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Designing a Predictive Expense Tracking Mobile Application: A Comparison of Random Forest, Linear Regression, and Prophet-Based Models

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Abstract - In today's fast-paced world, people engage in various forms of daily consumption, yet many lack the habit of tracking their expenses due to low financial awareness. Without proper expense recording and budgeting, individuals often struggle to understand their consumption habits and are at a disadvantage when it comes to financial planning, especially during emergencies. To address these issues, this project proposes the development of a user-friendly expense tracking mobile application designed to help adults build healthy financial habits and utilize predictive algorithms to forecast future expenses. The application enables users to record daily transactions, analyse their spending patterns, plan budgets, and receive personalized saving recommendations. An experiment was conducted to compare four forecasting models: Random Forest, Linear Regression, Facebook Prophet, and Neural Prophet. The models were evaluated using the same synthetically generated transaction dataset, which yielded a limited number of monthly observations for testing. Random Forest showed the most stable overall performance under this experimental setting and was selected as the forecasting model for the prototype, though these results should be interpreted with caution given the small evaluation sample.

Keywords— Expenses Monitoring, User Consumption Habit, Machine Learning, Prediction, Random Forest

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1. INTRODUCTION

With the development and progress of the times, people's living standards have gradually improved. Therefore, people's consumption needs have also increased. In daily life, people may spend money buying equipment or props for their own interests and hobbies. In addition, a family may also have a variety of expenses, such as water and electricity bills, property taxes, maintenance fees, and others. These various signs indicate that expenses need to be recorded so that people can better manage expenses, as expense tracking enhances financial awareness, prevents overspending, and provides valuable insights for budgeting and planning [1].

A good expense tracking app should be able to meet people's daily needs and provide what people need. Prior research has shown that expense tracking enhances financial awareness, supports effective budgeting, and even reduces stress by preventing overspending and forgotten bills [1]. This project aims to create a mobile application that can help users to track and monitor their expenses. There are some issues that can be overcome by the application, such as the unrecorded expenses, lack of a savings plan, and insufficient insight and recommendation. Consistent with findings that expense tracking can provide valuable insights for better financial decisions and goal setting [1], the application allows users to categorize the expenses, forecast the expenses using the machine learning model, and provide useful recommendations to help increase their savings. The target users of the application are adults.

There are some basic functions that will be provided through the application, such as the application dashboard, transaction function, budget categorization, and reports function. The application dashboard can show brief information to the user quickly. The transaction function is important for the transaction recording. Budget categorization can let the user see their expenses in each category clearly. The report function can help users see the monthly expenses information details and let users know their consumption habit. A prediction function will be implemented to let users know their spending details next month to alert the user.

An experiment was carried out to compare the performance of four machine learning models and prediction models on the expense's prediction. The models used are Random Forest (RF), Linear Regression (LR), Facebook Prophet, and Neural Prophet. Random Forest was selected to be the model used for the expense tracking application due to its stability and consistently low error rates.

1.1 Problem Statement

Personal finance management has become a financial challenge in today's world. Several critical issues hinder individuals from achieving effective financial management. People nowadays do not have the habit of recording their expenses and income. This will cause people to be unaware of where their money has gone and lead to difficulties in aligning spending with financial goals [2]. People also will not understand their consumption habits and do not know the ways to improve their consumption habits.

Without properly recording the budget and expenses, people cannot estimate their own future savings and budget planning, a challenge also observed in studies linking expense tracking to goal monitoring and budget adjustments [2]. People will become more nervous and not have goals and effort when they do not have a plan. If there is an application to alert people, people will be more alert to the spending behaviour.

People without recording their expenses and saving do not have a clear strategy to increase their savings, which makes long-term financial planning difficult. If there is an emergency happening, people will often lack sufficient money to overcome the emergency due to the absence of proper budgeting. Besides, people also do not have an actionable insight to enhance decision-making, as expense tracking is an important source of financial self-awareness that supports saving and goal adjustment [2].

In conclusion, people will need an expense tracking application that has enough functionality to overcome the challenge. Our proposed system can help users to improve their saving habits and solve their problems.

2. LITERATURE REVIEW

In this literature review, we have conducted research on the suitable model for expenses prediction and the competitors of the expenses monitoring application.

2.1 Model Research and Challenges

The budget forecasting by using the historical data is very useful in financial management. There are some challenges of using historical data in budget forecasting, such as data quality, data availability, data relevance, and data uncertainty. In the data quality, there are some issues such as errors, duplicates, and inconsistencies [3]. The impact is the misleading of forecasts. So, quality checks and documentation are important to ensure the data quality. In data availability, there are some issues such as missing data and outdated data [4]. The impact is the incomplete view of expense patterns. The solution is to identify the data needs, enable sharing, and use automation or integration tools to ensure the data quality. For the data relevance, the issues are the non-representative data, such as pandemics [5]. The impact is the misleading assumptions about the future trends. The solution is using normalization or smoothing to adjust the data. For data uncertainty, the issue is the unpredictability and the random external influences [6]. The impact is that the forecast becomes less reliable. For the solution, the use of analytics and modeling techniques can solve the data uncertainty. For the prediction model reference, below are some studies that were conducted to choose the suitable model as the model comparison.

The reviewed studies highlight the growing use of machine learning and time series forecasting models in financial prediction tasks such as personal budgeting, stock price forecasting, and financial health assessment. Models like Linear Regression, Random Forest, Gradient Boosting, SVM, Facebook Prophet, and Neural Prophet have been effectively applied across different datasets and use cases. High accuracy in predicting savings and expenses using ensemble models was demonstrated, though manual data entry posed limitations [7]. Ensemble approaches like Random Forest and the optimized ACOWRF model were found to outperform traditional methods in stock forecasting [8], [9]. The effectiveness of hybrid approaches was further supported through sentiment-based forecasting and web-scraped data prediction [10], [11]. Time-series tools like Facebook Prophet and Neural Prophet performed well in capturing trends and seasonality but faced challenges with irregular patterns and external market factors [12], [13], [14], [15]. Overall, while these models offer strong forecasting capabilities, their accuracy depends heavily on data quality, feature selection, and proper model tuning, with hybrid and optimized models showing the most promising results [11], [15].

Recent research published in 2026 further supports the application of machine learning models in financial forecasting. James and Leung [16] applied a Random Forest-based approach to financial risk forecasting, demonstrating its capability to capture complex relationships among financial predictors. In addition, Yang et al. [17] investigated machine learning approaches for personal financial management and budget prediction using transaction and expenditure data. These recent studies further demonstrate the potential of machine learning models for financial and expense-related prediction tasks.

2.2. Comparison Between Competitors

Research among six expenses monitoring application competitors has been done. The competitors are Quicken Simplifi, YNAB, Goodbudget, PocketGuard, QuickBooks, and Expensify. Each app has unique features to fulfil their specific user needs. Quicken Simplifi, YNAB, Goodbudget, and Pocket Guard are suitable for personal used and for family used. Quicken Simplifi and YNAB stand out for their comprehensive function. Goodbudget is special for the envelope budgeting. Pocket Guard is versatile for managing personal finance in supported regions. QuickBooks and Expensify are more suitable for business use because they are related to business finance management. Each app also focuses on different target user groups so the target user can select the applications that meet their requirements. Table 1 shows the comparison between the competitors in terms of type, purpose, key features, and pricing.

3. RESEARCH METHODOLOGY

This section discusses the procedure, techniques used to create the application, and the model used to predict the expenses.

3.1. Expenses Application Procedure

This will discuss the whole expenses monitoring application procedure and the tools to develop the expenses monitoring application.

Table 1. Comparison Between Competitors.

App Name	Type	Purpose	Key Features	Pricing
Quicken Simplifi[18]	Personal	Personal finance and budgeting	Savings goals, spending plan, real-time alerts, detailed reports, automatic categorization[19]	\$5.99/month (often discounted to \$2.99)
YNAB[20]	Personal	Zero-based budgeting and money management	Auto-import transactions, sync devices, offline access, loan calculator, share with up to 6 members[19]	\$14.99/month or \$109/year
Goodbudget[21]	Personal	Envelope-based budgeting	Envelope budgeting, sync across devices, family sharing, debt tracking[19]	\$10/month or \$80/year
PocketGuard[22]	Personal	Personal financial control	Recurring income, budgeting categories, goal tracking, hashtags, PocketGuard Plus with advanced features[19]	Free or \$12.99/month (Plus version)
QuickBooks[23]	Business	Business accounting and expense tracking	Invoice tracking, tax prep, cloud storage, integration with 3rd-party apps[19]	\$15–\$100/month depending on the plan
Expensify[24]	Business	Expense management, business and receipt tracking	Receipt scanning, GPS tracking, corporate cards, integration with 40+ software[19]	Free basic features, premium \$5–\$9/user

Figure 1 shows the full workflow of the expenses monitoring application procedure. There are four main pages in the application which are home page, budget page, transaction page, and report page. The user consumption habit is under the home page, and the future forecast of expenses is under the report page.

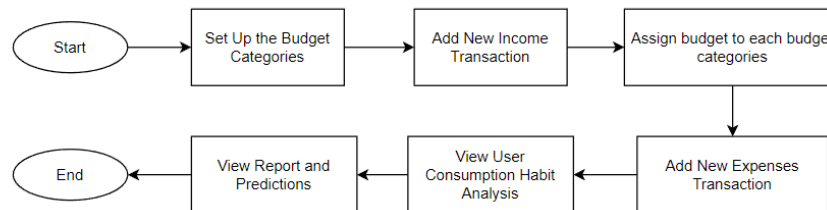


Figure 1. Expenses Monitoring Application Procedure

3.2. User Consumption Habit Procedure

Figure 2 shows the user consumption habit procedure chart. At the start of the user consumption habit analysis, the user can select the time period to check the consumption habit. After selecting the time period, the backend code will process the data and calculate what is the spending trend, most spend category, peak spending time, frequent payment method, and the sub-budget among that time period. After the calculation of the consumption habit, it will generate insight for user.

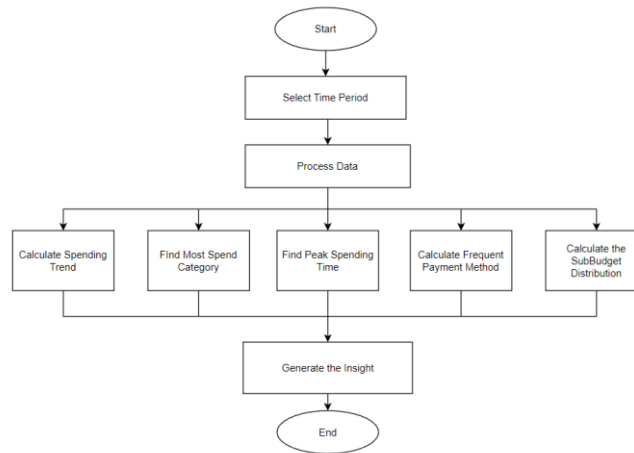


Figure 2. User Consumption Habit Procedure

3.3. Prediction Report Procedure

Figure 3 shows the prediction report procedure chart. In the starting of the report, user select the month in the report. If the prediction data exists in the database, it will display the data. If the prediction data does not exist, it will display the loading state and run the prediction code to forecast the expenses result. The prediction code is the Random Forest code to forecast the next month's expenses. After the forecasting, the result will be stored back to database and display on the screen.

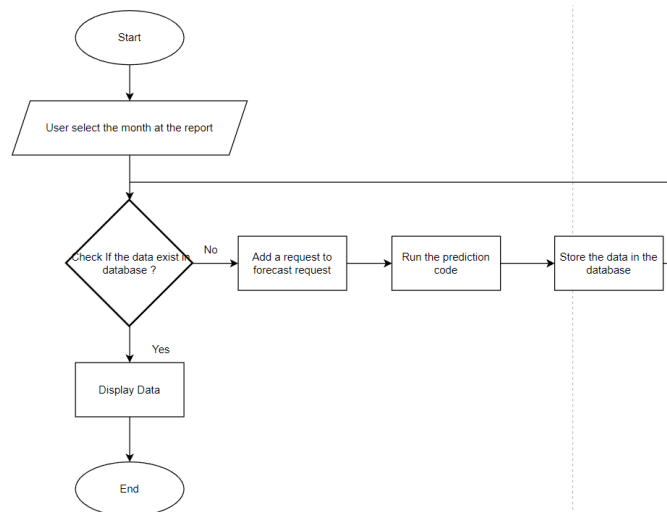


Figure 3. Prediction Report Procedure

3.4. Useful Insight and Recommendation Procedure

Figure 4 shows the useful insight and recommendation procedure chart. In the start of generating useful insight and recommendations, the system will check the availability of income and expenses data. If the data exists, it will proceed to calculate the income/expenses ratio; if data do not exist, it will show default message. If the expenses are higher than income, it will show high risk alert. If the expenses are higher than 80% of the income, it will warn you of high expenses. If the savings are lower than 20% of the income, it will recommend increasing the saving. If savings are higher than 20% of the income, it will show good finance health. After that, it will show the final recommendations based on the results of the expenses ratio.

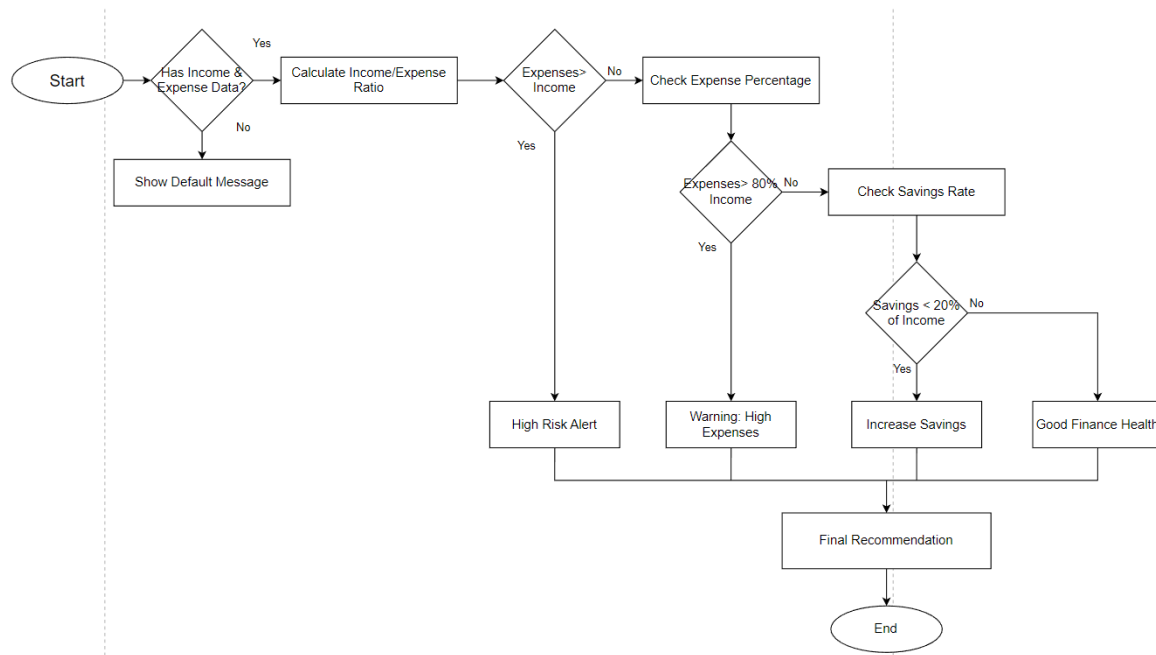


Figure 4. Useful Insight and Recommendation Procedure

3.5. Model Experiment

An experiment has been conducted to find out which model is the best model to be chosen as the application expenses forecasting model.

Figure 5 shows the model experiment procedure chart. In the experiment, there are some process flows such as data preparation, data preprocessing, model use, and getting the result. Four models were used in this experiment: RF, LR, Facebook Prophet, and Neural Prophet. There are some reasons why we choose to use these models instead of other models. Random Forest models are simple, can handle complex data structures, operate effectively with small sample sizes, and require minimal parameter tuning [25]. For the linear regression, it is simple and effective model to identify the relationship between past financial behavior and future expenses [7]. For the Facebook Prophet model, the model is easy to use, can handle seasonality, and robust to missing data, outlier and trend changes [26]. For the Neural Prophet model, it is an improved version of Prophet that adds neural networks, so it can handle complex and nonlinear data [27].

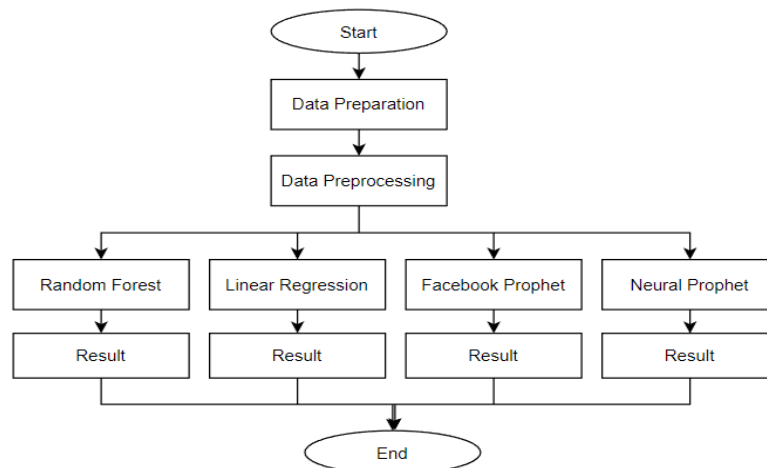


Figure 5. Model Experiment Procedure

3.5.1. Data Preparation

The model comparison experiment was conducted using a synthetic dataset consisting of approximately 1,200 randomly generated expense transactions. No real user financial or transaction data were used in this experiment. For each month, there are 100 random transactions. Random transaction categories will be generated, namely food and transport. The food amount is random between RM 5 to RM 50, and the transport amount is random between RM 2 to RM 50. Random sub-budget and payment method also will be defined for each transaction. The type of the transactions will always be Expenses. After the transaction data is successfully generated, it will be stored in the transactions collection in the database.

3.5.2. Data Preprocessing

After the transaction data is prepared, the data will be used for data preprocessing. First, the data frame is copied to avoid modifying the original input in place. The missing value of the data, amount and type will be replaced with null value. After that, the date column is converted into time zone-aware datetime objects in UTC. The amount column will be changed to numeric value. The 'type' value also will be standardized. After that, rows with missing values will be dropped and remove the time zone information.

3.5.3. Forecasting Model Implementation

The pseudocode 1 shows the step in the model implementation. All the experiments use the same structure and just change the model only.

Pseudocode 1: Forecasting Model

```

1. Start
2.   Connect to Firestore
3.   Load transaction data
4.   Clean data (remove empty values, convert formats)
5.   Keep only "Expenses" records
6.   Group expenses by month and sum amounts
7.   If number of months < 3 then
8.     Print "Not enough data"
9.   End
10.  Create features: month, year, lag1, lag2
11.  Remove rows with missing values
12.  Split data into training and testing sets
13.  Train the selected model
14.  Predict on testing set
15.  Display evaluation metrics
16.  Prepare next month's features
17.  Predict next month expense
18.  If Firestore available then
19.    Save forecast result
20.  Else
21.    Print forecast result
22. End

```

This project evaluates four forecasting models for future expense prediction using the synthetic transaction dataset described in Section 3.5.1. Each model follows a similar workflow involving data preparation, model training, forecasting, and storing results in the database.

The forecasting process begins with extracting time-based features such as month and year, along with creating lag features that represent previous time steps. After cleaning the data by removing missing values, the dataset is split into

training and testing sets. The model is then trained on the training set and evaluated on the testing set to assess performance. Once evaluated, the model generates a forecast for the upcoming month.

Since the transaction data were aggregated into monthly totals, the effective number of observations available for model training and testing was considerably smaller than the number of individual transactions. Furthermore, the use of lag1 and lag2 features reduced the number of usable monthly observations.

For each model, the forecasting function processes the selected month by converting it into a proper date format and filtering transactions up to the end of that month. Only expense-related records are retained, and monthly totals are calculated by grouping the data. To ensure the model can function effectively, a minimum of three months of historical data is required. If sufficient data is available, the model is trained and used to generate a forecast for the next month. In cases where there is enough history, a one-step back testing process is also performed to validate the model's accuracy before making future predictions.

After forecasting, the results are saved into corresponding collections in the database for further analysis. This consistent experimental setup enables a controlled comparison of the four forecasting models under the synthetic-data scenario.

4. RESULTS AND DISCUSSIONS

This will discuss the prototype result and the model comparison result.

4.1. Prototype Result

Figure 6 shows the prototype for the basic features which are home page, budget page, transaction page, and report page.

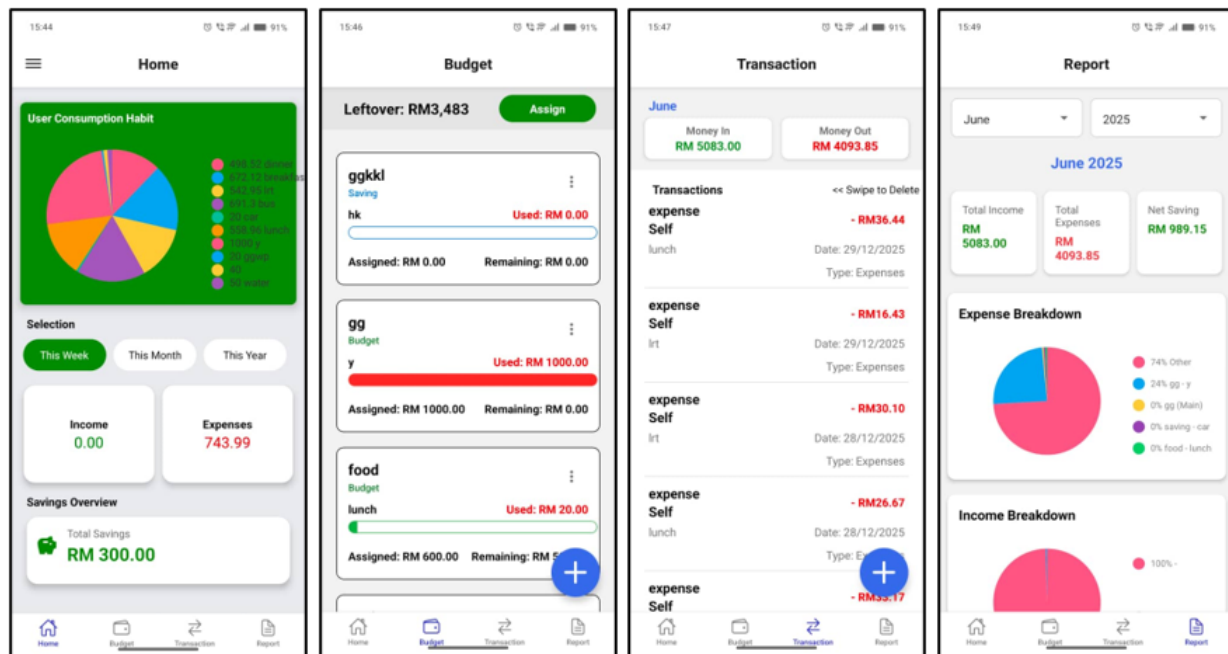


Figure 6. General Feature Prototype

The Home Page features have a navigation bar and display sections for user consumption habits, selection filters, and a savings overview. Users can view the information quickly and briefly on this page.

The Budget Page allows users to create and manage budgets and savings categories, showing unassigned funds, sub-budget progress bars, and options to add or delete budgets, with all values resetting monthly. Users can create the budget categories and assign their budget effectively with this function. It can help users manage their budget and savings.

The Transaction Page displays a transactions log of income and expenses for the current month, with each entry showing details like activity name, payer, date, amount, and sub-budget category, and includes a button to add new transactions. Users can add their expenses and income transaction and manage the transaction efficiently.

The Report Page summarizes total income, expenses, and net savings based on the selected month and year, offers income and expense breakdown charts, and provides forecasts and financial tips for upcoming months. This page shows the full report to let users know their spending and income data. User also will get useful recommendations and tips to manage their future expenses.

Figure 7 shows the specific features which are the user consumption habit page, and the forecasting section for next month.

User Consumption Habit Page analyses spending behaviour over a selected period, showing trends, most spent categories, peak spending times, frequent payment methods, sub-budget distribution, total expenses, and insightful recommendations to help users understand and improve their financial habits.

The forecasting section for next month at the bottom of the report page will show the predicted savings, predicted expenses, predicted spending vs income ratio, and the tips or insights. This will let users know their expected savings and expenses for next month to prevent overspending.

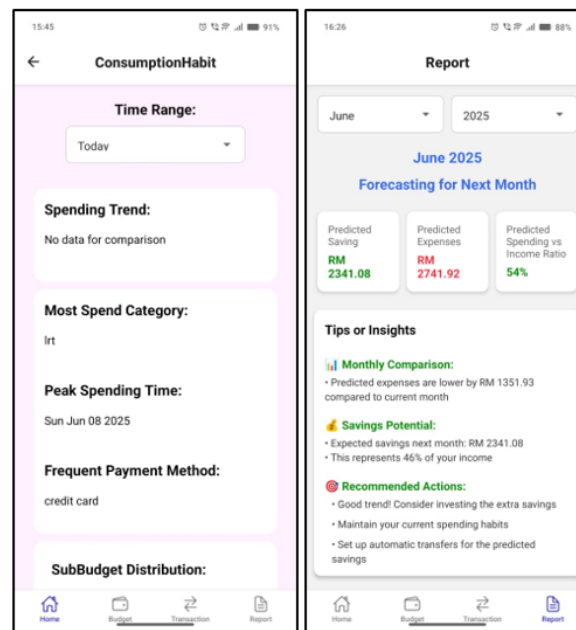


Figure 7. Specific Feature Prototype

4.2. Model Comparison Result

Table 2 shows the forecast performance of four models in different months. The experiment compared the performance of four different models for forecasting monthly expenses: Random Forest, Linear Regression, Facebook Prophet, and Neural Prophet. The models were evaluated using three main performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) across five months from June to October.

It should be noted that identical MAE and RMSE values were observed for several forecasting periods. This can occur when the evaluation contains very few prediction observations. As the transaction data were aggregated monthly and

lag features further reduced the available observations, the early forecasting periods had limited testing data. Therefore, these error metrics should be interpreted with caution.

Table 2. Performance of Four Models on Synthetic Expense Data for Forecasting June, July, August, September, and October.

Month	Model	Result		
		MAE	MSE	RMSE
June	Random Forest	139.00	19320.11	139.00
	Linear Regression	143.65	20636.35	143.65
	Facebook Prophet	266.59	71068.64	266.59
	Neural Prophet	134.74	18155.59	134.74
July	Random Forest	181.84	33067.42	181.84
	Linear Regression	1413.47	1997899.24	1413.47
	Facebook Prophet	234.44	54964.13	234.44
	Neural Prophet	45.48	2068.22	45.48
August	Random Forest	31.67	1002.79	31.67
	Linear Regression	318.03	101141.32	318.03
	Facebook Prophet	2.57	6.62	2.57
	Neural Prophet	217.80	47436.05	217.80
September	Random Forest	126.48	24986.71	158.07
	Linear Regression	561.66	374826.04	612.23
	Facebook Prophet	258.92	67041.45	258.92
	Neural Prophet	150.18	22554.27	150.18
October	Random Forest	186.66	37596.10	193.90
	Linear Regression	264.74	82962.38	288.03
	Facebook Prophet	227.58	51792.38	227.58
	Neural Prophet	483.46	233732.87	483.46

With prior research demonstrating the predictive strength of ensemble methods in finance, the use of Random Forest to forecast the clean energy stock prices [8], our findings, we also confirm the trends in the personal expenses forecasting domain. The Random Forest model has stable performance in some months and outperforms other weaker models. For example, it maintained low errors in June (MAE = 139.00, RMSE = 139.00) and July (MAE = 181.84, RMSE = 181.84), compared to Linear Regression's much higher errors (MAE = 1413.47, RMSE = 1413.47 in July). It also performed well in September (MAE = 126.48, RMSE = 158.07) and October (MAE = 186.66, RMSE = 193.90), indicating relatively stable performance within the synthetic experimental setting.

The experiment aimed to compare the four models for forecasting monthly expenses using synthetically generated transaction data. The results indicated that Random Forest provided relatively stable overall performance among the

evaluated models under the synthetic experimental setting. Random Forest is an ensemble model that can capture complex, non-linear relationships in the data. It is robust to outliers and noise, which are often present in real-world financial data. It handles missing values and categorical data more flexibly compared to other models. Like prior findings in other domains, such as weather forecasting in tropical regions where Random Forest achieved high accuracy [28] and rainfall prediction in Malaysia where Random Forest showed strong performance [29], our study also shows its effectiveness.

The final deployment of the Random Forest model supports monthly savings predictions and expense tracking in the app, helping users make better financial decisions and promoting long-term financial wellness.

5. CONCLUSION

The expense tracking application is designed to help users monitor their spending habits, manage budgets, and improve savings through key features like transaction recording, consumption analysis, budgeting, and reporting. The project includes a comparative analysis of six existing applications, research on suitable prediction models, and the development of a prototype with detailed wireframes and implementation steps. Random Forest showed the most stable overall performance among the evaluated models using the synthetic dataset in this experiment. However, these results should not be interpreted as evidence of equivalent performance on real-world user transaction data. Future work should validate the models using larger and more realistic real-world datasets, explore additional machine learning models, perform hyperparameter tuning, and enhance the existing application features to further improve its accuracy and functionality.

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AUTHOR CONTRIBUTIONS

Li Wei Tai: Documentation, Literature Review, Research Methodology, Experiment and Result, Validation, Writing;
Li Zhe Poh: Supervision, Writing, Review & Editing;
Md Ismail Hossen: Review.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. <https://publicationethics.org/>

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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