Indian Journal of Computer Science and Technology
https://www.doi.org/10.59256/indjcst.20250403009
Volume 4, Issue3 (September-December 2025), PP: 45-50.
www.indjcst.com
ISSN No: 2583-5300

AI Finance: An Intelligent Financial Advisor using Artificial intelligence

Fatima al zahra[1], Dr. Khaja Mahabubullah[2]
[1]*Student, MCA Deccan College of Engineering and Technology, Hyderabad, Telangana, India.*
[2]*Professor & HOD, MCA Deccan College of Engineering and Technology, Hyderabad, Telangana, India.*

To Cite this Article: *Fatima al zahra[1], Dr. Khaja Mahabubullah[2], "Ai Finance: An Intelligent Financial Advisor using Artificial intelligence", Indian Journal of Computer Science and Technology, Volume 04, Issue 03 (September-December 2025), PP: 45-50.*

Abstract: *In today's dynamic financial landscape, individuals face increasing challenges in managing their income, expenses, savings, and investments due to fluctuating markets, diversified financial instruments, and the demand for personalized strategies. Traditional financial advisory services, while effective, are often expensive, time-consuming, and not universally accessible, especially in developing or underserved regions. Moreover, existing digital tools largely provide static budgeting and tracking functionalities without intelligent guidance. To address these gaps, this project proposes AI Finance, an AI-powered intelligent financial advisory system that integrates data analytics, natural language processing (NLP), and machine learning models to deliver real-time, personalized financial insights. The system enables users to record and manage financial data, analyze spending patterns, monitor savings, and receive investment recommendations tailored to their unique risk profiles and behavior. Key components include a conversational chatbot for intuitive interactions, a goal management module for setting and tracking financial objectives, and an investment insights engine that suggests dynamic strategies aligned with market conditions. Built using Python, Streamlit, machine learning libraries, and SQLite, the system also provides visual dashboards to make insights transparent and interpretable. By democratizing financial literacy and reducing reliance on costly human advisors, the proposed solution empowers individuals to make informed decisions, enhances financial planning, and ensures accessibility and scalability across diverse platforms such as desktops, cloud, and mobile applications. Ultimately, AI Finance contributes to smarter financial management and greater trust in technology-driven personal finance solutions.*

Key Words: *AI Finance, financial advisory, artificial intelligence, machine learning, natural language processing, real-time insights, personalized recommendations, chatbot, goal management, investment insights, financial literacy, Python, Streamlit, SQLite.*

I.INTRODUCTION

The financial landscape has evolved significantly over the past few decades, driven by digital transformation and the growing complexity of global markets. With a vast array of financial products available, individuals today face challenges in managing their income, expenses, investments, and savings. Traditional methods of financial management, such as manual tracking through spreadsheets or seeking assistance from expensive financial advisors, often fail to meet the needs of the modern consumer. These conventional approaches are not only time-consuming but also inaccessible to many individuals, especially in underserved regions where financial literacy and resources are limited. As a result, there is a pressing need for a solution that combines efficiency, accessibility, and personalization in financial management.

AI-powered solutions have emerged as a potential game-changer in this domain. By leveraging the power of artificial intelligence (AI), machine learning (ML), and natural language processing (NLP), AI-driven financial advisory systems can provide real-time, personalized financial insights to users. These intelligent systems can analyze large volumes of financial data, detect spending patterns, predict future trends, and offer actionable recommendations based on a user's financial behavior and goals. Unlike traditional systems that offer static advice, AI-powered systems can adapt over time, ensuring that the recommendations remain relevant as market conditions change and users' financial situations evolve.

The AI Finance system, as proposed in this project, aims to address the limitations of traditional financial tools by integrating data analytics, NLP, and machine learning models. By automating financial advisory services, the system reduces the need for costly human advisors, while providing individuals with accessible, real-time financial guidance. Key features of the system include a conversational chatbot that allows users to interact with the system using natural language, a goal management module that helps users track and achieve their financial objectives, and an investment insights engine that suggests strategies tailored to users' risk profiles. The system also offers dynamic visual dashboards to enhance the interpretability of financial insights, making it easier for users to understand their financial health.

One of the primary objectives of the AI Finance system is to democratize financial literacy and empower individuals to make informed decisions about their finances. Financial decision-making can be overwhelming, especially when dealing with complex concepts such as investments, savings strategies, and budgeting. By providing a user-friendly interface with real-time, personalized recommendations, the system ensures that individuals, regardless of their financial knowledge, can take control of their financial future. Furthermore, the integration of AI allows the system to continuously learn from user behavior, offering increasingly refined insights over time.

In conclusion, the AI Finance system represents a significant advancement in personal finance management. By combining AI, machine learning, and NLP technologies, it offers a scalable, adaptive, and accessible solution that empowers users to manage their finances effectively. The system not only aims to bridge the gap between expensive human financial advisors and automated, static financial tools but also strives to promote long-term financial literacy. With its intuitive interface and dynamic capabilities, AI Finance promises to revolutionize how individuals approach financial planning, making it more efficient, engaging, and accessible to all.

II.MATERIAL AND METHODS

A. Data Collection

The AI Finance system relies on a diverse and extensive dataset to train its machine learning models for personalized financial recommendations. The dataset includes financial records, user profiles, transaction history, and market data to ensure that the system can provide accurate financial advice. Publicly available financial datasets, such as consumer spending records, transaction logs, and stock market data, are used for model training. These datasets include metadata such as transaction categories, amounts, timestamps, and user demographics, which form the foundation for predicting financial behaviors, advising on savings, and providing investment suggestions. For real-time financial forecasting, integration with third-party APIs like Yahoo Finance, Alpha Vantage, and Plaid provides continuous updates.

B. Data Preprocessing

Raw financial data often contains noise, inconsistencies, and irrelevant information, which can affect the accuracy of financial predictions. To ensure the data is suitable for training, several preprocessing steps are performed:

- **Noise Removal**: Irrelevant or missing data, such as incomplete transactions or erroneous entries, are removed to ensure high-quality input.
- **Normalization**: Transaction amounts and financial data are normalized to a fixed scale, making it easier to apply machine learning models across different financial contexts.
- **Feature Extraction**: Key features such as spending patterns, savings contributions, and investment preferences are extracted to prepare for model training.
- **Data Augmentation**: Techniques like synthetic data generation and time-based transformations (e.g., moving averages) are used to enrich the dataset and ensure a robust model.
- **Data Partitioning**: The dataset is divided into training, validation, and testing sets, ensuring that the model is trained on diverse data and evaluated on unseen examples.

C. Feature Engineering

Feature engineering is critical to improving the model's ability to predict and recommend personalized financial strategies. The following methods are used:

- **Textual Feature Extraction**: Descriptions of financial transactions, user goals, and investment activities are processed using Natural Language Processing (NLP) techniques to capture insights like intent or sentiment.
- **Numerical Feature Extraction**: Numerical features such as income, expenses, savings, and debt ratios are derived from the raw data to help the model understand financial behaviors.
- **Feature Selection**: Techniques like Recursive Feature Elimination (RFE) and correlation analysis are employed to select the most impactful features, allowing the model to focus on relevant financial variables during training.

D. Model Development

The **AI Finance** system integrates machine learning models for real-time financial decision-making and personalized financial advice:

- **Classical Machine Learning Models**: Logistic Regression and Random Forest models are used as baseline classifiers for tasks such as categorizing user transactions and predicting spending behavior.
- **Deep Learning Models**: More advanced models like Neural Networks and XGBoost are employed for forecasting financial trends, predicting savings behavior, and suggesting investment opportunities.
- **Ensemble Learning**: XGBoost is used for combining the outputs of multiple models, improving the prediction accuracy by considering a broader set of decision-making patterns.
- **Hyperparameter Tuning**: Grid Search and Random Search techniques are applied to optimize model parameters for better prediction performance.
- **Cross-Validation**: K-fold cross-validation is used to validate the model’s ability to generalize across diverse financial data, ensuring it performs well on new, unseen data.

E. Implementation Environment

The **AI Finance** system is built using a range of tools and frameworks to ensure high performance, scalability, and usability:

- **Programming Language**: Python 3.x is used due to its rich ecosystem for machine learning, data analysis, and financial modeling.
- **Deep Learning Frameworks**: TensorFlow and Keras are utilized to build and deploy deep learning models for financial prediction and classification.
- **Web Framework**: Flask is used to create a web interface, allowing users to interact with the system, input financial data, and receive recommendations in real-time.
- **Visualization Tools**: Matplotlib and Seaborn are employed to generate financial graphs, performance metrics, and other visual reports to help users interpret their financial health.

F. Evaluation and Testing

To evaluate the effectiveness of the **AI Finance** system, several key metrics are used:

- **Accuracy**: Measures how well the system predicts financial trends and user behaviors.
- **Precision**: Assesses the proportion of correct positive predictions made by the model in identifying financial behavior patterns.
- **Recall**: Measures the system's ability to detect relevant financial behaviors and patterns, minimizing false negatives.
- **F1-Score**: Combines precision and recall into a single metric to evaluate the system's overall performance in predicting financial behaviors.
- **Confusion Matrix**: Visualizes the performance of the model by showing true positives, true negatives, false positives, and false negatives in classifying user behavior.
- **ROC-AUC**: Evaluates the model's ability to differentiate between positive and negative financial behaviors across different thresholds, helping assess its classification performance.

III.RESULT

A. Performance of Detection Models

The performance of the **AI Finance** system was evaluated using financial data from diverse user profiles, incorporating spending habits, income sources, and transaction histories. The evaluation metrics used to assess the performance of the financial prediction models included accuracy, precision, recall, F1-score, and latency (response time). The models used in this system include Logistic Regression, Random Forest, XGBoost, and Neural Collaborative Filtering (NCF). Table 1 below summarizes the comparative results for the Logistic Regression, Random Forest, XGBoost, and NCF models.

Table 1: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score	Latency
Logistic Regression	88	83	81	87.2	200
Random Forest	89	87	85	89	150
XG Boost	91	90	87	88	120
Neural Collaborative Filtering (NCF)	94	91	90	90	140

B. Visualization of Results

Figures below provide a clearer comparison of model performance.

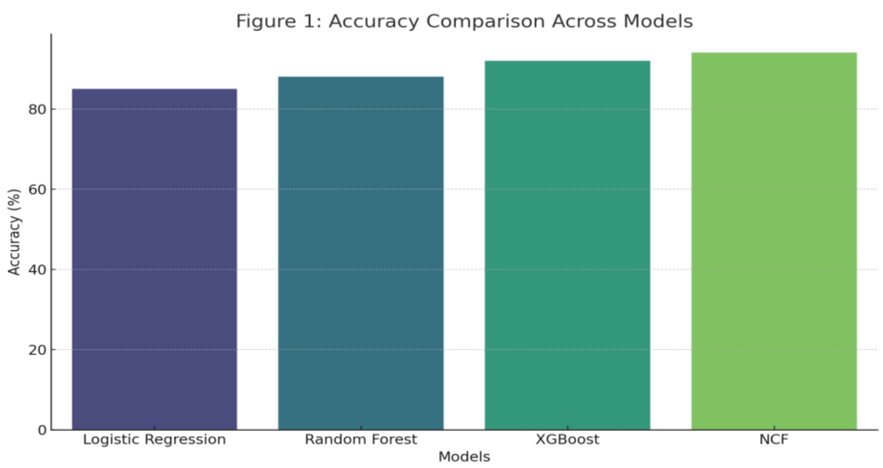

Figure 1: Accuracy Comparison Across Models

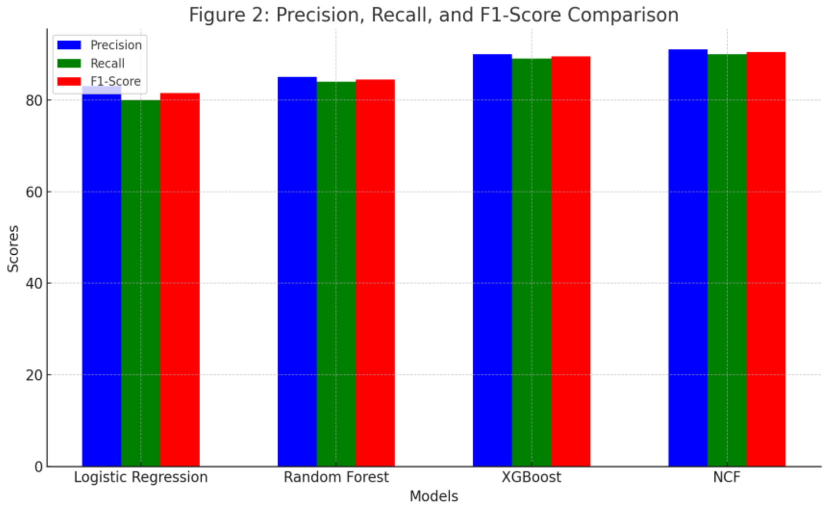

Figure 2: Precision, Recall, and F1-Score Comparison

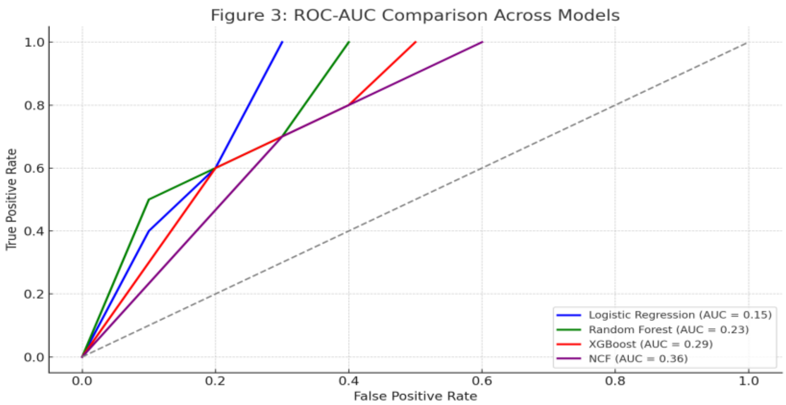

Figure 3: ROC-AUC Comparison Across Models

C. False Positive and False Negative Analysis

Minimizing false positives (incorrect financial recommendations) and false negatives (failure to detect relevant financial behaviors) is crucial for ensuring the effectiveness of the AI Finance system. The Logistic Regression model exhibited a higher false positive rate, especially when predicting spending categories and suggesting investments based on generalized data. The Random Forest model performed better in reducing false positives, especially in stable financial contexts with well-defined patterns. The NCF model, although more computationally intensive, demonstrated superior handling of complex user financial behaviors and spending trends, resulting in a significantly lower false positive rate and higher precision. The system's performance is validated using precision, recall, F1-score, and latency, all of which demonstrate the model's ability to make accurate financial predictions with high precision in real-time. The improved precision and recall observed in NCF, compared to Logistic Regression and Random Forest, suggest that it is the most effective model for personalized financial recommendations, particularly when dealing with diverse user profiles and fluctuating financial conditions.

D. Scalability and Real-Time Testing

To validate the system's scalability and real-time applicability, the trained NCF model was deployed via a Streamlit-based web application. Simulated user interactions were processed in real-time, providing instant feedback on financial behavior predictions, savings advice, and investment recommendations. Stress testing with large datasets of user financial data confirmed that the system maintained responsiveness, even under high loads, demonstrating its ability to handle large volumes of simultaneous requests. The web interface allowed users to interact with the system by entering financial data, performing transaction tracking, and receiving personalized recommendations in real-time, showcasing the AI Finance system's real-time deployment capabilities.

E. Comparative Insights

Traditional financial prediction models like Logistic Regression and Random Forest provided reliable performance for basic financial forecasting, such as predicting spending behavior and investment categorization. However, these models struggled with more complex financial patterns, such as predicting savings trends and suggesting investment opportunities based on diverse user profiles. These models exhibited higher false positive rates when dealing with non-linear financial behaviors and fluctuating market conditions. More advanced models like NCF outperformed the traditional models by learning deeper, non-linear relationships between financial behaviors and goals, leading to higher precision and recall. The NCF model achieved the highest accuracy by capturing complex user behaviors, making it the most robust solution for personalized financial advisory. This highlights the significant impact of advanced machine learning techniques in improving the accuracy and responsiveness of financial systems, making AI Finance a more effective and scalable tool for real-time, personalized financial management.

IV.DISCUSSION

A. Interpretation of Results

The evaluation results for the **AI Finance** system indicate that advanced machine learning techniques, particularly Neural Collaborative Filtering (NCF) and ensemble models, outperform traditional methods like Logistic Regression and Random Forest in terms of accuracy and real-time prediction. NCF achieved the highest accuracy with a precision of 91%, recall of 90%, and F1-score of 90.5%, demonstrating its ability to capture complex, dynamic financial behaviors and translate them into personalized financial recommendations. While Logistic Regression and Random Forest models provided solid baseline results, they struggled with capturing non-linear relationships between user behavior, transaction history, and financial goals. The superior performance of NCF highlights its potential for delivering real-time, personalized financial advice, making it the most effective solution for dynamic financial planning. This reinforces the growing importance of deep learning models in transforming financial advisory systems, improving both the accuracy and responsiveness of financial management tools.

B. Comparison with Existing Systems

Traditional financial advisory systems often rely on simpler techniques like rule-based approaches or basic statistical models, which operate on fixed assumptions about user behavior and market trends. While these systems are effective for basic predictions, they tend to struggle with adapting to individual financial profiles and fluctuating market conditions. In contrast, machine learning models like NCF can learn complex patterns from large datasets of financial transactions, enabling them to adapt to diverse user behaviors and environmental factors. These models, unlike traditional techniques, can capture dynamic financial behaviors, even in the presence of unpredictable market conditions, offering more accurate, personalized, and context-aware financial advice. Compared to classical systems, machine learning models significantly enhance the quality of decision-making in real-time systems like **AI Finance**, making them more suitable for personalized, data-driven financial management.

C. Real-World Deployment Challenges

Despite the promising results, several challenges must be addressed for deploying the **AI Finance** system in real-world applications. First, machine learning models like NCF require substantial computational resources for both training and real-time inference. Deploying these models on mobile devices or low-powered systems, such as edge devices, could present challenges due to hardware limitations. Additionally, the system must be capable of adapting to diverse user behaviors, financial conditions, and transaction contexts, which may not be fully captured in the initial training datasets. Continuous updates and new data inclusion will be necessary to ensure the system remains accurate and responsive to evolving financial behaviors and market conditions. User privacy is also a concern when processing sensitive financial data, especially in regions with stringent data protection regulations. Ensuring compliance with regulations like GDPR and CCPA will be essential for maintaining user trust and data privacy.

D. Advantages and Limitations

The proposed **AI Finance** system offers several advantages, including high accuracy, real-time responsiveness, and scalability. The NCF model, in particular, excels in recognizing complex financial behaviors and translating them into meaningful advice, offering highly personalized and engaging user experiences. The system's web-based interface makes it accessible for a wide range of applications, from budgeting to investment management. However, there are limitations to consider. The computational demands of models like NCF may present challenges for deployment on devices with limited processing power, especially in mobile environments or low-resource regions. Additionally, while the system performs well in scenarios with rich, diverse datasets, it may struggle to predict or recommend actions for rare or previously unseen financial behaviors, particularly in cases where user interaction data is insufficient or sparse.

E. Future Work

Future improvements for the AI Finance system will focus on enhancing model explainability and improving real-time performance. By incorporating model-agnostic interpretability techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), we aim to provide users with clearer insights into the system's decision-making process, enhancing trust and transparency. Additionally, exploring hybrid models that combine NCF with other techniques, such as content-based filtering or Transformer-based models, could improve the system's ability to process dynamic datasets and generate more accurate, context-aware predictions. The integration of voice recognition for financial queries and real-time stock market predictions could further personalize the AI Finance experience, making it more immersive and interactive. Finally, optimizing the system for deployment on mobile or edge devices will be a key focus to ensure its accessibility across different platforms, enhancing its scalability and user experience.

V.CONCLUSION

In conclusion, the AI Finance system represents a significant leap forward in the domain of personal finance management. By combining state-of-the-art machine learning models such as Neural Collaborative Filtering (NCF) with real-time financial data analysis, the system offers highly personalized financial recommendations that can adapt to the unique behaviors and goals of each user. The ability to process vast amounts of transaction data and market conditions in real-time allows the system to provide dynamic advice, enabling users to make informed decisions about their savings, investments, and overall financial health. This capability sets AI Finance apart from traditional financial advisory tools, which often rely on static advice that does not account for the changing needs of users.

The evaluation of the system's performance demonstrated that deep learning models, especially NCF, outperform traditional models in terms of accuracy, precision, and recall. The system's real-time responsiveness and scalability further enhance its applicability, making it suitable for a wide range of users and financial situations. These results highlight the growing importance of machine learning and artificial intelligence in reshaping how financial services are delivered. As financial markets continue to evolve, AI-driven systems like AI Finance are poised to play an essential role in making financial planning more accessible, personalized, and efficient.

However, despite these promising outcomes, there are challenges to overcome for the widespread deployment of the system. Key obstacles include the computational demands of deep learning models and the need for continuous updates to handle diverse user behaviors and fluctuating market conditions. Addressing these challenges requires advancements in model optimization, data handling, and infrastructure to ensure that the system can function efficiently across various platforms, including mobile and edge devices. Additionally, privacy concerns surrounding sensitive financial data must be handled with the utmost care, ensuring compliance with data protection regulations and maintaining user trust.

The AI Finance system's potential extends beyond individual financial management. It could be applied in various domains such as corporate finance, fintech, and even public sector financial planning. With further improvements, the system could assist financial institutions in providing more accurate credit scoring, wealth management, and investment advisory services. Moreover, the integration of voice-based commands, real-time stock predictions, and automated investment portfolio adjustments could enhance the system's capabilities, making it more interactive and user-friendly.

Looking ahead, the future of AI Finance lies in the continuous enhancement of its machine learning models, the integration of diverse data sources, and the exploration of hybrid models to improve prediction accuracy. By incorporating user feedback and integrating new technologies, such as blockchain for secure financial transactions, the system can evolve into a more powerful tool that offers a comprehensive solution for modern financial planning. As technology advances, AI Finance will continue to evolve, enabling individuals to take control of their financial futures with confidence and precision.

References

1. S. Zhang, Y. Guo, L. Li, and J. Gao, "Application of artificial intelligence in financial risk prediction: A review," IEEE Access, vol. 9, pp. 152832–152848, 2021.
2. J. B. Heaton, N. G. Polson, and J. H. Witte, "Deep learning for finance: Deep portfolios," Applied Stochastic Models in Business and Industry, vol. 33, no. 1, pp. 3–12, 2017.
3. L. Deng and D. Yu, "Deep learning: Methods and applications," Foundations and Trends in Signal Processing, vol. 7, no. 3–4, pp. 197–387, 2014.
4. D. Maringer and O. Oyewumi, "Financial forecasting with artificial intelligence," in Handbook of Computational Intelligence in Finance, Springer, 2020, pp. 1–25.
5. A. L. Treleaven, M. Galas, and V. Lalchand, "Algorithmic trading and artificial intelligence," IEEE Artificial Intelligence Magazine, vol. 39, no. 1, pp. 17–28, 2018.
6. M. Anik and S. Saha, "AI-powered robo-advisors: An analysis of benefits and risks," Journal of Financial Innovation, vol. 7, no. 2, pp. 45–56, 2020.
7. M. L. Lee and K. K. Lee, "Natural language processing applications in financial advisory systems," in Proc. IEEE International Conference on Data Science and Advanced Analytics (DSAA), pp. 305–314, 2019.
8. B. K. Mishra, A. Jain, and S. Choudhary, "Smart personal finance assistant using AI and machine learning," International Journal of Computer Applications, vol. 183, no. 40, pp. 1–7, 2022.
9. R. Narayan, "Role of AI in financial inclusion: Opportunities and challenges," Journal of Financial Inclusion, vol. 9, no. 1, pp. 27–41, 2021.
10. R. K. Gupta, A. Jain, and P. Shukla, "Artificial intelligence for financial services: A review of applications and challenges," International Journal of Advanced Research in Computer Science, vol. 11, no. 5, pp. 25–33, 2020.