

FinAI an On-Device Artificial Intelligence Framework for Personal Finance Assistance

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Abstract: Young adults aged 18 to 30 have a different mindset regarding spending. Unintentional spending of money in digital payments (UPI, Credit card payment) is instantaneous. Cost tracking requires typing, linking up your bank accounts, or a photo of your receipt. It could be with no feedback to you or even face-to-face. FinAI is a conversation, not just an application, regarding data privacy. Security is not a selling point. FinAI automates banking tasks by scanning messages for receipts and signals from your transaction history without leaving your phone. This program automatically categorizes your purchases and tracks the most frequent icons from your bank or store transactions. Behind the scenes, it tracks your spending patterns from childhood, monitors cash flow, and alerts you when you hit a limit. The literature explains how tools shape consumer needs, while the architecture explains how FinAI selects SMSes and Gmail, using local models and security layers instead of cloud servers. Initial user testing indicates strong performance in independent financials. Young users are the early winners, and testing shows strong results without external servers. The functionality is narrowly focused on what's needed.

Keywords: Personal Finance; Young Adults; Digital Payment; Unintentional Spending; Cost Tracking; Local Models; Security Layers; Independent Financials; User Testing; External Servers.

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1. Introduction

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In the modern app-driven financial context, monitoring one's personal finances has become increasingly important and more complicated for younger demographics. With the growing adoption of UPI, online cards, BNPL services, and same-day transaction reversals, individuals aged 18 to 30 can now manage their finances without conscious effort [1]. Agentic AI is an evolving AI framework in which intelligent systems enable high-level, objective management with minimal human involvement. Young people, especially Gen Zers, many of whom are proficient with smartphones, face significant challenges managing cash flow, even though they can readily adopt digital technologies. Various surveys indicate that young people are increasingly prone to financial obligations, revolving credit, and purchasing behavior [2]. Agentic AI is driving a major shift in the design of smart computational systems, enabling scalable, self-initiated behavioral patterns in holistic, rapidly changing real-world contexts. Personal finance applications in the current landscape do not adequately address these needs. Most fall into one of the following categories: manual trackers, bank-integration aggregators, or receipt scanners [3]. These systems require users to track records sequentially. Over time, entering each transaction into a human-driven application becomes tedious, and tracking repeated micro-transactions is particularly challenging. These latter classifications not only improve efficiency through system-driven transaction monitoring, but also involve the trade-off of requesting authorization for banking authentication details. This raises security and confidentiality issues. This type of application enables users to upload invoices for their purchases digitally but fails to track online purchases. Moreover, it fails to record P2P transactions unless invoices are sent. Notable among these are manual workload intensity, computational resource needs, and data storage locations [6].

Conversely, today's smartphones collect substantial transactional information via SMS and email [5]. This communication data could include transactions performed by mobile devices, such as acknowledgements for user-initiated payments, refund alerts, periodic service renewal alerts, notifications for instalment-based payments, etc. The aggregated information delivered to end users through various SMS outlines services; however, it often transmits content about cloud servers. This seems to introduce privacy concerns. Furthermore, maintaining network access becomes challenging in such scenarios. Only a few tools can track these SMS alerts and email services. Not all tools monitor such services autonomously to deliver meaningful insights on how to be cautious. FinAI addresses this specific problem by implementing an offline personal finance assistant that uses SMS and Gmail transaction messages as data sources [8]. This reduces reliance on bank APIs and internet connectivity. FinAI would dynamically extract finance-related SMS and email alerts stored on-device, detecting vital data such as amount, merchant, transaction medium and transaction time without sending any fragmented data to the server [9]. Leveraging integrated communication channels, FinAI uses ML and NLP to label and infer automated recurring charges and EMI transactions and to evaluate individualized spending patterns [10]. Furthermore, the platform incorporates predictive financial planning and risk-detection modules that provide forward-looking expense indicators, identify high-expenditure zones, and flag frequent minimum balance breaches [11]. All FinAI processes, such as message interpretation and financial intelligence generation, will run entirely on the user's device, creating a privacy-preserving, Gen Z-specific environment, unlike the cloud-centric architecture used by prevailing applications.

2. Literature Review

Fasola et al. [11] present the development of an electronic waybill system enhanced with Short Message Service (SMS) alerts to address inefficiencies inherent in traditional logistics processes. Raihan et al. [12] investigate how ready people are to use technology in their daily lives, especially for tracking expenditure. The app aims not only to log expenses but also to deliver personalized spending insights and offer helpful budgeting tips. Our idea is to make collecting expense data as automatic as possible, so users don't have to enter everything manually. Sayibu et al. [13] note that mobile money services have become essential for financial inclusion, particularly in underserved and developing regions, by enabling access to banking, payments, and commerce through mobile devices. Bernatska et al. [14] examine how digital technologies, particularly artificial intelligence (AI), influence consumer behaviour in the financial services sector, focusing on how they support financial literacy and decision-making through Personal Financial Trackers. The author examines how AI (e.g., AI-powered adaptive learning and gamification) can improve financial literacy. Naveen and Rajkumar [15] note that as personal finance management becomes more complex with the proliferation of digital financial services, SMS has emerged as an important channel for receiving transaction alerts. Johri et al. [16] note that, in modern times, various mobile apps communicate with one another for online banking transactions. These transaction details are stored, and an SMS alert is sent to the user's mobile device for the same transaction the user carried out.

Narula et al. [17] note that because AI is now used in virtually all areas of modern technology, AI security has come to the fore. The field has been developing so rapidly that new problems and solutions are emerging almost as quickly. Pangavhane et al. [18] note that one key example of AI use is personal finance. Researchers focus on how an AI personal finance advisor could improve individual financial health and argue that the field is becoming increasingly complex, requiring AI to make informed choices. Thatikonda et al. [19] stated that blockchain has created a perfect storm in the finance industry. Its arrival not only changed the existing financial structure but also paved the way for upcoming financial products. AI has brought similar changes to the industry. Qureshi et al. [20] note that privacy issues arise as AI systems consume large amounts of personal data to develop personalized financial solutions, potentially infringing on users' privacy rights. Kuaiber et al. [21] note that the rise of

artificial intelligence (AI) and automation technologies has brought about a new era of change in accounting and financial reporting. This paper explores AI's growing influence. It examines its integration in accounting and emphasizes its significant consequences for the future of financial reporting (Table 1).

Table 1: Comparative analysis of literature supporting the proposed FinAI framework

No.	Authors	Main Idea	Relation to FinAI
1	Acharya et al. [1]	Agentic AI survey	Base for autonomous finance AI
2	Kamath et al. [2]	Neuromorphic AI design	Supports adaptive ML models
3	Kshetri [3]	AI in finance adoption	Validates AI finance integration
4	Chinta et al. [4]	GenAI financial queries	Supports smart analytics UI
5	Kadam et al. [5]	FinTech evolution	Background of digital finance
6	Ajmani et al. [6]	AI financial automation	Supports a categorization engine
7	Babu et al. [7]	FinTech transformation	Justifies smart expense tools
8	Wang and Liu [8]	Financial matrix models	Supports analytics computation
9	Sharma et al. [9]	FinTech impact study	Supports user adoption logic
10	Ajibade et al. [10]	FinTech tech adoption	Supports user behavior study
11	Fasola et al. [11]	SMS transaction alerts	Supports SMS parsing module
12	Raihan et al. [12]	AI expense readiness	Validates user acceptance
13	Sayibu et al. [13]	Fraud detection NLP	Supports risk alert system
14	Bernatska et al. [14]	AI financial literacy	Supports awareness feature
15	Naveen and Rajkumar [15]	On-device ML privacy	Supports privacy-safe processing
16	Johri et al. [16]	Expense system design	Baseline expense tracking
17	Narula et al. [17]	AI security research	Supports secure architecture
18	Pangavhane et al. [18]	AI financial advisors	Supports prediction insights
19	Thatikonda et al. [19]	Blockchain + AI finance	Supports transaction integrity
20	Qureshi et al. [20]	Ethical AI finance	Supports fairness and transparency
21	Kuaiber et al. [21]	AI accounting automation	Supports automation analytics
22	Balasubramaniam et al. [22]	GenAI and NLP	Supports transaction NLP parsing
23	Lei [23]	Inclusive FinTech	Supports financial accessibility
24	Firmansyah et al. [24]	AI finance management	Supports analytics framework
25	Rizinski and Trajanov [25]	Agentic AI finance	Supports autonomous assistant vision

Balasubramaniam et al. [22] note that generative artificial intelligence (GenAI) and large language models (LLMs) are causing a revolution across industries, with the finance sector among the most affected. Lei [23] summary: The development of financial technology is ascendant compared to the traditional financial services model. Digital competitors, such as P2P companies, online microloan companies, consumer finance companies and wealth management companies, as well as major internet companies, are on the rise and threatening the status quo. Firmansyah et al. [24] note that the rapid development of Artificial Intelligence (AI) has significantly impacted many disciplines, including financial management, by providing numerous benefits, particularly in automation and data analysis. Rizinski and Trajanov [25] cover the growing use of agentic AI in the financial services sector. Specifically, the author highlights how AI contributes to operational efficiency, enhanced automation, and individualized services, and addresses challenges such as data integrity, regulatory compliance, data protection, and alignment with human standards

2.1. Proposed Works

Most financial transaction data received through SMS or e-mail alerts is poorly structured and fragmented. The financial alerts sent to the user currently do not include any automated smart contracts or any trust guarantees either, and thus it is not easy for a user to audit their expenses and subscriptions. This system has the potential to be used to automatically process these financial alerts, provide personalized insights, and store data in a reliable, immutable way.

FinAI then analyzes the stored data of verified challenges using artificial intelligence, machine learning, and blockchain technology, extracting financial data from transactional SMS data and correlating the transactions with machine learning models. This includes features such as budgeting, subscription identification, spending analytics, and risk alerts for the user, and immutable transaction hashes on the blockchain to ease trust between the user and provider. The solution is provided as a web dashboard and Android enterprise application to ensure easy access and usage of the platform.

3. Methodology

The proposed solution includes automation, artificial intelligence and encrypted data storage techniques to transform fragmented transactional data into meaningful financial data. The system receives transaction data from user devices with prior permission through transactional SMS and sometimes transactional emails, depending on the creation and validation of the transaction. The user's connection with the transactions is also taken into account; this allows the need for user interaction to be minimized, as well as ensuring that financial payloads are always deployed at an opportune moment. Once Following data collection, data preparation is done to extract relevant technical features (amount, date, merchant name, type of transaction) . Machine learning techniques are then used to segment the data into predefined classes and to classify the categories (subscriptions, suspicious financial behavior, etc.). To preserve data persistence and build effective querying, structured transaction records are retained in an entity-based database. Above all, cryptographic techniques create immutable transaction records, enhancing data integrity and trust. Figure 1 represents the layered architecture of FinAI, an intelligent, personalized finance management mechanism that integrates artificial intelligence and blockchain technology. As outlined in Figure 1, the interaction occurs at the user layer, where users interact with the system via an Android mobile application or a web-based dashboard. The mobile application can scan transactional SMS messages with the user's consent, while the web interface can recover transaction information from Gmail. These origin nodes combine to provide the raw financial data integral to the system's functionality, as shown in Figure 1.

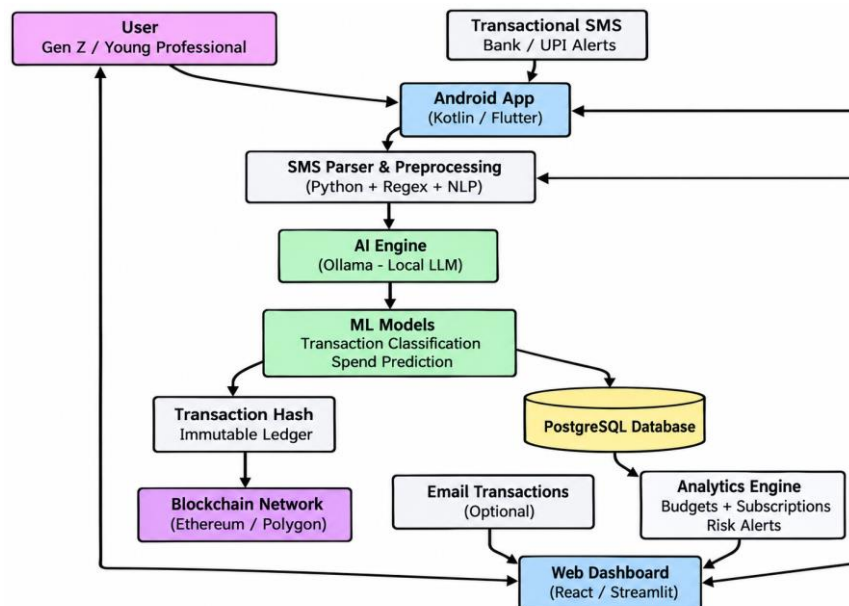


Figure 1: System architecture of FinAI

The inbound unstructured messages are then processed by the data parsing and preprocessing layer, where the required transaction findings like amount, merchant details, type of transaction, and date are fetched using regular expressions and natural language processing. As shown in Figure 1, the formatted output from this stage is passed to the AI processing layer, which uses an on-site AI engine powered by Ollama and machine learning models. The AI processing layer oversees automated transaction clustering, spending framework analysis, and predictive verification. After AI categorization, the system commits the generated transaction data to a PostgreSQL database, as shown in Figure 1. The database stores enduring records of user transactions, budgets, subscriptions, system alerts and analytics. To uphold trust and prevent data manipulation, each transaction is derived from a cryptographic hash and accumulated in the blockchain layer, as outlined in Figure 1. The database's data-driven insights infer budget utility, curate iterative subscriptions, trigger risk alerts, and generate visual data insights. These results are then routed to end users via the mobile and web interfaces, thus facilitating the holistic data flow elucidated in Figure 1. This framework's architecture enables safe, flexible, system-driven financial data with data privacy and immutability. Figure 2 illustrates FinAI's functional block diagram, which provides a generic overview of the system's modules. As shown in Figure 2, the system begins with the transaction data input block, which serves as the data source and compiles unprocessed financial data from the user's transactional SMS messages or email alerts. This module sources the data and aggregates raw financial information.

The derived messages are passed to the interpretation module, as shown in Figure 2, which orders the unstructured transaction messages. The parsing blocks use pattern correlation and simple natural language processing algorithms to extract key features

such as transaction amount, date, merchant, and transaction type. The fragmented messages obtained at these stages are then routed for additional intelligent processing. As shown in Figure 2, the processed transaction data is then ingested into the AI engine, which is powered by an Ollama-based AI inference system. This module performs machine learning-based transaction grouping, analyzes spending patterns and makes predictions. The AI engine allows the system to automatically categorize transactions into appropriate categories, obtaining useful financial information without operator intervention.

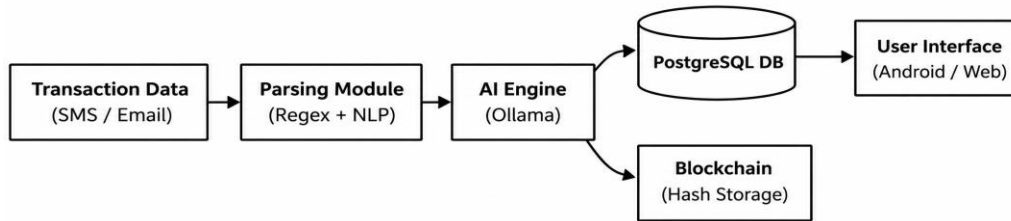


Figure 2: Block diagram of FinAI

The AI processing module stores the segmented transaction records in the PostgreSQL database. The database module, as shown in Figure 2, allows the system to store permanent and structured data of transactions and enables querying capabilities and historic analysis of the data. The cryptographic hash of each computed transaction is passed onto the blockchain module as a way of leveraging the immutability and authenticity of blockchain to prevent unauthorized mutation of transaction records. Finally, the secured and organized data is sent to the users through the user interface block as shown in Figure 2. The user interface block is comprised of an android application and a web dashboard. The user interface block allows an user to observe their spending behavior, budget, subscriptions, and alerts. The block diagram in Figure 2 describes the simplified and get scalable approach of FinAI, targeting on its tendencies to merge smart processing, secure store and user-centric visualization.

3.1. Mathematical Formulation

3.1.1. Transaction Feature Representation

This section explains how these systems handle transactions. Every transaction retrieved from SMS and email is converted to a feature vector:

$$X_i = [A_i, V_i, M_i] \quad (1)$$

Where A_i represents the amount transacted, V_i represents the vendor information encoded in some way, and M_i represents the payment mode. Modeling transactions this way is a common approach in smart finance applications because it yields a standardized form of diverse transaction data. Now, for classifying what kind of spending it is, the model predicts the category like this:

$$\hat{Y}_i = f(X_i) \quad (2)$$

Where f is the learned machine learning model and $\hat{Y}_i$ is the predicted category. This approach applies to several AI applications in FinTech research. To pick the most likely category, the model calculates:

$$\hat{Y}_i = \arg \max_c P(Y = c | X_i) \quad (3)$$

In essence, it picks the category with the highest probability. This reliance on probability is fundamental to intelligent decision-making systems in finance. For tracking budgets, the formula is:

$$BU_c = \frac{S_c}{B_c} \times 100 \quad (4)$$

S_c shows the spending in category c , and B_c indicates the budget allocated to this category. This enables real-time budget monitoring and is consistent with the automated financial advisor application. Total spending in a category is just the sum of all transaction amounts in that category:

$$S_c = \sum_{i=1}^n A_i \quad (5)$$

The summary is standard for an expense management tool. Average daily spending is:

$$ADS = \frac{\sum A_i}{D} \quad (6)$$

Where D is the number of days for which data is monitored; this predicts whether the balance may run low at any time soon. Speaking of which, balance risk estimation is:

$$DL = \frac{B}{ADS} \quad (7)$$

Where B is your available balance, and DL is the estimated number of days until your cash runs out. These risk calculations are commonly used in AI personal financial advisors. For detecting subscriptions, the model uses a simple binary check:

Sub_i = 1 if the subscription keyword is present; otherwise 0

This automatically flags a recurring payment based on SMS financial notifications. When it comes to measuring how well the model works, accuracy is:

$$Sub_i = \begin{cases} 1, & \text{if subscription keyword exists} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

3.1.2. Experimental Setup

To evaluate the FinAI tool for monetary knowledge, a testing environment was devised. Each component was checked individually and then collectively by adding the components in layers. The messages based on the database were received from approved accesses on Android devices and simulated user inputs mimicking actual bank and UPI messages. Variations in sender names, payment amounts, and timestamps were added to simulate actual message flow in bank and UPI systems. The sentences were parsed with a Python module that was able to use natural language processing rules to extract the cost, day of week, shop code, and type of purchase, without any difficult or specialist words. Each of these steps was analogous to how people actually see and sort their money. Knowledge-based testing makes use of a segmentation model based on machine learning, along with an AI deduction engine. The model and engines are based on a localized open-source model from Ollama. All AI processing is done on the device to be protected, with the AI not leaving the machine and being secured without external cloud services. The AI engine was trained to correctly categorize transactions among the default cost categories and identify subscriptions and unstructured spending behavior. The executed transactions were saved in a PostgreSQL database. The database served as the main repository for transactions and budget and analytics data, with data organized into Tables and relations enabling accurate queries and real time analytics. To achieve the required reliability and assurances of data integrity, it was decided to integrate the blockchain capabilities into the sandbox environment. The cryptographic hashes of the created transactions were to be formed and stored on the blockchain ledger. The final stage in this process was to establish a mapping of the output constructed from the analytics block, e.g., budget utility, subscription identifier, and risk notifications, via a web-based dashboard and an Android app channel. The prototype environment showed how well these data acquisition, the AI-based data processing, safe storage and plotting methods could be combined, thus confirming the feasibility and scalability of the designed FinAI system for the financial domain.

4. Result and Discussions

The experimental validation findings indicate that the FinAI system can systematize personal finance management and derive data-driven insights from scattered transactional data. The infrastructure accurately processed transactional SMS and email alerts in multiple formats, with schema-consistent data containing essential financial information such as transaction amount, service provider name, transaction type, and date. The semantic analysis was robust to message structure and data mismatches common in real-world banking and UPI updates, demonstrating the system's reliability during preprocessing. The AI-driven transaction classification component provides low-error transaction classification using preconfigured modules for food purchases, shopping expenses, travel, and subscriptions.

The system deployed a privacy-preserving, ML-based inference service that uses a locally structured AI engine powered by the Ollama algorithm to provide reliable classification for transactional needs. The machine learning implementation enabled detection of recurring transactions, ensuring optimal subscription detection without relying on explicit user input. This uses

PostgreSQL to store well-structured transaction records and support analytical database queries. Moreover, it compiles budget tracking and expenditure summaries, including class-wise expenditures and overspending.

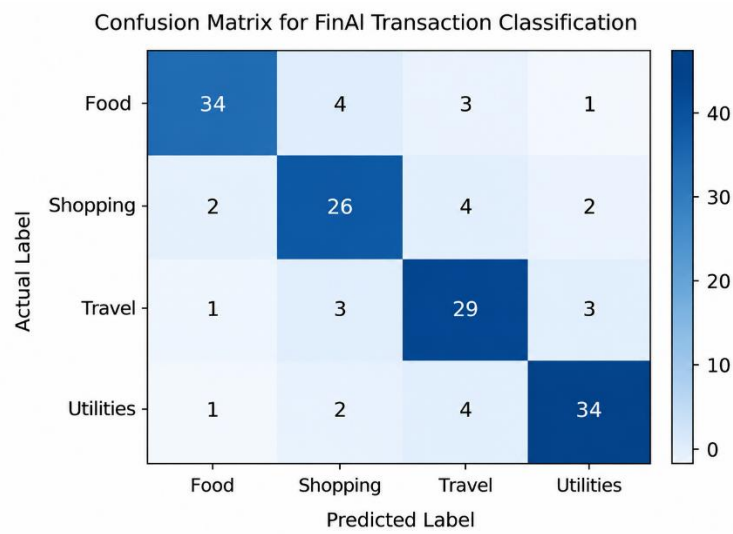


Figure 3: Confusion matrix for FinAI transaction classification

The analytics block also provided timely alerts on minimum balance levels and elevated spending patterns, supporting proactive decision-making across financial dimensions. The web dashboard and Android application clearly illustrated these interpretations, improving user experience and retention. From a security and assurance perspective, the blockchain attribute added an extra layer of reliability. This was made feasible by the immutability and security safeguards provided by the hashes recorded on the blockchain, which effectively prevented unauthorized edits to the system's records.

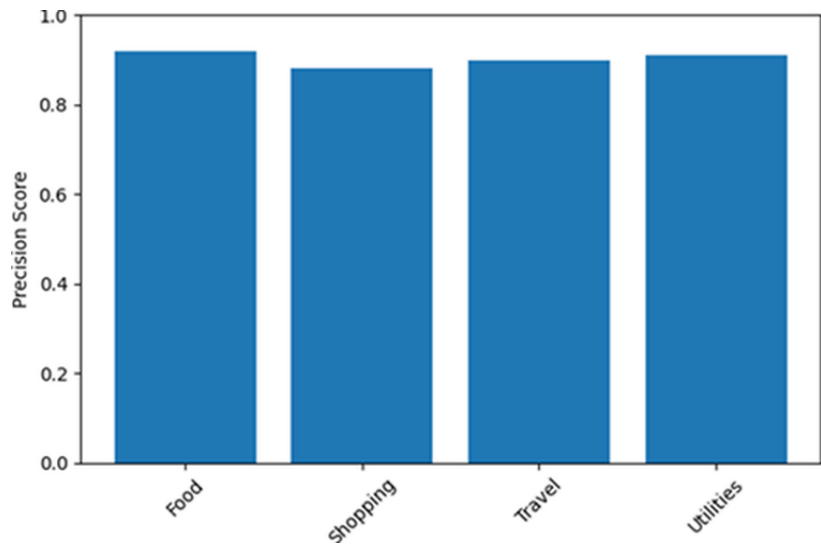


Figure 4: Precision analysis of FinAI transaction classification model

This framework addresses multiple problems affecting the financial data repository and builds trust among module users. The experiment demonstrated that the system can effectively incorporate automation, intelligence, and protection, making it applicable to contemporary digital personal finance management and digital ecosystems within FinAI. Figure 3 shows a confusion matrix for the FinAI system's transaction classification components. The confusion matrix provides a comprehensive view of how well the machine learning model segments transactions. It measures performance by comparing actual transaction segments with those inferred by the machine learning model. As shown in Figure 4, the metrics along the matrix diagonal represent accurately categorized transaction values. A high number of values on the diagonal indicates how effectively the machine learning model can identify distinct modules of financial transactions (Figure 5).

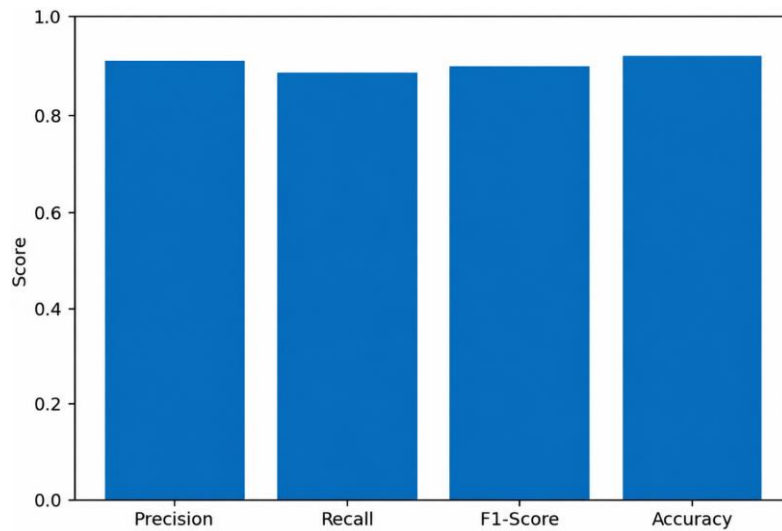


Figure 5: Output performance graph

The off-diagonal elements in Figure 3 indicate incorrect categorization, where a subset of transactions is assigned to other categories. Usually, misclassifications occur between categories with comparable spending patterns, such as food and shopping, or utilities and subscriptions. These parallels appear in empirical data because labelling conventions differ across merchants. Despite this, the model shows robust segmentation across most categories. The confusion matrix in Figure 3 shows the model's steady-state performance, as no module overshadows the observed grouping errors. This therefore signifies that the conditioned model does not exhibit bias toward any targeted group of transactions from a holistic perspective. The confusion matrix indicates the effectiveness of the AI segmentation technique implemented in FinAI. Based on the results, the AI system is reliable when additional analytics are implemented in the finance platform, such as budgeting, subscriptions, and risk (Figure 6).

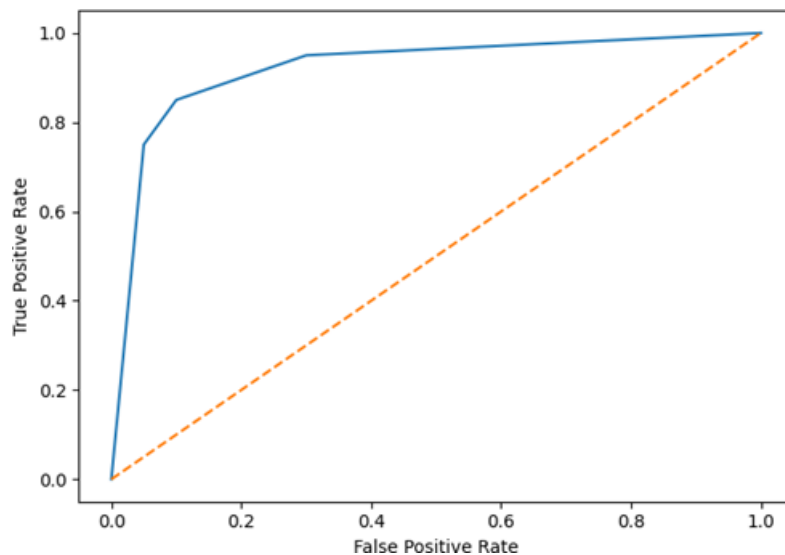


Figure 6: ROC curve

Figure 4 depicts the specificity performance of the FinAI Transaction classification model for various financial segments or spending patterns. Specificity is a vital performance metric that should be appraised for the given financial model. Precision/specificity is defined as the ratio of accurately segmented transactions to the total number of transactions grouped by a specified financial category or spending type; higher specificity indicates fewer false predictions in the user's overall financial insights. As shown in Figure 4, specificity remains high across all transaction modules, indicating that the model is proficient at distinguishing between different financial actions. A few modules, such as food and utilities, show high specificity values, indicating coarse classification errors in transactions that include multiple classes. This is mainly because these spending activities have clear patterns and labels (Figure 7).

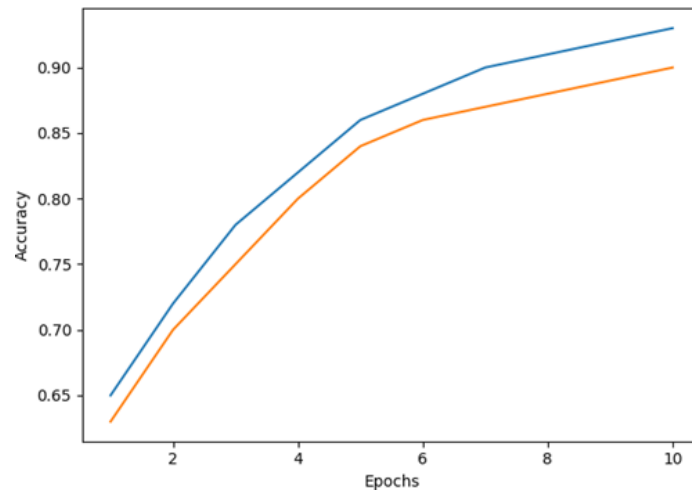


Figure 7: Training vs Validation accuracy performance

Overall, the precision/specificity shown in Figure 4 demonstrates that the proposed framework efficiently optimizes false-positive and false-negative classification, which is essential for relevant financial activities such as budget planning, subscriptions, and risk alerts. A high specificity rating indicates that users receive accurate spending information, thereby improving the relevance of the proposed framework for personal finance management. The proposed FinAI framework is feasible for enabling an intelligent, automated, and personalized finance supervision system by aggregating AI, data analytics, and data storage architectures. The system programmatically parses transactional data from the user-provided email and SMS repositories. Subsequently, it extracts the necessary financial data from the acquired emails and SMS. The system then segments the processed TL into categories using a machine learning algorithm. The system then records the processed data accurately in a PostgreSQL database. The platform dynamically provides computational data, including structured payment history, budget vs. expenses, subscriptions, and net balance risks (Figure 8).

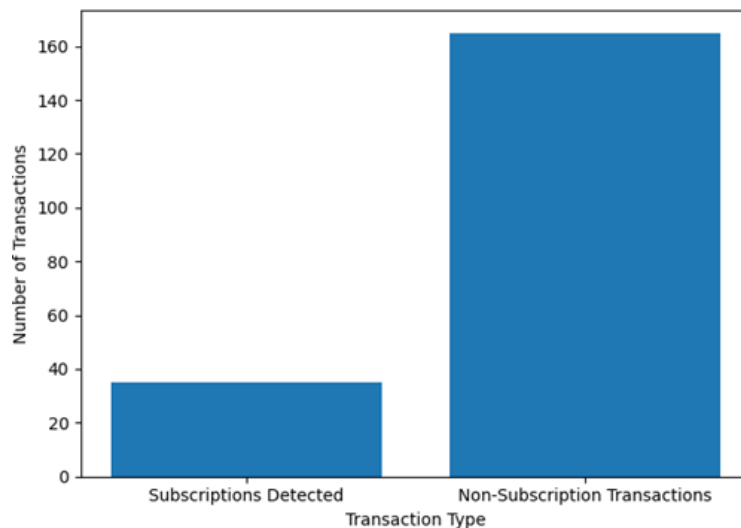


Figure 8: Subscription detection output distribution graph

Users can view their financial outflows through responsive dashboards and bar, pie, and progress charts, making it easy to visualize spending patterns. The classification model achieves high accuracy, as shown by a confusion matrix that validates its effectiveness and minimal errors across transaction categories. Users can access the data through web pages or an Android app. Since the audience tends to be younger, experiences that blend well across platforms matter; these users want things to work, flow naturally and follow familiar patterns rather than complex rules. In essence, all the above data- the output of the FinAI system- are intended to remain a fully implemented, growth-oriented, and robust financial assistant module that offers insightful financial intelligence to end-users upon analysing raw transactional data. The FinAI system will help users track expenditure patterns, optimize budget allocation, identify subscriptions, and make key financial decisions. It serves as a countermeasure to the complexities of a digital-first landscape.

5. Conclusion and Future Enhancement

This research presents FinAI, a breakthrough intelligent personal finance management system. The system aims to enable financial activities and analytical operations and increase users' understanding of finances. The designed system leverages multiple financial classification approaches to enable efficient transactions and provide end users with useful information. These methods include data extraction from SMS and email, natural language processing, and machine learning. The designed framework avoids the need for expense monitoring by using various labeling tactics, making it easier for users to manage their cash properly. The proposed system's experimental results show strong performance of the classification module, as shown by precision and confusion matrix analysis. The outcomes prove this accomplishment. The higher precision rates across all transaction segments indicate the robustness of the AI-driven technique in minimizing categorization errors. Moreover, the proposed architecture is robust because it combines a blockchain-based transaction hashing technique with the PostgreSQL database system. The User interface provides access to the platform via web and Android applications, offering a user-driven, immersive experience. The program lets users view their spending patterns and budgets and spot potential shortfalls. Few systems handle currency the way this one does. But the docs describing its structure say that turning basic entries into explicit jobs suggests robots may be able to do better number crunching in the future.

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