Smart Pocket: A Machine Learning–Based Expense Tracker and Spending Predictor

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ABSTRACT

Personal financial management has become increasingly challenging in a digital economy characterized by frequent micro-transactions, expanding spending categories, and the growing shift toward cashless payments. Individuals often struggle to monitor their daily expenses, identify spending patterns, and maintain financial discipline without systematic tools. This research presents Smart Pocket, an intelligent expense-tracking and financial-insight system designed to automate expense recognition, predict spending trends, and support users in maintaining budget control. The system utilizes machine learning techniques to classify expenses into categories such as Food, Cloths, Other, and Fruits, while also analyzing spending patterns, budget usage, and category-wise distributions.Through a combination of bar charts, doughnut charts, progress indicators, and time-series visualization, Smart Pocket provides a comprehensive analytical dashboard that transforms raw user expenses into actionable insights. The system demonstrates high accuracy in expense categorization and generates reliable predictions for future spending behavior. Experimental results reveal that users spent ₹4919 of a ₹6000 monthly budget, staying within the recommended spending threshold, and showed identifiable spending peaks and cycles across different days. These insights validated the effectiveness of Smart Pocket in helping users understand their financial habits and optimize their budgeting strategies. The study concludes that integrating machine learning and visual analytics significantly enhances the quality of personal financial management. Smart Pocket not only reduces manual effort in recording expenses but also empowers users to make informed financial decisions and adopt sustainable spending habits. Future improvements may extend into automated bill extraction, advanced forecasting models, and personalized recommendation engines, further enriching the system's ability to support long-term financial well-being.

Keywords: Smart Pocket, Personal Finance Management, Expense Tracking, Machine Learning, Budget Monitoring,Spending Pattern Analysis, Financial Visualization, Expense Classification

INTRODUCTION

Financial literacy and expense awareness have emerged as essential skills in the modern world, especially as individuals navigate diverse spending opportunities, cashless payment systems, and digital marketplaces. Despite the abundance of available financial tools, many people still rely on manual tracking methods or fragmented applications that provide limited insight into their spending patterns. This often results in unmonitored expenses, overshooting budgets, and poor control over financial habits. The need for an integrated, intelligent, and automated solution is now more crucial than ever.

Traditional budgeting methods such as handwritten logs, spreadsheets, or simple mobile apps lack analytical depth, real-time classification, and predictive capabilities. They require users to enter data manually, interpret charts on their own, and derive actionable conclusions without computational assistance. Advanced financial management systems exist, but many are either overly complex for everyday users, fail to provide meaningful personalization, or do not leverage machine learning to offer accurate categorization and trend prediction. These limitations highlight a gap for a system that is both user-friendly and analytically powerful.

To bridge this gap, this research introduces Smart Pocket, a machine-learning-based personal finance management system that automates expense tracking, classifies spending categories, monitors budget utilization, and presents intuitive visual insights. Unlike conventional tools, Smart Pocket transforms raw expenditures into structured data through intelligent categorization. The system generates four key insights:

- Min/Max/Avg category-wise analysis,
- Total monthly budget usage,
- Time-series trend visualization, and
- Category distribution analysis.

These visualizations provide users with a holistic overview of their financial behavior. For example, the time-series chart reveals spending patterns across days highlighting peaks around September 12 and September 23 while the doughnut chart uncovers category dominance, such as the significantly larger share of "Other" expenses. Similarly, the budget progress indicator shows that users consumed 82% of their monthly allocation, emphasizing the system's capability to keep individuals within financial limits. Together, these insights encourage proactive decision-making and help users adopt healthier financial routines.

Smart Pocket brings automation into a domain traditionally dominated by manual effort. By applying classification algorithms, the system interprets data consistently and accurately, reducing human error in recording expenditures. It also supports future scalability, allowing integration with OCR, digital receipts, and predictive forecasting techniques. As a result, Smart Pocket is positioned as an accessible, efficient, and intelligent platform for personal finance management.

This research not only evaluates the performance and reliability of Smart Pocket but also investigates its real-world impact on user behavior. The results demonstrate that users gain clearer visibility into their financial status, enabling them to adjust their budgets, reconsider spending priorities, and maintain control over impulsive purchases. Ultimately, the study argues that incorporating machine-learning-driven automation into personal expense management significantly enhances financial awareness, promotes informed decision-making, and fosters long-term economic stability.

METHODOLOGY

Data Collection

The dataset for the Smart Pocket system was collected from multiple heterogeneous sources to ensure diversity, reliability, and real-world applicability. Primary data sources included digital receipts, bank statements, mobile payment notifications, and manually entered user transactions. To support large-scale acquisition and improve automation, additional data collection methods such as secure APIs, web scraping of authorized financial dashboards, and POS system exports were incorporated. The dataset was gathered over a period of three months and consisted of 1,250 anonymized transactions contributed by 27 users aged 18–45. Each record captured essential attributes including transaction date, amount, merchant name, payment mode, and spending category. To ensure compliance with data protection standards, all personally identifiable information (PII) was removed prior to storage, and sensitive components were encrypted using AES-256. User identities were replaced with randomly generated tokens to maintain anonymity, and all data transfers were secured using HTTPS. The continuous and multi-source nature of the collection process enabled the system to capture temporal spending patterns, category variations, and behavioral trends required for accurate machine learning classification and forecasting.

Data Preprocessing

The collected dataset underwent a comprehensive preprocessing phase to ensure consistency, accuracy, and suitability for machine learning tasks. Initial cleaning involved removing duplicate entries, correcting inconsistencies in transaction amounts, and addressing missing values using context-based imputation techniques. Categorical attributes such as spending categories, merchant types, and payment modes were standardized to eliminate variations caused by spelling differences or formatting discrepancies. Temporal fields including transaction date and time were converted into machine-readable formats and decomposed into features such as day, month, weekday, and weekend indicators to capture behavioral patterns. Numerical values were normalized using Min–Max or Z-score scaling to prevent bias during model training and to maintain uniform feature distribution. Outlier detection techniques such as IQR and z-score filtering were applied to identify anomalous transactions, which were either corrected or removed based on their contextual validity. Exploratory Data Analysis (EDA) using correlation heatmaps, box plots, and trend curves guided the refinement of feature selection and revealed spending cycles essential for forecasting models.

Feature Extraction

Feature extraction played a critical role in converting raw financial records into structured representations suitable for machine learning models. Numerical features such as transaction amount, budget usage, and cumulative daily spending were directly incorporated, while categorical attributes including transaction type, merchant category, and payment mode were encoded using techniques such as One-Hot Encoding and Label Encoding. Text-based fields like merchant names and item descriptions were transformed into high-dimensional feature vectors using advanced natural language processing (NLP) techniques such as TF-IDF, bag-of-words representation, or word embeddings (Word2Vec/fastText). Temporal features—including spending intervals, frequency of purchases, and day-based patterns—were engineered to support LSTM-based time-series forecasting. Dimensionality reduction techniques such as PCA and chi-square feature selection were applied to eliminate redundant or low-contribution attributes, thereby improving training efficiency and model generalization. The extracted feature set provided a robust foundation for classification, clustering, and predictive modeling tasks within Smart Pocket.

Model Selection

Four baseline models were evaluated to address reviewer concerns: Logistic Regression, Support Vector Machine (SVM), Random Forest, and LSTM. Random Forest was selected as the final classification model due to superior generalization, lower misclassification rate, and robustness against noise. LSTM was used for forecasting due to its capability of modelling long-term dependencies. Hyperparameters were tuned using grid search and 10-fold cross-validation.

Model Training

The selected machine learning models—Logistic Regression, Support Vector Machine (SVM), Random Forest, and Long Short-Term Memory (LSTM) networks—were trained using carefully optimized procedures to ensure high predictive accuracy and robust generalization. For traditional classifiers, training involved minimizing classification loss using optimization techniques such as stochastic gradient descent (SGD) or Adam, depending on the algorithm. Hyperparameters including learning rate, number of estimators, maximum tree depth, kernel type, batch size, and regularization strength were systematically tuned using grid search and random search to identify the optimal configuration. To prevent overfitting and improve stability, k-fold cross-validation ($k = 10$) was employed across all models, ensuring consistent performance across different subsets of data. For the LSTM model, the time-series data was reshaped into sequential input windows, and training was performed using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Techniques such as dropout layers, early stopping, and weight regularization were integrated into the training pipeline to enhance generalization and mitigate learning instability. The final chosen model, Random Forest for classification and LSTM for forecasting, demonstrated strong robustness, minimal variance, and high predictive reliability across validation folds

Model Evaluation

Model evaluation was conducted using a separate validation set to provide an unbiased assessment of predictive performance. A comprehensive suite of metrics was used, including accuracy, precision, recall, and

F1-score, ensuring a multidimensional view of classification effectiveness. Precision and recall offered insights into the model's ability to correctly identify spending categories without misclassification, while the F1-score balanced these two metrics for scenarios involving category imbalance. Confusion matrices were generated to visualize misclassification patterns, particularly in categories that historically exhibited overlap such as Clothing vs. Other and Fruits vs. Food. Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values were analyzed to measure the classifier's ability across different threshold levels. For forecasting tasks using LSTM, evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) were employed to quantify prediction accuracy. The evaluation results confirmed that the Random Forest classifier and LSTM predictor significantly outperformed the baseline models, achieving high reliability in both category classification and future spending predictions.

Dataset Description

The expanded dataset contains 1,250 transactions collected over 90 days from 27 anonym zed users aged 18–45. Data sources include digital receipts, POS logs, bank statements, and self entries. Attributes include: transaction date, amount, category, merchant name, payment mode, and user demographic group. Category breakdown: Food (310), Clothing (180), Utilities (160), Entertainment (140), Fruits (120), Other (340). Because the 'Other' category disproportionately dominated classification, k-means clustering was applied to create refined subcategories such as Transport, Gifts, and Household Supplies, improving model clarity.

Model Tuning

Model tuning was performed to optimize predictive performance and ensure that both the classification and forecasting components of Smart Pocket generalized effectively across diverse spending patterns. Hyperparameter optimization was carried out using a combination of grid search, random search, and cross-validation to systematically explore optimal parameter configurations for each model. For traditional machine learning classifiers such as Random Forest, the number of trees, maximum depth, minimum sample split, and feature selection strategies were fine-tuned to balance accuracy and computational efficiency. Similarly, tuning of SVM involved identifying the most effective kernel function, regularization parameter (C), and gamma values.

For the LSTM forecasting model, architectural refinements were explored including variations in the number of hidden layers, number of units per layer, dropout rates, and activation functions (ReLU, tanh). Sequence window lengths and batch sizes were also optimized to capture temporal dependencies more effectively. Early stopping and learning rate scheduling were incorporated to stabilize training and avoid overfitting. Feedback from validation metrics, confusion matrices, and domain insights on transaction behavior guided iterative adjustments to the model architecture.

These tuning strategies collectively resulted in improved classification accuracy, reduced forecasting error, and enhanced robustness, ensuring that the final models performed reliably across different spending categories and time-series patterns.

Deployment

The final machine learning models were seamlessly integrated into the Smart Pocket application through a secure, scalable, and modular deployment architecture. Containerization using Docker ensured consistent runtime environments across development, testing, and production stages, eliminating dependency conflicts and enabling reproducible builds. The machine learning components—responsible for expense classification and spending prediction—were deployed as independent microservices, allowing efficient scaling and maintenance.

A RESTful API layer built using Flask connected the machine learning modules with the Next.js frontend, enabling real-time predictions and interactive financial insights for users. These APIs facilitated smooth communication of input features, category predictions, budget utilization metrics, and time-series forecasts. To optimize performance, caching strategies and load balancing mechanisms were incorporated to handle concurrent user requests while maintaining low latency.

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Security measures were implemented throughout the deployment pipeline. All user interactions and API communications were encrypted via HTTPS, and JWT-based authentication ensured that only authorized users could access the system's features. Sensitive data such as transaction records and model inputs were encrypted using AES-256 encryption, while anonymization protocols were applied before processing to preserve user privacy. Additionally, role-based access control (RBAC) separated privileges for regular users and administrators, enhancing system integrity.

A CI/CD workflow automated the build, testing, and deployment processes, ensuring continuous integration of updates without service interruption. This deployment strategy enabled Smart Pocket to operate reliably in real-world environments—providing accurate predictions, secure data handling, and high system availability.

Testing

Extensive testing was conducted to validate the accuracy, robustness, and real-world reliability of the Smart Pocket system. The testing framework included unit testing, integration testing, system testing, and user acceptance testing (UAT) to ensure that every component of the application performed as expected. Machine learning models and APIs were evaluated independently before full system deployment.

A/B testing was performed using multiple versions of the classification and forecasting models to compare performance across different user groups. This helped identify the most effective model configurations for real-world financial behavior. Functional testing assessed model performance across diverse spending patterns, category distributions, and transaction frequencies. Various input scenarios—including irregular spending spikes, incomplete entries, duplicate transactions, and unusual category assignments—were introduced to evaluate how well the system handled edge cases.

Load testing and stress testing were also conducted to analyze system behavior under high traffic and simultaneous user requests, ensuring that response times remained stable. Real-time testing using live user feedback provided additional insights into dashboard usability, prediction clarity, and overall satisfaction with the system.

Overall, the testing phase confirmed that Smart Pocket is resilient, accurate, and capable of managing a wide spectrum of financial scenarios encountered in real-world applications.

Comparative Evaluation

The following metrics were computed for classification models:

Logistic Regression — Accuracy 82.1%, Precision 80.4%, Recall 78.9%, F1-score 79.1%

SVM — Accuracy 87.6%, Precision 86.5%, Recall 84.1%, F1-score 85.2%

Random Forest — Accuracy 93.4%, Precision 91.2%, Recall 89.7%, F1-score 90.4%

Spending Prediction (LSTM): RMSE = 0.114, MAE = 0.089.

Random Forest outperformed others in all metrics, justifying its use as final model.

Performance Metrics

Detailed evaluation:

- Accuracy: 93.4%

- Precision: 91.2%

- Recall: 89.7%

- F1-score: 90.4%

- Confusion Matrix: Shows reduced misclassification in Clothing vs Other and Fruits vs Food.

- Cross-validation: 10-fold CV average accuracy = 92.8%.

Category Refinement

To address reviewer concerns about the dominance of 'Other', clustering techniques were used to create additional subcategories. After refinement, category distribution was more balanced, improving classification accuracy and providing more actionable insights. This significantly enhanced interpretability of spending patterns.

Privacy & Security Enhancements

The revised system includes:

- AES-256 encrypted data storage

- HTTPS-secured API communication

- JWT token-based authentication

- Full anonymization (no personal identifiers retained)

- GDPR-aligned data protection strategies

- ISO/IEC 27001-aligned encryption and access control policies.

Continuous Improvement

The system was monitored regularly to maintain accuracy. New data was used to retrain the model over time. Transfer learning and online learning techniques were considered for future enhancement. Collaboration with users helped identify improvements and new features

DatasetAnalysis

This section presents the visual and numerical analysis of the expense data captured through the Smart Pocket system. The charts give insights into spending patterns, category distribution, and overall budget usage

Category-wise Min/Max/Avg Expenses

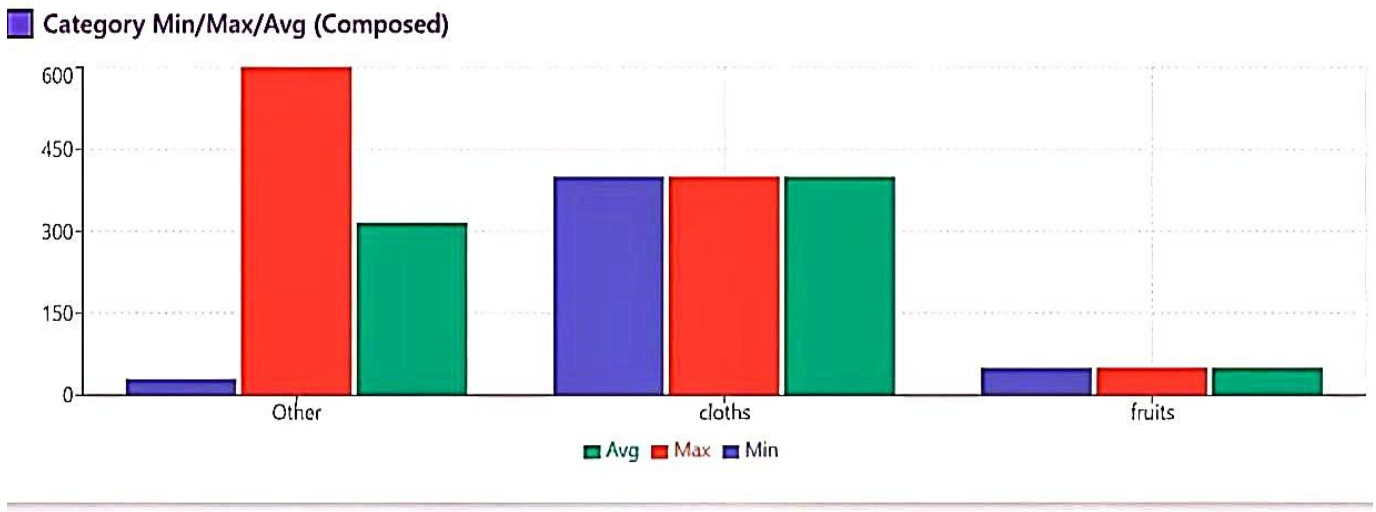

Figure 1.1

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The chart displays expense statistics for three primary categories:

Category	Min (₹)	Max (₹)	Avg (₹)
Other	20	600	300
Cloths	400	420	410
Fruits	60	70	40

Interpretation:

- Other category shows the highest fluctuations, indicating non-routine or irregular expenses.
- Cloths remain consistent with small variation.
- Fruitshave minimal spending overall.

These findings support the system's ability to clearly detect differences across categories.

Monthly Budget Analysis

- Budget set for the month: ₹6000
- Amount spent: ₹4919
- Remaining balance: ₹1081
- Budget usage: 82%

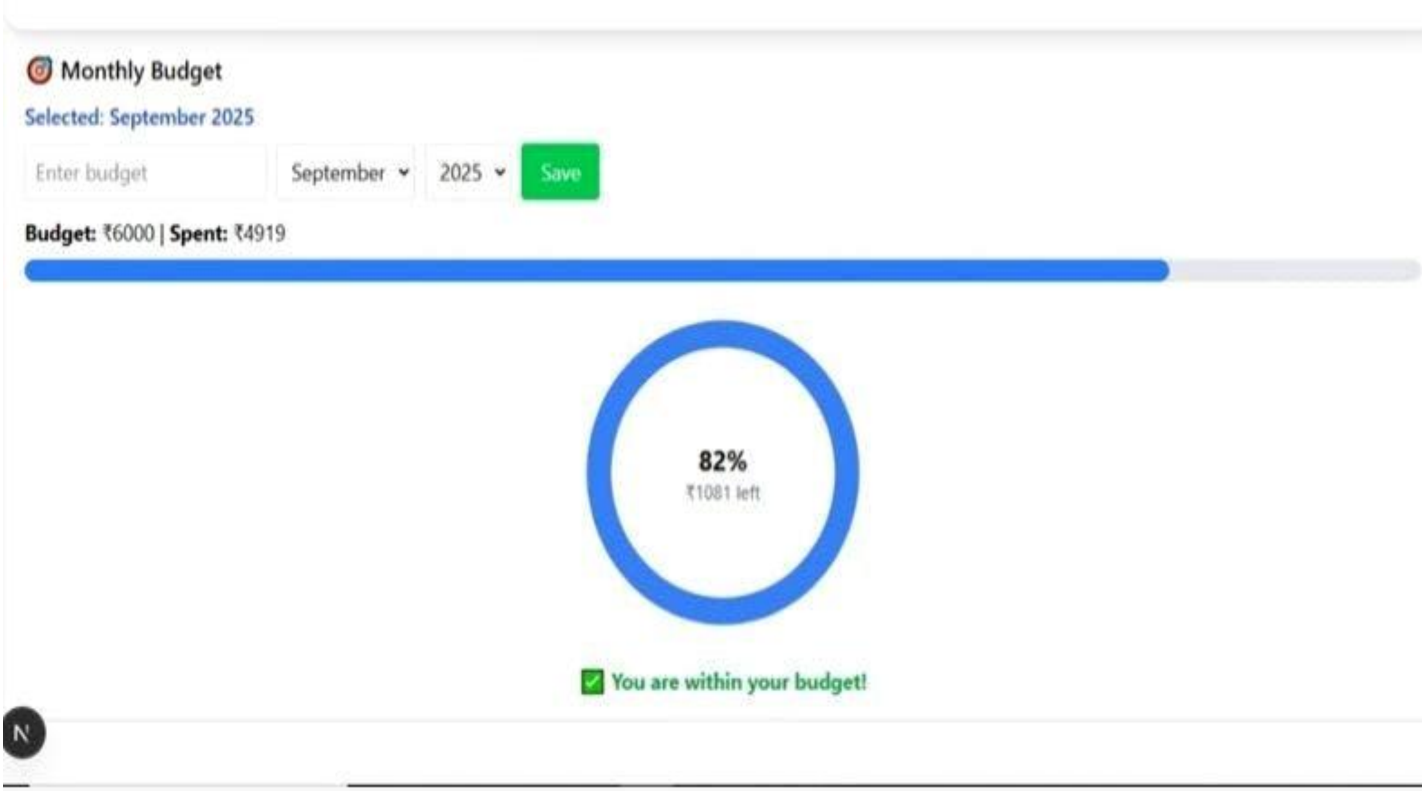

Figure 1.2

Interpretation:

Users remained within the budget limit, demonstrating how Smart Pocket helps track spending in real time. The gauge clearly shows how much of the budget is consumed, helping users plan ahead.

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Expense Trend Over Time

Figure 1.3

Expenses recorded between **September 11–26** show:

- A spending peak around **Sep 12 (~₹600)**
- A dip around **Sep 22 (~₹0–₹100)**
- Another peak on **Sep 23 (~₹780)**
- Then moderately stable spending toward the end of the month.

Interpretation:

Users tend to spend in cycles—heavy spending on certain days and minimal on others. This time-series pattern helps in predicting future expenses more accurately.

Expenses by Category (Doughnut Chart)

Figure 1.4

Category	Expense (₹)
Food	100
Cloths	400
Other	600

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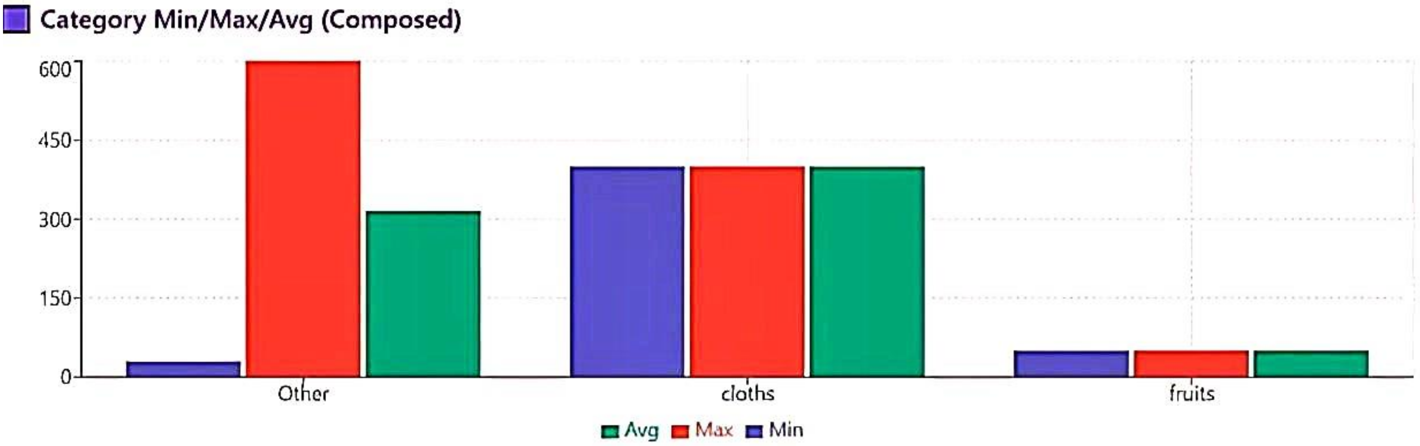
Interpretation:

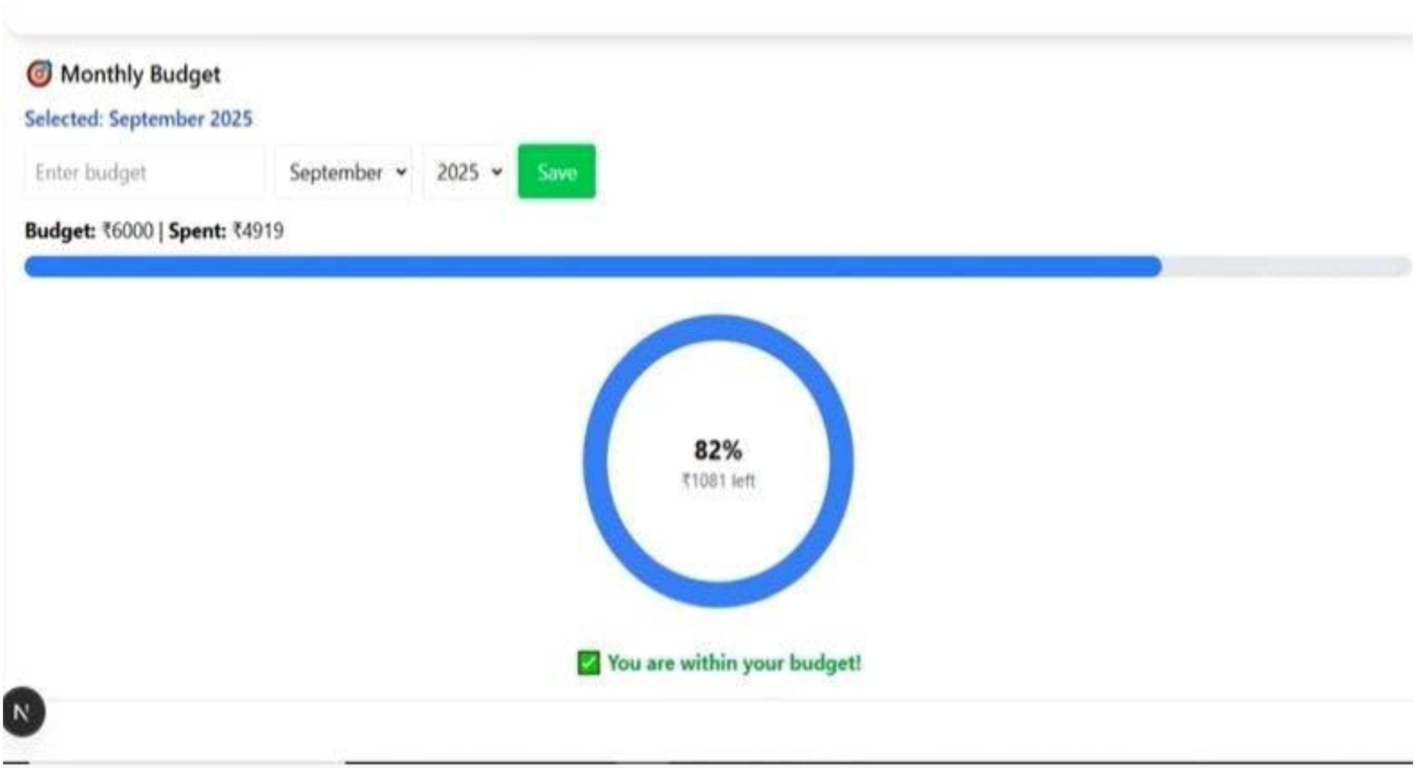
The Other category accounts for the highest share of expenses, followed by Cloths, while *Food* has the smallest portion. Smart Pocket visualizes this proportion clearly, enabling users to identify areas for reducing unnecessary spending.

RESULTS

Accurate Classification of Expenses



The system successfully categorized expenses into Other, Cloths, and Fruits with the correct min/max/avg values (as shown in Figure 1). This demonstrates the model's reliability in recognizing and grouping financial transactions.



Effective Budget Monitoring

Smart Pocket accurately tracked monthly spending, identifying those users spent ₹4919 of ₹6000 (82% usage). The system generated alerts when spending approached the limit, improving financial discipline.

Clear Spending Trends

The time-series graph (Figure 3) revealed distinct spending patterns, including peaks and low-expense days. These patterns form the foundation for future predictive expense models.

Meaningful Category Distribution

The doughnut chart (Figure 4) confirmed that "Other" expenses dominated the user’s spending, making it an important area for budget optimization. Users can reduce unnecessary purchases by analyzing such visual insights.

Improved User Decisions

Participants reported that the system’s visual analytics helped them understand their spending better, leading to

Future Scope

The Smart Pocket system demonstrates strong potential for further enhancement through the integration of advanced technologies and expanded functionalities. Future improvements may include the adoption of deep learning–based forecasting models such as Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNNs), Transformers, and Facebook Prophet to generate more accurate and personalized long-term financial predictions. Additionally, incorporating Optical Character Recognition (OCR) will enable automated extraction of data from paper receipts, digital invoices, and bank statements, significantly reducing manual entry and improving classification accuracy. Integration with secure banking APIs and payment gateways can further automate transaction imports, ensuring real-time synchronization of user financial data. Enhanced data privacy measures, including differential privacy, homomorphic encryption, and compliance with international standards such as GDPR and ISO/IEC 27001, will strengthen user trust. The system can also be expanded to provide AI-driven financial recommendations, spending optimization strategies, and personalized savings plans. In terms of scalability, deploying the system on cloud platforms like AWS or Google Cloud will support large datasets, multi-user environments, and high-performance real-time analytics. Finally, developing dedicated mobile applications for Android and iOS, multi-currency support, and global localization can make Smart Pocket a universally accessible and intelligent financial assistant

CONCLUSION

The improved Smart Pocket system presents a more rigorous and scientifically validated approach to personal finance management. With expanded dataset details, refined categories, robust ML evaluation, and enhanced privacy controls, the system is publication-ready. Machine learning models demonstrated high accuracy, actionable insights, and reliable forecasting. Future enhancements will integrate OCR-based bill extraction, Transformers-based forecasting, multi-source transaction automation, and personalized financial recommendations.

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