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FinSmart: An AI-Assisted Smart Budgeting and Expense Insight Application

Rupesh Prajapati, Vignesh Kamath, Touhid Khan, Ashish Yadav, Dr. Preethi Warrier
Rupesh.17184@sakec.ac.in , Vignesh.17376@sakec.ac.in , Touhid.16923@sakec.ac.in , ashish.17208@sakec.ac.in , Preethi.warrier@sakec.ac.in
Department of Electronics & Computer Science, Shah & Anchor Kutchhi Engineering College, Chembur, Mumbai, India

Abstract:
Modern world is changing rapidly like new things coming as AI, Machine learning, Cyber Security but LLM platforms like claude, chatgpt, gemini etc, payment systems also got alot better like UPI is literaly everywhere now & paying take only 2 second. but here is where the problem comes, nobody actually build a proper tool that show you when to stop spending or atleast analyse you spending behaviours or how you can avoid inflation effect by putting money into market properly. its just convineant to spend but nothing to control it, Gen Z user especialy they just tap & pay without even thinking. so ya, there is definately a real need for smarter kind of finance management system that help peoples to spend genuinly by keeping saving, taxation & investment concept in mind. so thats what FinSmart is — this system use React-FastAPI architechture & it offer budget monitoring, analysis & also fact-checking of you past investment or spendings. with data analysis, financial health score & integrated SIP, Lumpsum tools FinSmart helps user understand there spending by intuitivly controlling it.

Index Terms*—Personal Finance Management, Expense Categorisation, Budget Planning, Machine Learning, Artificial Intelligence, NLP Classification, Overspending Alerts, Investment Allocation, SIP Calculator, FastAPI, React.js, PostgreSQL, Rule-Based Financial Insights, FinTech Advisory System*

I. INTRODUCTION

Okay so many user are frequently making digital payment without even tracking there spending limits & this leads to alot of uncertanity about where there money actually goes. this paper is basically describe the design & devlopment of a smart assistanse platform — one that monitor user spending behaviour & help user to understand finance terms better. UPI & other online gateways have make it so easy to transact that people do it like 10-15 times a day sometime without maintaining any kind of structure record. this lead to inefficent financial management & reduce savings, specialy in the contex of rising inflation & changing economic condition.

So the proposed platform it aim to support individual by analysing there transaction data, identifying spending pattern & generating actionable insight for better money management. The sytem ivolved machine learning technique for automatic expense categorization using natural language processing along rule based logicfor better recommendation. Also platforms provied basic financial guidance to users, strategies without directly guiding to specific stock market shares. the application made via modern architurewhere Reactjs for building frontened, fast ap serve as api handlimg from postgresql, and for database also. . by integrating machine learning model with scalable web technologies the platform offers colaborative approach to understanding user spending data & improving financial decision-making through intelligent budgeting & market-aware saving insight.

IV. METHODOLOGY

A. Hybrid Expense Categorization Model

Accurate cost classification or categoryization is an essential necessity for intelligent budgeting & financial insight generation. FinSmart apply a hybrid classification framework merging deterministic rule-based keyword correspondance with supervised machine learning. this approach guarentee high precision for ordinary & widespread transaction while maintaining adaptability for invisible explanation.

The classification pipeline comprises of two sequential layers — Rule-Based Keyword Engine as Primary Layer & Machine Learning Classifier as Fallback Layer. this hybrid design improve interpretabilty & dependabilty which are vital in financial application.

The first layer of classification is a deterministic keyword-matching mechanism. a predefined keyword dictionary map frequent & prevalent transaction-related term to cost kind such as Food, Transport, Shopping, Bills, Healthcare, Education, Rent, Entertainment & Salary. transaction depiction are preprocessed by converting content to lowercase & tokenising utilising regular expression. whole-word correspondance is implemented to prevent substring misclassification — for illustration the keyword 'gas' will not wrongly match 'vegas' which is a very common type of error in these kind of systems.

II. LITERATURE REVIEW

The rapid evolution of Artificial Intelligence (AI) & financial technology (fintech) have significently transformed the financial advisory landscape. traditional advisory model, often characterised by high operational cost & limited accessiblity, are increasingly being supplmented or replaced by AI-driven systems capable of delivering scalable & personalised financial guidance [1].

Recent research highlights the growing role of AI-powered financial agents & robo-advisors in democratising investment service [1], [2]. Takayanagi et al. investigate the effectivness of generative AI agents as personalised financial advisors [1]. there study demonstrated that large language model (LLM)-based advisors can efectivly elicit investor preference & influence decision-making behaviour. however the research also identified critical limitation, including difficultys in resolv- ing conflicting preference & user overreliance on persuasive conversatonal styles even when advice quality decline. these finding reveal that while conversational AI can enhance engagement & trust, personalisation accuracy remain a decisive factor in ensuring financial suitabilty. this directly allign with the core objective of FinSmart platform which emphasise structured preference elicitation & decision-support validation rather than purely conversatonal interaction.

The broader fintech ecosystem have further expanded through the devlopment of robo-advisors & AI-driven automation framework [2]. robo-advisors leverage machine learning, data analytics & automation to provide cost-effective portfolio management solution. the literature emphasise accessiblity, portfolio rebalancing & algorithmic efficiency but also raises concern related to transparency, data privacy & regulatory compliance. these challenges indicate that future financial advisory system must integrate explainabilty & ethical AI consideration into there architecture to maintain user trust & regulatory alignment.

Machine learning application in financial forecasting also provide foundational support for intelligent advisory system [3]. techniques such as regression analysis, ARIMA models, neural network & ensemble method have demonstrated strong predictive performance in dynamic financial environment. these forecasting model can enhance stock prediction, spending pattern analysis & personalised financial planning module, reinforcing predictive intelligence capability.

Similarly AI application in finance extend to algorithmic trading, risk management, fraud detection, credit scoring & robo-advisory system [4]. AI systems can process high-dimensional financial data, detect hidden pattern & improve risk-adjusted decision-making. however persistent challenges such as explainabilty, algorithmic bias & systemic risk remain critical research concern. conversational AI & virtual assistant

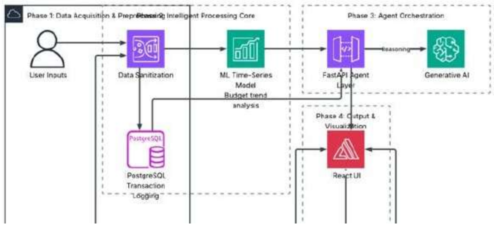

Fig. 1. Architecture of the Proposed System

If a keyword is detected in the tokenised description, the corresponding category is assigned with complete & entire confidence — Confidence = 1.0. this guarentee deterministic, explainable & extremely consistent & stable classification for often happening transaction pattern.

B. TF-IDF Feature Extraction

If no rule-based match is found, the system activates the machine learning layer. transaction depiction are transformed into numerical feature vector employing Term Frequency-Inverse Document Frequency (TF-IDF). the TF-IDF representation is calculated as — TF-IDF(t, d) = TF(t, d) log(N/DF(t)) — where TF(t,d) is the term frequency of word t in document d, DF(t) is the number of document containing term t & N is the total number of document. TF-IDF helps reduce the influence of common word while emphasising discriminative term relevant to specific expense categorie.

C. Logistic Regression Classifier

The extracted TF-IDF feature are passed to a supervised Logistic Regression classifier trained on labeled transaction sample. Logistic Regression model the probability of category prediction as — P(y|x) = 1 / 1 + e^-(B0 + B1x1 + ... + Bnxn). the category with the utmost & preeminent probability is selected as the predicted label. Logistic Regression was selected due to high interpretabilty, low computational overhead, fast inference performance, suitabilty for small structured dataset & clear decision boundries. the ML fallback return prediction with moderate confidence — Confidence = 0.6 — this value signify probabilistic classification instead than deterministic rule correspondance.

D. Hybrid Model Justification

Financial system need clear & explainable decision-making process. a solely rule-based system lacks adaptabilty while an entirely machine learning-based system may reduce interpretabilty. the hybrid approach in FinSmart offers high precision for common transaction, adaptabilty for unseen description, clear traceabilty of classification source whether rule or ml & regulatory-friendly explainabilty. this makes the system suitable for fintech environment where trust & auditabilty are essential for user & also for regulatory body.

play increasingly central role in banking & financial service [5]. virtual assistant enhance customer engagement, automate service delivery & support digital financial transformation. however conversational system must balance user interaction quality with financial accuracy & regulatory compliance.

A. Research Gap

Despite substantial advancement in AI-based financial system, existing literature reveal several limitation. many robo-advisors focus primarily on portfolio optimisation while underemphasising behavioural finance & user spending habit. conversational AI agents often prioritise engagement & personalisation but may compromise recommendation reliability. furthermore machine learning forecasting model are frequently isolated from user-facing advisory platform. limited integration exist between spending control, inflation awareness & investment advisory within single unified system — & thats a big gap that nobody have properly address yet.

B. Contribution of FinSmart

The proposed FinSmart platform aims to address these gap by integrating AI-driven stock prediction model, personalised spending analysis, conversational guidance with structured preference validation, risk transparency mechanism & inflation-aware investment insight. unlike traditional robo-advisors that focus solely on portfolio automation, FinSmart propose a hybrid intelligent advisory framework combining predictive analytics, conversational AI & financial literacy support within unified application architechture.

III. PROPOSED WORK

A. Problem Description

The rapid developement of banking sector , most user still struggle with finanical small problems and sudden developement alos in banking sector. ThereFore this issue is addressed by our finSmart solution.

Data Fragmentation — Most people have different different souce of imcome and mostly there spending is atmost into small purchases like bills, groceries , movies etc. Therefore it is hard to maintain focus on one specific major spending.

The Literacy Gap — Traditional apps and website provide informataion but not analysis or insights, also some people and layman cannot understand difficult data or analysis, like pie chart, bar graph, line graph etc.

Lack of Proactive Guardrails — most apps only show historical data. There is an absence of real-time active tracking that alert a user before they limit a category budget. this is honestly one of the biggest problem & nobody is really solving it properly.

E. Limitations

Like any system there is limitations here too. limited first training dataset is a issue. english-language dependency is another problem. static keyword mapping require periodic revision & there is no multilingual support in present version. future improvement may contain gradual learning & multilingual NLP support which would make the system much more better & accessible for more peoples.

V. EXPERIMENTAL RESULTS

Interactive Dashboard Overview

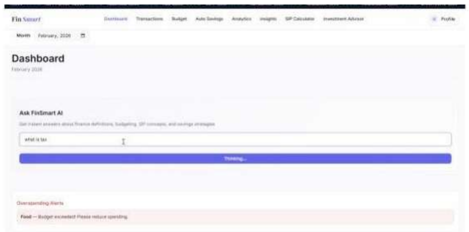

Fig. 2. Dashboard/home page

The User Interface serve as the primary data visualisation layer. it incorporate real-time stock ticker via outside APIs & render cost distribution employing Chart.js. the 'Ask FinSmart' interface show the integration of Conversational AI, offering user with a low-friction procedure to query sophisticated & multifaceted financial data archived in the backend. honestly when you first see it working its pretty impressive how everything just come together in one screen.

The methodology illustrate the data lifecycle. raw transaction input undergo feature engineering — classification & normalisation — before being passed to the Logistic Regression for trend analysis. the arising vector are then processed by a FastAPI-based Agent which use Prompt Engineering to convert numerical prediction into natural language financial advice that user can actually read & understand without needing technical background.

Data Shown Using Diagrams

Fig 3. Analysis Dashboard

The Analytical Dashboard present a longitudinal view of the user's Burn Rate. using Chart.js on the React frontend the system overlays monthly earning against classified expenditure. the ML Layer compute the delta between these value to generate

High Barrier to Advisory — professional financial advice is frequently expensive or untouchable by high minimum balance. most regular people cant even access decent investment guidance without paying alot.

B. Proposed Architecture

The architechture of FinSmart dee[ly] follow a Decoupled Tier-Three Web Pattern, guarenties that the heavy financial calculation & AI processing do not slow down the user interface at all.

Frontend Layer (React) — state management uses Re- act Hooks/Context to maintain the Monthly Balance across distinct categoryies. visualisation Engine employ Chart.js to convert PostgreSQL data into spending heatmap & trend line. dynamic UI have responsive form for transaction entry & dy- namic slider for the SIP/Lumpsum calculator which honestly make the whole experience alot more better.

Backend Layer (FastAPI) — RESTful API handle asynchronous request for transaction CRUD processes guarenteeing high accurancy. Financial Logic Engine is a dedicated module for computing Compound Interest, Step-up SIPs & Risk-based Asset Allocation. AI Integration is a gateway to an LLM like OpenAI or Gemini to power the 'Ask FinSmart' chatbot using prompt engineering to ensure financial definitions persist exact & true.

Database Layer (PostgreSQL) — relational schema store user profile, grouped expenditure & budget limit. data integrity use Foreign Keys to link transaction to particular type & user guarenteeing precise & correct historical reporting.

a Monthly Health Status, alerting user if there cost trajectory exceeds there historical earning pattern. seeing this visual side by side is honestly one of the most useful feature in the whole app.

Data Advisor


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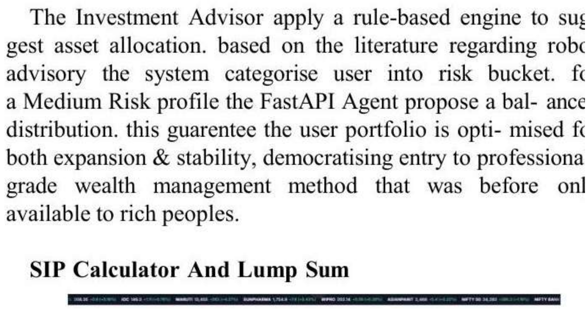
Fig. 4. Recommendation Function

The Investment Advisor apply a rule-based engine to suggest asset allocation. based on the literature regarding robo-advisory the system categorise user into risk bucket. for a Medium Risk profile the FastAPI Agent propose a bal- anced distribution. this guarentee the user portfolio is opti- mised for both expansion & stability, democratising entry to professional-grade wealth management method that was before only available to rich peoples.

SIP Calculator And Lump Sum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SIP Calculator And Lump Sum

Fig. 5. SIP Lumpsum Calculator

The SIP (Systematic Investment Plan) Calculator use a compound interest formula — M = P x ((1+i)^n - 1) / i x (1 + i) — where M is the maturity value, P is the monthly contribution, i is the monthly interest rate & n is the number of month. the visualisation differentiate between the Principal Amount & Estimated Returns, offering user with a plain & understandable financial roadmap for long-term goal accomplishment. once you see how much your money can grow just by investing small amount every month, it really change the way you think about saving.

VI. FUTURE SCOPE AND CONCLUSION

Looking ahead we plan to expand this app with advanced AI & Natural Language Processing. imagine asking the app about you financial future & getting a personalised prediction back — that kind of thing. to make life easier, the app will securely sync with you bank to track spending automatically so no more manual entries which is something alot of user have been asking for with the helps of OCR technique.

We also want to help user money work harder. by using market sentiment analysis the app can automatically invest small portion of you budget into high-performing stocks. our goal is to use AI not just as a tool but as a game-changer that aligns with global goal for prosperity of all type of user. We are moving toward a digital-first future & while there are problems to overcome, the opportunity to build a smarter new normal is huge & we think FinSmart is one good step toward that direction.

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