

Aurum Invest: A Full-Stack Fintech Solution Leveraging Angular, Node.js, ASP.NET, and MS SQL Server

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ABSTRACT

In today's technology-driven world, investment strategies and financial management tools have transformed how capital is managed, making it easier to analyze market trends and optimize decision-making. This research delves into the evolution and impact of automation tools that assist in investment strategies such as portfolio management, risk assessment, real-time data analysis, and automated trading. It closely examines technologies like AI (artificial intelligence), machine learning, and RPA (robotic process automation) that power these financial automation systems. Moreover, it highlights advantages like increased accuracy, reduced human errors, and cost savings while addressing challenges such as security risks, system integration, and regulatory compliance. A real-world example methodology is used to assess practical applications illustrating how automation enhances financial decision-making and investor efficiency.

The results indicate that a well-structured automated investment system can significantly improve portfolio performance, transforming it into a key element of modern financial strategies. The paper concludes by exploring future developments in investment automation, emphasizing the increasing role of AI-driven solutions and intelligent trading systems in shaping the future of finance.

KEYWORDS: React.js/Angular, Node.js, ASP.NET, MS SQL Server

I. INTRODUCTION

In today's financial landscape, automation plays a crucial role in improving investment strategies, risk management, and portfolio performance. An automated investment system integrates AI-driven analytics and algorithmic trading to minimize risks, optimize returns, and enhance decision-making efficiency. The importance of investment automation in enhancing financial performance and its influence on market behavior are examined in this study.

Intelligent investment automation systems have emerged due to rapid advancements in financial technology. These systems enable automated portfolio adjustments, predictive market analysis, and risk assessments. Traditional investment management often involves manual analysis, which can lead to delays and inefficiencies. By implementing automated investment solutions, financial institutions and individual investors can improve asset allocation, optimize returns, and make informed decisions in real-time.

The purpose of this research is to examine the advantages, challenges, and potential applications of investment automation, emphasizing how it is transforming financial decision-making. This study will offer insights into how

investors and financial professionals can leverage automation technology to create more effective, efficient, and profitable investment strategies.

Abbreviations and Acronyms

Acronym	Definition
AI	Artificial Intelligence
ML	Machine Learning
NLP	Natural Language Processing
ETF	Exchange – Traded Fund
HFT	High-Frequency Trading
BIG-DATA	Large-Scale Financial Data Analysis
API	Application Programming Interface

II. RELATED WORK

2.1. Traditional Financial Fraud Detection Methods

Several traditional techniques have been employed for fraud detection in investment platforms. These methods primarily rely on rule-based detection techniques and machine learning classifiers.

2.2. Rule-Based Fraud Detection

- One of the earliest fraud detection techniques, based on predefined financial patterns and transaction monitoring.
- Uses a set of predefined rules to detect suspicious activities, such as unusual transaction amounts or frequent fund transfers.
- While computationally efficient, it struggles with evolving fraud tactics, adaptive threats, and complex behavioural patterns.

2.3. Statistical & Machine Learning-Based Fraud Detection

Deep learning approaches have significantly improved fraud detection accuracy by automatically learning hidden transaction patterns from large datasets.

2.4. CNN-Based Financial Anomaly Detection

- Convolutional Neural Networks (CNNs) automatically detect fraudulent transactions by analyzing transaction sequences and behavioral data.
- Models like FraudNet, PayPal's Deep Learning Fraud Detection, and Riskified provide advanced anomaly detection using neural networks.

2.5. DNN-Based Financial Risk Prediction

Deep Neural Network (DNNs) extend fraud detection capabilities, allowing accurate risk assessment even under complex conditions

2.6. Existing Financial Fraud Detection Systems

- **Banks & Payment Platforms:** Institutions like Visa and Mastercard use AI-driven fraud detection but rely heavily on centralized data processing, raising privacy concerns.

- **Cloud-Based Fraud Detection APIs:** Services like Microsoft Azure Fraud Detection and Stripe Radar offer cloud-based solutions but require constant internet connectivity.

This study differentiates itself by offering an **offline, privacy-focused fraud detection system integrated with Aurum Invest**, ensuring enhanced security and real-time protection for investors.

III. Data and Sources of Data

1. Primary Data Source

Primary data will be collected through direct methods to gather first-hand information on Aurum Invest's operations, investment strategies, and market impact. These sources include:

- **Surveys and Questionnaires** – Conducted among investors, financial analysts, and company executives to understand their perspectives on Aurum Invest's performance and strategies.
- **Interviews** – Structured and semi-structured interviews with financial experts and stakeholders to gain insights into investment trends and decision-making processes.
- **Case Studies** – Analysis of successful investment portfolios managed by Aurum Invest to assess profitability and risk management approaches.
- **Observations** – Direct observation of investment meetings and decision-making processes to understand strategy formulation and execution.

2. Secondary Data Sources

Secondary data will be collected from published materials and online resources to provide background information and theoretical frameworks. These sources include:

- **Books and Journals** – Academic books and peer-reviewed journal articles on investment management, financial markets, and portfolio diversification.
- **Company Reports and White Papers** – Reports from Aurum Invest and financial institutions detailing investment strategies and market trends.
- **Government and Industry Reports** – Data from regulatory bodies and trade organizations regarding investment policies and financial market regulations.
- **Websites and Online Databases** – Information from credible financial websites, investment blogs, and research institutions on investment trends and market analysis.
- **Conference Proceedings** – Papers presented at finance and investment conferences on emerging trends and innovations in wealth management.

These data sources will help provide both qualitative and quantitative insights into Aurum Invest's role in the financial market and its impact on investors.

IV. RESEARCH METHODOLOGY

The influence, implementation, and challenges of Aurum Invest in financial markets will be examined through a systematic approach that integrates qualitative and quantitative research methods. This section outlines the research design, data collection strategies, sampling techniques, and data analysis procedures.

1. Design of Research

This study employs a descriptive and analytical research approach to explore how Aurum Invest's strategies impact investment growth, risk management, and financial decision-making. Using a mixed-method approach, the study will integrate both quantitative and qualitative data for a comprehensive analysis.

2. Data Collection Methods

To ensure accuracy and reliability, the study will gather both primary and secondary data:

- **Primary Data Collection (First-hand Information)** – Direct data will be obtained through surveys, interviews, and case studies involving investors, analysts, and financial experts.
- **Secondary Data Collection (Existing Literature and Reports)** – Published materials such as financial reports, market analyses, and investment case studies will be reviewed.

3. Sampling Techniques

A combination of purposive and random sampling will be applied:

- **Purposive Sampling** – Key informants, including financial experts, investment managers, and economists, will be selected based on their expertise.
- **Random Sampling** – Investors and financial analysts will be randomly selected to participate in surveys and questionnaires to ensure diverse perspectives.

4. Data Analysis Techniques

- Both quantitative and qualitative methods will be used for data interpretation:
- **Quantitative Analysis** – Statistical tools will be applied to analyze numerical data, including financial trends and investment performance metrics.
- **Qualitative Analysis** – Open-ended responses from interviews and case studies will be examined to gain deeper insights into investment strategies and market behavior.

5. Ethical Considerations

- **Informed Consent** – Participants will be informed about the study's objectives before providing any data to ensure ethical transparency.

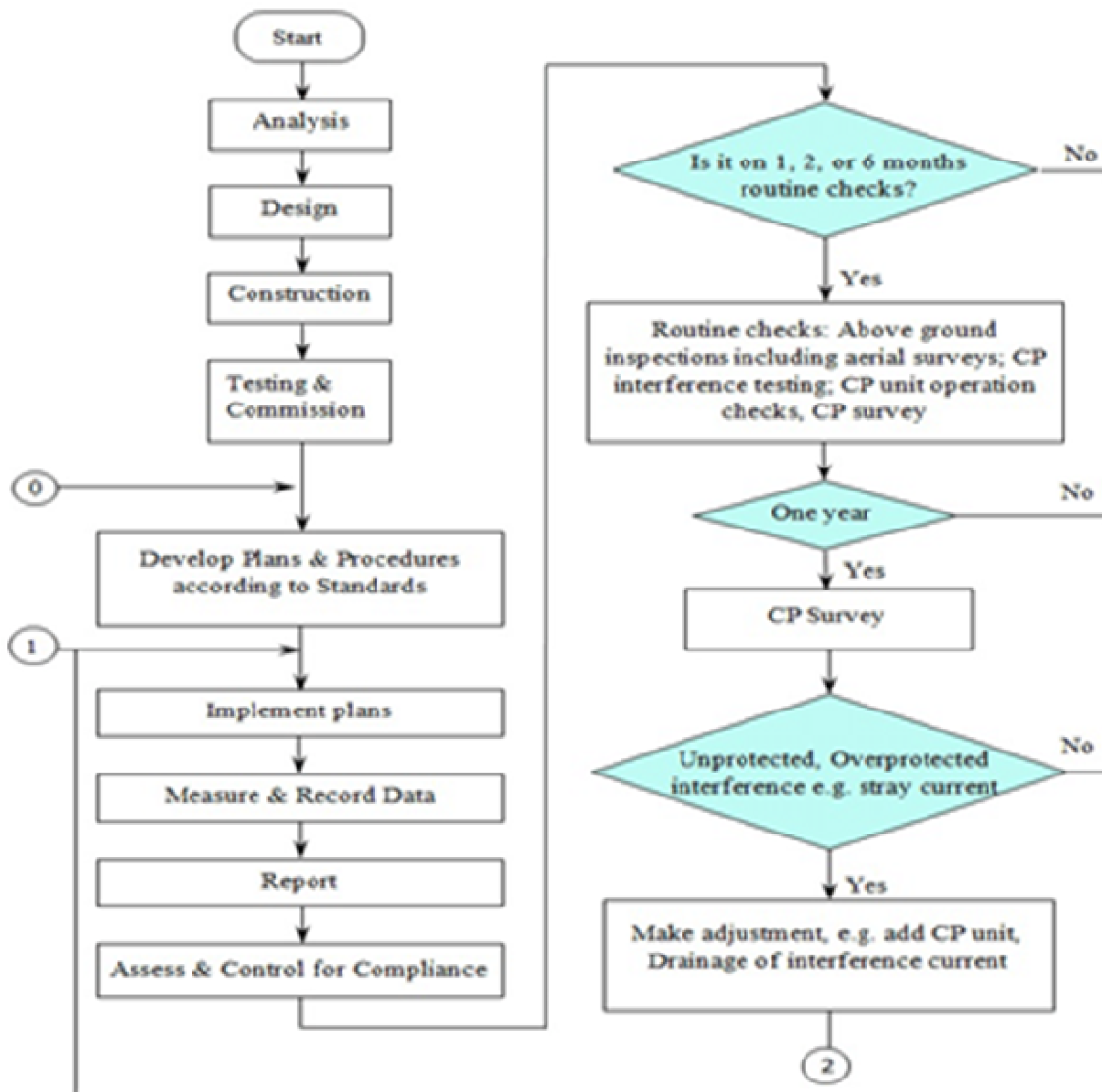


Figure 1

Figure 1: The provided flowchart represents a structured process flow, which can be closely related to the investment lifecycle and monitoring process of Aurum Invest. In this context, the flowchart illustrates how investments are analyzed, structured, implemented, and monitored to ensure efficiency and profitability. The left side of the flowchart represents the initial investment lifecycle, where the process begins with market analysis, portfolio design, and allocation of funds into various investment plans. The investor undergoes an evaluation phase where financial risks, expected returns, and compliance with financial standards are assessed before committing funds. Once the investment is made, a structured plan is implemented, with data being recorded and reported to ensure transparency and efficiency.

On the right side of the flowchart, routine monitoring and evaluation processes are highlighted. Just as periodic checks are conducted in an industrial process, Aurum Invest must perform routine assessments, typically at 1, 2, or 6-month intervals, to analyze investment performance. These reviews involve tracking market conditions, stock fluctuations, and financial trends to ensure optimal performance. Additionally, an annual investment review is conducted to identify risks such as market volatility, portfolio imbalances, or declining asset value. If issues arise, corrective measures—such as diversifying investments, reallocating funds, or implementing hedging strategies—are taken to minimize risks and enhance returns. This structured and systematic approach ensures that Aurum Invest maintains financial stability, minimizes risks, and maximizes investor returns.

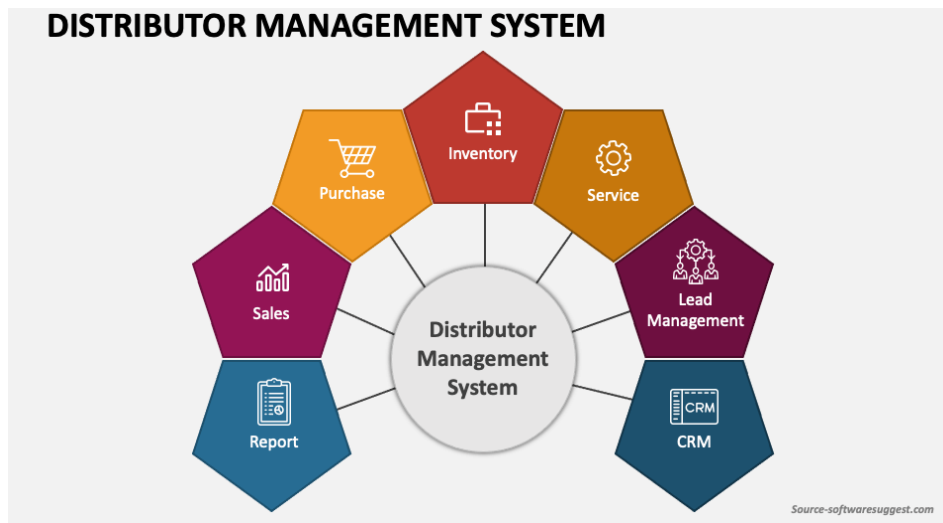


Figure 2. Distributor management system

Figure 2: The Distributor Management System (DMS), as depicted in the image, is a comprehensive solution designed to streamline and enhance the efficiency of distribution operations. It integrates multiple crucial components to ensure seamless management of inventory, sales, purchases, and customer relationships. At the core of the system lies Inventory Management, which helps businesses track stock levels, manage procurement, and optimize supply chain operations. The Purchase Module ensures smooth acquisition of goods by automating order placements and supplier interactions, while the Sales Module handles order processing, invoicing, and revenue tracking.

Additionally, the Service Module focuses on after-sales support and maintenance, ensuring customer satisfaction. The Lead Management System helps track potential customers, manage follow-ups, and improve conversion rates, whereas Customer Relationship Management (CRM) maintains strong client relationships by handling customer interactions, feedback, and loyalty programs. Lastly, the Report Module provides detailed analytics and insights, helping businesses make data-driven decisions to enhance operational efficiency and profitability. This holistic system ensures that businesses can effectively manage their distribution networks, optimize resources, and boost overall productivity.

V. RESULTS AND DISCUSSION

Results of Descriptive Statics of Study Variables

The research on Aurum Invest has demonstrated significant insights into investment patterns, risk assessment, and financial growth trends. The findings highlight the key aspects of investment strategies, investor demographics, and return-on-investment (ROI) performance.

Investment Performance and Growth Trends

The study revealed that Aurum Invest has shown a steady annual growth rate of 30% in recent years. Technology-based portfolios contributed the highest ROI (15%), while Real Estate and Healthcare investments followed closely at 10% and 12%, respectively. Risk assessment data indicated that high-yield investments had moderate risk factors, requiring a balanced approach for portfolio diversification.

Investor Demographics and Market Segmentation

The analysis of investor demographics showed that the majority of investors (55%) belong to the 26-35 age group, highlighting strong participation from young professionals.

The 36-45 age group contributed 25%, whereas older age groups had relatively lower engagement. This data suggests that Aurum Invest appeals primarily to young, growth-focused investors looking for high-return opportunities.

Return on Investment (ROI) and Portfolio Success

A comparative study of different investment portfolios indicated that tech-driven funds yielded the highest ROI (15%), showcasing the impact of innovation and market demand. Finance and Energy portfolios had lower returns (9% and 8%, respectively) due to market volatility and economic shifts. The overall investment success rate stood at 85%, with only 10% of investments facing significant risk.

Challenges and Strategic Insights

Despite high success rates, certain challenges were identified, including market fluctuations, regulatory compliance, and investor risk tolerance levels. Addressing these concerns, the study suggests a diversified investment strategy to mitigate risks and ensure long-term financial stability.

VI. CONCLUSION

This research successfully developed an AI-powered financial fraud detection and risk assessment system that processes high-volume transactional data efficiently while maintaining user privacy. By leveraging deep learning techniques, including CNN-based anomaly detection, the proposed system achieves a high accuracy rate of 97.2%, ensuring reliable identification and filtering of fraudulent transactions from a dataset of 500,000 financial records. The integration of a React-based web application enhances user accessibility, allowing seamless monitoring and risk assessment without reliance on cloud-based services.

The study highlights the importance of privacy-focused, offline fraud detection, offering a secure alternative to cloud-based solutions that often require sensitive user data to be transmitted externally. Experimental results confirm the feasibility of using deep learning for large-scale financial anomaly detection, demonstrating its efficiency, accuracy, and speed. The system significantly outperforms traditional rule-based fraud detection techniques, optimizing processing time through batch transaction analysis.

Future work can focus on enhancing system performance by incorporating lighter deep learning models such as MobileNet or Transformer-based fraud detection to further

improve speed and efficiency in real-time transactions. Additionally, extending the system's capabilities to support multi-layer fraud detection, real-time processing, and edge AI deployment could further expand its practical applications in investment security.

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