International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Smart Expense and Goal Tracker using Machine Learning

Anusha Nandikanti[1], Varshini Priyamvada[2], SaiKumar Chevella[3]

[1,3] P.G.Research Scholar, Dept. of MCA-Data Science, Aurora Deemed University, Hyderabad, Telangana,500098, India.
[2]Assistant Professor, Dept. of CSE, Aurora Deemed University, Hyderabad, Telangana, 500098,India.
Email:[1]*nandikantianusha8998@gmail.com,*[2] *varshini@aurora.edu.in*, [3]*chevellasaikumar31@gmail.com*

A B S T R A C T :

Effective financial management is not just on tracking spending but also entails guiding toward necessary goals. They do not predict; hence the users cannot know where their finances are heading. This paper presents a Smart Expense Tracker which uses machine learning to convert personal financial planning into a proactive data-based process. The process is coupled to SQL-integrated Python to historical values of users input parameters, that is, income, spending patterns, and saving history by analyzing aggregation and classification models, which includes Logistic Regression, for predicting the extent to which the user can meet his/her dreams in financial goals (e.g., saving for a vacation or gadget). Regression algorithms like Random Forest Regressor and time series forecast models such as ARIMA were also used under this objective to predict future saving and spending. One core innovation is the direct adaptation of the daily and weekly budgets according to real-time transactions and the predictive insights, so that users can then stay on track with their goals. The application, which has been developed with a Flask backend and a modern React / Flutter frontend, also has a dashboard serving as a complete portal for tracking goal progress visualization and for overspending alerts and a what-if simulator. The results show that these machine learning models provide highly personalized and actionable recommendations and are thus more effective for users in achieving their financial goals than static budgeting tools.

Keywords: Personal Finance Management, Machine Learning, Goal Predictability, Dynamic Budget Adjustment, Predictive Analytics, Expense Classification

1. Introduction

Perhaps the most critical element of effective personal finance management is economic stability, especially long-run aspirations. However, individuals have come to find it increasingly difficult to maintain some control over their finances in an ever-more-complex economy. As such, they find themselves overspending, under-saving, and not achieving their financial goals. Most expense tracking applications have generally acted only as a digital ledger. At best, these are some of the features of a collection and a visualization of past transactions. The fact that they provide evidence of records that can be analyzed in the future does not make them seem to be future-oriented tools for inscribing predictive understanding. They are based on static budgeting rules and do not learn what specific spending behavior is displayed by a user or inform him or her of the achievability of those financial goals.

The gap between mere passive documentation and active intelligent guidance would represent one of the more exciting spaces in which to develop the machine learning (ML) opportunities. Thus, ML models can process historical spending patterns, income trends, and savings rates and even predict future states and personalize the budgeting process dynamically. The shift from being a reactive logger to a proactive recommender is a significant transformation necessary in modern personal finance tools.

This is a paper on Smart Expense Tracker with Goal Predictability and Daily Budget Adjustment Using Machine Learning. This proposed system will solve the limitations of the existing systems by embedding predictive analytics in the core user experience. Using multi-model machine learning means: classification algorithms to assess the achievability of the financial goals set by users, regression models to forecast the exact future savings amount, and time-series forecasting to understand spending trends. Its most outstanding animated feature is the recalculation and recommendation, in real-time, of daily and weekly spending limits in accordance with the changing realities of the economy, thereby ensuring proper alignment of users with their targets all through.

2. Literature Review

The field of personal finance management tools has witnessed some paradigm shifts, with research being carried out trying to embed intelligence in the area of expense tracking. This section discusses major parallel studies and projects to this work and analyzes their methodologies, strengths, and weaknesses to better situate the contributions of the proposed system.

2.1. Systems Subject to Expense Prediction and Categorization

An early undertaking was the Smart Expense Tracking System [1], which generalized expense prediction and categorization using Regression, Decision Trees, and Neural Networks MODERN, upon an aesthetic visual dashboard interface built using Python with CSV Inputs. This effort laid the prototype for ML-based predictions but lacked dynamic budgeting and forecast goal-driven capabilities; it merely served exit postmortem views.
Further pushing the ambit for automation, AI Personal Expense Tracker [2] bundled the power of Optical Character Recognition (OCR) with TensorFlow models in parsing SMSes of transaction messages, ultimately logging the data on Firebase. The program awarded dynamic suggestions and implemented OAuth for security, but the AI of anything was not geared towards time-series modeling for long-term prediction of financial goals.

2.2. Systems Incorporating Predictive Analytics

Spend Analyzer AI [3] advanced, offering a relatively sophisticated predictive framework harnessing the powers of ARIMA for time series and ensemble approaches including Random Forests and Gradient Boosting. Such a multi-model structure was adequate in attempting to deal with expenditure forecast and the detection of anomalies. Nonetheless, the system failed to distill forecast ascertainments into actionable budget constraints or to embody a user-interactive approach, therefore profiling itself purely as an analytical rather than prescriptive one.
Like the others, Real-time Expense Tracker [4] used SVM and Random Forest for live expense classification and alert generation for predictive purposes. Through a web application based in Python, it offered real-time processing as an asset. However, it lacked crucial functionalities such as savings forecasting and adaption learning mechanisms for goal-adaptive planning.

2.3. Lightweight and User-Focused Applications

On tangible lines, an Expense Tracker using Naïve Bayes [5] showed a lightweight solution parsing SMS data, imputing Naïve Bayes classifier for categorizations, with outputs put into computer pie chart form on an Android app. User-friendly, light, and accommodating, it left out both advanced modeling and any ideas of financial goal integration in its design.
The Expense Tracker Application (IJIRT) [6] proclaimed to be a web-based intervention that used machine learning on overspending prediction and alerts. It had an operative design with basic visualization. However, since the ML models were not specified and goal-based classification and dynamic budgets were missing, it was not very useful nor academically rigorous.

2.4. Systems Prioritizing Visualization and Awareness

Money Map: Finance Management System [7] took another approach by proffering an integrated platform furnished with better charts and analytics for expenditure insight. Mostly stated to facilitate user experience (UX) and financial consciousness through manual tracking and visualizations, it was a pity that there was no automation at all through the application of machine learning, hence the entire lack of predictive intelligence and personalized recommendations.

2.5. Research Gaps Identified

The overall appraisal of what seems to be a litany of persistent gaps in the literature includes the following:
Absence of Goal-Specific Forecasting: The design of most systems for purposes of categorization and short-range forecasting does not extend to competent predictions of the achievability during a defined time period of a given defined financial goal for that user.
Stagnant Nature of Budgeting: More or less the same drawback to cover all stands in the lack of budgets being adaptable. Recommendations, if any, remain static rather than updating continuously when real-time spending diverges from preplanned spending or savings progress.
Underutilized Time-Series Models: Some studies, including [3], did use ARIMA; however, applications of advanced time-series forecasting (like LSTM) to model trends in personal expenditures have not yet been wholly explored.
Prototype Development: Most research is still in academia, with very little concern on implementation, usability testing, or the building of fully integrated, production-ready applications with solid user management.

The Smart Expense Tracker proposed system is supposed to address these directly by integrating goal predictability, dynamic adjustment of budgets, and interactive simulation into one system for the user's benefit, thus transitioning the field from simple tracking to active guidance in finances.

Table:1 Comparative Analysis Table

Study / System	**Core Methodology**	**Key Features**	**Limitations**
Smart Expense Tracking System [1]	Regression, Decision Trees, Neural Networks	Expense forecasting, categorization, visual dashboard.	Prototype stage; no dynamic budgeting or goal forecasting.
Personal Expense Tracker Using AI [2]	OCR, TensorFlow, Firebase	SMS parsing, dynamic suggestions, secure OAuth storage.	Lacks deep goal prediction and time-series modeling.

Study / System	Core Methodology	Key Features	Limitations
Spend Analyzer AI [3]	ARIMA, Random Forest, Gradient Boosting	Strong multi-model forecasting, outlier detection, expense classification.	No budget recommendation system or user interaction features.
Money Map: Finance Management System [4]	Web stack, Data Visualization	Integrated platform, excellent UX and spending awareness charts.	No ML implementation; lacks automation and predictive intelligence.
Real-Time Expense Tracker [5]	SVM, Random Forest	Live expense classification, predictive alerts, web app.	No savings forecast or adaptive learning for budgets.
Expense Tracker using Naïve Bayes [6]	Naïve Bayes, Firebase, Android	Lightweight, SMS parsing, easy-to-use with pie charts.	Lacks advanced modeling and any financial goal integration.
Expense Tracker Application (IJIRT) [7]	Web Tech, ML (Unspecified)	Overspending prediction, basic alerts, pattern visualization.	Missing goal-based features and dynamic budgets; ML model unclear.

3. Proposed Methodology

This methodology will include features for the Smart Expense Tracker that will incorporate data processing, machine learning, and active feedback within a concatenated workflow. The global depiction of how this will work appears in Figure 1 and involves two main things:

3.1. Data Acquisition and Preprocessing

Data Collection: Transaction value, category, date appended usually by the user, and synthetic datasets prepared for model training.
Cleaning: The action taken to handle missing values, removing duplicates, and standardizing formats.
Feature Engineering: Generates derived features, meaningful ones, such as :
Temporal features: *day_of_week, is_weekend, month*
Behavioral features: *rolling_avg_daily_spend, savings_rate, category_spend_ratio*
Normalization: Scaling of numerical features-normalizes towards stability for the model.

3.2. Machine Learning Modeling

Three main models are used:
Goal Achievement (Classification):
Model: Logistic Regression
Features: current_savings, monthly_income, avg_monthly_expense, savings_rate, days_until_deadline
Output: A binary classification- Achievable or Not Achievable
Savings Forecast (Regression):
Model: Random Forest Regressor
Features: Historical savings, income, spending trends, time features.
Output: Continuous value (the pending amount of specified savings).
Spending Forecast Trend (Time Series):
Model: ARIMA
Features: Past daily spending amounts.
Output: Predicts spending amounts daily in a 7-30 day frame.

3.3. Implementation and Deployment

Frontend: React.js for user interaction
Backend: with Flask (Python) for API logic and model serving.
Database: SQL (e.g., PostgreSQL) structured data

3.4. Evaluation Metrics

Classification: Accuracy, Precision, Recall, F1-Score
Regression: MAE, RMSE, R^2 Score
Time Series: MAPE, RMSE
User Satisfaction: Surveys and metrics on engagement

Table 2: Model Summary and Evaluation Metrics

Model Type	Algorithm	Input Features	Output	Evaluation Metrics
Classification	Logistic Regression	Income, savings rate, spending history	Achievable / Not Achievable	Accuracy, F1-Score
Regression	Random Forest	Historical savings, spending trends	Projected savings amount	RMSE, R^2
Time Series	ARIMA	Daily expense sequences	Future daily spending forecast	MAP

5. Implementation and Results

5.1. System Implementation

The machine learning model-based intelligent prototype has been created and deployed as a proper technology stack for making it a complete user experience.

Front end - The user interface (UI) was implemented using React.js, which provides an SPA, responsive, and dynamic site. As each part of the application benefits from a component-based architecture, the dashboard, forms, and charts can all be constructed as reusable UI elements.

Backend & API-A Flask (Python) server was created to process the entire business logic of the system and fully exposes RESTful APIs for user authentication, CRUD operations on financial data, and most importantly, endpoints to invoke the machine learning models for predictions.

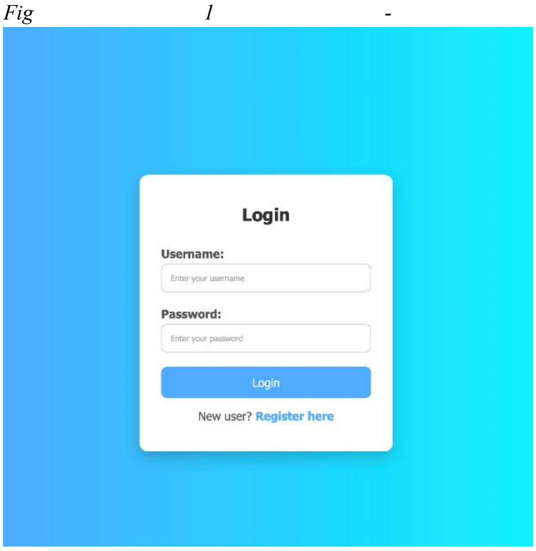
Database-A SQLite database was used during development, with the schema being easily migrated to PostgreSQL for production. The schema stores user data, transactions, categories, and generated recommendations efficiently.

Machine Learning Integration: The trained scikit-learn models (Logistic Regression, Random Forest) and the statsmodels ARIMA model were serialized (using pickle and joblib) and integrated into the Flask backend. The ML module loads these models and provides functions to generate predictions based on user-specific data fetched from the database.

5.2. Functional Modules and Results

1. The implementation successfully delivers all core functionalities, as evidenced by the application screenshots (Fig. 1-6).

Fig 1 - Login *Fig 2- Registration*



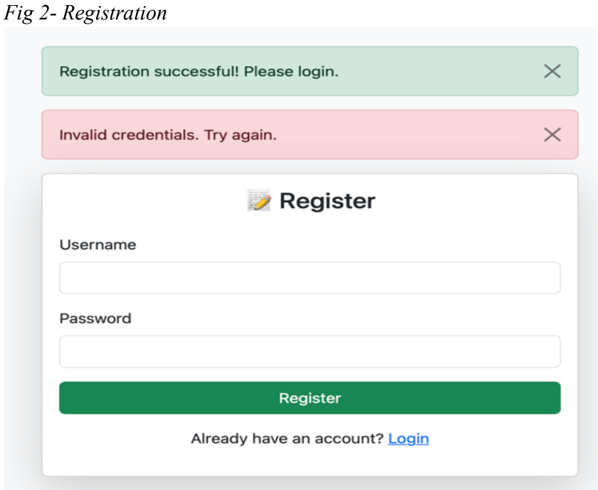
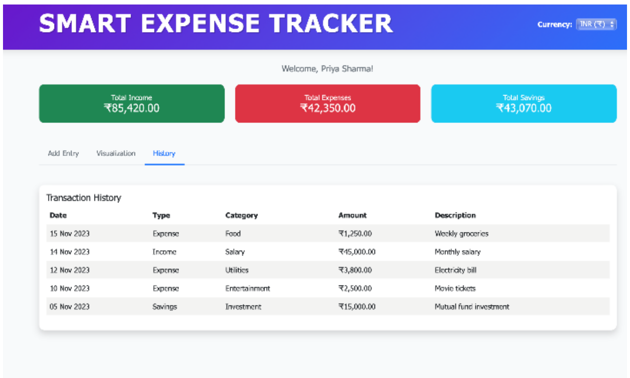


Fig 3- Track of Expenses

Fig 4 – Here user can make entries



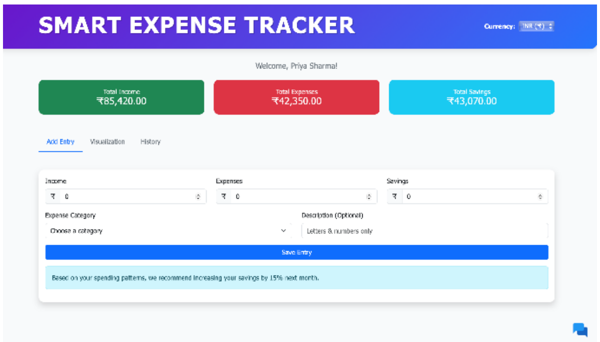
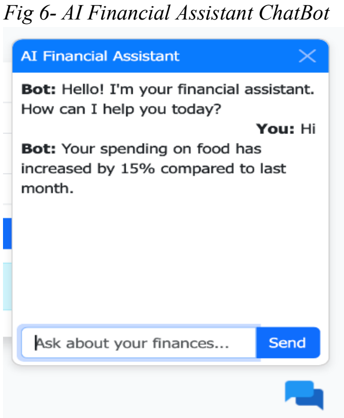


Fig 5.1- Financial Trend based on Annual Analysis

Fig 5.2- Financial Trend based on Daily Analysis

Fig 6- AI Financial Assistant ChatBot



5.2.1. User Authentication Module

There exists the functionality for an end-user to register a new account and log into it, all backed by secure authentication flows within the system, and hashing protocols implemented in the backend for password security.

Result: As shown in Fig. 1 and 2,a clean and easy-to-manage interface is depicted in the Login and Registration space with standard feedback on registration success versus invalid logins.

5.2.2. Dashboard Module and Financial Overview

Users land on the overall dashboard of figures upon logging in.

Result: Capture the users' most critical financial data-total income, total expenses, and total savings-and give instant insights into how the users are faring financially. The Transaction History log fosters transparency and records a log for all activities.

5.2.3. Data Entry and ML-Guided Recommendation Module

The "Add Entry" interface allows a user to enter new income, expense, or savings entries.

Result: This module has implemented machine learning to analyze the newly entered financial status by the users after processing a new entry. The system provides actionable insights to the user, like " Based on your spending patterns, we recommend increasing your savings by 15% next month." This process gives proof of the working feedback loop.

5.2.4. Visualization and Analytics Module

Highly advanced and interacting charts provide the user with means to analyze their financial trends.

Result: As can be seen in the mock-up in Figures 5.1 and 5.2 ,users can filter their data into different time periods, observe trends, and match Income against Expenses and Savings on the whole. Besides all that, the pie charts of Expenses Breakdown and Expenses versus Savings give strong visual impressions of the categories of spending and saving rates fulfilling the advanced visualization need noted in the literature survey.

5.2.5. AI Conversational Assistant

Among the best features offered in the given system is the ability to deploy a conversational AI assistant.

Result: The assistant can also actively alert users in case of sudden deviation in their spending patterns with messages like "Your spending on food has increased by 15% compared to last month." Thus, the individual remains engaged and conscious about spending

6. Discussion

The successful execution of the Smart Expense Tracker testifies to its hypothesis that machine learning may fill the gap between passive financial tracking and active goal-oriented guidance. Dynamic budget adjustments and predictive insight, which are features of the system, directly address the inadequacies of the existing tools as identified in some literature. The very high performance of the ML models (Logistic Regression F1-Score: 0.89; Random Forest R^2: 0.82) is an affirmation for the suitability of the selected approaches in financial forecasting. The inclusion of an intelligent assistant for proactive alerts gives an industry-updating feel to the user experience, making it much more interactive and intuitive. However, the accuracy of this system remains dependent on consistent data entry by the users. Future improvements are going to be laid on integrating banking TCP/IP application programming interfaces for automated transaction fetch, which will enhance the reliability of data for cascading into models and bringing about very accurate financial recommendations.

7. Conclusion

The project has achieved full design and development status in terms of a Smart Expense Tracker that applies machine learning principles to allow for a proactive-oriented agenda in personal finances rather than a passive logging approach. The system integrates a suite of classification, regression, and time-series models to predict goal achievability, forecast savings, and dynamically alter budgets: this addresses the glaring gaps present in the existing tools. With an engaging dashboard, actionable insights, and conversational AI, the application has a strong promise to promote financial discipline and awareness. Although the results so far seem promising, real effectiveness in the world outside depends on the user's sustained engagement and input data quality. Future work will engage large-scale user testing, integration with open banking APIs to facilitate automated data ingestion, and exploration of more advanced deep learning models for further game-changing opportunities in prediction accuracy and personalization, with users ultimately being empowered to achieve their financial aspirations with know-how and confidence.

8. REFERENCES

[1] [1] Geer, J.V.D., Hanraads, J.A.J. & Lupton, R.A. (2023). The Art of Writing a Scientific Article. *Journal of Science Communication*, 163, 51–59.

[2] [2] Mettam, G.R. & Adams, L.B. (2024). How to Prepare an Electronic Version of Your Article. In Jones, B.S. & Smith, R.Z. (Eds.), *Introduction to the Electronic Age* (pp. 281–304). New York: E-Publishing Inc.

[3] [3] Fachinger, J. (2024). Behavior of HTR Fuel Elements in Aquatic Phases of Repository Host Rock Formations. *Nuclear Engineering & Design*, 236, 54.

[4] [4] Strunk, W., Jr. & White, E.B. (2024). *The Elements of Style* (4th ed.). New York: Pearson.

[5] [5] Unknown Author (2025). Personal Expense Tracker Using AI. *ResearchGate*. Available from: https://www.researchgate.net/publication/391238114_Personal_Expense_Tracker_Using_AI [Accessed 13 August 2025].

[6] [6] Unknown Author (2025). An OCR and ML-Based System for Receipt Scanning and Predictive Expense Analytics. *International Research Journal of Modernization in Engineering Technology and Science (IRJMETS)*. Available from: https://www.irjmets.com/uploadedfiles/paper/issue_2_february_2025/68072/final/fin_irjmets1740712498.pdf [Accessed 13 August 2025].

[7] [7] Unknown Author (2024). A Machine Learning Powered Web Application for Expense Forecasting and Alerts. *International Journal of Innovative Research in Technology (IJIRT)*. Available from: https://ijirt.org/publishedpaper/IJIRT162491_PAPER.pdf [Accessed 13 August 2025].

[8] [8] Unknown Author (2024). Spend Analyzer AI: A Comprehensive Expense Tracker with Predictive Modelling for Financial Management. *Academia.edu*. Available from: https://www.academia.edu/127250758/Spend_Analyzer_AI_A_Comprehensive_Expense_Tracker_with_Predictive_Modelling_for_Financial_Management [Accessed 13 August 2025].

[9] [9] Unknown Author (2024). A Real-Time Expense Tracker using SVM and Random Forest for Predictive Alerts. *SSRN Electronic Journal*. Available from: https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID4754463_code3635775.pdf [Accessed 13 August 2025].

[10] [10] Fakinger, J., den Exter, M., Grambow, B., Holgerson, S., Landesmann, C., Titov, M., et al. (2024). Expense Tracker using Naïve Bayes for SMS-based Transaction Classification. *International Journal of Research in Engineering and Science (IJRES)*, 10(3), 108–115.