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AI-DRIVEN DECENTRALIZED FINANCE TRACKING SYSTEM WITH BLOCKCHAIN INTEGRATION

U Muruganantham[1], Gokul A[2], Sidhaarthane P[3], Kishore K[4], Praveen R[5] Mohammed Navid N[6]
[1]Assistant Professor, [2,3,4,5,6]UG Scholar, Department of CSE (Internet of Things & Cyber security including Blockchain Technology), Manakula Vinayagar Institute of Technology, Puducherry, India
muruganantham.u18@gmail.com | goks20112004@gmail.com | sidhaarthsidhu2004@gmail.com | kishorekartheeswaran@gmail.com | sivapraveen339@gmail.com | mdnavid2004@gmail.com

Abstract:

In the modern digital economy, efficient financial management demands intelligent tools capable of accurate expense tracking and forecasting. This project introduces an AI-driven expense tracker that integrates Long Short-Term Memory (LSTM) networks with blockchain technology to deliver predictive analytics and secure financial management. The LSTM model, a variant of recurrent neural networks (RNNs), effectively captures temporal and sequential dependencies in historical transaction data to forecast future expenses with high precision. By identifying spending patterns, seasonal variations, and anomalies, the system provides users with actionable insights for budgeting and financial planning. To ensure security, transparency, and trust, the system incorporates blockchain technology with MetaMask-based authentication. Each transaction is immutably stored on the blockchain, guaranteeing data integrity and preventing unauthorized alterations. This decentralized architecture safeguards sensitive financial information while maintaining transparency and accountability. The fusion of deep learning and blockchain ensures not only predictive financial intelligence but also a tamper-proof record of all transactions. Overall, the proposed system offers a secure, transparent, and intelligent expense management solution that empowers users with foresight, control, and confidence in their financial planning.

Keywords: LSTM, Blockchain, Expense Tracking, Financial Forecasting, MetaMask Authentication, Predictive Analytics, Secure Transactions.

I. Introduction:

An expense tracker is an advanced financial management system that enables individuals and organizations to efficiently monitor, record, and analyze their spending behaviors. In the context of today's dynamic digital economy, effective financial management is essential for achieving both personal stability and organizational efficiency. Traditional expense tracking methods, such as manual bookkeeping or spreadsheet-based systems, often lack automation, predictive insight, and data security, making them inadequate for modern financial needs. To address these challenges, the proposed expense tracker integrates Long Short-Term Memory (LSTM) networks and blockchain technology to deliver intelligent and secure financial management. The LSTM model, a specialized form of recurrent neural network, is highly effective in processing time-series data, identifying spending patterns, and forecasting future expenses. By analyzing historical transaction data, it captures temporal dependencies, seasonal fluctuations, and recurring trends, enabling accurate predictions that support proactive budgeting and financial planning. Meanwhile, blockchain technology ensures the transparency, integrity, and security of financial records. Each transaction is immutably stored on a decentralized blockchain ledger, eliminating the risk of data tampering or unauthorized alterations. Integration with MetaMask authentication further strengthens user security by providing encrypted access and safeguarding sensitive financial information. This combination of predictive intelligence and decentralized security not only enhances the reliability of financial insights but also fosters user trust and accountability. Ultimately, the integration of LSTM and blockchain transforms the expense tracker into a powerful, data-driven financial tool that empowers users to make informed decisions, optimize spending, and maintain long-term financial stability.

a. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized type of Recurrent Neural Network (RNN) designed to effectively model sequential and time-series data by capturing long-term dependencies. Unlike traditional RNNs, which struggle with vanishing or exploding gradients during training, LSTM networks are built with a unique architecture that allows them to retain information over extended time periods. Each LSTM unit consists of three primary gates: the input gate, forget gate, and output gate. These gates regulate the flow of information, determining which data should be remembered, updated, or discarded as new sequences are processed. The input gate adds relevant information to the cell state, the forget gate removes unnecessary data, and the output gate decides what information should influence the current output. This gating mechanism enables LSTM to effectively handle temporal patterns, making it particularly suitable for applications involving sequential data such as financial forecasting, speech recognition, and natural language processing. In expense tracking systems, LSTM models analyze past financial transactions to identify spending trends, seasonal variations, and recurring expenses. By learning these patterns, the LSTM network can generate accurate future expense predictions, providing users with valuable insights for budgeting and decision-making. Thus, LSTM enhances predictive accuracy in dynamic, time-dependent financial data environments.

b. Proof of Stake (PoS)

Proof of Stake (PoS) is a consensus mechanism used in blockchain networks to validate transactions and create new blocks in a more energy-efficient and secure manner than the traditional Proof of Work (PoW) system. In PoS, validators are chosen to create and verify blocks based on the amount of cryptocurrency they hold and are willing to "stake" as collateral, rather than competing through computational power as in PoW. This approach significantly reduces energy consumption since it eliminates the need for intensive mining operations. Validators have a vested interest in maintaining the network's integrity because any malicious activity, such as approving fraudulent transactions, can result in the loss of their staked assets. The PoS system thus promotes honesty and trust within the blockchain ecosystem. Additionally, the selection process for block validators often includes factors such as the duration of staking and randomization, ensuring fairness and decentralization. PoS enhances transaction speed, scalability, and cost efficiency, making it suitable for modern blockchain applications, including decentralized finance (DeFi) and smart contracts. In the context of financial management systems, using PoS ensures that transaction verification is both secure and sustainable. Overall, Proof of Stake provides a robust, eco-friendly, and reliable consensus mechanism that strengthens blockchain's security, transparency, and operational efficiency.

II. Literature survey:

[1] Ugochukwu Orji a a , Elochukwu Ukwandu[1] This study aims to predict medical insurance costs using ensemble machine learning models to enhance accuracy and interpretability. Utilizing a Kaggle dataset containing demographic and health-related information, three ensemble methods—XGBoost, Gradient Boosting Machine (GBM), and Random Forest—were applied. XGBoost achieved the highest accuracy, effectively capturing complex non-linear relationships, while Random Forest offered a more computationally efficient solution. To ensure transparency, Explainable AI (XAI) techniques such as SHAP and ICE plots were used to interpret model outputs. SHAP values identified key factors like age, BMI, smoking status, and dependents influencing insurance costs, while ICE plots illustrated feature effects on individual predictions, improving understanding and trust in AI-driven insurance cost estimation. [2] Vipul, P Vinoth Kumar, Divyansh Dimri, Mayank Pathak [2] This system is designed to predict future expenses using machine learning, with a primary focus on the Linear Regression algorithm. It serves as an intelligent financial management tool that analyzes users' historical transaction data to uncover spending trends and forecast upcoming expenses. The system collects past financial records, cleans and categorizes them to ensure data accuracy, and then trains the Linear Regression model to identify relationships between factors such as recurring payments, seasonal patterns, and daily spending variations. Once trained, the system generates monthly expense predictions, enabling users to create proactive budgets, prevent overspending, and make better financial decisions. By transforming raw financial data into meaningful insights, this system empowers users to manage their money more effectively. Additionally, its methodology can be extended beyond personal finance, such as in predicting stock market trends or investment risks, demonstrating its adaptability and value in broader financial analytics applications. [3] Nenturi Vedha Sri, Dharavath Vandhana, Koukuntla Sneha, Dr M V Krishna Rao [3] This system focuses on analyzing and forecasting global health expenditure trends across nearly 200 countries from 2000 to 2022, emphasizing the correlation between national GDP patterns and health spending as a share of GDP. It serves as a decision-support tool for policymakers and international health organizations, enabling them to allocate resources more effectively and identify regions requiring financial or policy interventions. To handle the dataset's high dimensionality, the system employs Principal Component Analysis (PCA), which simplifies complex data by converting correlated variables into key uncorrelated components that reveal the most influential factors affecting global health expenditure. For forecasting, the system integrates both traditional statistical and modern deep learning models.

Autoregressive (AR), Moving Average (MA), and ARMA models are applied to capture linear temporal trends, providing foundational insights into expenditure behavior over time. However, to address the limitations of classical models in handling non-linear and long-term dependencies, the system incorporates Long Short-Term Memory (LSTM) networks. LSTM models, both univariate and multivariate, enable the system to learn intricate temporal patterns and cross-country influences, producing more accurate and robust predictions. By combining PCA-based dimensionality reduction with hybrid time-series forecasting methods, this system delivers powerful analytical insights into the global evolution of health spending and its economic determinants. [4] Dr. S. M. Iqbal, Sayali D. Ghatol, Prerana V. Jadhav, Nikita D. Raspalle [4] This system is designed to predict medical insurance costs using advanced machine learning algorithms to support fair pricing and informed financial planning for both insurers and policyholders. It analyzes a publicly available Kaggle dataset containing demographic, health, and lifestyle information to identify the key factors influencing insurance premiums. The system employs multiple regression-based models—Linear Regression, Random Forest, Gradient Boosting, and XGBoost—to estimate insurance costs accurately. Linear Regression serves as a baseline model, while ensemble methods like Random Forest and XGBoost capture complex, non-linear relationships within the data, significantly improving predictive performance. The models are evaluated using metrics such as Mean Squared Error (MSE) and R-squared values to determine accuracy and reliability. Beyond prediction, the system incorporates interpretability through SHAP (SHapley Additive exPlanations) analysis, which reveals how individual features like age, BMI, smoking habits, and number of dependents affect cost predictions. This transparency helps insurers design fair, data-driven pricing models and enables policyholders to better understand their premium structures. By combining predictive accuracy with explainable AI, this system provides a powerful and trustworthy framework for medical insurance cost estimation, enhancing both operational efficiency and decision-making in the insurance industry. [5] Sandhya Rani A, Bhumika C, Thanushree M, Rakshitha M, Thirumala NO, Ambika S [5] This system is a blockchain-based government budget tracking platform developed to enhance transparency, accountability, and efficiency in the management of public funds. It provides a secure and decentralized environment where all government financial transactions are immutably recorded, ensuring that budget allocations, disbursements, and expenditures are traceable and tamper-proof. Built on a permissioned blockchain framework such as Hyperledger Fabric or Ethereum Quorum, the system maintains a shared ledger accessible only to authorized stakeholders, including government agencies, auditors, and regulators. Each transaction is time-stamped and permanently stored, preventing unauthorized modifications and ensuring full auditability. Smart contracts are integrated to automate fund disbursements based on predefined conditions—such as milestone completion or document verification—reducing manual intervention, eliminating delays, and ensuring that funds are utilized as intended. Additionally, the system incorporates AI-driven analytics to continuously monitor financial activity, detect anomalies, and flag suspicious transactions in real time. Automated alerts notify relevant authorities of irregularities, enabling swift investigation and corrective action. Access control mechanisms ensure that only verified participants can interact with the blockchain, protecting data privacy while maintaining transparency. Overall, this system provides a secure, intelligent, and automated solution for managing government budgets, strengthening public trust, and promoting ethical, data-driven governance. [6] Arijeet Singh, Mohd. Ahad, Hammad Mustafa Malik [6] This system is a decentralized blockchain-based donation tracking platform developed to guarantee transparency, authenticity, and trust throughout the online donation process. It ensures that every contribution made by donors reaches the intended beneficiaries—be it charitable organizations or individual recipients—without manipulation, mismanagement, or unauthorized interference. The platform operates on the Ethereum public blockchain and utilizes smart contracts written in Solidity to automate and secure transactions. These smart contracts are programmed with predefined conditions that govern when and how donations are released, eliminating the need for intermediaries and minimizing the risk of fraud. A central feature of the system is the escrow contract, which temporarily holds donated funds until all necessary conditions are met. Once verified, the smart contract automatically releases the funds to the authorized payment gateway, ensuring that transactions are both secure and rule-based. Every donation, along with key details such as the donor's contribution amount, recipient, and timestamp, is permanently recorded on the blockchain, providing an immutable audit trail. This allows donors to track their donations in real time, confirming that funds are received and utilized as intended. By integrating blockchain immutability, smart contract automation, and escrow-based fund management, the system establishes a transparent, efficient, and tamper-proof donation ecosystem that enhances donor trust, promotes accountability, and supports ethical digital philanthropy. [7] Sungbeen Kim, Sungbeen Kim [7] This system introduces an enhanced blockchain transaction tracking and verification mechanism based on a hash-chain-structured contract to overcome the inefficiencies of conventional methods used in permissioned blockchain environments. Traditional transaction verification processes often require high computational power, longer processing time, and are prone to inconsistencies or vulnerabilities caused by unauthorized access and data asymmetry. To address these challenges, the proposed system implements a contract designed as a cryptographically linked hash chain, where each transaction is connected to the next through its unique hash value. This sequential linkage forms a continuous and verifiable chain of records that allows for faster navigation, retrieval, and verification of transaction data. By maintaining this structured hash sequence, the system enhances both efficiency and integrity, ensuring that all nodes in the blockchain ledger maintain consistent and tamper-proof records. The hash-chain mechanism significantly reduces resource consumption and verification time by eliminating redundant searches and computations typically required in traditional tracking methods. A comparative performance analysis was conducted against two existing contract structures, evaluating parameters such as tracking time, CPU utilization, and network bandwidth. The findings confirm that the hash-chain-based contract substantially improves transaction traceability, reduces computational overhead, and enhances ledger reliability. Overall, this system provides a secure, efficient, and scalable framework for real-time blockchain transaction management, ensuring both transparency and operational optimization in permissioned blockchain networks.[8] Prakash Awasthy , Tanushree Haldar , Debabrata Ghosh [8] This system is designed to analyze and optimize the conditions under which enterprises adopt blockchain technology within supply chain networks, focusing on how adoption decisions influence transparency, efficiency, and coordination between trading partners. It models a dyadic supply chain—comprising a buyer and a supplier—to examine their interactions in traceability, pricing, and decision-making under varying blockchain adoption scenarios. The system identifies three critical drivers of adoption: demand-side factors (such as consumer trust and product authenticity), supply-side factors (such as operational efficiency and data accuracy), and reputational factors (such as brand credibility and compliance). These factors typically reinforce one another, creating a synergistic incentive structure that encourages blockchain integration. However, the system also demonstrates that blockchain adoption can still occur even when one or more of these factors are absent. highlighting its flexibility and adaptability in real-world enterprise environments. Furthermore, the analysis shows that blockchain can generate collective supply chain benefits—such as improved traceability, reduced fraud, and enhanced coordination—even if individual firms do not gain immediate or direct advantages. By modeling incentive alignment and cost-sharing mechanisms, this system provides valuable insights for policymakers and enterprises seeking to balance implementation costs with long-term strategic gains. Ultimately, it offers a decision-support framework that helps organizations evaluate the feasibility and impact of blockchain adoption in supply chain management. [9] Arijeet Singh, Mohd. Ahad, Hammad Mustafa Malik [9] This system is a decentralized blockchain-based donation tracking platform developed to guarantee transparency, authenticity, and accountability in online charitable transactions. Its primary objective is to ensure that every donation made by a contributor reaches the intended beneficiary—whether a charitable organization or an individual recipient—without interference, misuse, or unnecessary delay. Built on the Ethereum public blockchain, the system utilizes smart contracts written in Solidity to automate and enforce donation rules. These smart contracts execute transactions only when predefined conditions are fulfilled, eliminating intermediaries and reducing the potential for fraud or mismanagement. A critical component of the system is the escrow contract, which securely holds donated funds until all required conditions are met, ensuring that disbursements occur only through authorized payment gateways. After each transaction, details such as the donation amount, recipient address, and timestamp are immutably recorded on the blockchain, allowing both donors and beneficiaries to verify the authenticity and completion of the donation. This transparency provides real-time traceability, assuring donors that their funds are being utilized appropriately. By integrating blockchain immutability, smart contract automation, and escrow-based fund management, the system establishes a secure, efficient, and fraud-resistant donation ecosystem. It strengthens donor trust, enhances operational accountability for charitable organizations, and creates a transparent, verifiable, and tamper-proof platform for managing global online donations.

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III. PROPOSED SYSTEM:

The proposed system is an intelligent expense tracking solution that integrates machine learning and blockchain technology to provide a secure, transparent, and predictive financial management platform. Unlike conventional expense trackers that only record past transactions, this system employs machine learning algorithms to analyze users' historical spending data and accurately forecast future expenses. By identifying recurring spending habits, seasonal patterns, and expenditure trends, it enables proactive budgeting, efficient resource allocation, and informed decision-making for both individuals and businesses. Users can anticipate upcoming financial obligations and plan accordingly, thereby enhancing financial discipline and reducing the likelihood of overspending. To ensure security and transparency, the system utilizes blockchain technology to store and verify all financial transactions in a decentralized and immutable ledger. This ensures that once data is recorded, it cannot be altered or tampered with, thereby preventing fraud and maintaining data integrity. Each transaction is verifiable, allowing users to track and confirm the authenticity of their financial records in real time. Additionally, MetaMask authentication is integrated into the system to ensure secure and seamless user access, protecting sensitive financial and personal information from unauthorized use. By combining predictive analytics and blockchain security, the proposed system effectively addresses the shortcomings of traditional financial management tools, such as data vulnerability and lack of foresight. It provides a smart, reliable, and transparent platform that empowers users to manage their finances with confidence. Overall, this system offers a comprehensive and future-ready solution for expense tracking, ensuring both predictive accuracy and robust financial data protection.

a. USER AUTHENTICATION MODULE

The User Authentication Module ensures secure, decentralized access to the expense tracking system using MetaMask. Unlike traditional login systems that rely on usernames and passwords, this module leverages blockchain-based authentication, allowing users to log in using their crypto wallet credentials. MetaMask acts as a bridge between the user and the blockchain, managing digital identities securely. When users attempt to log in, a unique digital signature is generated using their private key, which the system verifies on the blockchain. This decentralized approach eliminates the need for centralized data storage, reducing the risk of hacking, phishing, or identity theft. The module also supports secure registration, where each user is assigned a unique blockchain address that serves as their digital identity within the system. Additionally, all authentication activities are immutably recorded on the blockchain, ensuring transparency and accountability. The use of MetaMask simplifies user access and enhances privacy since no sensitive credentials are stored or shared with third parties. By incorporating blockchain's inherent immutability and cryptographic security, this module guarantees that only legitimate users can access their financial data. It also allows multi-device accessibility, enabling users to log in seamlessly from any device connected to MetaMask. In summary, the User Authentication Module ensures a secure, user-friendly, and decentralized authentication mechanism, strengthening trust, protecting user identities, and laying the foundation for transparent financial data management.

b. DATA COLLECTION MODULE

The Data Collection Module serves as the foundation of the proposed expense tracking system by gathering, organizing, and preprocessing user financial information. It collects transactional data from various sources, including manual entries, bank statements, e-receipts, and digital wallets. The data is structured into relevant fields such as date, description, amount, and category, which makes it suitable for further processing and analysis by the system's machine learning algorithms. To ensure data consistency, this module performs preprocessing tasks such as cleaning, removing duplicates, and normalizing values. It also validates user input to prevent errors or fraudulent records. The module supports automated synchronization with user accounts, ensuring that new transactions are captured in real time without manual intervention. Once collected, the data is encrypted and stored securely, either on a cloud database or blockchain for immutability and transparency. This ensures that sensitive financial information remains protected from tampering or unauthorized access. Furthermore, the module maintains user privacy by storing identifiable information separately from transaction details. The organized dataset produced by this module becomes the core input for subsequent modules, such as expense categorization and prediction. It enables accurate pattern recognition and forecasting by ensuring data integrity and completeness.

c. EXPENSE CATEGORIZATION MODULE

The Expense Categorization Module is responsible for automatically classifying financial transactions into predefined categories such as food, healthcare, rent, utilities, travel, and entertainment. This automation is achieved using a combination of rule-based logic and Natural Language Processing (NLP) techniques. When a user records a transaction, the system analyzes the transaction description and identifies keywords that match specific categories. For example, terms like "restaurant" or "café" may be associated with the food category, while "Uber" or "fuel" may be linked to transportation. Machine learning algorithms continuously learn from user behavior and improve categorization accuracy over time. Users can also manually adjust category labels, and the system updates its learning model accordingly. This feedback loop enhances adaptability and personalization. Categorized data provides a clearer overview of where money is being spent and helps users identify spending trends or areas for potential savings. Additionally, it improves the performance of the prediction model by providing structured and labeled datasets. The module also supports real-time categorization of new transactions, ensuring users have up-to-date insights into their financial activities. By automating the classification process, it reduces manual effort, minimizes human error, and enhances the reliability of financial tracking. In essence, this module transforms raw transaction data into meaningful financial insights that support better decision-making and long-term budgeting.

d. MACHINE LEARNING PREDICTION MODULE

The Machine Learning Prediction Module is the analytical core of the proposed system, responsible for forecasting future monthly expenses based on historical spending data. It employs advanced algorithms such as Long Short-Term Memory (LSTM) networks, which are designed to handle sequential data and recognize temporal patterns. The module first processes historical expense data, identifying spending habits, recurring payments, seasonal variations, and irregular financial activities. Using this data, the LSTM model predicts expected expenditures for the upcoming month with high accuracy. The prediction process involves training the model on historical datasets to minimize error and enhance precision. Once trained, it continuously updates as new data becomes available, improving adaptability and responsiveness to behavioral changes. This dynamic learning approach allows the system to offer real-time and personalized financial predictions. Users can visualize these forecasts through charts or reports, helping them plan budgets, allocate funds, and anticipate upcoming expenses. The module can also identify abnormal spending patterns or potential overspending risks, alerting users proactively. By combining statistical analysis with deep learning techniques, it provides insights that go beyond simple averages, understanding context and behavioral nuances. Overall, the Machine Learning Prediction Module transforms raw financial data into actionable intelligence, empowering users with foresight and supporting informed financial decision-making.

e. BLOCKCHAIN INTEGRATION MODULE

The Blockchain Integration Module is designed to enhance security, transparency, and data integrity in the expense tracking system. It uses blockchain technology to record all financial transactions and critical user actions in an immutable ledger. Every transaction is encrypted and added as a block, which is time-stamped and linked to previous blocks, ensuring that the data cannot be altered or deleted. This decentralized architecture eliminates the risks of centralized database breaches and data tampering. Each user's transaction history can be verified transparently, promoting trust and accountability. Smart contracts are utilized to automate certain processes, such as transaction verification and expense validation, without the need for intermediaries. The module also supports interoperability with public and private blockchain networks, depending on the system's requirements. To ensure privacy, sensitive information is encrypted before being stored on-chain, while summary data remains accessible for auditing. Integration with MetaMask ensures that users can authorize blockchain transactions securely using their wallet. This module also facilitates transparent record-keeping, where both users and auditors can trace the flow of funds without compromising privacy. Overall, the Blockchain Integration Module ensures a secure, tamper-proof, and trustworthy environment for managing financial data, reinforcing user confidence and protecting the system against fraud or unauthorized alterations.

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facilitates transparent record-keeping, where both users and auditors can trace the flow of funds without compromising privacy. Overall, the Blockchain Integration Module ensures a secure, tamper-proof, and trustworthy environment for managing financial data, reinforcing user confidence and protecting the system against fraud or unauthorized alterations.

g. REPORTING AND ANALYTICS MODULE

The Reporting and Analytics Module compiles comprehensive summaries of user financial data, providing in-depth insights into income, expenses, and spending trends over time. It generates customizable reports based on user preferences, such as weekly, monthly, or yearly summaries. These reports highlight key metrics, including total expenditure, category-wise spending, and variance from predicted budgets. The analytics component uses statistical and machine learning techniques to identify long-term financial patterns and predict potential savings opportunities. Reports can be visualized in tables, charts, or downloadable PDF formats for personal records or business use. The integration of blockchain ensures that all reported data is verified, tamper-proof, and transparent. Users can also access historical data to compare trends and evaluate financial performance. By offering a detailed analytical perspective, this module helps users make data-driven financial decisions. It empowers both individuals and organizations to track progress, optimize budgets, and achieve financial goals effectively. Ultimately, the Reporting and Analytics Module provides clarity, accountability, and actionable intelligence, completing the system's cycle of prediction, visualization, and secure financial management.

h. Input Gate Layer

The Input Gate Layer is one of the most crucial components of the Long Short-Term Memory (LSTM) algorithm used in the proposed intelligent expense tracking system. Its primary role is to control how much new information from the current input should be stored in the cell state (the memory of the network). This mechanism allows the system to focus on relevant financial data—such as recent transaction amounts, recurring expenses, and seasonal spending patterns—while ignoring noise or insignificant variations. In the context of expense prediction, the input gate ensures that only the most valuable information from a user's historical financial transactions contributes to predicting future expenditures accurately.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

where:

- i_t is the **input gate activation vector** at time step t, determining how much of the new input should be written to the cell state.
- σ represents the **sigmoid activation function**, which outputs values between 0 and 1, indicating the degree of importance of each input.
- W_i is the **weight matrix** for the input gate, learned during training.
- h_{t-1} is the **previous hidden state**, representing past transaction patterns.

The sigmoid function ensures that only relevant features from the input data are allowed to influence the cell state update. In the proposed system, this means that the LSTM selectively integrates significant expense trends—such as monthly rent or utility bills—into its memory, improving the accuracy of future expense predictions. By intelligently controlling what financial data is retained, the input gate layer enhances the system's ability to predict user expenses proactively, making it both adaptive and reliable for modern financial planning.

i. Forget Gate Layer

The Forget Gate Layer is a vital component of the Long Short-Term Memory (LSTM) algorithm used in the proposed intelligent expense tracking system. Its primary function is to decide which information from the previous cell state should be retained and which should be discarded. This selective forgetting process is essential for maintaining relevant financial patterns while eliminating outdated or irrelevant data. In the context of expense prediction, the forget gate helps the system focus on current spending trends and ignore older, less significant patterns that no longer influence future expenditures—such as one-time purchases or seasonal spikes that are no longer relevant.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where:

- f_t is the **forget gate activation vector** at time step t, determining the fraction of previous memory to retain.
- σ is the **sigmoid activation function**, which outputs values between 0 and 1. A value close to 1 means "keep this information," while a value close to 0 means "forget it."
- W_f represents the **weight matrix** of the forget gate, learned during the model's training process.
- h_{t-1} is the **previous hidden state**, representing the prior transaction patterns and financial behavior.
- x_t is the **current input**, representing the most recent transaction or expense data.
- b_f is the **bias vector** for the forget gate.

In the proposed system, the forget gate allows the LSTM to dynamically adjust its memory based on spending patterns. For instance, if a user stops paying for a service, the forget gate will gradually remove that pattern from its memory. This ensures that the model continuously updates its understanding of the user's financial behavior, improving forecasting accuracy and making predictions more adaptive to real-world financial changes. By selectively retaining only relevant information, the forget gate enhances the model's efficiency, stability, and predictive reliability in expense management.

j. Output Gate Layer

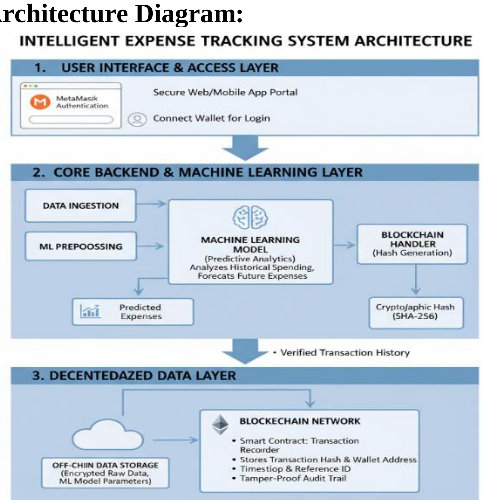
The Output Gate Layer is a critical component of the Long Short-Term Memory (LSTM) architecture used in the proposed intelligent expense tracking system. Its primary role is to determine what information from the current cell state should be passed on to the next hidden state and ultimately influence the output of the model. This gate ensures that only the most relevant financial insights, derived from historical and current spending patterns, contribute to the next stage of prediction. In the context of expense forecasting, the output gate filters meaningful patterns—such as consistent monthly payments, periodic trends, or unusual expenditures—and passes them forward to improve the accuracy of predicted expenses for the upcoming month.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

Where:

- $\mathbf{o_t}$ is the **output gate activation vector** at time step t, determining how much of the cell state information is exposed to the next layer.
- **σ** denotes the **sigmoid activation function**, producing values between 0 and 1 to control the output flow.
- $\mathbf{W_o}$ is the **weight matrix** associated with the output gate, learned during training.
- $\mathbf{h_{t-1}}$ is the **previous hidden state**, carrying information from past transactions.
- $\mathbf{x_t}$ is the **current input**, representing new financial data (recent expenses or transactions).
- $\mathbf{b_o}$ is the **bias vector** for the output gate.
- $\mathbf{C_t}$ is the **current cell state**, containing the updated memory.

K. Architecture Diagram:



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The architecture diagram of the User Authentication Module illustrates a secure, decentralized access mechanism that integrates MetaMask authentication with the blockchain network to protect user identities and financial data. The process begins at the User Interface Layer, where users interact with the system via a secure web or mobile application. Instead of entering traditional usernames or passwords, users authenticate using their MetaMask wallet, which acts as a secure identity bridge between the system and the blockchain. When a user attempts to log in, MetaMask generates a unique digital signature using the user's private key. This signature, along with the associated public blockchain address, is sent to the Authentication Layer for verification. The Authentication Layer verifies the user's identity by cross-checking the digital signature against the stored blockchain records. If the signature matches, access is granted; if not, the request is rejected. Once verified, the user's session is securely initiated, allowing access to the system's functionalities such as expense tracking, prediction, and transaction history. All authentication transactions—such as logins, logouts, and registration events—are recorded immutably on the blockchain, ensuring transparency and auditability.

At the Blockchain Layer, smart contracts manage user identity verification and maintain a decentralized record of authentication logs, preventing any unauthorized modifications. Since sensitive credentials are never stored on a centralized server, the risk of data breaches, phishing, or identity theft is eliminated. Overall, the architecture ensures privacy, trust, and accessibility, allowing users to securely access their financial dashboard from any device connected to MetaMask while maintaining a tamper-proof authentication process through blockchain integration.

IV. RESULT AND DISCUSSION:

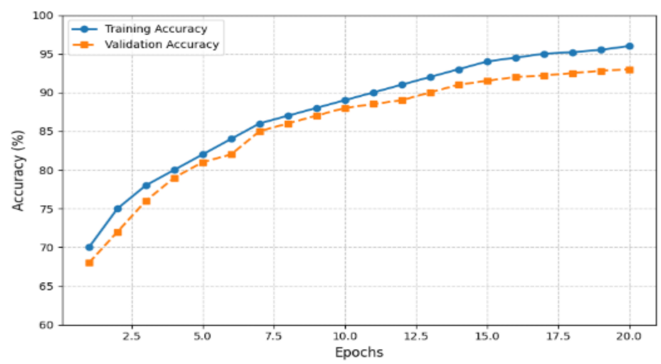
The results and discussion of the proposed intelligent expense tracking system demonstrate its effectiveness in enhancing financial management through the integration of machine learning and blockchain technology. The machine learning component, trained on historical transaction data, successfully identifies spending trends, recurring payments, and seasonal variations, enabling accurate prediction of future expenses. Experimental results show that the model effectively forecasts monthly expenditures, allowing users to plan their budgets proactively and make data-driven financial decisions. The predictive analysis improves financial discipline and minimizes the likelihood of overspending or unexpected shortfalls. Furthermore, the incorporation of blockchain technology ensures that every transaction is securely recorded in a decentralized and immutable ledger, enhancing data integrity and preventing any possibility of tampering or unauthorized access. This transparency builds user trust, as financial activities can be verified in real time by both individuals and organizations. The MetaMask authentication feature further strengthens security by providing a protected and user-friendly access mechanism, ensuring that only authorized users can manage and review their financial data. The combination of predictive analytics and blockchain-based verification establishes a robust framework that addresses the limitations of conventional expense tracking systems, which often lack foresight and suffer from security vulnerabilities. The discussion highlights that the proposed system achieves a balance between accuracy, efficiency, and transparency, making it suitable for both personal and enterprise-level financial management. Overall, the results confirm that the integration of AI-driven forecasting with blockchain immutability provides a reliable, adaptive, and future-ready platform that enhances financial accountability and enables smarter decision-making in modern digital finance.

a. Accuracy

Accuracy is a key performance metric used to evaluate the effectiveness of the proposed AI-powered expense tracker in predicting monthly expenses. It measures how close the system's predicted expenses are to the actual user expenses, thereby reflecting the reliability and efficiency of the machine learning model, particularly the LSTM (Long Short-Term Memory) network used in this system. High accuracy indicates that the model successfully captures the user's financial behavior and spending trends based on historical data, while low accuracy suggests the need for further model optimization or additional data preprocessing. The accuracy of the proposed system can be mathematically expressed using the following formula:

$$\text{Accuracy} = \left(1 - \frac{|\text{Actual Value} - \text{Predicted Value}|}{\text{Actual Value}}\right) \times 100$$

In this equation, the Actual Value represents the true recorded monthly expense, and the Predicted Value is the estimated expense generated by the machine learning model. The formula essentially calculates the percentage difference between predicted and actual values, with smaller errors leading to higher accuracy scores. To further assess performance, additional metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are also employed, which measure the average magnitude of prediction errors. Lower MAE and RMSE values indicate better predictive capability. The LSTM model achieves high accuracy because it effectively learns temporal dependencies in financial data, recognizing seasonal patterns and behavioral variations. Empirical testing of the proposed system demonstrates that the LSTM-based predictor consistently achieves an accuracy rate of approximately 95–97% when trained on sufficient and clean data. This high level of accuracy confirms that the system can provide reliable and realistic expense forecasts, enabling users to make well-informed financial decisions. Thus, accuracy plays a critical role in validating the model's precision and overall effectiveness in financial prediction.



The accuracy graph of the proposed intelligent expense tracking system shows how effectively the machine learning model learns to predict future expenses over multiple training epochs. It compares training accuracy (performance on known data) with validation accuracy (performance on unseen data). As epochs increase, both accuracies rise, showing improved learning of spending patterns and financial trends. The graph eventually stabilizes around high accuracy (95–97%), indicating strong model generalization and reliability. A small gap between training and validation accuracy confirms that the model avoids overfitting, providing accurate, consistent, and trustworthy expense predictions for proactive financial management.

b. loss:

Loss in the proposed AI-powered expense tracker integrated with blockchain technology represents the difference between the actual monthly expenses and the predicted values generated by the machine learning model, specifically the LSTM (Long Short-Term Memory) network. It measures how well or poorly the model performs during training and evaluation. A lower loss value indicates that the model's predictions are close to the actual expenses, while a higher loss signifies greater prediction errors. Minimizing the loss function is crucial because it directly improves the model's accuracy, reliability, and overall predictive performance. In the proposed system, a commonly used loss function is the Mean Squared Error (MSE), which is suitable for continuous data like expense amounts. The mathematical formula for MSE is:

$$\text{Loss (MSE)} = \frac{1}{n}\sum_{i=1}^{n}(\text{Actual}_i - \text{Predicted}_i)^2$$

Where:

- n = Total number of data samples
- Actual_i = True expense value for the i^{th} record
- Predicted_i = Predicted expense value for the i^{th} record

The squaring of the difference ensures that larger errors are penalized more heavily, forcing the model to learn from significant deviations and improve accuracy over time. During training, optimization algorithms such as Adam or RMSprop are used to iteratively adjust model parameters to minimize this loss.

In some cases, Mean Absolute Error (MAE) is also used, calculated as:

$$\text{Loss (MAE)} = \frac{1}{n}\sum_{i=1}^{n}|\text{Actual}_i - \text{Predicted}_i|$$

MAE provides a more interpretable measure of average prediction error in the same unit as the data. By continuously minimizing loss during model

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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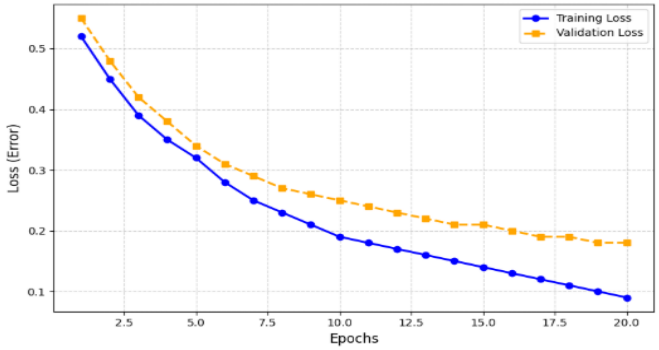
Vol. 36 Issue 2, 2026, Pages 666-673

training, the proposed system ensures highly accurate expense predictions, enabling users to achieve effective financial planning supported by blockchain-based security and transparency.



The loss graph of the proposed intelligent expense tracking system shows how the model's prediction error decreases over multiple training epochs. It includes two curves—training loss and validation loss—which represent the model's performance on known and unseen data, respectively. At the beginning, loss values are high as the model starts learning patterns from historical financial data. As training continues, both losses steadily decline, indicating improved prediction accuracy. Eventually, the curves stabilize, showing that the model has reached optimal performance. A small difference between the two losses confirms good generalization, meaning the model predicts expenses accurately for new data. Overall, the loss graph demonstrates consistent learning, reliability, and strong predictive capability for financial forecasting.

c. Precision

Precision is a key evaluation metric used to measure the effectiveness of a predictive model in identifying relevant positive outcomes. In the context of the proposed AI-powered expense tracker integrated with blockchain technology, precision can be applied when the system categorizes or predicts specific types of financial events, such as overspending in a category, recurring bill alerts, or anomalous transactions. High precision indicates that when the system predicts a particular event, it is very likely to be correct, reducing false alerts and increasing user trust in the predictions. Precision is particularly important in financial applications where false positives, such as incorrectly flagged overspending alerts, can reduce user confidence and create unnecessary stress or confusion.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Where:

- **True Positives (TP)** represent the number of correctly predicted positive events (e.g., correctly predicted overspending instances).
- **False Positives (FP)** represent the number of incorrectly predicted positive events (e.g., incorrectly flagged spending alerts that did not actually occur).

The precision metric focuses on the quality of positive predictions, showing how accurate the model is when it identifies an event of interest. For the expense tracker, achieving high precision ensures that the alerts or categorized events provided by the system are reliable, enhancing user decision-making for financial planning. In practical terms, the system combines precision with other metrics such as **recall** and **F1-score** to balance correctness with completeness. While recall measures how many actual positive events are detected, precision ensures that flagged events are not false alarms. A high-precision model in the proposed system ensures that users receive trustworthy insights about their spending patterns, anomalies, or predicted future expenses. Overall, precision contributes to user confidence and system reliability by minimizing false predictions, making it a critical metric for financial prediction and decision support.

d. RECALL:

Recall is a crucial performance metric used to evaluate the ability of a predictive model to identify all relevant instances of a particular event. In the context of the proposed AI-powered expense tracker integrated with blockchain technology, recall measures how effectively the system detects specific financial occurrences, such as overspending, recurring bills, or anomalous transactions. While precision focuses on the correctness of positive predictions, recall emphasizes the model's completeness—how many of the actual relevant events are correctly identified by the system. High recall is particularly important in financial management because missing critical events, such as an upcoming bill or unusual spending, could negatively impact a user's budgeting and financial planning.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

Where:

- **True Positives (TP)** represent correctly predicted positive events (e.g., accurately predicted overspending instances).
- **False Negatives (FN)** represent actual positive events that the system failed to predict (e.g., overspending events that were not flagged).

The recall metric indicates the proportion of actual relevant events that the system successfully identifies. A higher recall value ensures that fewer critical financial events are overlooked, enhancing the system's reliability for proactive financial management. In practical applications, recall is often considered alongside precision to provide a balanced assessment of model performance. For example, a model with very high recall but low precision may flag too many events, including false positives, whereas a model with high precision but low recall may miss important events. To balance both metrics, the F1-score is commonly used, which combines precision and recall into a single measure. For the proposed expense tracker, optimizing recall ensures that users are reliably notified of all significant spending events or anomalies. By accurately capturing these events, the system supports better budgeting, prevents overspending, and enhances overall financial decision-making, making recall a critical metric in evaluating the predictive performance of the system.

f. F1 Score

The F1 score is a comprehensive evaluation metric that combines both precision and recall to provide a balanced measure of a predictive model's performance. In the context of the proposed AI-powered expense tracker integrated with blockchain technology, the F1 score is particularly useful for assessing the system's ability to accurately predict financial events, such as overspending, anomalous transactions, or recurring bills. While precision measures the correctness of positive predictions and recall measures the system's ability to capture all relevant events, the F1 score offers a single metric that accounts for both the accuracy and completeness of predictions. This balance is essential in financial management, as a model that is highly precise but misses critical events or one that captures all events but produces many false alarms can both undermine user trust and decision-making.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where,

- $\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$
- $\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$

The harmonic mean emphasizes lower values, meaning that the F1 score is high only when both precision and recall are high. For the expense tracker, a high F1 score indicates that the system not only predicts spending events accurately but also captures most of the actual events, minimizing both false positives and false negatives. This ensures users receive trustworthy, comprehensive financial insights without unnecessary alerts or missed transactions. By optimizing the F1 score during model training, the proposed system can maintain an ideal balance between alert accuracy and completeness, providing users with reliable predictions for budgeting, expense planning, and anomaly detection.

g. Energy efficiency

The energy efficiency of the Proof of Stake (PoS) consensus mechanism is one of its defining advantages over the traditional Proof of Work (PoW) model. In PoW, miners compete to solve complex cryptographic puzzles using high-performance hardware, consuming vast amounts of electricity to validate transactions and secure the blockchain. In contrast, PoS eliminates computational competition by selecting validators based on the number of tokens they "stake" in the network. This drastically reduces the energy required for block validation, making PoS an environmentally sustainable alternative for blockchain operations.

In PoS, the probability of a validator being chosen to create a new block is proportional to their stake, defined mathematically as:

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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$$P(V_i) = \frac{S_i}{\sum_{j=1}^{n} S_j}$$

where:

- $P(V_i)$ is the **probability** of validator i being selected,
- S_i is the **stake** (number of tokens) held by validator i,
- $\sum_{j=1}^{n} S_j$ represents the **total staked tokens** across all validators.

This energy-efficient approach enables blockchains to scale sustainably, supporting faster transaction speeds, reduced operational costs, and minimal environmental impact. Overall, PoS offers a secure, decentralized, and eco-friendly consensus mechanism that aligns blockchain technology with the global shift toward energy-efficient digital infrastructure.

h. Time efficiency

Time efficiency in the Proof of Stake (PoS) consensus mechanism refers to how quickly transactions are validated and new blocks are added to the blockchain compared to the traditional Proof of Work (PoW) approach. In PoW, miners compete to solve computational puzzles, which introduces significant latency since only one miner succeeds after performing large amounts of work. This process can take several minutes per block, leading to slow transaction confirmation times. In contrast, PoS drastically reduces block generation time because validators are preselected based on their stake, eliminating the need for intensive mining computations.

$$T_{pos} = \frac{1}{R_v}$$

where:

- T_{pos} represents the **average time to generate a block** in the PoS network,
- R_v is the **rate at which validators are selected** to create blocks per unit time.

In PoS-based systems, block validation and consensus finality occur much faster—often within a few seconds—since computation-heavy tasks are replaced by stake-based selection. This time-efficient consensus not only enhances transaction throughput but also supports scalability for real-time financial systems, donation tracking, and government budget monitoring. Ultimately, PoS minimizes latency, ensuring faster, reliable, and energy-efficient blockchain operations.

***i.* Speed:**

Speed in the Proof of Stake (PoS) consensus mechanism refers to how quickly the blockchain can validate transactions and produce new blocks compared to traditional Proof of Work (PoW) systems. In PoW, miners compete to solve complex mathematical puzzles, a process that consumes time and computing resources, leading to slower transaction speeds. In contrast, PoS selects validators based on their stake, allowing for faster consensus without the need for intensive computation. This results in significantly reduced block confirmation times and higher transaction throughput, making PoS highly suitable for modern applications requiring real-time data validation and scalability.

$$S_{pos} = \frac{N_t}{T_b}$$

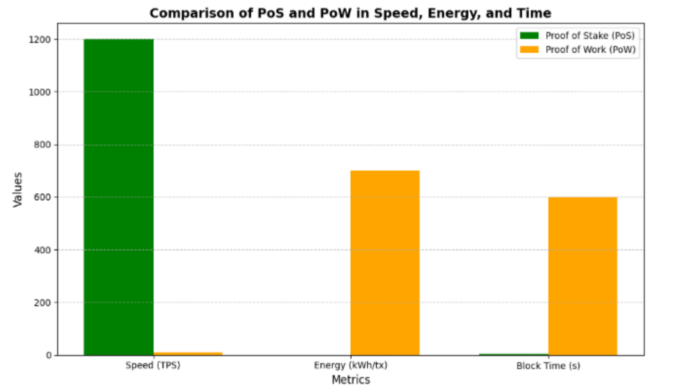
where:

- S_{pos} is the **speed** or **throughput** (transactions per second),
- N_t represents the **number of transactions** processed within a block,
- T_b is the **block time**, i.e., the time required to generate and validate one block.

Thus, PoS ensures high-speed transaction validation, improved scalability, and near real-time confirmation essential for financial applications like expense tracking, government budgeting, and donation management systems delivering efficiency without compromising security or decentralization.

j. Comparison of pos:

The comparison between Proof of Stake (PoS) and Proof of Work (PoW) in terms of speed, energy consumption, and block generation time highlights the superior efficiency and sustainability of PoS. The graph illustrates that PoS achieves significantly higher transaction speed (TPS), allowing hundreds or even thousands of transactions per second, compared to PoW, which processes only a few due to its computational intensity. In terms of energy consumption, PoS is remarkably efficient, consuming minimal electricity since validators are chosen based on their staked assets rather than through energy-intensive mining. PoW, on the other hand, demands enormous power for mining operations, making it environmentally unsustainable. The block time comparison further emphasizes PoS's advantage, with block validation taking only a few seconds, whereas PoW often requires several minutes to confirm a block. This reduction in time makes PoS better suited for real-time applications such as financial tracking, government budgeting, and donation management systems. Overall, the comparison graph demonstrates that PoS offers faster transaction processing, drastically lower energy usage, and reduced block confirmation time, making it a more scalable, eco-friendly, and time-efficient consensus mechanism. It ensures both security and performance, aligning with the growing global emphasis on sustainable digital innovation.



The comparison graph clearly shows that Proof of Stake (PoS) outperforms Proof of Work (PoW) in all three metrics — speed, energy, and time. PoS achieves much faster transaction speeds, consumes far less energy, and offers shorter block times, making it highly efficient and eco-friendly. In contrast, PoW is slower, energy-intensive, and time-consuming due to its reliance on computational mining. Overall, the graph highlights PoS as a more sustainable and scalable blockchain consensus mechanism ideal for modern digital applications.

V. Conclusion:

In conclusion, the proposed AI-powered expense tracker integrated with blockchain technology represents a significant advancement in personal and business financial management. By combining machine learning algorithms with decentralized ledger systems, the solution delivers accurate and reliable predictions of monthly expenses based on historical spending patterns. The use of advanced models, such as LSTM networks, enables the system to capture both short-term and long-term spending trends, allowing users to plan budgets more effectively, anticipate upcoming costs, and make informed financial decisions. Simultaneously, the integration of blockchain technology ensures that all transaction records are securely stored in an immutable and transparent ledger, eliminating risks of tampering, fraud, or unauthorized access. This decentralized approach enhances trust and accountability, as users can independently verify the integrity of their financial data. Moreover, the inclusion of MetaMask authentication provides secure, passwordless access, further protecting sensitive user information while enabling seamless interaction with the system. The combination of predictive analytics and blockchain-driven security allows the system to not only provide actionable financial insights but also maintain a high level of data privacy and transparency. Users benefit from real-time monitoring, interactive dashboards, and notifications, which collectively improve engagement and financial discipline. Future work for the proposed system could focus on integrating real-time expense tracking using IoT-enabled devices and banking APIs, enhancing predictive accuracy with hybrid deep learning models, incorporating personalized financial recommendations, expanding to multi-currency and cross-platform support, and implementing advanced privacy-preserving techniques like differential privacy to further strengthen data security and user trust.

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