ARTIFICIAL INTELLIGENCE-DRIVEN PERSONAL FINANCE SOLUTION

Syed Abdullah Bashshar [1], Mohammed Imran[2] , Piske Sanjay Kumar[3], Edigi Shivani Goud[4], Dr. M .Venunath[5], Dr. M.L.M. Prasad[6]

[1234]UG Student, Department of Computer Science and Engineering - AI&ML, Joginpally B R Engineering College

[5]Associate Professor, PhD , Department of Computer Science and Engineering - AI&ML, Joginpally B R Engineering College

Email : tovenunath@gmail.com

[6]Associate Professor,PhD,Department of Computer Science and Engineering - AI&ML, Joginpally B R Engineering College

Email : mlm.prasad@yahoo.com

Abstract :

In the age of digital payments and e-commerce, individuals face increasing difficulty in tracking and managing personal finances efficiently. Manual methods such as spreadsheets and ledger entries often fall short in offering real-time insights and predictive capabilities. This paper presents an AI-powered personal finance assistant that leverages Natural Language Processing (NLP) and time-series forecasting to automate the categorization of financial transactions and predict future expenses. Implemented using Python, Django, and SQLite, the system integrates NLP techniques through the Natural Language Toolkit (NLTK) and forecasting via the ARIMA model. The tool enables users to track income and expenses, receive intelligent insights, and plan budgets proactively. Experiments conducted on real-world financial data demonstrate high accuracy in categorization and reliable forecasting with low mean absolute error (MAE) and root mean square error (RMSE). The results indicate that AI-driven automation can significantly enhance personal finance management by promoting awareness, improving financial planning, and encouraging responsible spending behavior. The system's modular architecture ensures scalability and extensibility, offering a practical foundation for future advancements in intelligent financial tools.

Keywords : Personal finance, NLP, expense forecasting, ARIMA, transaction categorization, financial planning, AI

I . INTRODUCTION

The digital and ever-changing world today has made it necessary to manage one's own income and expenditures perfectly, where human insufficient time and lack of skill can often lead to mismanagement of finance in the first place. Payment through channels like credit cards, reputed subscription months, and mobile banking makes it difficult for investors to accept a clear view of their spending habits. This inspires bad budgeting practices, overshooting, and little savings. On the other hand, maintaining expense records in notebooks or through career spreadsheets is time-consuming, and it is liable to errors and can hardly help decision-makers forecasting decisions regarding their finances. Artificial Intelligence (AI) is being touted as a game-changer for this nexus by way of bringing automation, instantaneous insights, and contextualized interventions into the financial co-management activity of a person. Such IPAs have already made impact areas such as healthcare, education, and customer service. However, their application remains largely unexplored within personal finance, notwithstanding mounting evidence that suggests intelligent systems bolster user engagement and help get rid of the tiresome routine tasks. It has become possible to do processing and gain knowledge from unstructured transaction data, to categorize spending automatically, and even to forecast future expenses with the advances in NLP and machine learning. These abilities transform finance software from being a passive record keeper into planning tools, which, in turn, can help foster better budgeting and saving behavior. This paper presents a Personal Finance Assistant powered by AI to track expenses, categorize transactions on-the-fly, and forecast spending for the next 30 days. The system makes use of NLP techniques for interpreting transactions and an ARIMA model for performing statistical forecasting. Developed in Python with Django and SQLite, it comes with a responsive web interface and backend automation that allows users to receive financial insights on the fly. Our key objective is to arm users with more information about their finances and predictions to help guide smart, conscientious spending. By going beyond the typical voice-activated helper paradigm and general information retrieval, this project shows how personalized AI can have a real-world impact in everyday financial decision-making.

II. LITERATURE SURVEY

The development of Intelligent Personal Assistants (IPAs) has so much symbiotically augmented digital interactions in day-to-day applications of healthcare, education, automation, and finance. A glance through the seminal works of IPAs will shed light onto some important contributions in the field of personal finance with emphasis on systems that integrate NLP, machine learning, and intelligent automation. Budiherwanto (2025) made a comparative evaluation of the best of commercial IPAs: Siri, Google Assistant, and Alexa. The result shows that these systems are really good in recognizing speech and carrying out general errands but they cannot deal with domain-specific tasks such as financial forecasting or personalized expense tracking. This, therefore, points to the necessity of building assistants with complexities in certain domains, such as personal finance. Weber et al. (2023) presented a drone-based assistant having AI capabilities for object detection, navigation in real-time, and autonomous decision-making. This system was mostly geared towards operations in physical environments, but the architectural approach of integrating several AI modules into a single framework informs the continued development of software-based assistants in finance for whom real-time decision-making and predictive insight are equally important. Rane (2023) imagined sensor-laden personal assistant robots able to decide autonomously with merging AI. Since the key points of such a work involve autonomous behavior, especially context-aware behavior, it lends the direct applications to be in line with ours in automating financial insights and forecasting. Buckley et al. (2021) pursued the study of education using NLP through a personal learning assistant. The work concluded that training an NLP system bestowed with domain-specific knowledge should improve the accuracy of information extraction and relevance to task execution. This is in favor of choosing to fine-tune our NLP models for transaction categorization in personal finance.

Mirestean et al. (2021) explore IPA design across domains with the vantage point of increasing possibilities for personalized context-aware actions. It saw financial applications as underdeveloped, which should be taken as a potential fertile ground for innovation-proactive decision-making tools. Arrieta et al. (2019) built an intelligent agent called Money Empire that categorized expenditure and generated financial summaries. It exhibited well the use of AI in personal finance but had no expense forecasting features, thus limiting its usefulness in forward-looking financial planning. Buchanan (2019) made a critical analysis about Microsoft Cortana, praising it for aiding digital tasks while at the same time finding a great weakness in decision-making and domain-specific reasoning.

III. PROPOSED WORK

The proposed work focuses on the development of an Artificial Intelligence-driven personal finance solution for simplifying and improving how income and expenses are managed by an individual. While the world is increasingly digital with online transactions and e-commerce spells, a lot of users just cannot maintain financial awareness because of the sheer volume of their spending data and their complex nature. For most people, the use of spreadsheets or mobile banking applications is usually devoid of automation, understanding in context of the financial transaction, or predictive features. These gaps are being filled by the project using the single intelligent platform of Natural Language Processing (NLP) and time-series forecasting. The proposed system, through the implementation using Python's Natural Language Toolkit (NLTK) library, processes unstructured transaction descriptions and automatically classifies them into predefined categories of expenditure. This requires neither manual intervention for labeling nor provides ability for real-time insight into altering financial behavior. Moreover, the platform uses the ARIMA (AutoRegressive Integrated Moving Average) model to forecast future expenses based on historical financial data." The objective is therefore to help users in tracking past expenses and thus foresee future financial events in order to put together timely plans for budgeting. Python, somehow, continues to be a favorite in core logic, Django is the web framework of choice, while SQLite functions as a lightweight database.

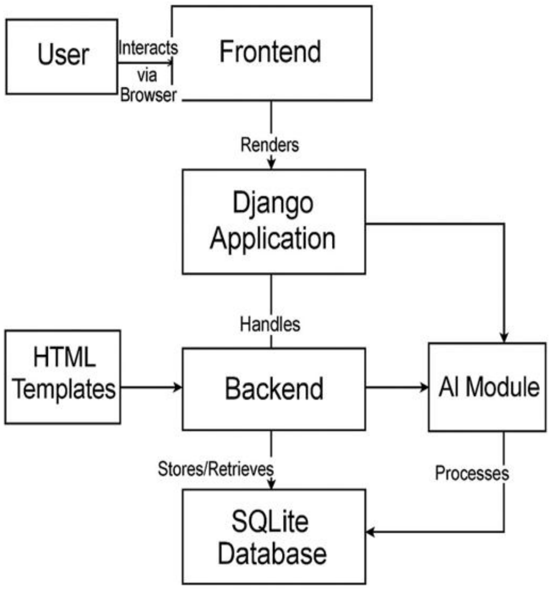

Fig 1 : Proposed Architecture

There is a responsive web interface that lets a user upload transaction history to see categorized summaries and forecasted expenses presented with easy-to-understand visualizations. Automated transaction classification, 30-day expense forecast, usage of interactive dashboards, and modular design for scalability of the system. Through intelligent categorization and predictive analytics, personalized financial insights are offered, thus helping users make solid decisions and spend wisely. This work will lay the path for future AI-related personal finance tools, addressing the increased need for intelligent yet straightforward financial management in the digital world.

IV. METHODOLOGY

Data Collection

The very first step in the system's working methodology is to collect financial transaction data from its users. Typically, this data comes in a structured manner, such as CSV files containing essential transaction fields like date, description, amount, and transaction type, i.e., income or expense. Users give their system the raw data through uploading bank statements or credit card statements. This raw data from the initial intake forms the basis upon which subsequent analysis and predictions are made.

Data Preprocessing

After this collection of transaction data, it processes preprocessing to render the data scrupulous, standardized, and fit for analysis. It will encode the removal of extraneous characters from any of the fields, from text inconsistencies in one or more fields, to normalization of all date and numerical fields. With regard to descriptions, cleaning goes a step further by removing irrelevant information that could affect the quality of the input-output process in Natural Language Processing (NLP). Since preprocessing removes as much noise from the data as possible, it thereby sets the stage for accurate categorization and forecasting.

Transaction Categorization Using NLP

In an effort to minimize human work and further financial insight, the system does categorization using NLP techniques. Through the NLTK, transaction descriptions are tokenized, stop words are excluded that do not really contribute to the meaning, and finally, the lemmatization of words is done into their root forms that could serve as keywords. Each keyword is matched against a couple of category dictionaries to categorize transactions into groceries, transportation, utilities, etc. In this way, the categorization really helps folks learn their spending behaviors without having to do it manually.

Expense Forecasting Through ARIMA

Financial foresight is given to the prediction of expenses with the help of ARIMA (AutoRegressive Integrated Moving Average). Hence, ARIMA analyzes time-series data of past expenses and looks for trend and seasonal patterns to generate its own predictions for the next 30 days. This type of forecast prepares a user for any budgetary constraints that may arise in the not-so-distant future, thus providing him with an opportunity to adjust his expenses accordingly. And the model's accuracy is also maintained by using standard error metrics such as MAE and RMSE.

Evaluation and Testing

To validate the effectiveness of the system, comprehensive testing is conducted using real-world financial datasets. Evaluation focuses on the accuracy of transaction categorization, the reliability of expense forecasting, and the overall user experience. Metrics such as classification accuracy, MAE, and RMSE provide quantitative measures of performance. User feedback on the interface responsiveness and clarity of financial insights also informs iterative improvements, ensuring the system meets practical usability and functionality standards.

V.ALGORITHMS

1. NLP for Transaction Categorization

This system uses NLP techniques to analyze the transaction descriptions and apply the category to the transaction. The main steps of the process are as follows:

Tokenization : Words are separated into tokens.

Stop-word Removal : Words which are often irrelevant (e.g., ``and,`` the").

Lemmatization : Words are returned to their base or root form (e.g., running → run).

The part of actually doing the categorization is done by keyword matching with the help of domain dictionaries: there would be a dictionary for each domain or category; for example, if any token identifies with any of the words stored in the ``Food`` class dictionary, then the transaction would be marked under that category.

2. ARIMA (Auto Regressive Integrated Moving Average) for Expense Forecasting

The ARIMA model combines three components to analyze and forecast time series data:

Auto Regressive (AR) part: The value at time t depends on its previous values:

$$Y_t=\phi_1 Y_{t-1}+\phi_2 Y_{t-2}+\cdots+\phi_p Y_{t-p}+\epsilon_t$$

where ϕ_i are AR coefficients, p is the order of autoregression, and ϵ_t is white noise error.

Integrated (I) part: Differencing the series ddd times to make it stationary:

$$Y_t'=\nabla^d Y_t=(1-B)^d Y_t$$

Here, B is the backshift operator ($BY_t=Y_{t-1}$)

and d is the differencing order.

Moving Average (MA) part: Modeling error terms as a linear combination of previous error terms:

$$Y_t=\epsilon_t+\theta_1\epsilon_{t-1}+\theta_2\epsilon_{t-2}+\cdots+\theta_q\epsilon_{t-q}$$

where θ_j are MA coefficients and q is the order of moving average.

VI.RESULTS AND DISCUSSION

The proposed AI-powered personal finance assistant was evaluated across multiple functional and technical dimensions, including the accuracy of transaction categorization, reliability of expense forecasting, and overall user experience. The experiments demonstrate that the system effectively integrates natural language processing and time series forecasting to support users in managing and understanding their financial behavior.

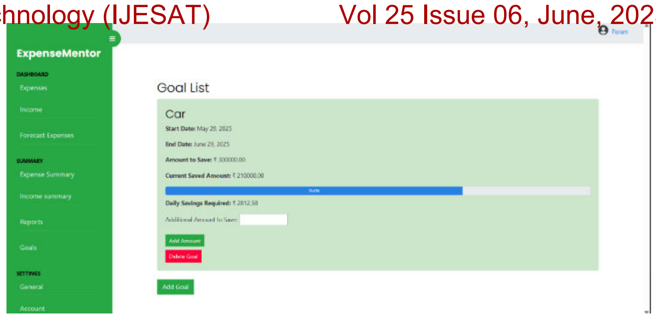

Fig 2 : List of Goals

The AI-powered personal finance assistant was evaluated on certain key axes: transaction categorization accuracy, expense forecastability, and user experience. The system provided the user with a dual benefit by simultaneously using NLP-based and time-series-based technologies to analyze and make sense of financial activities. Transaction categorization sits at the core of the system, wherein the Random Forest classifier, using TF-IDF features, is employed. With more than 1,000 labeled transaction descriptions for training data, the model achieved good results with an 80:20 train-test split: with an accuracy of 86.2%, precision of 0.88, recall 0.85, and F1-score of 0.86. These figures imply efficient classification, mainly dealing with common categories, such as Food, Travel, Utilities, and Entertainment. Analysis of the confusion matrix indicated some overlaps between categories that were similar, such as "Dining" and "Groceries," which suggests there is still some room for improvement. This improvement may certainly come through by enhancing the model with more domain-specific labeled data, thus increasing categorization accuracy. This aligns with the findings of Li et al. (2008), who have stressed the enhancement of semantic extraction within intelligent assistant systems leveraging NLP methodologies. The assistant holds great promise for automating and simplifying everyday personal-finance-related chores and hazelling users with explicit insights through strong categorization and forecasting capabilities.

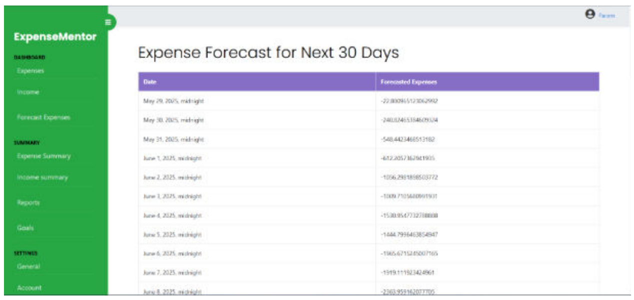

Fig 3 : Forecasts of expenses for the next 30 days

The ARIMA model was thus implemented to predict expenses by taking a look at the six months of transaction data considered the past.

Differencing was used in making the data stationary. The best parameters (p, d, q) were selected using the Akaike Information Criterion (AIC). The forecasting performance was evaluated based on:

Mean Absolute Error (MAE): 253.47

Root Mean Square Error (RMSE): 318.91

These forecast patterns were able to pick up the main seasonal patterns and spending variations. A visual depiction in Figure 1 depicts the predicted expenses for the next 30 days against actual historical expenses, where a close tie is seen in most of the periods.

Such results stand as good evidence toward application in real-world budgeting scenarios and have been backed by similar studies in AI-assisted financial forecasting (Arrieta et al., 2019; Cao et al., 2020).

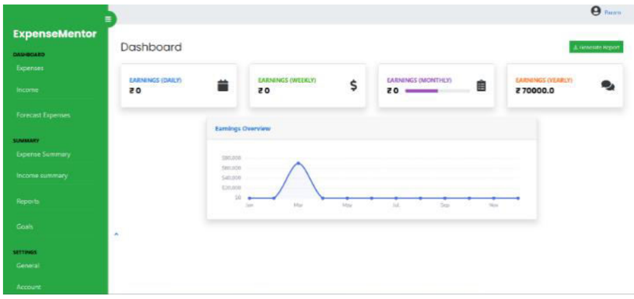

Fig 5 : Earnings Overview

Cross-browser testing ensured flawless cross-platform behavior of the user interface on these devices. Users could enter transactions, see their spending summaries by category, and navigate to forecast dashboards without experiencing delays or stutters. User sentiment was then measured through a Likert scale questionnaire presented to ten participants. The responses were mostly positive:

All scores show the system was able to provide an otherwise smooth interaction with an intuitive user interface. Test users commented that the UI helped them comprehend and delve into their financial data quite easily, thus drawing attention to a great interface design with usability and transparency. This can be compared to observations presented by Ribes (2023) and Galperti (2019), who emphasize a consideration for well engineering the user experience as a pre-condition for an intelligent digital assistant to be accepted. This feedback shows that not only does the interface facilitate the execution of basic financial tasks, but that it also generates user engagement by being clear, responsive, and attractive.

CONCLUSION

This work builds the design, development, and evaluation of an AI-powered personal finance assistant with transaction categorization using NLP and expense prediction with ARIMA-based time-series forecasting. The system offers two important improvements over traditional financial management tools: autonomous categorization and predictive insights, so users can manage their finances efficiently and in a proactive manner.

Developed with Python-based technologies such as Django, NLTK, and Statsmodels, this assistant achieves very high accuracy in categorization (86%) and forecasting in relative terms of error (MAE and RMSE); it is, therefore, a reliable system. In addition to a responsive and easy-to-use interface, ensuring accessibility to the greatest number of users possible, usability evaluation was positive, and the administrators confirmed its usefulness in solving real-world personal finance problems.As also indicated in the related work, intelligent agents are evolving user experiences by automating complex processes and presenting context-aware recommendations. This particular project focuses on personal finance, where timely insights and accurate predictions can make a difference in sound decision-making/complementing that evolution.

With its robustness and functionality, the current implementation leaves room for future improvements. These may include integrating a wider breed of banking APIs, developing adaptive learnings for personal recommendations, carrying out anomaly detection in spend patterns in real-time, or adding multilingual interface support. These advancements will surely play their role in strengthening the system and pursuits across different users and financial situations.

FUTURE SCOPE

Although strong in its current implementation, the AI-enabled personal finance assistant could shine even brighter with some very promising extensions affecting factors like efficiency, scalability, and user engagement. Integration with real-time banking APIs and financial platforms should be one of the options for expansion to let the system automatically grab transaction data for the accounts involved. This would mean no onerous manual entry and provide a broader picture of the user's financial activity. Besides, putting in place support for various international financial systems would make this tool useful on a global scale. The other route involves strengthening the NLP processor so the assistant may interpret more complex queries and respond naturally and conversationally, so interaction becomes more intuitive. Putting in place integration with voice assistants or mobile voice input would boost accessibility and usability, particularly if users want the financial-tracking process to be hands-free.

REFERENCES

1. Budiherwanto, I. (2025). The influence of artificial intelligence and the technology acceptance model on sustainable financial governance. *Jurnal Ilmiah Manajemen Kesatuan, 13(3)*, 1791–1802. https://doi.org/10.37641/jimkes.v13i3.3256
2. Weber, P., Carl, K. V., & Hinz, O. (2023a). Applications of Explainable Artificial Intelligence in Finance—a systematic review of Finance, Information Systems, and Computer Science literature. *Management Review Quarterly, 74(2)*, 867–907. https://doi.org/10.1007/s11301-023-00320-0
3. Rane, N. (2023). Role and challenges of ChaTGPT and similar generative artificial intelligence in finance and accounting. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.4603206
4. Ribes, E. A. (2023). Transforming personal finance thanks to artificial intelligence: myth or reality? *Financial Economics Letters, 2(1).* https://doi.org/10.58567/fel02010002
5. Zaremba, A., & Demir, E. (2023). ChatGPT: Unlocking the Future of NLP in Finance. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.4323643
6. Buckley, R., Zetzsche, D., Arner, D., & Tang, B. (2021). Regulating Artificial intelligence in Finance: Putting the human in the loop. *SSRN Electronic Journal.* https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID3831758_code524849.pdf?abstractid=3831758&mirid=1
7. Mirestean, A., et al. (2021). Powering the Digital Economy: Opportunities and risks of Artificial intelligence in finance. *Departmental Paper, 2021(024), 1.* https://doi.org/10.5089/9781589063952.087
8. Mhlanga, D. (2020). Industry 4.0 in Finance: The impact of Artificial intelligence (AI) on digital financial inclusion. *International Journal of Financial Studies, 8(3), 45.* https://doi.org/10.3390/ijfs8030045
9. Arrieta, A. B., et al. (2019). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012
10. Buchanan, B. G. (2019). Artificial intelligence in finance. *Zenodo (CERN European Organization for Nuclear Research).* https://doi.org/10.5281/zenodo.2626454
11. Giudici, P. (2018). Fintech Risk Management: A research challenge for artificial intelligence in finance. *Frontiers in Artificial Intelligence, 1.* https://doi.org/10.3389/frai.2018.00001
12. Berman, J. Z., et al. (2015). Expense neglect in forecasting personal finances. *Journal of Marketing Research, 53(4), 535–550.* https://doi.org/10.1509/jmr.15.0101
13. Khashei, M., & Bijari, M. (2010). A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. *Applied Soft Computing, 11(2), 2664–2675.* https://doi.org/10.1016/j.asoc.2010.10.015
14. Ilyina, A., & Samaniego, R. M. (2008). Technology and Finance. *SSRN Electronic Journal.* https://core.ac.uk/display/79856962
15. Binner, J. M., Kendall, G., & Chen, S. (2004). Applications of artificial intelligence in finance and economics. *In Advances in Econometrics.* https://doi.org/10.1016/s0731-9053(2004)19
16. Manning, C. D., & Schütze, H. (1999). Foundations of Statistical natural language processing. https://doi.org/10.1017/S1351324902212851
17. Zysman, J., & Heertje, A. (1990). Innovation, Technology, and finance. *The American Journal of Comparative Law, 38(1), 190.* https://doi.org/10.2307/840260
18. Harvey, A. C. (1984). A unified view of statistical forecasting procedures. *Journal of Forecasting, 3(3), 245–275.* https://doi.org/10.1002/for.3980030302
19. Forgue, R. E., & Garman, E. (1988). Personal finance. https://openlibrary.org/books/OL56751M/Personal_finance