

AI-Driven Personal Finance Management: Predictive Expense Forecasting and Behavioural Clustering

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ABSTRACT

Financial planning and expense management have become increasingly essential as individuals struggle to monitor daily spending, interpret financial behavior, and plan future investments effectively. With the rapid growth of digital transactions and diverse expenditure categories, manual financial tracking becomes complex, time-consuming, and prone to errors. Traditional financial management systems, such as spreadsheets and basic budgeting tools, allow users to store transaction data but lack advanced analytical capabilities, making accurate prediction of future expenses difficult and leading to inefficient financial decisions. To address these limitations, the proposed system introduces an intelligent financial prediction and analysis platform developed using the Django framework with a MySQL (Structured Query Language-based relational database management system) database for secure data storage and management. The system incorporates email-based One-Time Password (OTP) authentication using the Simple Mail Transfer Protocol (SMTP) to ensure secure and verified user access. A Long Short-Term Memory (LSTM) deep learning model is utilized to analyze historical financial data and predict future expenses by capturing temporal patterns and trends. Additionally, K-Means clustering is applied to group expenses into different categories, enabling users to better understand their spending behavior and identify financial patterns. The system further integrates sentiment analysis using VADER (Valence Aware Dictionary and Sentiment Reasoner) to evaluate user feedback and classify it as positive, negative, or neutral, supporting continuous system improvement. By combining predictive modeling, clustering techniques, sentiment evaluation, and secure authentication mechanisms, the system provides automated financial insights, personalized recommendations, and enhanced decision-making support, helping users manage finances more efficiently.

Key words: Financial Prediction, Expense Analysis, Sentiment Analysis, Machine Learning, Deep Learning, Django Web Framework.

1. INTRODUCTION

Anticipating future outcomes has become an essential capability across multiple economic domains, particularly for shaping decisions at both local and regional governance levels [1]. Within the business environment, especially in wholesale and retail trade, the projection of financial measures plays a central role in guiding operational and strategic actions, including production scheduling, sales planning, and inventory control. This sector is uniquely complex due to fluctuating consumer preferences, pronounced seasonal demand patterns, and the impact of external forces such as economic conditions and political developments [2]. Despite these challenges, estimating key financial metrics—such as revenue streams, expenditure levels, and overall profitability—is fundamental for designing effective corporate strategies, sustaining long-term growth, and maintaining competitive positioning. In particular, profit estimation supports efficient cash flow

management, liquidity planning, and performance evaluation, making it an indispensable component of financial decision-making in retail-oriented enterprises.

To predict the future trajectory of financial variables, as shown in Fig. 1, it is necessary to analyze their historical progression over time. In certain technical fields, such behavior is often modeled using mathematical formulations like partial differential equations. However, when sufficiently large datasets are available in economic contexts, advanced analytical methods—especially those based on time series modeling—can be employed to capture patterns and forecast future values. The growing reliance on historical time series information highlights its importance as a predictive foundation in modern analytics [3]. Such data enables organizations to anticipate upcoming trends and make informed decisions about revenues, costs, and profit, which are vital for effective planning and operational success in retail businesses [4].



Fig. 1: Finance Management

Revenue forecasting, in particular, serves as a cornerstone for cross-functional decision-making: finance teams can estimate profitability and funding needs, sales units can evaluate demand levels, procurement departments can optimize purchasing strategies, marketing teams can assess campaign effectiveness, and logistics divisions can align supply chain operations accordingly. Moreover, accurate projections of sales and expenses can assist investors in predicting fluctuations in retail stock performance. Profit, defined as the surplus remaining after deducting direct costs from total revenue, acts as a key indicator of financial health and enables comparisons across competing firms [5]. Therefore, reliable profit forecasting is instrumental in supporting strategic choices and ensuring sustained financial stability.

1.1 Problem Definition

The central challenge in personal financial management is transforming voluminous, raw transaction data into accurate, actionable, and personalized insights regarding future financial status. Users typically struggle with two key aspects, accurately predicting future expenses given non-linear trends, seasonal variations, and irregular large payments traditional methods often fail to capture the complex temporal dependencies inherent in spending habits. Understanding how and why money is spent, beyond simple category totals. Users need to identify underlying spending patterns, detect anomalies, and link their qualitative financial feelings to quantitative expense data.

2. LITERATURE SURVEY

Shiyyab et al. [6] proposed an AI disclosure index to quantitatively evaluate the extent of AI adoption within financial institutions and to analyze its relationship with financial performance. The study

emphasizes that transparent reporting of AI usage enhances stakeholder confidence and supports better governance practices. By systematically measuring disclosure levels, the research provides insights into how organizations communicate their AI integration strategies and highlights the importance of standardized disclosure frameworks. It further supports policymakers and regulatory authorities in formulating guidelines that ensure accountability, transparency, and ethical deployment of AI systems in the banking sector. Yaseen, et al. [7] investigated the role of transparency, fairness, and trust in influencing the adoption of AI technologies within financial environments. The study demonstrates that transparency acts as a primary driver of trust, which directly impacts user acceptance of AI systems. It also shows that fairness perception plays a critical role in mitigating concerns related to algorithmic bias, thereby improving system credibility. Additionally, the research identifies variations in adoption readiness across different professional groups and regions, highlighting the influence of experience and exposure to AI. The findings emphasize that regulatory compliance and the development of explainable and unbiased AI models are essential for fostering adoption in highly regulated financial sectors. El Hajj, et al. [8] utilized a mixed-methods approach combining quantitative surveys and qualitative analysis to assess the adoption of AI and ML in financial markets. The study identifies widespread use cases such as algorithmic trading, fraud detection, credit scoring, and customer service automation. It also explores challenges including regulatory compliance, ethical concerns, workforce transformation, and data privacy issues. The findings emphasize the need for continuous skill development and organizational adaptation to fully leverage AI technologies in finance.

Aleksandrova, et al. [9] conducted a comprehensive review of AI adoption across finance, insurance, and financial controlling, focusing on the economic implications and technological advancements in these sectors. The study identifies key trends such as increased automation, enhanced predictive analytics, and improved risk assessment capabilities. It also highlights challenges including regulatory constraints, implementation costs, and skill gaps. By analyzing existing literature, the authors establish a strong relationship between AI integration and the evolution of financial systems, emphasizing its role in driving efficiency and innovation. Yang, et al. [10] explored the behavioral and perceptual factors influencing the adoption of GenAI in financial advisory services. The study developed a research framework based on SDL and AIDUA models to examine how personalization, human-like empathy, and continuous learning capabilities of AI systems affect user trust and acceptance. The findings reveal that users are more likely to adopt AI-generated financial advice when it demonstrates contextual understanding and adaptive responses. The study also highlights the importance of perceived authenticity and usefulness in shaping user attitudes toward AI-driven financial decision support systems. Shaban, et al. [11] investigated the relationship between AI-driven financial transparency and corporate governance using quantitative techniques such as SEM and regression analysis. Based on data collected from corporate professionals, the study demonstrates that AI significantly enhances governance effectiveness, improves risk management practices, and increases stakeholder engagement. It also highlights AI's role in automating compliance processes, while acknowledging challenges such as algorithmic bias, data privacy concerns, and the need for updated regulatory frameworks.

Artene, et al. [12] investigated the combined impact of AI, DT, and financial reporting systems on modern business environments, emphasizing how their integration enhances analytical capabilities and strategic decision-making. The study explains that organizations adopting AI-driven financial reporting can automate complex accounting processes, reduce human intervention, and improve accuracy in financial statements. It further highlights the role of neural networks in modeling complex

financial relationships, enabling pattern recognition, anomaly detection, and predictive analytics. The synergy between intelligent systems and DT initiatives is shown to create adaptive, data-driven ecosystems that improve transparency, operational efficiency, and long-term business value. Mhlanga, et al. [13] explored the impact of AI on digital financial inclusion through a conceptual and documentary review of scholarly and institutional sources. The study demonstrates that AI significantly enhances financial accessibility by improving risk assessment models, reducing information asymmetry, and enabling automated customer interaction through chatbots. It further emphasizes AI's role in strengthening fraud detection and cybersecurity mechanisms, thereby increasing trust and participation in digital financial systems, especially in underserved populations. Bayakhmetova, et al. [14] conducted an in-depth bibliometric analysis using Bibliometrix and Bibliophagy tools to map the intellectual structure of AI research in finance. Their findings reveal a strong upward publication trend with a 13.34% annual growth rate, indicating rapid expansion of the field. The study identifies dominant research clusters, including ML applications, financial inclusion strategies, and intelligent decision-support systems. Additionally, it highlights underexplored areas such as ethical AI design, regional inequalities in adoption, and limited deployment in low-resource environments, while also identifying leading journals and contributors shaping the research landscape. Liu, et al. [15] evaluated the capabilities of ChatGPT-4o in financial reasoning by designing structured, multi-step analytical tasks that simulate real-world financial problem-solving. The study benchmarks AI performance against human analysts using task-specific evaluation metrics, revealing that while the model performs effectively in structured reasoning and data interpretation, it faces limitations in handling highly complex or ambiguous financial scenarios. The research underscores the potential of conversational AI in financial analytics while also identifying areas requiring improvement.

3. PROPOSED SYSTEM

This research presents a comprehensive, data-centric framework designed to enable personalized expense prediction and intelligent investment guidance through advanced analytics and machine learning techniques, as illustrated in Fig. 2. The system is developed using the Django web framework and extends beyond conventional financial tracking by integrating predictive modeling and behavioral analysis to enhance financial awareness and decision-making. At its core, the architecture combines two major ML approaches: an LSTM model for capturing temporal dependencies in expense data and generating accurate time-series forecasts, and a K-Means clustering algorithm for identifying hidden spending patterns and segmenting user behavior.

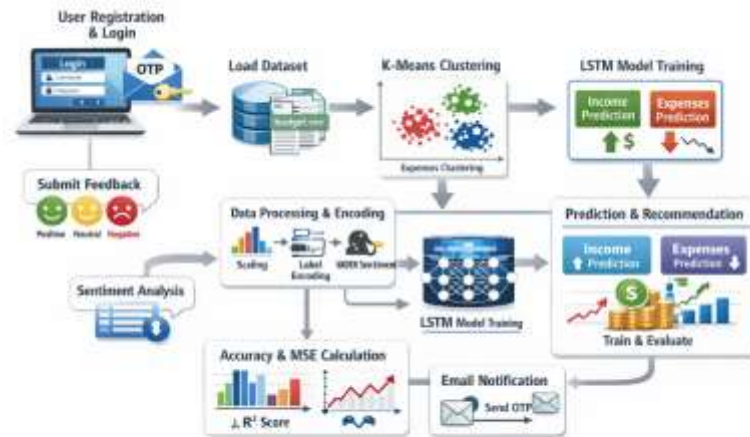


Fig. 2: Proposed System architecture

The system follows a structured three-layer architecture consisting of a MySQL database for secure storage and user management, a Python-based backend responsible for preprocessing and ML computations, and an interactive web interface that facilitates seamless user interaction. Security is ensured through a multi-level authentication mechanism that incorporates Base64-based password encoding along with OTP-based 2FA via SMTP, thereby safeguarding user accounts and sensitive financial information. Once authenticated, users upload their financial dataset (budget.csv), which is processed using Pandas, where date features such as year, month, and day are extracted, and both numerical and categorical data are normalized using MinMaxScaler and StandardScaler to prepare it for ML models. The system then applies K-Means clustering on expense categories and amounts to group similar spending behaviors, enabling users to visualize and understand their financial habits more effectively. Simultaneously, the LSTM model is trained on historical daily expense data to learn sequential patterns and generate accurate future expense predictions, with performance evaluated using metrics such as score and MSE. These predicted values are further utilized in the recommendation module, where a practical surplus is computed by comparing estimated expenses with a generated income approximation, allowing the system to suggest potential savings or investment opportunities. In addition to quantitative analysis, the framework incorporates a qualitative feedback mechanism where users can submit feedback that is analyzed using VADER sentiment analysis, enabling continuous monitoring of user satisfaction and system performance. The analyzed sentiment results are stored in the database to support ongoing improvements and adaptive system behavior. Overall, this integrated pipeline combines forecasting, clustering, recommendation, and sentiment analysis into a unified system that not only predicts future financial trends but also delivers personalized, actionable insights, thereby empowering users to make informed and effective financial decisions.

3.1 LSTM

The LSTM is a specialized type of Recurrent Neural Network designed to overcome the vanishing gradient problem, enabling it to learn long-term dependencies essential for time-series forecasting (like expense trends). Its core strength lies in the memory cell and three gates that regulate the flow of information: the Forget Gate decides which information to discard from the cell state; the Input Gate decides which new information to store in the cell state; and the Output Gate determines which

part of the current cell state is outputted as the hidden state for the current timestamp. This gating mechanism allows the LSTM to remember patterns that occurred months ago (like annual fees or seasonal spending) and integrate them effectively into the current day's expense prediction as depicted in Fig. 3.

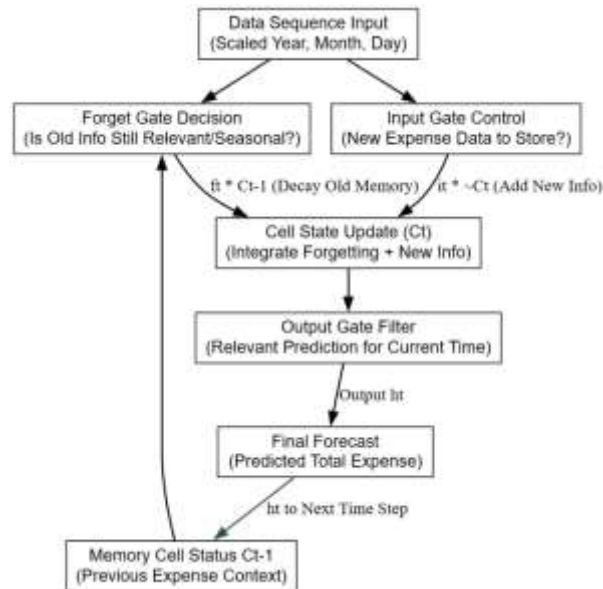


Fig. 3: Internal Workflow of LSTM.

Data Sequence Preparation: Raw time features (year, month, day) and total expenses are scaled. Input features are reshaped into sequences (3D format: [samples, timesteps, features]) required by the LSTM.

Forward Pass (Per Timestep): For each input sequence, the data passes through the gates sequentially:

- **Forget Gate:** Multiplies the old cell state by a value between 0 and 1 (output of a sigmoid function) to decide what to discard.
- **Input Gate:** Determines new information to add to the cell state (using sigmoid for filtering and tanh for creating candidate values).
- **Cell State Update:** The old cell state is updated by forgetting old info and adding new info.
- **Output Gate:** Determines the final output (hidden state) based on the new cell state.

Prediction: After processing the sequence, the output from the final LSTM layer feeds into a dense layer to produce the single-day expense forecast.

Backpropagation: The prediction error is calculated using the Mean Squared Error (MSE) loss function, and weights are adjusted using the Adam optimizer.

Iteration: Steps 2-4 are repeated over multiple epochs (1000 in the code) to minimize the loss and optimize model performance.

4. RESULTS DESCRIPTION

Fig. 4 illustrates the application of the K-Means clustering algorithm for analyzing expense behavior patterns. The clustering model groups transaction records into clusters based on similarities in

spending categories and expense amounts. Each cluster represents a distinct pattern of financial activity that helps identify how expenses are distributed across different categories. The graphical representation provides insights into spending trends and financial behavior. This clustering analysis assists users in understanding their expense distribution and supports better financial planning.

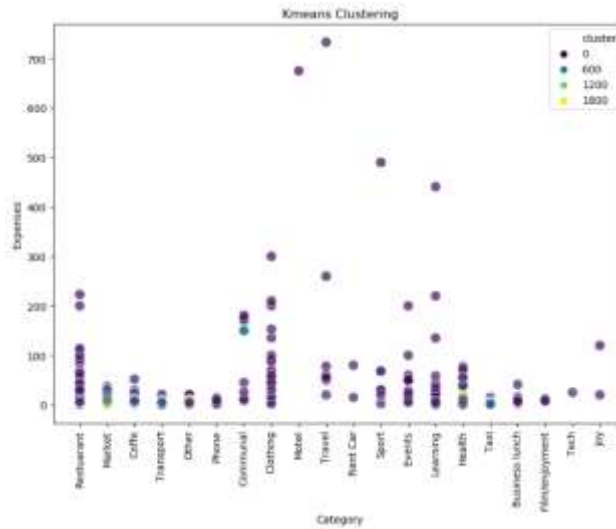


Fig. 4: K-means clustering for personal finance

Fig. 5 depicts the evaluation results of the Long Short-Term Memory (LSTM) deep learning model used for expense prediction. The model performance is measured using evaluation metrics including Accuracy of 0.9993 (99.93%) and Mean Squared Error of 35.41. A graphical comparison between predicted expenses and actual test expenses is also displayed to illustrate the effectiveness of the prediction model. The graph demonstrates how closely the predicted values follow the actual financial expense patterns. This evaluation confirms the ability of the LSTM model to accurately forecast future financial expenses.

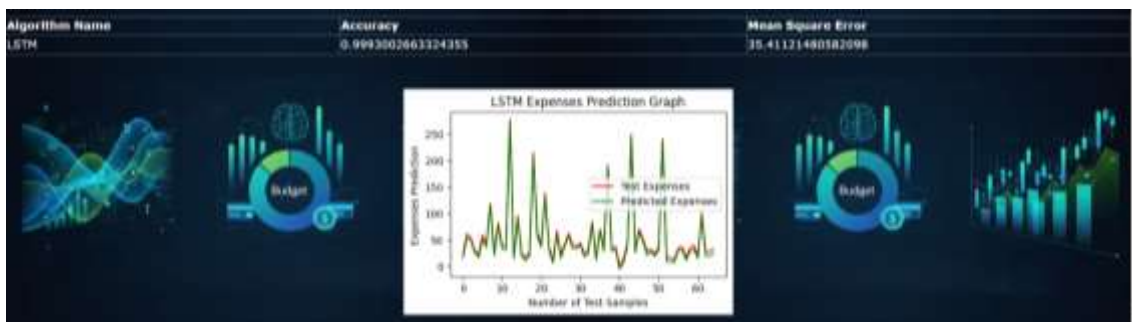


Fig. 5: LSTM Model Evaluation Screen

Fig. 6 illustrates the budget recommendation module of the system where financial predictions are used to generate investment suggestions. Based on the predicted expenses calculated by the LSTM model, the system estimates the user’s expected financial expenditure. For example, if the system assumes an income of 45,648 units and predicted expenses of 36,987 units, the recommended investment amount is calculated as 8,661 units. This module helps users allocate their income efficiently and make better financial planning decisions.



Fig. 6: Recommend budget Screen

Fig. 7 depicts the feedback analysis module of the Personal Finance Manager system. In this stage, users can submit feedback regarding their experience with the financial recommendation services. The system processes the feedback using VADER sentiment analysis to classify the feedback as positive, negative, or neutral. In the displayed example, the system identifies the feedback sentiment as Neutral. This analysis helps evaluate user satisfaction and improves the overall effectiveness of the financial management platform.



Fig. 7: Predicting Feedback Screen

5. CONCLUSION

This research successfully integrates ML and DL techniques to provide personalized financial insights and enhanced decision-making support. K-Means clustering is utilized to analyze user spending behavior by grouping expenses into meaningful categories. The LSTM model accurately forecasts future expenses based on historical financial data. These combined techniques enable users to make informed decisions regarding budgeting and investment planning. The system also incorporates sentiment analysis to evaluate user feedback and improve overall user interaction. A Django-based web interface ensures seamless visualization of prediction graphs and clustering results. Performance metrics such as MSE and R^2 score validate the accuracy and reliability of the predictions. Overall, the system delivers a comprehensive and efficient solution for personal finance management.

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