

An Artificial Intelligence-Based Framework for Intelligent Fund Accounting Transformation

Ola Popoola FCCA

A Freelance Finance Consultant, UK.

Mail Id: ola@apexbroker.co.uk

Article Received 04-07-2026, Revised 16-08-2026, Accepted 02-09-2026

Author(s) Retains the Copyrights of This Article

Abstract

The investment fund sector generates huge amounts of financial transactions, which need proper accounting, reconciliation, and management of regulations. Conventional fund accounting systems tend to rely on human intervention, which poses difficulties of operational efficiency, error- reduction, and scalability. The study suggests a framework with Artificial Intelligence to convert fund accounting functions using machine learning to detect anomalies. Since, relatively few datasets, which cover the public fund accounting, are available, a proposed synthetic dataset, consisting of 10,000 financial transaction entries, was created in order to approximate investment accounting processes. Four machine learning models are deployed and compared on the basis of accuracy, precision, recall, F1-score, ROC-AUC metrics to evaluate Logistic Regression, Random Forest, XGBoost and Support Vector Machine with around 97% accuracy. The findings indicate that AI-based solutions can be used to successfully detect irregularities in accounting and enhance operational intelligence. The study provides information that adds a research-backed model that could aid in intelligent automation of the future, monitoring risks and decision-making in investment fund management.

Keywords: Artificial Intelligence, Fund Accounting, Machine Learning, Investment Funds, Financial Automation, Anomaly Detection, Predictive Analytics.

I. Introduction

A. Background

Fund accounting is a sensitive activity in the investment fund sector which involves proper keeping of financial books, computation of net asset values (NAV), transactions and compliance with regulations [1]. Fund accounting operations are traditionally based on manual operations, rule-based operations, and human verification, which may prove to be ineffective as the size of investment portfolio and the number of transactions grows [2]. Emerging investment opportunities, complicated financial products and international controls have put pressure on fund managers. The error of reconciliation, a delay in reporting, and inability to detect financial inconsistencies may have an impact on decision-making and investor confidence [3]. The recent innovations in the field of Artificial Intelligence (AI) and machine learning is an opportunity to change the fund accounting process by automating, introducing smart analysis, and predictive insights [4]. Hence, the idea of looking into AI-driven solutions has become necessary in finding more efficient, accurate and scalable fund accounting systems.

B. Research Problem

The classical fund accounting systems have shortcomings that include reliance on manual processes, non-existence of automation and difficulty in handling large volume of financial information. Compounding transactions poses challenges in identifying abnormalities, conducting timely reconciliation, and ensuring that compliance

is accurate [5]. Existing accounting technologies often lack predictive capabilities and intelligent decision-support mechanisms.

C. Research Motivation

The research is motivated by the fact that there is an increasing urge towards smart automation in Investment funds industry. Financial operations now give rise to greater complexities, which the conventional accounting methodologies just cannot handle efficiently and accurately [6]. This paper can examine the use of AI and machine learning methods to improve the performance of fund accounting based on automated analysis and detection of anomalies. The study is a step towards creating a data model that can aid the next level of intelligent investment management systems.

D. Research Objectives

Aim

The paper aims at establishing an AI-centered framework that can detect an accounting anomaly and facilitate reconciliation, as well as enable intelligent decisions.

- To create a synthetic dataset of accounting activities of investment funds.
- To test machine learning models to identify accounting anomalies.
- To examine how AI helps to enhance fund accounting processes.
- To suggest an AI-empowered change model to the operation of investment funds.

E. Novel Contribution

The study presents a new AI-based accounting system for funds that integrates the fields of

synthetic financial data generation with machine learning-driven anomaly detection to fund investment operations. This paper uniquely compares experimental models of fund accounting in terms of evaluating the problems of fund accounting, thus differentiating primary operative determinants of intelligent accounting decisions and automation rates, whereas previously available research addressed general financial automation in general.

II. Related Work

A. Financial Process Automation using Artificial Intelligence

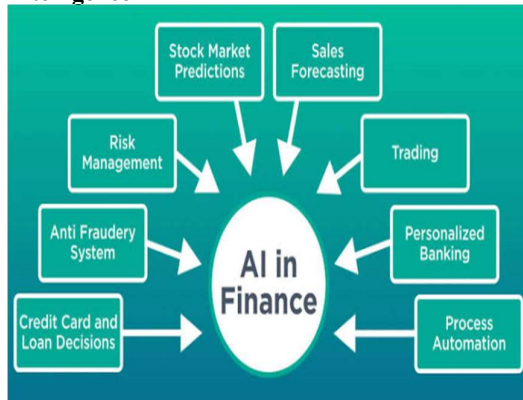


Fig. 1. Financial Process Automation using Artificial Intelligence

The impact of Artificial Intelligence (AI) on enhancing the automation of financial processes through automated tasks that are performed manually by substituting manual procedures with data-driven, smart ones is described in the previous studies. Machine learning, deep learning, and natural language processing are some AI technologies that have been used in automated transaction processing, financial forecasting, compliance monitoring, and decision support [7]. AI systems have the potential to go through huge amounts of financial data in much faster and more accurate timeframes than with conventional rule-based systems. AI has proven to be of immense usefulness in financial institutions through the reduction of the cost of operation, enhanced reporting quality, and diminution of human mistakes [8]. All the current studies focus on banking, insurance and trading applications, with little focus being given to investment fund accounting operations [9]. The fund operations, which involve NAV calculation, reconciliation and regulatory reporting, are complicated and thus need specialized AI structures [10].

B. Applications of machine learning to Financial Risk and Anomaly Detection



Fig. 2. Application of Machine learning to Financial Risk and Anomaly Detection

Machine learning has emerged as a relevant topic in the exploration of financial risk management as it offers the potential to find complex patterns and establish suspicious behaviors on large data sets. Some research has used supervised learning methods, such as Logistic Regression, Decision trees, Random forest, Support Vector machines, and Gradient Boosting models in their financial classification and prediction problems [11]. These models have proved to be helpful in detecting fraudulent transactions, credit risks and irregularities of operations. Unsupervised learning algorithms, such as clustering algorithms and Isolation Forest algorithms have been explored to identify unknown anomalies in absence of predefined labels [12]. Machine learning methods can be used in investment fund accounting to facilitate automated reconciliation, transaction monitoring as well as detection of accounting discrepancies [13].

C. Digital transformation and Intelligent Accounting Systems

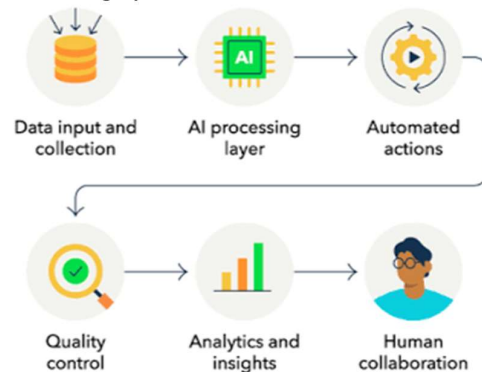


Fig. 3. AI based Accounting Process

Intelligent accounting system can improve financial processes by automating the data collection process, improving the accuracy of reports and promoting

real time financial information. Accounting systems that include AI help to classify automatically, perform predictive analysis, and track financial operations round the clock lessening the reliance on manual methods. The study [14] has verified that organizations that use intelligent accounting technologies record better efficiency in their operations, less time in processing and better decision making processes. Majority of the available research studies however examine AI adoption in corporate accounting, auditing scenario and in enterprise resource planning [15]. Some of the research on the use of intelligent systems with specific application to investment fund accounting has been conducted, with its complicated transactions, portfolio estimations, and regulatory demands posing unique operational issues [16].

D. AI Implementation Issues in Investment Fund Management

The financial organizations tend to struggle with issues of data availability, data quality, model transparency, compliance with regulation and integration with current accounting infrastructure [16]. Explain ability and reliability are vital qualities of AI systems to consider in investment fund management because high-quality financial reporting and decision making are crucial in the sector [17]. Scientists have pointed out that black-box machine learning models can evoke trust challenges among the financial practitioners based on inadequate knowledge on prediction outcomes [18]. Moreover, the expenses on the development and assessment of AI solutions are limited by non-availability of publicly accessible investment fund accounting datasets [19]. Generation of data and controlled laboratory conditions can offer alternative data testing methods and keep data confidential [20].

E. Research Gap

Despite the effectiveness of Artificial Intelligence and machine learning with respect to financial automation, risk analysis, and anomaly detecting that existing studies reveal, there is a lack of research on the specifics of AI-driven transformation within investment fund accounting [21]. There are no studies in the existing literature that can evaluate machine learning models applicable to fund accounting tasks experimentally in full because publicly available datasets are not publicly available. Current methods offer a low level of analysis of reliable AI, efficiency of its operation, and detection of anomalies [22]. Hence, this study fills those gaps by creating a synthetic dataset and testing AI models to transform intelligent fund accounting.

III. Proposed AI-Based Fund Accounting Framework

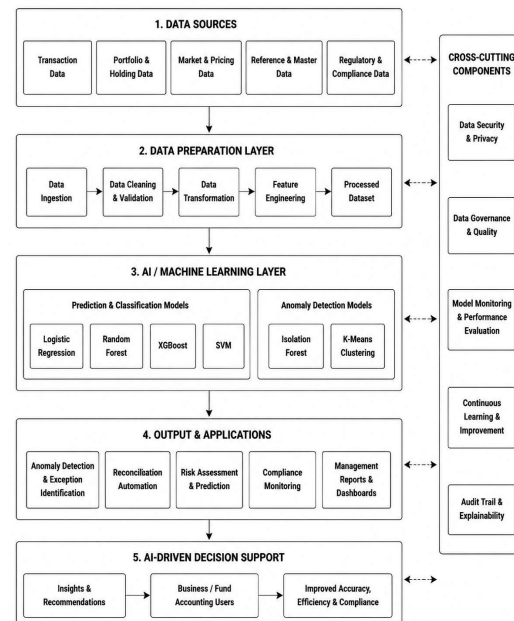


Fig. 4. Proposed AI-Based Fund Accounting Framework

The planned AI-supported funds accounting system is a systematic method to change the traditional processes of investment fund accounting based on artificial intelligence and machine Learning [23]. The framework comprises five primary layers, including some data sources, data preparation, AI/machine learning processing, output generation, and a decision support provided by AI.

The former layer gathers pertinent financial data such as transaction data, portfolio holdings, market pricing data, reference data, and regulatory compliance data. The ingested data is transformed in the data preparation layer, where the data ingestion, data cleaning, data validation, data transformation and feature engineering methods are used to enhance data quality and transform the data to be analyzed [24].

The models examine accounting trends, find anomalous transactions, and make predictive information about the risks of finances and operational effectiveness [25].

The output layer introduces the model results to the real-world use like detecting anomalies, automating reconciliations, checking risks, monitoring compliance and reporting management. Lastly, AI-based decision support layer offers practical suggestions to fund accounting professionals to enhance accuracy, efficiency, transparency, and regulatory compliance [26]. Cross-cutting elements, such as data security, governance, model evaluation, on-going learning, and explain ability keep the framework reliable, scalable, and capable of supporting future intelligent operations of investment funds.

IV. Research Methodology

A. Research Design

The present study uses an experimental form of quantitative research methodology to assess effectiveness of Artificial Intelligence (AI) and machine learning to revolutionize the work of investment funds accounting. Since no publicly-available fund accounting datasets are available, a synthetic dataset is constructed to provide a simulation of realistic investment fund accounting activity. The experimental method allows to compare several machine learning algorithms systematically in terms of predetermined metrics of performance [27]. Python analytical experiments are implemented with the use of data preprocessing, model training, testing, and evaluation processes to define the appropriateness of the base AI models to fund accounting solutions.

B. Development and description of dataset.

It develops a synthetic investment fund accounting dataset to capture the operations carried out in the up-to-date fund management conditions. The data is represented by simulated financial transaction, portfolios, reconciliation, compliance and risk-related data. The dataset generated can emulate real patterns in the operation of investment funds and preserve the privacy of data and eliminate reliance on confidential financial data with 10,000 rows and 10 columns.

The dataset has several attributes of accounting behavior, such as:

- Transaction amount
- Transaction frequency
- Asset category
- Portfolio value
- Settlement duration
- Reconciliation accuracy score
- Compliance status
- Reporting delay
- Risk indicator
- Accounting anomaly label

The status of accounting transactions is expressed by the target variable:

0 = Normal accounting activity

1 = Unusual or suspicious accounting operation.

The dataset allows experimenting and benchmarking a solution based on AI in fund accounting.

C. Preprocessing and Feature Engineering of data

Prior to the actual process of machine learning algorithms, the dataset is subject to preprocessing processes that enhance data quality and the effectiveness of the model. Data cleaning is done to eliminate inconsistencies, missing data, and duplication. Encoding methods can be used to convert categorical variables into numeric representations, which enable machine learning models to work with financial features [28].

Feature engineering is run to determine significant account indicators, as well as enhance predictive power. New attributes are used to create such derived features as transaction risk score, reconciliation efficiency, and compliance level of deviation. Moreover, numerical characteristics are normalized to apply equal contribution in the training of the model.

The process of standardization is symbolized as:

$$X' = \frac{X - \mu}{\sigma}$$

where:

- X' represents the normalized feature value,
- X represents the original feature value,
- μ represents the mean value of the feature,
- σ represents the standard deviation.

Data undergoes processing to obtain training and testing data elements, split of data is based on 80:20 ratio where 80% of information is used to train the model and the remaining 20 percent is used to test the performance of the model.

D. Machine Learning Models

This study will compare various machine learning models to determine the best one suitable in fund accounting transformation using AI.

Logistic Regression

The Logistic Regression is implemented as a foundation model of classification in prediction of accounting anomalies.

The likelihood function is defined as:

$$P(Y = 1) = \frac{1}{1 + e^{-z}}$$

In which $p(Y=1)$ is the likelihood of an abnormal transaction and of course the weighted sum of the input features, z .

Random Forest

Random Forest is used as an ensemble learning algorithm whereby several decision trees are used to enhance the accuracy of classification and minimize over fitting.

$$\hat{Y} = \text{mode}\{T1(X), T2(X), T3(X), \dots, Tn(X)\}$$

The probability distribution is then calculated using the formula below,

$$P(Y = c | X) = \frac{1}{N} \sum_{i=1}^N I(Ti(X) = c)$$

Where:

- $P(Y=c|X)$ = probability of class cc
- N = number of trees in the forest
- I = indicator function
- $Ti(X)$ = output of individual decision tree

XGBoost

The choice of the Extreme Gradient Boosting (XGBoost) is driven by the fact that it performs well in prediction in structured financial data.

The XGBoost Optimization formula is:

$$Obj = l = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

Where, $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda ||w||^2$

- $l(y_i, \hat{y}_i)$ = loss function measuring prediction error
- $\Omega(f_k)$ = regularization term
- T = number of leaves in the tree
- W = leaf weights
- γ = regularization parameters

Support Vector Machine (SVM)

The application of SVM determines the best decision boundaries between the normal and abnormal transactions in accounting. It works well in high-dimensional data in which complicated classification patterns are present. For nonlinear financial patterns, SVM applies kernel transformation:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$

Where:

- $K(x_i, x_j)$ = kernel function
- $\phi(x)$ = transformed feature space

E. Model Evaluation Metrics

The classification models are evaluated by the conventional machine learning assessment measures such as accuracy, precision, recall, F1-score and ROC-AUC. The accuracy measures are tests of overall prediction correctness, whereas the measures of precision are tests of the model in detecting anomalous accounting transactions [29]. The F1-score gives a mixed measure of precision and recall, at the same time, ROC-AUC is a measure of the ability of the model to distinguish normal and abnormal fund accounting operations.

F. Pseudo Code

1. Load dataset
2. Remove irrelevant attributes
3. Handle missing values and encode categorical features
4. Normalize numerical features
5. Split dataset into training and testing sets (80:20)
6. Initialize machine learning models:
 - a. Logistic Regression
 - b. Random Forest
 - c. XGBoost
 - d. Support Vector Machine
7. For each model M:
 - a. Train M using training dataset
 - b. Predict accounting anomalies on test data
 - c. Calculate Accuracy, Precision, Recall, F1-score, and ROC-AUC
8. Compare performance of all models
9. Identify best-performing model
10. Analyse important accounting features influencing predictions

Fig. 5. Pseudo Code

The pseudo-code outlines the methodical process of the implementation of the machine learning framework. The algorithm begins with loading and preparation of data of synthesizing fund accounting by cleaning, encoding and feature scaling. Various

classification models are trained on processed data and are assessed on the basis of performance measures.

G. Flow Diagram

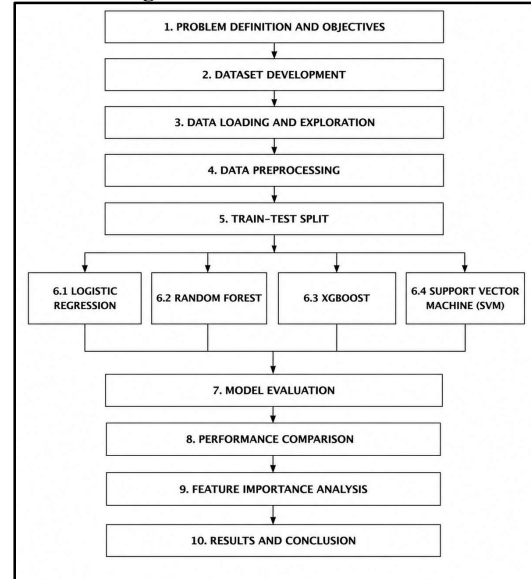


Fig. 6. Flow Diagram

The flow diagram of methodology is the entire research process of creating an AI-based fund accounting system. It starts with problem definition and synthetic data set generation, then data exploration, preprocessing and train test splitting. The four machine learning models, such as Logistic Regression, Random Forest, XGBoost, and SVM are trained and assessed.

V. Experimental Results and Analysis

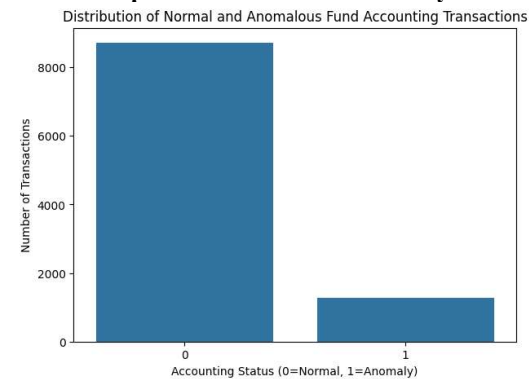


Fig. 7. Distribution of normal and abnormal Fund Accounting Transactions

The analysis of the class distribution provides the percentage of normal and abnormal fund accounting transactions in the synthetic data having 10,000 observations. Most of the transactions are considered normal accounting but a lesser percentage is likely to be anomalies. This imbalance is representative of real financial settings whereby irregular transactions are less common.

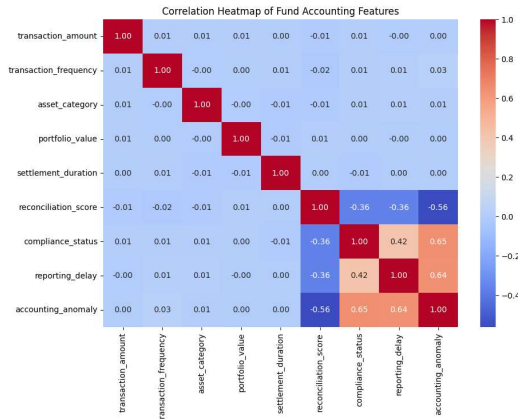


Fig. 8. Correlation Heatmap of Fund Accounting Features

The results of the analysis show that reconciliation score, compliance status, and reporting delay are more strongly correlated with the accounting anomalies than other features. Extremely low score in reconciliation and high report delays are related with high likelihood of anomaly.

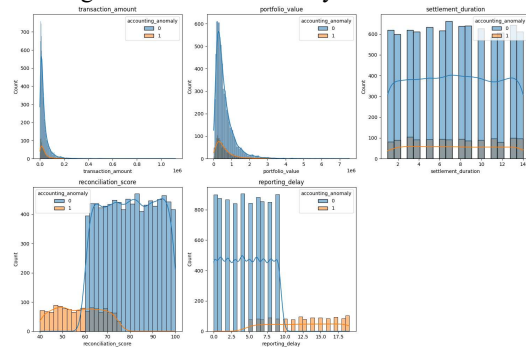


Fig. 9. Analysis of Fund Accounting Results of Variables by their features

The results of the feature distribution analysis depict differences in behavior of normal and anomalous transactions on key accounting variables, such as amount of the transaction, portfolio value, settlement period, reconciliation score, and reporting delay.

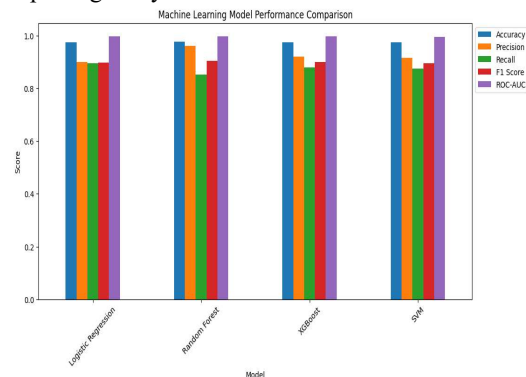


Fig. 10. Comparison of performance between machine learning models

The predictive performances are high around 97%, across all the models and it shows the usefulness of

machine learning in analyzing fund accounting. Some of the considered methods, ensemble-based models like Random Forest and XGBoost, offer better results, because they can capture the interplay of more intricate relationships in the patterns of financial transactions.

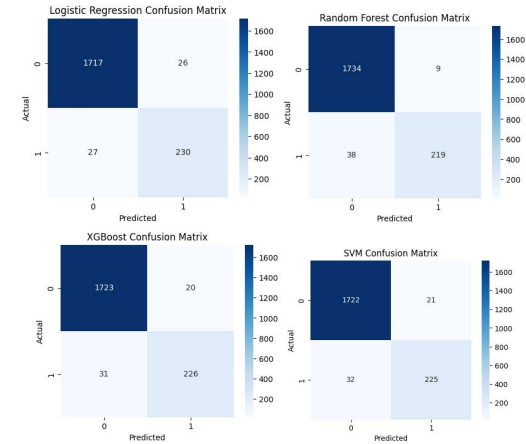
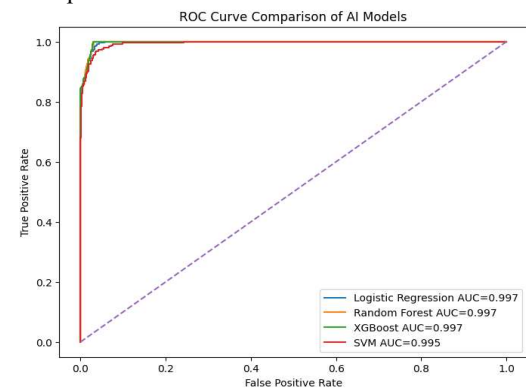


Fig. 11. The Classification Models Confusion Matrix Analysis

The confusion matrices give a comprehensive analysis of the classification results of the four machine learning models. The findings indicate that all algorithms are able to detect normal and anomalous accounting transactions with minimal classification errors. The XGBoost and Random Forest have better capacity to detect anomaly because they demonstrate less false negative and false positive classifications.



The ROC curve is used to assess classification capability by comparing the performance in terms of true positive and false positive. All models achieved high ROC-AUC values, implying that they discriminate well between normal and abnormal transactions. The findings validate the claim that AI-based classification can be employed to successfully identify accounting anomalies. Both XGBoost and Random Forest are very reliable in providing predictive performance in regards to intelligent fund accounting applications.

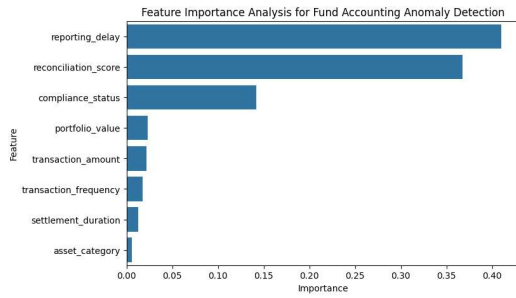


Fig. 13. Importance Analysis of features to fund accounting anomaly detection

The feature importance analysis shows the most significant variables that help predict anomalies in the form of the Random Forest model. These results imply that the indicators of operational efficiency and regulatory compliance have a considerable impact on accounting abnormalities.

Discussion

TABLE I. Model Comparison Summary

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Logistic Regression	0.9735	0.898438	0.894942	0.896686	0.996868
Random Forest	0.9765	0.960526	0.852140	0.903093	0.997394
XGBoost	0.9745	0.918699	0.879377	0.898608	0.997370
SVM	0.9735	0.914634	0.875486	0.894632	0.994658

The experiment has shown that AI-based machine learning models can be effectively used to change the investment fund accounting processes by detecting anomalous transactions correctly. The considered models demonstrated good classification rates, which validates the ability of AI to enhance operational stability, risk identification, and accounting automation. The studies fill the gaps that currently exist in terms of scarce empirical assessment and absence of specialized fund accounting data by establishing an experimental framework based on synthetic data provision. One of the crucial findings is that operational indicators, specifically reporting delay, reconciliation score, and compliance status have a tremendous impact on the prediction of the anomalies that are beneficial intelligence in intelligent fund accounting system.

Limitation

- The synthetic fund accounting dataset is generated and might not fully reflect the intricate financial behaviours that are witnessed in the real fund management set-ups.
- The experiment tests a chosen machine learning classification, yet no attempts at smart AI like deep-learning, explainable AI, and real-time AI deployment systems were tested, thereby restricting the exploration of larger AI capabilities.

VI. Future Research Directions

Further experiment can be made in terms of the validation of the suggested framework by means of the real data of fund accounting in the industry where the collaboration should be arranged. Explainable AI techniques will be incorporated in further research to enhance model transparency and incorporate trust. Also, deep learning, generative AI, and intelligent accounting agents can be discussed to create more adaptable and autonomous fund management systems.

VII. Conclusion

The study shows that accounting of investment funds can be revolutionized with the help of Artificial Intelligence and machine learning tools that detect anomalies automatically and offer suitable decisions. The framework created is effective to assess various classification models in terms of a synthetic fund accounting data and to stress on the relevance of operational indicators in the detection of accounting anomalies. The findings can fill any existing gaps in the literature as they offer an experimental AI-based solution aimed at fund accounting applications. Machine learning algorithms like Random Forest, XGBoost, and SVM performance are very promising in analyzing pattern of a transaction in financial transactions. The research provides a basis of future AI-oriented, scalable and dependable fund accounting system.

References

- [1] Anuar, A.A., Mohamad, M.T.B. and Sulaiman, A.A.B., 2025. Mapping the presence of artificial intelligence in investment fund: a systematic review. *Discover Artificial Intelligence*, 5(1), p.256.
- [2] Singireddy, J., 2025. *Smart finance: Harnessing artificial intelligence to transform tax, accounting, payroll, and credit Management for the Digital age*. Deep Science Publishing.
- [3] Onabowale, O., 2025. AI and real-time financial decision support. *International Journal of Advance Research Publication and Reviews*, 2(6), pp.329-350.
- [4] Milton, T., 2025. Artificial Intelligence in Economic and Financial Decision-Making: A Comprehensive Review. *Stout in Economics, Finance and Accounting*, 1(1), pp.01-17.
- [5] Kureljusic, M. and Karger, E., 2024. Forecasting in financial accounting with artificial intelligence—A systematic literature review and future research agenda. *Journal of Applied Accounting Research*, 25(1), pp.81-104.
- [6] Rohan, A., Hossen, M.D., Pranto, M.N., Hossain, B., Yoshi, A.M. and Islam, R., 2025. Artificial intelligence in financial market prediction: advancements in machine learning for stock price forecasting. *Frontiers in Artificial Intelligence*, 8, p.1696423.
- [7] Lakhchini, W., Wahabi, R. and El Kabbouri, M., 2022. Artificial intelligence & machine learning in finance: A literature review. *International Journal of Accounting, Finance, Auditing, Management and Economics*.
- [8] Shaikh, S., Khan, K., Sherwani, F.K. and Khan, M.U., 2024. Smart Trading: Unlocking Artificial Intelligence in Stock Market. *The Business & Management Review*, 15(3), pp.170-178.
- [9] Shahbazbeigi, A., 2024. Application of Artificial Intelligence and Machine Learning in Accounting and Auditing. *Transactions on Data Analysis in Social Science*, 6(2), pp.92-108.
- [10] Jaafar, M.A., 2025. The impact of artificial intelligence in detecting manipulations in financial statements. *Futurity Economics&Law*, 5(2), pp.51-72.
- [11] Baldan, C., Sapienza, E. and Zen, F., 2025. Artificial Intelligence (AI) in Exchange-Traded Funds: A Quantitative Modelling Approach Using the Markowitz Portfolio Theory. *Department of Economics and Management "DSEA", University of Padova. Available online: <https://papers.ssrn.com/sol3/papers.cfm>*.
- [12] Yüksel, S., Eti, S., Dinçer, H., Gökalp, Y., Olaru, G.O. and Oflaz, N.K., 2025. Innovative financial solutions for sustainable investments using artificial intelligence-based hybrid fuzzy decision-making approach in carbon capture technologies. *Financial Innovation*, 11(1), p.20.
- [13] Tewari, N., 2023. Artificial intelligence in finance and industry: Opportunities and challenges. *Decision Strategies and Artificial Intelligence Navigating the Business Landscape*. <https://doi.org/10.59646/edbookc5/009>.
- [14] Sheikh, N., 2025. Designing a Model of the Impact of Artificial Intelligence Capabilities in Accounting Systems on Reducing Errors in Financial Reports. *Management Strategies and Engineering Sciences*, pp.1-12.
- [15] Ahmed, A., Shah, A., Ahmed, T., Yasin, S., Longa, F.E.A., Hussaini, W. and Zubair, M., 2025. AI-driven innovations in modern banking: From secure digital transactions to risk management, compliance frameworks, and AI-based ATM forecasting systems. *Journal of Management Science Research Review*, 4(3), pp.1145-1183.
- [16] Kurian, B., Sabarish, S., Venkat, K. and Freeda, A., 2025, July. Intelligent Financial Assistant: Chatbot-Based Mutual Fund Advisory System. In *2025 6th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)* (pp. 1719-1726). IEEE.
- [17] Safi, W.A., 2025. THE IMPACT OF ARTIFICIAL INTELLIGENCE APPLICATIONS ON ASSET MANAGEMENT PREDICTION IN THE BANKING SECTOR IN THE KINGDOM OF SAUDI ARABIA. *Scientific Culture*, 11(4), p.661.
- [18] Johari, M.H.Y., 2025. Artificial intelligence in Zakat and Waqf management: Enhancing fund utilisation for tourism initiatives. *Journal of Islamic Accounting and Business Research*, pp.1-17.
- [19] Alshahmy, S. and Sahiner, M., 2024. Enhancing the issuance and monitoring of sustainable finance instruments through AI. In *Artificial intelligence, finance, and sustainability: Economic, ecological, and ethical implications* (pp. 217-241). Cham: Springer Nature Switzerland.
- [20] Oweis, K.A., 2025. The role of artificial intelligence in developing accounting: Automating processes and enhancing financial reporting in Saudi Arabia. *Management*, 29(1), pp.239-255.
- [21] Limajatini, L., Suhendra, S., Pangilinan, G.A. and Ilham, M.G., 2025. Integration of artificial intelligence in the financial sector innovation, risks and opportunities. *International Journal*

- of Cyber and IT Service Management (IJCITSM), 5(1), pp.58-70.
- [22] Liu, Y., 2025, November. Integration of Artificial Intelligence and Big Data in Financial Management: A Comprehensive Review and Case Analysis. In *2025 International Conference on Financial Innovation and Marketing Management (FIMM 2025)* (pp. 727-735). Atlantis Press.
- [23] Subburayan, B., Sankarkumar, A.V., Singh, R. and Mushi, H.M., 2024. Transforming of the financial landscape from 4.0 to 5.0: Exploring the integration of blockchain, and artificial intelligence. *Applications of block chain technology and artificial intelligence*, pp.137-161.
- [24] Sajid, M.H., Ali, A. and Jadoon, A.K., 2025. Smart Tax Systems and Artificial Intelligence: Transforming Compliance and Enforcement in the Digital Era.
- [25] Taghizadeh, A., Karaminezhad, K., Fakhri, N., Moghaddami, B. and Charkhian, D., 2025. Assessing innovation strategies in the digital economy through artificial intelligence-based criteria using CoCoSo method. *Journal of Intelligent Decision Making and Granular Computing*, 1(1), pp.237-255.
- [26] Paleti, S., 2025. *Smart finance: Artificial intelligence, regulatory compliance, and data engineering in the transformation of global banking*. Deep Science Publishing.
- [27] Manda, V.K. and Nihar, K.L., 2024. Artificial intelligence applications in the Indian financial ecosystem. *Artificial intelligence for risk mitigation in the financial industry*, pp.133-157.
- [28] C. Koneni and S. Lokula, "Evidence-Quality Telemetry for Cloud Incident Response: Detecting Gaps, Drift, and Integrity Failures in Large-Scale Observability Pipelines," *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, Boston, MA, USA, 2026, pp. 1-6, doi: 10.1109/ISDFS69419.2026.11459097.
- [29] V. K. B. Parasaram, V. T. Bathini, S. K. Nalluri and A. H. Sannidhanam, "A Sustainable AI-Enabled Predictive Maintenance Framework for Smart Industrial Systems Using Industrial IoT Data," *2026 Third International Conference on Innovations in Cybersecurity and Data Science (ICICDS)*, Pathum Thani, Thailand, 2026, pp. 440-447, doi: 10.1109/ICICDS70526.2026.11604878.
- [30] Valencia-Arias, A., Gaviria Rodríguez, D.Y., Verde Flores, L., Cardona-Acevedo, S., Raunelli-Sander, J.M., Agudelo Ceballos, E.J. and Cardona Valencia, D., 2025. Use of machine learning in the financial sector: an analysis of trends and the research agenda. *Discover Artificial Intelligence*, 5(1), p.280.
- [31] S. K. Nalluri, V. T. Bathini and V. K. B. Parasaram, "AI-Augmented Manufacturing Execution Systems for Precision Healthcare: A Scalable Framework for Smart Genomic and Proteomic Production," *2026 IEEE 2nd International Conference on Secure IoT, Assured and Trusted Computing (SATC)*, Houston, TX, USA, 2026, pp. 1-6, doi: 10.1109/SATC69565.2026.11542384.
- [32] Lazaroiu, G., Gedeon, T., Rogalska, E., Valaskova, K., Nagy, M., Musa, H., Zvarikova, K., Poliak, M., Horak, J., Crețoiu, R.I. and Krulicky, T., 2024. Digital twin-based cyber-physical manufacturing systems, extended reality metaverse enterprise and production management algorithms, and Internet of Things financial and labor market technologies in generative artificial intelligence economics. *Oeconomia Copernicana*, 15(3), pp.837-870.
- [33] Koneni, C., S. Lokula, and L. Panjiyar. "A Cloud-Native Approach to Statistical Anomaly Detection and Automated Data Quality Validation." *International Journal of Data Science and IoT Management System* 4.4 (2025): 533-543
- [34] V. K. Bharadwaj Parasaram, V. Teja Bathini and S. K. Nalluri, "An Intelligent Digital Framework for Clinical Trial Monitoring Using AI and Cloud-Based Software Platforms," *2026 2nd International Conference on Artificial Intelligence Systems (AIS)*, San Antonio, TX, USA, 2026, pp. 524-530, doi: 10.1109/AIS69919.2026.11621841.
- [35] Choithani, T., Chowdhury, A., Patel, S., Patel, P., Patel, D. and Shah, M., 2024. A comprehensive study of artificial intelligence and cybersecurity on bitcoin, crypto currency and banking system. *Annals of Data Science*, 11(1), pp.103-135.
- [36] Vishram Singh, 2026. "Enterprise Resource Planning for Financial Applications: Engineering, Architecture, and Design Principles," *International Journal of Scientific Research in Science and Technology*, Technoscience Academy, vol. 13(2), pages 653-661, April.
- [37] M. B K, V. K. Bharadwaj Parasaram, S. K. Nalluri and V. T. Bathini, "Attention-Guided Multi-Modal Deep Intelligence Framework for Early Cancer Detection Using Imaging and Genomic Signatures," *2026 International Conference on Data Science for Cyber-Physical Systems Resilience using Advanced Applications (ICDCA)*, BANGALORE, India, 2026, pp. 1-6, doi: 10.1109/ICDCA69396.2026.11620255.
- [38] C. Koneni and S. Lokula, "Silent Data Corruption in Distributed Genai-Augmented Data Pipelines: an Empirical Study of Hallucination-Induced Failure

Propagation," 2026 *IEEE 46th International Conference on Distributed Computing Systems Workshops (ICDCSW)*, Seoul, Korea, Republic of, 2026, pp. 137-143,

[39] Vishram Singh, "Real-Time Financial Data Validation Platform for Enterprise Accounting Systems", *IJCISIM*, vol. 18, no. 10s, pp. 467–481, Jul. 2026