to forecast future spending depending on user salary. These models' effectiveness in real-time expense prediction has been proven via examination.

Performance of SVM:

The SVM model showed admirable accuracy in predicting future costs. Measurements of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) highlighted the model's capacity to deliver accurate spending forecasts based on unique user profiles.

Performance of Random Forest:

The robust Random Forest model demonstrated performance that was on par with SVM. Low MAE and RMSE ratings demonstrate how well its predictions matched real spending patterns. It also gave accurate predictions.

B. Real-Time Expense Prediction:

When customers enter their current wage to receive real-time forecasts of their spending for the next month, the system seamlessly integrates machine learning models into its user interface. Users claimed that not only were these forecasts accurate, but they also helped them with their financial planning and decision-making.

This research is a cornerstone in the creation of useful tools that enable people to make wise financial decisions, safeguard their financial futures, and confidently negotiate the complex financial landscapes personal finance management continues to advance. The findings provide a positive pathway for future developments at the nexus of finance, machine learning, and user-centric financial empowerment.

VI. FUTURE SCOPE

A. Integration of More Machine Learning Models:

Even though SVM and Random Forest were used in this study, future work may incorporate the use of other machine learning models. The precision of expense estimates can be increased any more by investigating deep learning methods like neural networks or time-series forecasting algorithms.

B. Continuous Learning and Adaptation:

It is possible to improve the system's adaptability and ongoing learning. The system can react to changing user financial behavior by implementing reinforcement learning algorithms, which will eventually result in more precise predictions being made.

C. Enhanced User Interface and Mobile Application:

User engagement can be increased by creating specialized mobile applications with simple user interfaces. Integration with mobile wallets and tools for managing personal finances can offer a more complete financial experience.

D. External Data Sources:

To give customers a wider view of their financial health, the system can be expanded to include external data sources including economic indicators, market trends, and inflation rates.

E. A few prospective future ranges Additional Modules and Features:

Improve the spending tracker by including more sophisticated functions including financial goal monitoring, budgeting tools, predictive analytics, and configurable reports. Incorporate machine learning algorithms to provide recommendations for optimizations and insights into spending trends.

Use cloud-based storage to synchronize data between various devices. This guarantees that users may access their spending information on any device, anywhere. For easy data backup and recovery, look into integration with well-known cloud services like OneDrive, Dropbox, and Google Drive

VII. CONCLUSION

Finally, the real-time spending tracker software marks a big advancement in the field of managing personal finances. This method aids in the promotion of sound financial decision- making and the provision of real- time expense projections in addition to tailored insurance policy recommendations. It is positioned to enable people to successfully negotiate the complexity of personal finance, ultimately resulting in more secure and successful financial futures. This research is a testament to the revolutionary potential of technology in guiding our financial journeys as the convergence of machine learning and finance continues to develop. By leveraging cutting- edge technologies like AI and ML alongside a robust development stack (MERN), this

expense tracker delivers a seamless experience that bridges the gap between financial management and technological innovation. It empowers users to take control of their finances, avoid unnecessary expenditures, and stay aligned with their financial goals. In conclusion, this expense tracker is not just a tool but a comprehensive financial assistant designed to make financial management effortless, insightful, and secure. It offers a forward-thinking approach to tackling the complexities of expenses, ensuring stability, growth, and success for both individuals and businesses.

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