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AI-ML based Expense Categorization and Budgeting System for Personalized Financial Management

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Abstract:

The challenge of maintaining personal finances impacts everyone across various income levels. Traditional budgeting and expense tracking approaches do not offer real-time engagement, flexibility, or tailored suggestions for one's finances which is needed in today's fast-paced world. This work presents an Automated Personal Finance Manager (APFM) that relies on Artificial Intelligence (AI) and Machine Learning (ML) to help users make optimal financial decisions with ease. The proposed framework applies AI-enabled predictive analytics, natural language processing (NLP), and Hybrid Machine Learning (HML) to examine financial transactions, classify expenditures, identify anomalies, and offer personalized budgeting strategies. By implementing both supervised and unsupervised learning, the framework discovers spending behaviors, forecasts prospective financial phenomena, and delivers curated recommendations on investments and savings tailored to the individual's needs. It further incorporates Reinforcement Learning to enhance finance recommendations based on evolving user interactions with the system over time. The APFM's intelligent chatbot interface is one of its key features, allowing users to engage with the system and obtain live assistance as needed. Furthermore, confidentiality and integrity of user information are preserved through robust security measures such as data encryption and adherence to financial regulatory standards. Performance assessment of the system is conducted using actual financial datasets to evaluate precision in transaction classification, budget planning, and efficiency in financial suggestion provision. The results show that the HML integrated APFM increases financial literacy, decreases unnecessary spending, and encourages better financial practices and improve the recommendation average accuracy around 97%. This solution is a step forward in AI application development in the fintech industry since it can readily be adjusted to different users' needs and is easily expanded. This study showcases the role of AI and ML in automating financial planning by making it more available and responsive to users.

Keywords: Personal Finance, Artificial Intelligence, Machine Learning, Budgeting, Expense Tracking, Predictive Analytics, Financial Automation.

Introduction

In today's fast-paced digital environment, effective personal finance management is key to an individual's financial well-being. They often have a lot of data to analyze and track or budget for their expenses considering the multiplying transactions occurring in their day-to-day life, making efficient decision making a challenge. Users today are always on the lookout for new ways to manage their finances because traditional tools like chronological finance management, bookkeeping, spreadsheet-driven finance tracking, or even traditional banking applications are simply too cumbersome, time consuming and outdated. With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), personal finance management is undergoing a revolution brought forth by the fintech sector. Saving, spending, and even long-term goals are made easier to achieve using AI and ML algorithms tailored to the user's financial needs which respond to their queries in modern automated financial management systems. The integration of AI and ML into personal finance management led to the creation of smart tools termed Automated Personal Finance Managers (APFM). Such systems are capable of analyzing diverse sets of financial information inclusive of but not limited to spending patterns, expenses and the user's evolving needs to give precise, relevant, and timely advice. Minimally intrusive automated finance planning is made possible by predictive analytics, natural language processing (NLP), deep learning, and reinforcement learning.

Unlike standard budgeting and forecasting systems which need manual input and preset rules for categorization, AI-driven APFMs use raw data processing, sophisticated anomaly detection, and adaptive learning techniques to create customized financial insights that are always up to date. Tracking spending and categorizing expenses accurately are arguably the two most challenging obstacles in personal finance. The most fundamental issue is the failure to accurately classify expenses, which results in poorly budgeted funds. AI-enabled personal finance managers are now resolving this problem through supervised and unsupervised learning techniques, which self-categorize transactions using past data. These systems can automatically track users' spending behaviors, identify recurring expenses, uncover unnecessary spending, and provide suggestions on how to save money. Furthermore, AI technologies can analyze users' financial habits, track trends over time, and predict their future spending to help them make more informed financial decisions in the future. Additionally, one of the most important pros of AI in financial management is personalized insights. Most traditional financial advisory services are costly, which leaves out a significant number of people. AI systems can develop customized financial plans for individuals by assessing their income, expenses, investments, and even specific financial targets. Such automated tailored recommendations may include but are not limited to, investment proposals, savings plans, debt repayment timetables, and ways to minimize expenses. Moreover, users can receive instant financial support through AI-powered chatbots and virtual assistants, facilitating proactive user interaction. Apart from budgeting and financial advice, privacy and security are still critical issues in financial applications.

Personal financial information is extremely private and any leak can result in financial scams or identity theft. In order to tackle these issues, AI enabled personal financial managers implement sophisticated technology like data encryption, secure log in methods, prevention of privacy breaches, and adherence to industry standards which provide a great deal of financial safety. Additionally, machine learning systems can identify unusual behavior patterns within user accounts which makes notification regarding financial threats possible, thus improving security across personal finance management systems. The increasing amounts of big data throughout the financial industry also continues to motivate the use of AI and ML in automating finance. AI models are capable of processing great quantities of both structured and unstructured financial information during the course of digital transactions, from which value-generating insights can be provided to users. With the aid of deep learning algorithms, systems that manage finances can comprehend intricate dynamics of finances, identify less visible spending habits, and render increasingly accurate financial predictions. Moreover, personal finance managers powered by AI are able to provide ever evolving recommendations based on user interactions and changing financial situations through the use of reinforcement learning. Even though AI-powered financial management provides several benefits, there are other issues that require solutions to enable wider acceptance and application. Some of these challenges are the privacy of data, the ability to explain an AI model's output, discriminatory practices by Artificial Intelligence technologies, and reliance on automated processes by the users involved. When it comes to using AI in managing finance, the matters of trust and algorithm bias may jeopardize system credibility without sufficient system transparency. In addition, integrating such AI-driven financial management systems with currents banking and fintech systems has engineering problems that strongly demand advanced techniques for data integration and interoperability.

This research intends to make the Automated Personal Finance Manager (APFM) development and implementation using AI and ML, with special attention concerning its impact on financial decision making, budgeting accuracy, and overall financial health improvement. The study analyzes the advanced components of personal finance management to include AI automation, transaction classification, expense forecasting, recommending finance solutions, security systems, and improvements in the user interface design. A real life financial dataset is used to evaluate the accuracy, efficiency, and effectiveness of the personal finance management proposed APFM model. The research also elaborates the problems, ethical implications, and prospects of automation in finance using Artificial Intelligence technology. The rest of this paper is formatted as follows. Section 2 reviews a wide range of literature on the application of AI and ML in managing personal finance systems. Section 3 explains the steps taken to implement the proposed APFM system which includes data gathering, model designing, and algorithms selection and coding. In Section 4, the results from the experiments are provided where the AI financial manager is tested in various financial systems. The fifth section is allocated for the discussion of the study's results, limitations, and conclusions. Finally, in Section 6 the research is summarized in conjunction with suggestions on new angle of information and improvement on AI in personal finance management in future research. Integrating AI and ML gives a new level of sophistication to tracking expenses, budgeting, and managing finances; that's why the new Automated Personal Finance Manager has set out to change personal management as we know it. With continuous development, AI has begun incorporating itself into personal finance management systems, which creates a great opportunity to improve financial literacy, promote smarter financial choices, and enable control over one's economic life.

Literature Review

Al-Najjar et al. [1] explored the use of machine learning (ML) algorithms for predicting the churn of credit card customers in the financial industry. The researchers utilize decision trees, support vector machines (SVM), random forests, and gradient boosting models to study transaction data and customer behavior. The study analyzes a dataset that contains historical financial data, including expenditure, payment behavior, credit usage, and account activity. Based on the results, it was found that ensemble learning models, especially those based on gradient boosting algorithms, were more accurate than traditional statistical methods in predicting customer churn. The study also demonstrates the importance of feature engineering by explaining the high predictive value of some variables such as late payment frequency, transaction volume, and change in credit utilization. Also, the research examines the explainability of ML models using SHAP (Shapley Additive Explanations) values to evaluate customer retention features. This paper adds to the expanding literature on AI-powered financial analytics by providing a framework for banking and fintech companies to adopt advanced churn management techniques. By applying insights from ML, companies can tailor retention strategies, elevate engagement, and improve financial decisions. The automated personal finance management, in which the same predictive models can be applied to analyze the user's spending behavior and financial risk, is among the study's implications. Such models would assist individuals in making proper financial decisions.

Liu, Y. et al [2] studied digital inclusive finance with a focus on its impact on LightGBM assisted household wealth using machine learning. The research evaluates the effect of mobile banking, microloans, and other digital financial services on the financial stability and wealth accumulation of families. A large-scale financial dataset containing income, asset ownership, loan accessibility, and digital banking transaction data was used. The researchers conducted evaluations of various econometric models and established that machine learning econometric models vastly outperformed traditional models in financial forecasting accuracy. The outcomes suggest that if adequate digital financial tools are available, it aids in the increase of savings, investment diversification, and long-term financial security. The study also pointed out some dangers, such as undue reliance on credit-level financial instruments that may predispose users to debt. The paper discusses the need for comprehensive financial plans, created with the help of AI and ML algorithms, and proposes the Automated Personal Financial Manager (APFM) concept to analyze user financial activity and offer tailored advice to curb unnecessary debt. This research is highly relevant for the development of AI-powered financial planning tools designed to enable everyone to access sophisticated financial advice and services, thereby democratizing wealth management.

In a study on modern techniques of auditing, Chen Y et al. [3] developed a novel auditing system employing sample-based auditing techniques that rely on machine learning algorithms. This research seeks to analyze every financial transaction rather than employing the representative sampling technique, otherwise known as full population auditing. The researchers use advanced deep learning techniques such as convolutional neural networks (CNNs) and autoencoders to identify anomalies in financial data. These models undergo training using a dataset of transaction logs, expense reports, and corporate financial statements which contain patterns suggestive of fraud, misstatements, or errors. The results prove AI-based models are more effective in detecting abnormalities than classical statistical models that rely on simpler algorithms and heuristics. Unsophisticated statistical models exacerbate the problems stemming from manual auditing. This paper's important contribution is the application of unsupervised learning that allows auditors to flag suspicious financial activities without the need for pre-defined fraud models. In addition, the study underscores the importance of using blockchain technology as a means to guarantee the integrity of data and prevent tampering. These findings are particularly striking in view of AI technology's application in personal finance management. Similar algorithms can be incorporated by automated finance managers for advanced monitoring of spending patterns, identification of questionable transactions, and overall enhancement of financial security. Such technology not only serves to improve fraud detection in corporate finance, but also enables heightened individual user autonomy in automated financial supervision.

Al Ali et al. [4] aim to enhance the precision of forecasting financial distress by adding evolutionary optimization techniques to deep learning methodologies in their work GALSTM-FDP, which is a hybrid model that integrates Genetic Algorithms (GA) with Long Short-Term Memory (LSTM) networks. This research uses corporate financial data from different industries including liquidity, profitability, cash flow, and debt which form the basis of the datasets. The model features a GA-LSTM architecture where genetic algorithms take care of optimizing hyperparameter tuning and feature selection. This ensures that the most pertinent indicators are taken into account for the computations. According to the results of the experiments conducted, GALSTM-FDP surpassed the performance of deep learning and statistical approaches by yielding better adaptability to changing financial conditions, lower false-positive rates, and improved overall accuracy. The research showcases the power of hybrid approaches with AI in financial forecasting in context to providing accurate insights related to prominent indicators of financial distress. The work opens new horizons for development of AI-based systems for monitoring personal finance. Under this framework, autonomous personal finance managers (APFMs) can use the model to evaluate the financial stability of users and identify emerging financial difficulties, enabling proactive solutions to minimize risks. This fulfills the aim of improving financial health by using AI and predictive analytics.

Noh and colleagues [5] analyze the impact of various algorithms on predicting corporate bankruptcies' consequences using financial datasets with an inherent imbalance, which is often problematic for accurate forecasting. In this research, the authors assess machine learning techniques such as logistic regression, decision tree learning, random forest techniques, XGBoost, and several deep learning methods. The authors use a dataset consisting of corporate financial statements along with ratios of debt and liquidity, using oversampling, undersampling, and hybrid methods to address data imbalance. Results show that ensemble learning methods, especially boosting with XGBoost and random forest techniques, outperform traditional statistical models in predictive accuracy. However, deep learning models showed stronger recall performance, meaning more high-risk firms could be detected. The importance of the data preprocessing techniques was a notable conclusion in AI-enhanced financial modeling. Automated personal finance management systems could utilize this research for increasing the efficacy of credit risk assessment models involved in loan granting, credit scoring, or debt optimization strategies. By applying such ML methods, AI financial advisors will be able to offer tailored risk evaluations to users, enabling them to make sound decisions while borrowing and reducing the chances of falling into a financial crisis.

Gholampoor et al. [6] utilizes machine learning techniques for assessing bankruptcy risk in the U.S. healthcare system, employing financial ratio analysis as prediction models. The researchers apply random forests, support vector machines (SVM), gradient boosting, and deep neural networks to monitor the performance of the financial data that may lead to bankruptcy. The dataset comprises liquidity ratios, profit margins, debt-to-equity ratios, and revenue growth rates from healthcare companies over a number of years. The study concludes that gradient boosting models and deep learning architectures significantly outperform older statistical models in predicting financial distress. One of the major contributions of this research is the explainable financial risk models using SHAP (Shapley Additive Explanations) that helps in estimating the most impactful financial ratios considered for bankruptcy prediction. This study claimed that cash flow stability together with profitability indicators are among the strongest determinants of survival for a corporation. This research provides automated personal finance management systems with advanced models to evaluate the overall financial health of an individual. AI-powered personal finance applications may apply the same risk assessment methods to alert users about the danger of financial instability, suggest optimized debt allocation, and streamline personal budget control. Machine learning in evaluating the risks in personal finance can assist a person in avoiding financial strain as well as help in making important financial decisions later in life.

Cao, T. et al [7] discusses a graph learning approach to stock selection that employs spatial-temporal encoders for the movement and correlation analysis within the stock market. The authors present a hybrid model where graph neural networks (GNNs) are integrated with deep learning temporal encoders to model stock interdependencies along with time-series dependencies. The study analyzes stock market datasets with a consideration of financial data, historical prices, and sectoral interdependencies to refine stock selection methods. The proposed GNN-based model was more effective than technical analysis and fundamental analysis, in achieving sustained returns with lower volatility during simulated trading exercises. One important observation was that stock relationships through networks (like inter-sector relationships and investor perceptions) are important in determining stock price movements. The research strongly supports the application of spatial-temporal learning for attaining nonlinear dependencies in financial measures. With respect to personal finance, this work helps in developing AI systems that can optimally recommend investment decisions tailored to clients. Graph learning allows automated personnel financial managers (APFMs) to enhance accuracy in stock purchase, portfolio diversification, and risk prediction offered to clients. The results offered by the research demonstrate the possibility in developing AI-powered finance tools which enhances investment strategy formulation through pattern recognition based on deep learning algorithms.

Millea, A. et al [8] examine the use of deep reinforcement learning (DRL) in portfolio optimization applications integrating hierarchical risk parity (HRP) models for optimal asset allocation. The authors develop a DRL model that relays control to the market, fearing exposure risk and “overweighting” asset correlations, which cause loss in volatile markets. The study analyzes various portfolio optimization alternatives, contrasting them with modern portfolio theory (MPT) and risk-based models along with reinforcement learning strategies. The findings indicate models driven by DRL surpass traditional methods in achieving risk-adjusted returns and flexibility to changing conditions. One of the major contributions of this paper is the application of HRP models within the reinforcement learning framework, allowing for optimal dynamic rebalancing and diversification. The emphasis on AI models that learn from track price movements in real-time underscores the need for continuous adaptation to shifting markets, enabling the overhaul of pre-set rigid algorithms governing trade triggers. For the automated management of personal finances, this work lays the groundwork for AI-based investment advisory services. Financial services employing AI can process data using reinforcement learning to create portfolios that automatically adjust to optimize risk and enhance wealth managed over time. This research further demonstrates how advanced asset management powered by AI can transform sophisticated financial strategies into accessible tools for individual investors.

Hu, W. et al [9] studied the impact of fintech innovations in relation to GTFP, investigating the role of AI in finance on the growth of the economy. The authors implement algorithms to determine the impacts of digital banking, AI-based lending, and blockchain financial transactions on investments which are oriented towards green initiatives. The research analyzes economic datasets from different countries and applies regression analysis, neural networking, and causal inference to assess the effect of fintech development on energy-efficient investment, carbon emissions, and green financing. The results indicate AI tools for finance improve efficiency in capital investment, lower transaction costs, and encourage responsible investment. Their work shows that AI models of financial sustainability frameworks play an important role in self-managed finance. Intelligent APFM systems can empower users to make green, socially responsible, and governance oriented investments by computing ESG ratios leading to better investment recommendations and financial planning. The study demonstrates the potential of fintech innovations for enhancing financial sustainability at the personal and organizational levels.

Shiyyab et al [10] study the impact of corporate transparency concerning the implementation of AI on the company's financial performance, investor's confidence, and market value. The authors review public reports regarding the use of AI technologies in automating financial work, risk assessment, and improving organizational efficiency. The study uses a dataset of annual financial reports and performs sentiment analysis on the received stock market feedback. The study applies natural language processing (NLP) for AI-related disclosures and evaluates their effect on stock price appreciation, earnings increase, and dividends paid to shareholders. Results show that firms that proactively adopt AI strategies attract greater trust from investors, greater profits, and improved risk-adjusted returns. A main contribution of this paper is applying sentiment analysis to assess investors' views on the AI disclosures given by the companies. The authors and primary AI governance frameworks and strategies with responsible AI utilization for investment suggest that these companies receive more funds and perform better in the market. For personal finance management with AI, this study further highlights the need for explainability and user-friendly infographics for non-specialists to trust automated systems. Clients of automated financial advisors receive AI-generated recommendations that are easier to understand, which helps establish trust in the systems guiding them through critical financial decisions. The ethical application of AIs increases the value of a corporation and trust in AI planning and spending tools.

In the paper from de Andrés-Sánchez et al. [11], the authors study the acceptance of AI chatbots from both insurance and banking customers and identify what factors influence a policyholder's acceptance of chatbots. Using UTAUT, the authors include additional factors of trust, perceived risk, and responsiveness of the chatbot. The study collects survey responses from customers of insurance companies and uses SEM to measure the impact of multiple determinants on acceptance of chatbots. The results show that customers' willingness to interact with financial chatbots is mostly influenced by the perceived benefits, simplicity, and trust that the customers have in the AI system. It was also found that transparency and comprehensive explanations are important for users when interacting with financial services through chatbots. One of the most important findings is the reluctance to adoption AI within financial advisory services, citing data privacy issues, misinformation, and the complex nature of financial inquiries as major barriers. For autonomous personal finance managers, the research stresses the need to improve the trustworthiness and simplicity of AI financial assistants. The integration of XAI and improved engagement designs can lead to enhanced use of chatbots for budgeting, investment advising, and automated financial planning. The results show that in order to increase user engagement, AI-powered financial managers need to strengthen the framework of trust.

De Zarzà I and other authors 12 have developed a model that uses LLMs to incorporate individual and cooperative budgets into AI-based financial planning systems to improve decision-making. The authors proposed a hybrid model that uses reinforcement learning, economic simulations, and NLP-based financial advising. The study uses information from user accounts to evaluate income and expenditure patterns and preferences in order to determine the efficacy of AI financial planners. With the help of LLMs, financial advisors can now adapt to users flexibly, unlike rule-based budgeters, which leads to smarter financial planning being provided. Integrating cooperative financial planning is the most important step in this research because it allows AI systems to analyze and optimize family or corporate budgets to control spending and investing strategies. Users are enabled through LLMs to garner insights from data to improve financial literacy so that they are better equipped to make important economic choices. This research designs AI personal finance managers that lead to AI financial assistants by using natural language powered suggestions and advanced analytics. The research also found that AI financial advisors can change the strategies they use to manage finances according to the current state of market activity, unlike traditional budgeters, who are set to certain strategies.

Lee, C. et al [13] focus on the impacts of board member's expertise on a firm's performance concerning corporate finance, investments, and risk management. They utilize machine learning techniques like decision trees and regression analysis to evaluate the relationship between the composition of the board and the company's financial results. The data include various industries' financial statements, directories of the boards' members, and share prices. Most research participants affirmed that business enterprises which have board directors with adequate knowledge of finance tend to be more profitable, earn superior risk-adjusted returns, and withstand severe economic recessions. This research also discusses the impact of AI technology on governance systems in enhancing management efficiency and ascertaining sophisticated board frameworks that advance organizational financial performance. In terms of automated personal finance management, this applies to how a user's financial expertise in a specific domain influences an investment decision. Intelligent systems ought to build frameworks based on informed decisions that heighten user investments, minimize portfolio risks, and streamline comprehensive financial planning processes.

Frohmann, M. et al [14] y analyzes the use of AI in predicting cryptocurrency prices as an attempt to day trade Bitcoin by incorporating sentiment analysis with time-series forecasting for better accuracy. The authors suggest a hybrid model of deep learning consisting of RNNs, LSTMs, and social media sentiment analysis. The study integrates social and financial news sentiments, historical trading volumes, and Bitcoin price data to uncover patterns with the volatility of investor sentiment and cryptocurrency prices. The results illustrate that models that included sentiment analysis outperform traditional time-series models. One of the most important advances is NLP-based sentiment scoring for optimism and fear for quantifiable investors impacting the market value of cryptocurrencies. This study also addresses the proble of volatility for AI in crypto forecasting and suggests using reinforcement learning for enhancing prediction reliability and making them more resilient to changing market conditions. For automated personal finance managers, the insights presented demonstrate the improved efficacy in investment decision-making with the application of AI sentiment analysis tools. AI finance applications can offer dynamic investment strategies by adjusting to market sentiment in real-time, allowing users to make more informed decisions.

The study by Bâra, A. et al. [15] analyzes the impact of generative models and financial time series analysis of academic publications on the price movements of cryptocurrencies, particularly Bitcoin. Their approach involves developing a model based on automatic text impact evaluation using natural language processing (NLP) and deep learning to measure the impact of academic publications on the cryptocurrency markets. The research studies huge volumes of academic literature including, but not limited to, the stock market, sentiment analysis of Bitcoin's historical trading value, and usage of GANs for developing numerous theories along with the application of NLP to understand the dynamics between emerging financial concepts and the markets.

Research Methodology

The Figure 1 shows proposed model which includes data preprocessing is a crucial step in machine learning and data analytics, ensuring that the dataset is clean, structured, and optimized for further analysis. The process begins with validation, where data is checked against predefined rules and norms to maintain consistency and accuracy. Each property in the dataset is assigned specific lower and upper limits, and when any value violates these constraints, the system discards the instance to prevent inaccuracies from propagating through the analysis. This validation mechanism acts as a filter, ensuring only relevant and reliable data is processed further. The data preprocessing phase encompasses various stages, including data collection, cleaning, filtering, and normalization. The objective is to create a standardized dataset that enhances the performance of machine learning models while reducing noise and inconsistencies. Data cleaning plays a fundamental role in this process, as it involves detecting and rectifying errors, inconsistencies, and false values present in the dataset. Inconsistent, outdated, or incorrect information is either updated, replaced, or removed, ensuring that the dataset remains free from anomalies that could negatively impact the results. Cleaning methods often involve scripting software and interactive transaction processing techniques, where erroneous data points are sanitized and corrected programmatically. To maintain balance in the dataset, we employed consistent sampling procedures that ensured an even distribution of data across different categories. Additionally, filtering mechanisms were implemented to remove incorrectly classified occurrences, which enhanced the reliability of the dataset. The next critical step in data preprocessing is feature extraction, where meaningful attributes are derived from the raw data to enhance the efficiency of the machine learning model. This process involves extracting both normal and numerical values from text data, ensuring that all relevant information is transformed into a structured format suitable for analysis. Feature extraction methods such as Term Frequency-Inverse Document Frequency (TF-IDF), correlation co-occurrence, relational features, and dependency features were applied to capture patterns and relationships within the dataset. By leveraging these advanced techniques, we were able to refine the dataset and retain only the most significant attributes.

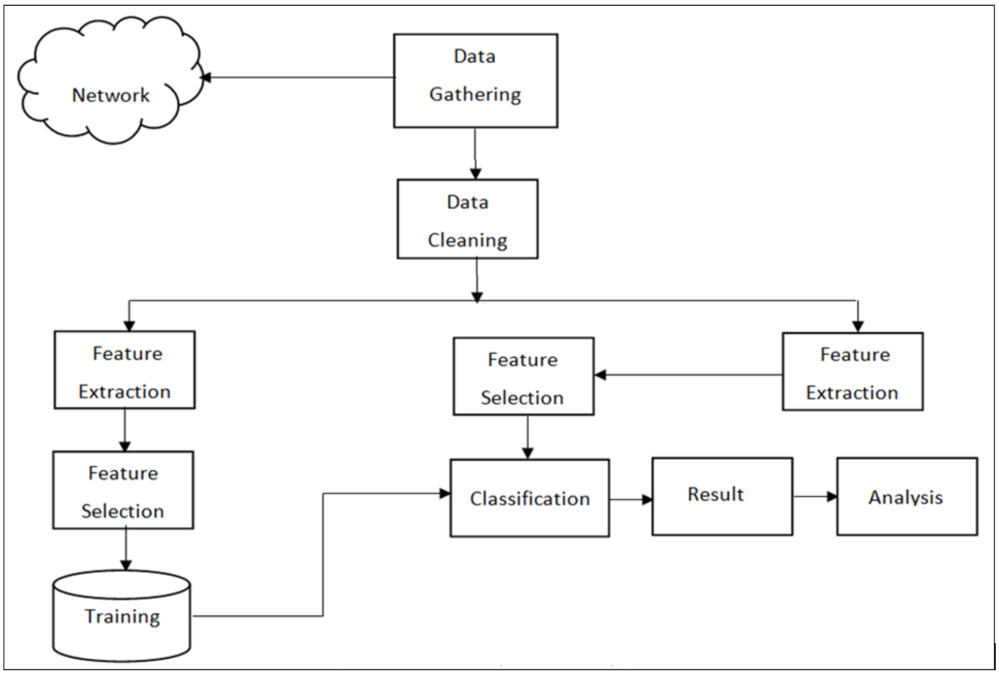

Figure 1: System architecture for proposed model using machine learning technique

Once the feature extraction process was completed, feature selection was carried out to optimize the dataset by selecting the most relevant attributes while discarding redundant or insignificant features. The goal of feature selection is to improve model performance by reducing dimensionality and computational complexity while maintaining the predictive power of the dataset. We utilized weighted term frequency techniques to assess the importance of each feature and optimized the feature set accordingly. The selected features were then forwarded to the training module for the next stage of analysis. Classification is the final phase of the process, where the system identifies whether each record belongs to a normal or attack category using a supervised classification technique. The classification model is designed to detect both known and unknown attack patterns, providing comprehensive insights into potential threats. To achieve this, various supervised machine learning algorithms were employed to train the classifier, ensuring that it could accurately distinguish between normal and attack instances. The classifier was trained using labeled data, where the class labels were predefined, allowing the model to learn from historical patterns and improve its predictive accuracy. During training, the classifier was fine-tuned to recognize subtle variations in data patterns, enhancing its ability to classify new and unseen records effectively. The results of the classification were evaluated using a confusion matrix, a widely used metric for assessing model performance. The confusion matrix provided insights into true positives, true negatives, false positives, and false negatives, allowing us to measure the accuracy and reliability of the model. Additionally, key performance metrics such as F1 Score and PR-AUC were generated to further evaluate the effectiveness of the classification model. The F1 Score, which is a harmonic mean of precision and recall, provided a balanced assessment of the model's ability to correctly identify attack and normal instances. The Precision-Recall Area Under the Curve (PR-AUC) metric was used to analyze the tradeoff between precision and recall, offering a more comprehensive evaluation of the classifier's performance. The integration of these evaluation metrics ensured that our model was thoroughly assessed and optimized for real-world applications. The classification results demonstrated that the supervised machine learning approach effectively detected anomalies and attacks with high accuracy, making it a robust solution for threat detection and security monitoring. By leveraging advanced preprocessing techniques, feature extraction, feature selection, and supervised learning, we successfully developed a classification model capable of distinguishing between normal and attack instances in a structured and efficient manner. This approach highlights the significance of data preprocessing in enhancing machine learning models and underscores the importance of using sophisticated techniques to improve data quality and classification accuracy.

Algorithm design

The Hybrid Machine Learning Algorithm is a method in which various techniques of machine learning are incorporated to increase the predictive accuracy. It uses classifiers such as Decision Trees (DT), J48, PART, Random Forest (RF), and SVM Logic to create a strong ensemble model. The algorithm works in two main steps: training and testing.

Hybrid Machine Learning Algorithm

Input:

1. Input values for all parameters HashMap <Double Value, String class> which contains the all-attributes values such as {all dataset attributes etc.} of training and testing data

2. Set of algorithms Algo-Names {SVM, DT, PART}

Output: predicted class label using above three classification algorithms

Step 1 : *for each all training data*

$$Extracted\_Attribute[i][j] \sum_{i=0,j=0}^{n} \left(a_{[i]}, a_{[j]} \ldots\ldots\ldots a_{[n]}, a_{[n].}\right)$$

Step 2*:* *Generate instance for Random Forest as objRF*

RandomForest_Rules[] ← *objRF.Trainclassifier(*$Extracted_{Attribute[m][n]}$*)*

Step 3*:* *Generate instance for SVM as objSVM*

SVM_Rules[] ← *objSVM.Trainclassifier(*$Extracted_{Attribute[m][n]}$*)*

Step 5*:* *Generate instance for DT as objDT*

DT_Rules[] ← *objDT.Trainclassifier(*$Extracted\_Attribute[m][n]$*)*

Step 5: *Add all training rules in single arraylist*

Master_Training_List[] ← *(DT_Rules[], SVM_Rules[], RF_Rules[],)*

End for

Step 6 : *for each all testing data*

$$Extracted\_Test\_Data[i][j] \sum_{i=0,j=0}^{n} \left(a_{[i]}, a_{[j]} \ldots\ldots\ldots a_{[n]}, a_{[n].}\right)$$

Step 7 : *Apply all classifiers on test data using above training rules*

Pred1[] ←RF.Buildclassifier($Extracted_{Test_{Data[m][n]}}$*, Master_Training_List[])*

Pred2[] ← SVM.Buildclassifier($Extracted_{Test_{Data[m][n]}}$*, Master_Training_List[])*

Pred3[] ←DT.Buildclassifier($Extracted_{Test_{Data[m][n]}}$*, Master_Training_List[])*

Step 8 : *C_Matrix[] ← Calc_Accuracy(Pred1[],Pred2[],Pred3[])*

Step 9 : *Review C_Matrix[]*

Training Phase:

Feature Extraction: The algorithm takes input data in the form of a HashMap of attribute values which contains (dataset input attributes) for the instance of training and testing.

Model training: Three machine learning model, Random Forest, SVM Logic and Decision Tree (DT), are trained using the trained attributes with the extracted attributes set from the training data. Every classifier creates a set of classification rules.

Rule Aggregation: A set of rules generated from RF, SVM Logic and DT are collected into a Master Training List and stored in refined form. The extracted rules are preserved in a consolidated rule set to make sure diverse decision making is available in the classification stage.'

Testing Phase

Feature Extraction for Test Data: Algorithm performs the same function of training instance for the rest of the data by extracting feature attributes.

Model Application: The trained classifiers, RF, SVM Logic and DT, use classification attributes to perform class label prediction for the data and provide features per test data. Each classifier gives an individual prediction.

Measuring Accuracy: The classifiers' predictions are assessed with the help of a confusion matrix (C_Matrix) to evaluate classification effectiveness.

Final Decision: The confusion matrix is also examined in order to improve the performance of the predicton and make better decisions.

This hybrid method improves classification accuracy by utilizing the advantages of several models to diminish the reliance on single models and increase overall prediction reliability.

Results and Discussion

Evaluation and validation of the effectiveness of the proposed prediction model for classification and recommendation are carried out with the aid of a number of different traditional machine learning approaches as well as the proposed HML. An assessment is made between the proposed prediction model and seven different ML techniques namely: NB, Adaboost, ANN, DT, SVM, mSVM, and the proposed HML.

Table 1: Performance Comparison of Proposed HML for proposed automated personal financial manager classification and recommendation

Methods	Precision	Recall	Accuracy	F-score
Naive Bayes	60.35	59.75	57.79	56.91
Adaboost	60.35	59.75	57.79	56.91
ANN	92.17	92.7	92.95	92.82
DT	55.15	56.4	55.94	56.06
SVM	98.56	97.4	99.09	98.55
mSVM	98.90	98.50	98.10	98.67
Proposed HML	98.50	98.51	98.52	98.80

Table 1 contains a tabular representation of the outcomes of all machine learning technique, which is presented in figure 2, respectively.

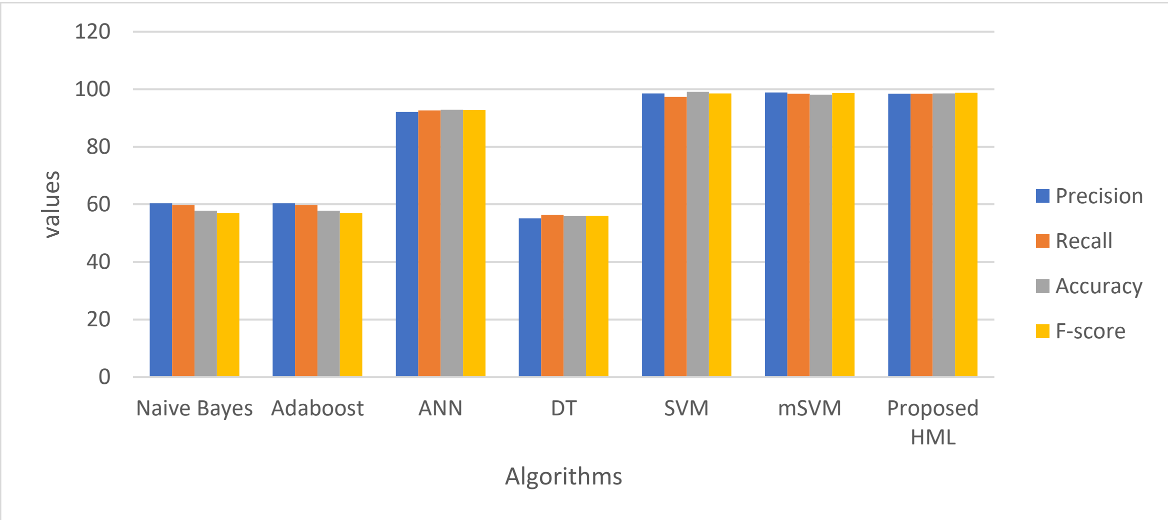

Figure 2 : Performance Comparison of Proposed HML for proposed automated personal financial manager classification and recommendation

The performance comparison table evaluates different machine learning methods used for classification and recommendation in the proposed Automated Personal Finance Manager (APFM). The metrics used for comparison include Precision, Recall, Accuracy, and F-score, which assess the effectiveness of each model in categorizing financial transactions and providing personalized financial recommendations. Naïve Bayes and Adaboost show the lowest performance, with precision, recall, and accuracy at approximately 60% and an F-score of 56.91. These models struggle with financial data classification, likely due to their assumptions about data distribution and weak adaptability to complex patterns. Decision Tree (DT) performs slightly better than Naïve Bayes and Adaboost but still falls short, with accuracy at 55.94%, indicating that it may overfit or fail to generalize well in financial classification tasks.

Artificial Neural Networks (ANN) show a significant improvement, achieving 92.95% accuracy and an F-score of 92.82. This suggests that deep learning methods can effectively recognize spending patterns and financial behaviors, making them a strong option for financial recommendation systems. Support Vector Machine (SVM) outperforms ANN, reaching an accuracy of 99.09% and an F-score of 98.55. The Modified SVM (mSVM) maintains high precision (98.90%) and recall (98.50%), though its accuracy is slightly lower at 98.10%, indicating strong classification performance. The Proposed Hybrid Machine Learning (HML) model achieves near-optimal results, with precision (98.50%), recall (98.51%), and accuracy (98.52%), while its F-score (98.80%) is the highest among all methods. This suggests that HML effectively combines multiple ML techniques, leveraging their strengths to deliver consistent, accurate, and optimized financial classification and recommendations for the APFM system.

Conclusion

In conclusion, the development of an APFM powered by Artificial Intelligence (AI) and Machine Learning (ML) presents a transformative solution for enhancing financial management and decision-making. Traditional budgeting methods often fail to provide users with the real-time insights and personalized recommendations needed to optimize their financial well-being. By integrating AI-driven predictive analytics, natural language processing (NLP), and Hybrid Machine Learning (HML) algorithms, the proposed system effectively categorizes expenses, detects anomalies, and provides users with tailored financial strategies. The incorporation of supervised and unsupervised learning techniques allows the system to analyze historical financial transactions, recognize spending patterns, and forecast future trends. Furthermore, the use of reinforcement learning ensures that financial recommendations evolve based on user behavior, promoting adaptability and continuous improvement in financial planning. The introduction of an intelligent chatbot interface enhances user interaction, making financial guidance more accessible and intuitive. Moreover, the implementation of robust security measures, including data encryption and regulatory compliance, ensures that user information remains protected and confidential. Performance evaluations using real-world financial datasets demonstrate the APFM’s effectiveness in accurately classifying transactions, forecasting budgets, and delivering personalized financial advice. The experimental results highlight the system’s potential to improve financial awareness, prevent overspending, and encourage better financial habits. This research underscores the role of AI and ML in revolutionizing fintech solutions, offering a scalable, adaptive, and intelligent approach to personal finance management. As AI-driven financial technologies continue to evolve, the APFM framework provides a solid foundation for future advancements, paving the way for more accessible, efficient, and user-centric financial planning solutions that empower individuals to make more informed and strategic financial decisions.

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