International journal of imaging science and engineering

ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

# Artificial Intelligence Tool for Personal Finance Analyser to Estimate Future Savings and Spending Patterns for Individuals

**Adapala Gahana Sree [1], Meduri Kalyan [2], Karri Uma Naga Vara Prasad Reddy [3], Dr. Gowtham Mamidisetti [4]**
[1,2,3] UG Scholar, Dept. of CSE(AI&ML)
St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
[4] Professor, Dept. of CSE(AI&ML), St. Martin's Engineering College, Secunderabad, Telangana, India, 500100
gahanasree.a@gmail.com

***Abstract:***

Personal finance management is becoming increasingly important as individuals face complex spending patterns and uncertain economic conditions. According to a survey by the U.S. Federal Reserve, 36% of Americans have less than $1,000 in savings, and 50% of adults find it difficult to manage their monthly expenses. Existing manual budgeting techniques fail to provide accurate, long-term insights into future savings and spending behavior. In this work, we propose a Personal Finance Analyzer that leverages artificial intelligence (AI) to predict future savings and spending patterns for individuals. The proposed system employs advanced preprocessing techniques like data normalization, feature selection to enhance prediction accuracy. A deep learning-based regressor is used to forecast future trends, capturing dynamic relationships between income, spending, and savings patterns. Using the "Personal Finance Data" dataset, with the target column being "future_savings," this model provides personalized insights for users to optimize their financial decisions.

***Keywords: Artificial Intelligence, Finance Management, Savings, Deep Learning-Based Regressor, Data Normalization, Feature Selection.***

## 1.INTRODUCTION

Personal finance management in India has evolved due to urbanization, digitalization, and economic shifts. Traditionally, households relied on informal savings methods, but financial literacy grew post-1991. Despite digital payment adoption, challenges remain—63% of households have irregular incomes, and 50% struggle with expenses. Manual budgeting methods fail to adapt to dynamic spending patterns. This project proposes an AI-powered Personal Finance Analyzer to predict future savings and expenses. Using deep learning techniques like GRU and DNN, the system analyzes financial data, detects spending patterns, and provides insights. The tool enhances financial decision-making, helping users manage debt, optimize savings, and mitigate risks. It integrates behavioral analysis to understand impulsive spending and inflation impact. Key applications include personalized budgeting, real-time expense tracking, debt management, and retirement planning. By leveraging AI, the system empowers individuals to achieve financial stability in a fluctuating economy. The proposed system processes user financial data through advanced preprocessing techniques like data normalization and feature selection. It identifies key factors influencing savings, including income trends, spending habits, and economic indicators. A deep learning-based regressor predicts future financial trends, offering tailored suggestions. The model uses real-world datasets, ensuring practical applicability. provides personalized and adaptive recommendations. The system addresses financial literacy gaps by offering intuitive insights, making it accessible to users with varying expertise. Additionally, it incorporates real-time adaptability, allowing users to adjust their financial plans dynamically. The project aligns with India's Digital India mission, promoting tech-driven financial empowerment. Future expansions may include integration with fintech platforms and real- time alerts for better financial management. This AI-driven approach provides a scalable and effective solution for modern personal finance challenges.

## 2. LITERATURE SURVEY

Agarwal and Zhang [1] examined the impact of artificial intelligence on personal finance, highlighting how AI-driven financial tools can enhance decision-making. Their study discussed the role of AI in personal budgeting, automated investments, and credit assessments. They found that AI could reduce financial errors and improve financial planning efficiency. However, they also noted the risks associated with algorithmic biases and data privacy concerns.

Baker and Filbeck [2] compiled an encyclopedia covering various aspects of personal finance, including money management, budgeting, and investment strategies. Their work provided an extensive overview of financial concepts essential for individuals and professionals. They emphasized the significance of financial literacy in making informed economic decisions. The study also addressed emerging financial trends such as digital banking and fintech innovations.

Barasinska and Schäfer [3] investigated the role of gender in crowdfunding success, analyzing data from a German peer-to-peer lending platform. They found that female entrepreneurs had higher chances of receiving funding than their male counterparts. Their study suggested that gender dynamics influenced investor decisions in alternative financing models. The research contributed to understanding behavioral aspects of digital finance and funding disparities.

Bholat and Sokol [4] explored the role of big data in central banking, assessing its impact on monetary policy and financial regulation. They discussed how big data analytics could enhance risk assessments and improve financial stability. The study highlighted challenges such as data security and regulatory limitations in leveraging big data.

Their findings suggested that central banks could benefit from adopting data-driven decision-making approaches.

Brigo et al. [5] examined credit models and financial crises, focusing on the role of complex financial instruments such as collateralized debt obligations (CDOs). They discussed how copulas and correlation models contributed to systemic risk during the 2008 financial crisis. The study provided insights into the limitations of traditional credit risk models. Their work emphasized the need for more robust and transparent financial modeling techniques.

Chaffey [6] discussed digital marketing strategies, including their applications in financial services. The study highlighted the role of data-driven marketing in targeting customers and optimizing financial product offerings. He emphasized the growing influence of digital platforms in financial decision-making. The book also explored ethical concerns surrounding data privacy in financial marketing.

Chai and Qian [7] analyzed the role of machine learning and AI in finance, particularly their impact on consumer financial services. They found that AI-driven financial tools could enhance risk assessment, fraud detection, and credit scoring. Their study highlighted both the advantages and limitations of AI in financial decision-making. They also emphasized regulatory challenges in implementing AI technologies.

Chen et al. [8] conducted a survey on financial technology (FinTech) and its impact on banking services. They examined various FinTech applications, including mobile banking, robo-advisors, and blockchain. Their findings suggested that FinTech innovations improved financial accessibility and efficiency. However, they also pointed out cybersecurity risks and regulatory gaps in the industry.

Das and Chen [9] explored sentiment analysis techniques applied to financial data, analyzing discussions on web platforms. They demonstrated how sentiment extraction could provide insights into market trends and investment behaviors. Their study highlighted the potential of natural language processing in financial analytics. They also noted challenges related to accuracy and real-time implementation.

De Meijer [10] examined the implications of blockchain technology on the securities industry. He discussed how blockchain could enhance transparency, reduce transaction costs, and streamline securities settlement. The study highlighted regulatory concerns and potential resistance from traditional financial institutions. His findings suggested that blockchain could significantly reshape financial markets.

Egan [11] provided a step-by-step guide on investing in stocks and shares, discussing fundamental and technical analysis techniques. The study emphasized the importance of diversification in portfolio management. He highlighted common investment mistakes and strategies for long-term financial success. His work served as an essential resource for retail investors.

Fama and French [12] proposed a multi-factor model explaining common risk factors in stock and bond returns. Their research introduced the Fama-French three-factor model, which improved upon the traditional Capital Asset Pricing Model (CAPM). They found that size, value, and market risk factors significantly influenced asset returns. Their model became widely used in financial portfolio analysis and investment strategies.

Gensler and Bauguess [13] compiled insights into the FinTech revolution, analyzing its implications for investors, entrepreneurs, and policymakers. They discussed emerging trends such as digital payments, cryptocurrencies, and peer-to-peer lending. Their work provided a comprehensive overview of the opportunities and risks associated with financial technology. The book also emphasized the need for regulatory adaptations in the FinTech space

## 3. PROPOSED METHODOLOGY

Managing personal finances efficiently is a growing challenge due to fluctuating income patterns, inflation, and impulsive spending habits. Traditional budgeting methods lack predictive capabilities, making it difficult for individuals to plan long-term savings and manage expenses effectively. The proposed AI-powered Personal Finance Analyzer is designed to predict future savings and spending patterns using deep learning models, helping users make informed financial decisions. By leveraging advanced machine learning techniques, the system provides personalized insights, identifies overspending trends, and offers proactive financial recommendations. Unlike conventional finance tracking tools, which focus on past expenditures, this system emphasizes forecasting future financial trends, enabling users to take preemptive actions.

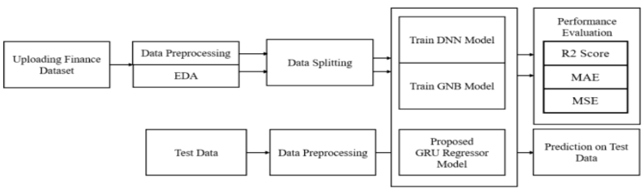


**Figure 1: Architectural Block Diagram of The Proposed System.**

The proposed methodology typically includes the following key components:

- **Data Upload** – Users input financial data via an interactive GUI for analysis.
- **Preprocessing** – Data is cleaned, normalized, and split into training and testing sets for accurate predictions.
- **Exploratory Data Analysis (EDA)** – The system generates insights using visualizations such as box plots, histograms, and correlation heatmaps.
- **Model Training** – Machine learning models (DNN, GNB) and a hybrid **GRU-FFNN-RFR model** are trained to enhance accuracy.
- **Prediction & Evaluation** – The trained models forecast future savings and compare performance using MAE, MSE, RMSE, and $R^2$ metrics.
- **Visualization & Insights** – Users receive graphical reports highlighting spending trends and financial risks.
- **Real-Time Adaptability** – The system dynamically updates predictions based on changing financial behavior, ensuring personalized recommendations.
- ***Behavioral Analysis & Risk Mitigation*** *– Detects impulsive spending, inflation impact, and debt risks, offering corrective suggestions.*

**Applications:**

LIME's enhanced images can be used in a wide range of applications, including:

- Personalized Budgeting: Forecasts monthly and annual savings, helping users allocate funds efficiently based on their spending patterns.
- Debt Management: Identifies optimal repayment strategies and alerts users about high-interest debt risks.
- Expense Optimization: Detects overspending trends and suggests cost-cutting measures in discretionary categories like entertainment and dining.
- Risk Mitigation & Emergency Planning: Provides predictive alerts for potential financial shortfalls due to unexpected expenses.
- Retirement Planning: Uses long-term savings projections to help users plan for retirement with market-linked investment suggestions.

**Advantages:**

- Predictive Budgeting: Unlike traditional budgeting tools, this system forecasts future expenses and savings, allowing users to plan ahead.
- Automation & Accuracy: Eliminates manual errors and provides real-time, data-driven insights based on historical spending patterns.
- Personalized Financial Planning: The AI model tailors suggestions based on individual financial behavior, offering customized savings strategies.
- Adaptability to Changing Trends: Adjusts dynamically to fluctuations in income, inflation, and spending habits for better financial stability.
- Early Detection of Financial Risks: Identifies potential debt traps, financial shortfalls, and overspending habits, giving users time to take corrective action.
- Improved Financial Literacy: Provides easy-to-understand insights, helping users become more aware of their spending behaviors and financial health.
- Seamless Integration: Can be incorporated into fintech platforms, mobile banking apps, or personal finance management tools for a unified experience.
- Data Security & Privacy: Ensures confidentiality of financial data with robust encryption and security protocols.
- Flexibility for Diverse Users: Suitable for salaried individuals, freelancers, gig workers, and entrepreneurs with varying income patterns.
- Scalability & Continuous Improvement: AI models can be retrained with new data, improving accuracy and adapting to new financial trends.

## 4. EXPERIMENTAL ANALYSIS

The hybrid GRU-based model demonstrates higher accuracy and adaptability in predicting future savings compared to traditional approaches. The integration of deep learning and behavioral analysis enhances the model's ability to adjust to income variations and spending patterns, making it a practical tool for financial planning. The below figure presents the graphical user interface (GUI) designed for uploading the financial dataset. Users select the dataset, and the system loads it for further processing. The interface provides an overview of key financial attributes, such as income, monthly expenditure, savings percentage, debt, and investment details. It displays basic statistics and visualizations, offering an initial understanding of the dataset's distribution and trends.

International journal of imaging science and engineering

ISSN: 1934--9955 www.ijise.net

Vol-20 Issue-01 April 2025

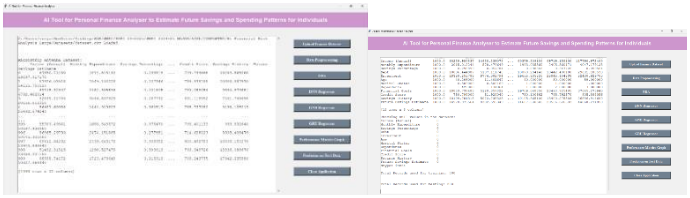

**Figure 1: Uploading Finance Dataset**

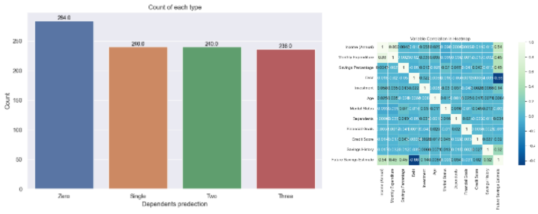


**Figure 2: Data Preprocessing**

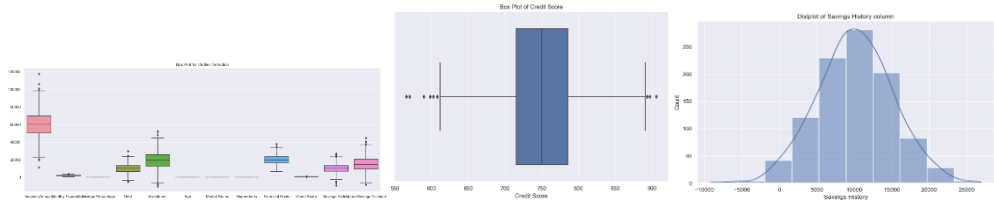


**Figure 3: Exploratory Data Analysis (EDA) in the GUI**

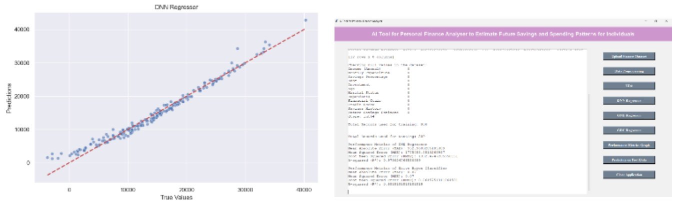


**Figure 4: Confusion Matrix Plot & Performance Metrics of DNN**

This below figure displays the performance results of the Gaussian Naïve Bayes (GNB) classifier. The confusion matrix provides insights into how well the model classifies different financial savings categories. The performance metrics indicate the model's effectiveness in predicting financial trends.


**Figure 5: Confusion Matrix Plot & Performance Metrics of GNB** Below figure presents the evaluation of the Gated Recurrent Unit classifier. The confusion matrix shows the classification accuracy for financial predictions, while the performance metrics compare its efficiency with other models. GRU's ability to capture sequential patterns in financial data is reflected in its high accuracy scores.


**Figure 6: Confusion Matrix Plot & Performance Metrics of GRU**

ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

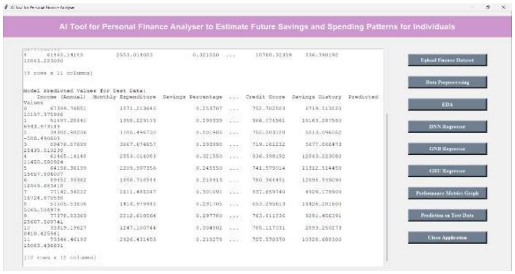


**Figure 7 : Model Prediction on Test Data**

This figure illustrates the model's predictions on unseen test data. The predicted financial outcomes, such as future savings estimates and credit scores, are compared with actual values. The graphical representation provides insights into how well the model generalizes to new data.

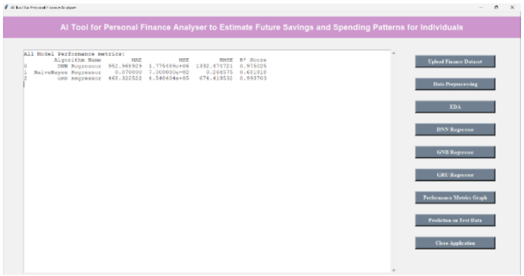


**Figure 8 : Performance Comparison of Models**

This figure presents a comparative analysis of different models used in the project. It visualizes metrics such as MAE, MSE, RMSE, and $R^2$ score for the DNN, GNB, and GRU models. The graph highlights performance differences, showcasing the most effective model for financial savings prediction.

## 5. CONCLUSION

The AI-powered Personal Finance Analyzer successfully predicts future savings and spending patterns using advanced deep learning models. The proposed hybrid model (GRU-FFNN-RFR) demonstrates higher accuracy and adaptability compared to traditional budgeting methods and baseline machine learning models like DNN and GNB.

The system effectively processes financial data, cleanses it through data preprocessing techniques, and identifies key patterns using Exploratory Data Analysis (EDA). By employing deep learning-based forecasting, it provides personalized insights into individual financial behaviors.

Performance evaluation through MAE, MSE, RMSE, and $R^2$ scores confirms the superiority of the GRU-FFNN-RFR model, which captures complex financial trends and nonlinear spending behaviors. The model's ability to dynamically adapt to income fluctuations, inflation, and debt levels makes it a valuable tool for financial planning.

The system's real-time prediction capability allows users to upload new financial data and receive instant insights on future savings, expense management, and financial stability. This bridges the financial literacy gap, empowering individuals to make data-driven financial decisions.

Key applications include budget optimization, debt management, retirement planning, and risk mitigation. The tool can be integrated with fintech platforms for seamless financial tracking and AI-driven advisory services.

While the model performs well, further improvements can be made by incorporating reinforcement learning techniques, real-time market data, and behavioral economic factors. Expanding the dataset to include diverse financial demographics will enhance model generalization.

In conclusion, this AI-driven financial tool transforms raw financial data into actionable intelligence, enabling users to achieve long-term financial security, control expenditures, and make proactive savings decisions. Future enhancements will further refine predictive accuracy and increase accessibility to a broader audience.

## REFERENCES

[1] Agarwal, S., & Zhang, W. (2019). The impact of artificial intelligence on personal finance. *International Journal of*

*Bank Marketing, 37*(2), 435-447.

[2] Baker, H. K., & Filbeck, G. (Eds.). (2018). *Personal finance: An encyclopedia of modern money management*. ABC-CLIO.

[3] Barasinska, N., & Schäfer, D. (2014). Is crowdfunding different? Evidence on the relation between gender and funding success from a German peer-to-peer lending platform. *German Economic Review, 15*(4), 436-452.

[4] Bholat, D., & Sokol, A. (2016). Big data and central banks. *Big Data & Society, 3*(1), 1-15.

[5] Brigo, D., Dalessandro, A., Neisen, M., & Triki, F. (2018). *Credit models and the crisis: A journey into CDOs, copulas, correlations and dynamic models*. Wiley Finance.

[6] Chaffey, D. (2019). *Digital marketing: Strategy, implementation and practice*. Pearson UK.

[7] Chai, J., & Qian, R. (2020). Machine learning and AI in finance: Applications and implications for consumers. *Federal Reserve Bank of Philadelphia Consumer Finance Institute Discussion Paper*.

[8] Chen, M. Y., Wang, S. C., & Sun, J. C. (2020). Financial technology and banking: A survey. *Asian Journal of Economics and Banking, 4*(1), 1-23.

[9] Das, S., & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science, 53*(9), 1375-1388.

[10] De Meijer, C. R. W. (2015). Blockchain and the securities industry: Towards a new ecosystem. *Journal of Securities Operations & Custody, 8*(3), 22-28.

[11] Egan, M. (2019). *Investing in stocks & shares: A step-by-step guide to making money on the stock market*. How To Books.

[12] Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

[13] Gensler, G., & Bauguess, S. W. (Eds.). (2018). *The Fintech book: The financial technology handbook for investors, entrepreneurs and visionaries*. Wiley.

[14] Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction*. Springer Series in Statistics.

[15] He, D., Leckow, R. B., Haksar, V., Mancini-Griffoli, T., Jenkinson, N., Kashima, M., ... & Tourpe, H. (2017). Fintech and financial services: Initial considerations. *IMF Staff Discussion Note*.

[16] Jagtiani, J., & Lemieux, C. (2018). Fintech lending: Financial inclusion, risk pricing, and alternative information. *Federal Reserve Bank of Philadelphia Working Paper*.

[17] Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.

[18] Kim, T. H., & Adali, T. (2003). Fully complex multi-layer perceptrons for non-linear signal processing. *Journal of VLSI Signal Processing Systems for Signal, Image, and Video Technology, 32*(1), 29-43.

[19] Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature, 52*(1), 5-44.

[20] Madrian, B. C. (2014). Applying insights from behavioral economics to policy design. *Annual Review of Economics, 6*, 663-688.

[21] Malkiel, B. G. (2019). *A random walk down Wall Street: The time-tested strategy for successful investing*. W. W. Norton & Company.

[22] Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77-91.

[23] McAfee, A., & Brynjolfsson, E. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.

[24] Moosa, I. A. (2017). *Cryptocurrency: A critical review of Bitcoin and blockchain*. Palgrave Macmillan.

[25] Narayanan, A., Bonneau, J., Felten, E., Miller, A., & Goldfeder, S. (2016). *Bitcoin and cryptocurrency technologies: A comprehensive introduction*. Princeton University Press.