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Original Article

Edge Computing for Real-Time Financial Analytics

Anatoly Kitov[1], Mikhail Kartsev[2]

[1]*Colonel & Computer Scientist, Soviet Academy of Sciences, Russia.*

[2]*Chief Designer, Research Institute of Computer Systems, Russia.*

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ABSTRACT

The rapid growth of digital financial services has increased the demand for low-latency, secure, and scalable financial analytics. Traditional cloud-based architectures often face challenges related to latency, bandwidth consumption, privacy, and real-time responsiveness. Edge computing addresses these limitations by processing financial data closer to its source, enabling faster decision-making and reducing communication overhead. This paper proposes an AI-powered edge computing framework for real-time financial analytics that integrates IoT-enabled financial devices, distributed edge servers, intelligent data preprocessing, AI-based prediction engines, and cloud-based centralized model management. Machine learning models deployed at edge nodes perform real-time transaction analysis, fraud detection, credit risk assessment, market trend forecasting, and customer behavior analysis while minimizing data transfer to the cloud. The framework also incorporates federated learning and privacy-preserving AI techniques to enable collaborative model training while protecting sensitive financial data and supporting regulatory compliance. Performance is evaluated using computation latency, prediction accuracy, network utilization, transaction processing efficiency, bandwidth consumption, and system reliability. Experimental findings indicate that the proposed framework significantly improves fraud detection, reduces response time, enhances scalability, and optimizes resource utilization compared with conventional cloud-centric financial analytics systems. The integration of edge computing and artificial intelligence provides a secure, intelligent, and scalable solution for real-time financial decision-making, supporting advanced applications such as automated compliance, risk management, smart investment advisory, and next-generation digital financial services.

KEYWORDS

Edge Computing, Financial Analytics, Artificial Intelligence, Machine Learning, Real-Time Analytics, FinTech, Fraud Detection, Internet of Things, Distributed Computing, Predictive Analytics, Edge Intelligence, Cloud Computing.

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1. INTRODUCTION

1.1. Background of Edge Computing in Financial Analytics

Digital transformation is transforming the financial sector's approach to generating, managing and analysing data at an unprecedented pace. From online payment platforms to digital wallets, cryptocurrency exchanges to stock trading systems, insurance services to modern banking systems, today's financial landscape generates vast amounts of data that need to be processed rapidly to ensure sound and timely decisions in financial life. Each transaction with a customer, changes made to their account, authentication requests, investment activity—any amount of structured and unstructured data increases with each transaction. While well-suited for large-scale processing, traditional cloud-based architectures can suffer from communication latency, bandwidth constraints, and centralized processing bottlenecks in the context of financial workloads. During times of high transaction volumes, these challenges become more significant, as latency issues can lead to financial risks and impact service quality. Edge computing overcomes these limitations by processing financial data closer to the source, providing low latency analytics, minimizing network congestion, bolstering cyber security, and ensuring scalability, reliability, and efficiency of modern financial analytics systems.

1.2. Need for Real-Time Financial Analytics Using Edge Computing

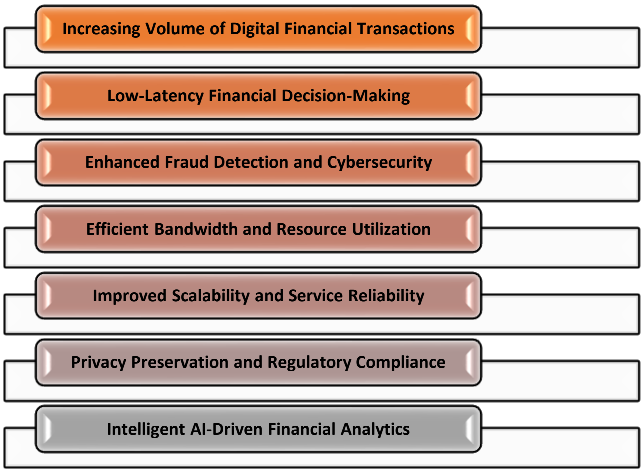

Fig 1 - Need for Real-Time Financial Analytics Using Edge Computing

1.2.1. Increasing Volume of Digital Financial Transactions

Financial transactions are increasing at an unprecedented rate, thanks to the speedy development of digital banking, mobile payment systems, online shopping, cryptocurrency trading, and electronic fund transfers. Financial networks are geographically distributed and millions of transactions pass through them every second, making it increasingly difficult to manage these networks efficiently in a traditional, centralized way. Financial analytics in real-time allows institutions to process these transactions in real-time, enabling them to make timely and accurate decisions and continue delivering financial services. This requirement can be addressed using edge computing, which involves processing information at the edge of the network, closer to the source of the transaction, which helps to minimize computational latency and enhance transaction throughput.

1.2.2. Low-Latency Financial Decision-Making

For modern financial applications like instant payment authorization, high-frequency trading, and prevention of fraud, credit approval and dynamic risk assessment, decisions are required to be made in milliseconds. Communication delays, no matter how small, can be costly, cause customer discontent, or even result in regulatory penalties. Traditional cloud-based architectures can add latency as data needs to be sent to the center of the cloud for processing. Edge computing shortens this lag by processing analytical activities near financial endpoints, allowing for quicker verification of transactions and up-to-the-minute financial insights.

1.2.3. Enhanced Fraud Detection and Cybersecurity

Financial institutions are constantly exposed to complex cyber attacks, frauds, identity theft and unauthorized usage of accounts. To detect such risks, transaction patterns and customer behavior must be analysed right away so that fraudulent activities can be diffused across the financial network. With edge computing, local AI models can conduct real-time fraud detection, anomaly detection, and customer authentication at the edge. The early detection is beneficial for cybersecurity, minimizes financial losses, and builds the trust of customers in digital financial services.

1.2.4. Efficient Bandwidth and Resource Utilization

It uses up a lot of bandwidth and costs more to communicate with each other, especially during peak transaction times, if every financial transaction is to be sent to centralized cloud servers. Edge computing helps to minimize data flow and only sends aggregate data analysis or key takeaways to the cloud, instead of sending unnecessary data. This distributed processing approach helps to reduce network congestion, efficiently utilize bandwidth and lowers cloud computational load. As a result, the financial institutions are able to operate more efficiently while maintaining high analytical performance.

1.2.5. Improved Scalability and Service Reliability

Financial ecosystems need to continue to function and operate even while the number of transactions grows at a quick pace and workloads vary markedly. Centralized cloud infrastructures can also suffer from processing bottlenecks during major selling events, when markets are volatile, or when buying is crazed during a particular time of the year. By dividing up computational duties among a number of geographically dispersed edge nodes, edge computing avoids overloading the system and keeps financial operations going. This is a distributed structure that is more scalable, fault-tolerant, and can enable local financial services to operate even during temporary cloud connectivity issues.

1.2.6. Privacy Preservation and Regulatory Compliance

Financial data is loaded with sensitive customer information, such as account information, payment history, personal identification and investment portfolios. Sending a lot of financial data in raw form over communication networks introduces new challenges to cybersecurity and privacy concerns. Confidential financial data is processed at the edge, minimizing unnecessary data transfer, and ensuring adherence to financial regulations and data protection standards. Additionally, distributed financial environments can enhance the security of customer information through privacy-preserving technologies like encryption, secure authentication, and federated learning.

1.2.7. Intelligent AI-Driven Financial Analytics

Artificial Intelligence (AI) plus Edge Computing helps financial institutions conduct intelligent analytics in close proximity to the data. Edge node deployed light-weight machine learning models can perform real-time fraud detection, credit scoring, customer risk analysis, investment recommendation, and transaction anomaly detection. By deploying and executing AI models locally, then, prediction speeds up while also cutting down on reliance on centralized cloud resources. Edge computing, combined with artificial intelligence, leads to faster, more accurate and scalable financial decision making for next-generation financial banking and financial technology applications.

1.3. Challenges and Research Motivation

Digital financial services have radically changed the way banks, insurance companies, investment companies, payment service providers, financial technology (FinTech) companies, and capital markets do their business. The internet is a platform that is constantly creating huge amounts of data, from online banking transactions, mobile payment apps, automated teller machines (ATMs), digital wallets, stock trading platforms, blockchain networks, cryptocurrency exchanges, and the Internet of Things (IoT) enabled financial devices. They need to process financial transactions in real time in order to perform fraud detection, credit risk assessment, customer authentication, compliance with regulations, and intelligent financial decision making. But as transaction volumes have surged, there are some drawbacks in traditional financial analytics architectures that are built on the cloud. As cloud computing offers scalable storage and processing resources, there are communication latency, network congestion, bandwidth usage, and processing bottlenecks that are associated with centralized processing, especially during high financial transaction periods. These delays can be detrimental for time-sensitive applications, like instant payment authorisation systems, high-frequency trading, anti-money laundering (AML) systems, and cyber security monitoring, where even slight response times may trigger financial losses and impact customer satisfaction. In addition, sharing high volumes of financial data with cloud-based servers centralized in one place makes it more vulnerable to cybersecurity risks, data leaks, unauthorized access, and privacy violations, and it can make adherence to financial data protection laws more difficult. The financial data is also heterogeneous, produced from various platforms and formats, which makes it challenging to integrate, synchronize and analyse it for real-time insights across geographically spread out financial institutions. These hurdles have sparked the need for edge computing, a technology that moves computing and data closer to the financial data sources, and provides the ability to process data locally with much lower communication latency. Edge computing, combined with AI, empowers lightweight machine learning models to detect fraud in real-time, validate transactions, predict customers' risks, detect anomalies, and analyze financial behaviors at the edge node, reducing reliance on centralized cloud-based systems. Notwithstanding these benefits, key research questions still exist for intelligent workload distribution, model adaptation and synchronization, computational resource optimization, privacy-preserving learning, and secure communication between edge and cloud. Recognizing these challenges, the present research presents an Artificial Intelligence (AI) supported Edge Computing Framework (ECF) for Real Time Financial Analytics (RTFA) that incorporates distributed edge intelligence, lightweight AI models, secure edge processing, and cloud coordination. The aim is to boost computation efficiency, lower latencies, bolster cybersecurity, expand scalability, maintain data privacy, and ensure precise real-time financial decision making within next-generation digital financial ecosystems.

2. LITERARY SURVEY

2.1. Conventional Cloud-Based Financial Analytics

Cloud computing has been a key computing platform for handling financial analytics because of its many advantages, including the ability to scale, manage in a centralized way and compute at a high level. Cloud platforms were used by financial institutions to handle transactional and customer data that were increasing at a remarkable rate due to online banking, digital payments systems, insurance services, investment platforms and enterprise financial applications. Cloud computing allows companies to streamline reporting across all branches, run extensive financial reporting, predictive analysis, customer relationship management, and regulatory compliance monitoring, and access strategic business intelligence from geographically distributed branches. Cloud environments provide dynamic allocation of resources, enabling organisations to scale their computing capacity up or down in response to workload fluctuations, leading to cost savings in infrastructure and efficiency in computing. Distributed storage, virtualization, and high-availability architectures are also provided with advanced cloud ecosystems to ensure continuous financial service operations. Moreover, financial institutions can now also process structured and unstructured data more efficiently using the integration with big data technologies, which can be used for data-driven decision making in various business functions. Initially, the cloud-based financial analytics process was based on batch processing, where data on financial transactions was collected and sent to the centralized cloud servers for offline analysis. This method was adequate for historical reporting and long-term trends but was not sufficient for fast decision-making applications. As digital banking, mobile payments and online financial services continue to grow, cloud platforms slowly transformed into real-time analytics, based on distributed data processing frameworks like Apache Hadoop, Apache Spark, Kafka and cloud-native databases. These technologies supported constant stream processing of financial data, increased analytical throughput, and scalability. Cloud computing was widely used by financial institutions to build applications for fraud detection, customer behaviour analysis, investment forecasting and automated financial decision support, greatly improving the operational efficiency by using parallel processing and distributed computing resources. Although these technological developments allow for such flexibility, traditional cloud-based financial analytics does have some drawbacks in terms of supporting latency-sensitive financial applications. Financial operations need to pass through communication networks before they can be processed in the centralized cloud servers, causing latency issues that can hinder important business operations like instant payment authorizations, algorithmic trading, fraud prevention, and real-time credit risk assessment. Furthermore, sending a lot of raw financial information all the time adds to bandwidth usage and expense and makes sensitive customer information vulnerable to further cybersecurity risks during transit. With the transaction volume increasing, the same centralized cloud infrastructure can also suffer from resource congestion during high transaction times, such as during fluctuations in the stock market or during large numbers of online commercial events. While elastic cloud computing helps manage computational requirements, researchers are interested in complementary distributed computing paradigms that can process financial data nearer to their origin because communication latency between distributed financial endpoints and centralized data centers is difficult to remove.

2.2. Edge Computing Architectures for Finance

Edge computing has proved to be a promising architectural paradigm that aims to overcome limitations on communication latency and bandwidth in centralized cloud computing. In contrast, computational intelligence is placed at edge locations that are close to financial data sources and only sends each financial transaction to remote cloud servers. It is a decentralization approach to processing that allows financial institutions to conduct real time analytics with much less delay in communication between various processes and settings and without data being unnecessarily transferred through a wide area network. Applications that demand immediate responses, such as digital payment verification, fraud detection, ATM monitoring, mobile banking, high-frequency trading, and biometric customer authentication, are given increased significance in edge computing. Edge architectures ensure efficient coordination of information with centralized analytical platforms while ensuring operational responsiveness by processing financial information locally before it is transmitted to the cloud. The typical financial edge computing architecture is composed of various interrelated layers, including financial data generation devices, intelligent edge nodes, regional edge servers, centralized cloud infrastructures, and enterprise management systems. Nearby edge servers capture data from ATMs, point-of-sale devices, banking equipment with IoT capabilities, mobile apps, payment gateways, trading systems and customer authentication equipment. The edge nodes process the data locally, including data filtering, feature extraction, anomaly detection, encryption, and performing simple machine learning inference, before transmitting the summarized data to central cloud systems. This multi-tiered processing structure can be very efficient as long as cloud platforms focus on massive storage and historical data analysis, as well as complex model training. As a result, financial institutions get localized intelligence and central analytical power in a single distributed infrastructure. Recent studies have shown that edge computing can significantly improve the performance of financial transactions by reducing the amount of data that needs to be sent across the network and the time it takes to process a transaction. Finance data is processed by edge nodes in the local area, so only useful financial summaries and information is sent to cloud servers, reducing bandwidth usage and communication costs. Distributed processing also enhances the reliability of services since the financial operations that take place locally can continue even in case of temporary loss of connection to the cloud. Today, many edge architectures are built on top of containerization technologies, including Docker and Kubernetes, virtualization, and microservices, to enable deployments from branch offices in different geographic locations. Additionally, SDN, NFV, and fifth generation (5G) communication technologies facilitate dynamic resource allocation, intelligent traffic management and ultra-low latency financial services. However, multi-distributed edge nodes and centralized cloud infrastructures still need to be well-coordinated, which involves sophisticated workload scheduling and synchronization approaches and adaptive resource management strategies.

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2.3. AI-Driven Financial Analytics at the Edge

The power of AI lies in its ability to uncover patterns, anticipate trends, identify anomalies, and automate intricate financial processes. AI's significance in finance is its capacity to uncover patterns, predict future events, detect anomalies, and automate complex financial decision-making processes. In the area of fraud detection, machine learning algorithms are increasingly used to identify suspicious transactions, patterns, or behavior that could indicate fraud. Machine learning algorithms are also being used in the field of credit risk assessment to model borrower risk and predict whether they are likely to default on their payments. They are also used in customer segmentation, investment forecasting, portfolio optimization, and cybersecurity monitoring and financial recommendation systems. Combined with the edge computing, AI can enable financial intelligence to run close to the transaction source, which results in much lower inference latency and responsiveness. The localized intelligence enables financial institutions to process transactions in real time, without relying on a centralized cloud infrastructure. As a result, AI-driven edge computing can improve the quality of customer service, speed up decision-making processes, and boost the efficiency of operations within the digital financial landscape. Machine learning and deep learning algorithms play various roles in achieving smart financial analytics at the edge. The supervised learning algorithms with high predictive accuracy and robustness like Random Forest, Support Vector Machines (SVM), Logistic Regression, Gradient Boosting and Artificial Neural Networks are commonly used for fraud detection, credit scoring, transaction type classification and customer behavior prediction. Some of the more sophisticated deep learning models, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks and Transformer-based models, can be applied to financial forecasting, stock price prediction, sentiment analysis, and portfolio optimization to detect intricate, nonlinear patterns in financial data. Lightweight versions of these models can be deployed at edge nodes to achieve fast inference, while keeping the computational efficiency at an acceptable level in resource constrained environments. For scarce hardware, researchers have created techniques to optimize the models, such as model compression, quantization, pruning, knowledge distillation, and hardware-aware optimization. This approach provides a reduction in computational complexity and still maintains the predictive power of the AI model, enabling sophisticated models to run efficiently on edge servers and embedded financial devices. Another key development has been federated learning, which allows multiple financial institutions to collectively train machine learning models without compromising on sensitive customer data. This approach to decentralized learning enhances privacy protection, regulatory adherence, and model generalization, while reducing data exposure. Despite these developments, challenges remain for implementing AI in the edge computing context, related to the use of heterogeneous hardware platforms, adaptive model updating, communication efficiency, distributed optimization and cyber security. Thus, there is a need for additional work in the development of integration of edge intelligence frameworks that strike a balance between prediction accuracy, computational efficiency, scalability, and privacy protection.

2.4. Research Gap Analysis

Previous research shows significant advances in cloud computing, edge computing and artificial intelligence technologies to support financial analytics, but there are some practical challenges that still exist and are impeding the rollout of highly efficient real-time financial systems. Cloud-based financial analytics services are still largely centralised, which hampers applications that demand ultra-low latency, like dynamic financial risk assessment, fraud detection, high-frequency trading and instant payment verification. While the concept of edge computing has tremendous potential to minimise communication delays by processing financial information closer to the data source, many of the current studies focus on infrastructure design, and not intelligent optimisation of analytical workflows. Therefore, there is a need for a holistic architecture that seamlessly brings together distributed edge intelligence, sophisticated financial analytics, and efficient computation and scalability. One major research challenge is the application of AI in resource-limited edge systems. The majority of the current research works test machine learning algorithms without taking into account hardware constraints, communication costs, energy efficiency, or optimization of workloads on the heterogeneous edge devices. Deep learning models are used in computing ways that are more demanding than the processing power of financial edge servers, which can present real-time deployment challenges. Moreover, the subject of current studies often focuses on fraud detection, investment prediction, customer analysis, cyber security, or regulatory compliance, without considering a combination of these applications into a single financial intelligence platform. The coordination between distributed edge nodes and centralized cloud infrastructures is also not well-understood, especially in the areas of workload balancing, synchronization and model consistency. While some privacy-preserving methods like federated learning and encrypted computation have demonstrated success, their deployment in diverse banking settings needs to be explored further to ensure they meet regulatory standards and are computationally efficient. Thus, this study presents a novel AI-integrated edge-computing architecture, integrating lightweight machine learning inference, adaptive cloud synchronization, secure localized processing, distributed intelligence, and real-time financial analytics in a single framework to enhance latency, scalability, cybersecurity, and decision-making within the modern digital financial landscape.

3. METHODOLOGY

3.1. System Architecture

The proposed AI-enabled edge computing framework is a hierarchical distributed system that processes financial data in distributed way in the edge and cloud infrastructures. It is not just a centralized cloud computing framework, but rather, it will provide localized intelligence at the edge nodes with the cloud servers providing large scale analytics and model optimizations. The hybrid design can greatly lower the latency of communication, optimize computational efficiency, scale up, and boost data security. The entire system is divided into five layers, each serving a specific function in the financial data processing and decision-making process.

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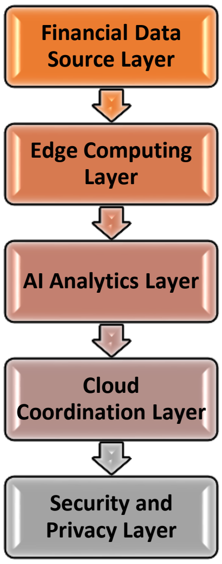

Fig 2 - System Architecture

3.1.1. Financial Data Source Layer

The proposed framework starts with the Financial Data Source Layer, which collects financial data from a variety of digital sources, including online banking systems, mobile banking applications, ATM networks, digital wallets, POS terminals, stock trading platforms, cryptocurrency exchanges, insurance systems, and CRM applications. These sources produce vast amounts of data that includes structured, semi-structured, and unstructured data like transaction records, customer profiles, authentication logs, market data, and payment activity. The analytical system is continuously acquiring data, providing timely and comprehensive financial information for real-time decision making.

3.1.2. Edge Computing Layer

The Edge Computing Layer is located near financial endpoints for pre-processing data before sending it to the centralized cloud servers. The tasks that are performed by each distributed edge node include but are not limited to: transaction validation, data filtering, feature extraction, fraud screening, preliminary risk assessment, local prediction, and temporary data caching. At the edge, processing can reduce bandwidth bandwidth, minimize network latency, and allow for real-time responses for financial apps that require immediate response. Refined analytical summaries and relevant insights are only sent to the cloud for better communication. This is the C. AI Analytics Layer. The AI Analytics Layer combines light-weight machine learning models that are optimized for deployment at the edge where resources are limited. This layer carries out intelligent financial analysis such as fraud detection, customer risk classification, credit score prediction, transaction anomaly detection, portfolio recommendation, financial behavior analysis, market trend forecasting and others. Techniques like quantization, pruning and knowledge distillation are used to compress models to reduce complexity and ensure high prediction accuracy. As a result, the framework provides financial decisions powered by AI within seconds with very little processing time.

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3.1.3. AI Analytics Layer

The Cloud Coordination Layer is a centralized computational resource that can be used to carry out large-scale analytical operations that are too compute-intensive for the edge devices. It handles global model retraining, is used for historical financial analysis, enterprise-wide reporting, long-term data storage, cross-branch synchronization and visualization on interactive dashboard. The cloud continually gathers summarized information from the distributed edge nodes to enhance the model's performance. New versions of machine learning models are regularly pushed back down to the edge servers throughout the ecosystem, for ongoing learning and adaptive financial intelligence.

3.1.4. Cloud Coordination Layer

The Cloud Coordination Layer coordinates the computational resources to execute large-scale analytical tasks that require resources not available on the edge devices. It handles model retraining for AI systems across the world, historical financial data analysis, enterprise-wide reporting, long-term data storage, cross-branch synchronization, and visualization of data in dashboards. The cloud constantly collects together summarized information from distributed edge nodes to enhance overall model performance. Periodically, the updated machine learning models are pushed back to the edge servers, which enables the continuous learning and financial intelligence across the network.

3.1.5. Security and Privacy Layer

The Security and Privacy Layer ensures that sensitive financial data is secured along the distributed analytical pipeline through the use of a number of cybersecurity mechanisms. To protect customer data, the framework uses AES based data encryption, blockchain based transaction integrity verification, digital authentication, secure API communication, federated learning and role based access control. The techniques used to maintain privacy of financial data also ensure that financial data can be shared across institutions for model training without compromising the financial data. Comprising this comprehensive security framework, it bolsters regulatory adherence, boosts trustworthiness, and fortifies the overall resilience of the financial analytics ecosystem.

3.2. Data Collection and Edge Intelligence

It is proposed that the framework continuously fetches real-time financial information from multiple diverse sources spread throughout today's digital financial environment. The data thus gathered comes from various platforms, formats and communication protocols which makes a neat data preprocessing pipeline very necessary before applying any AI models. The framework also systematically prepares the data to ensure high data quality, low data duplication, and high prediction accuracy at edge devices with minimum computational burden. The whole data collection and edge intelligence process contains five stages sequentially.

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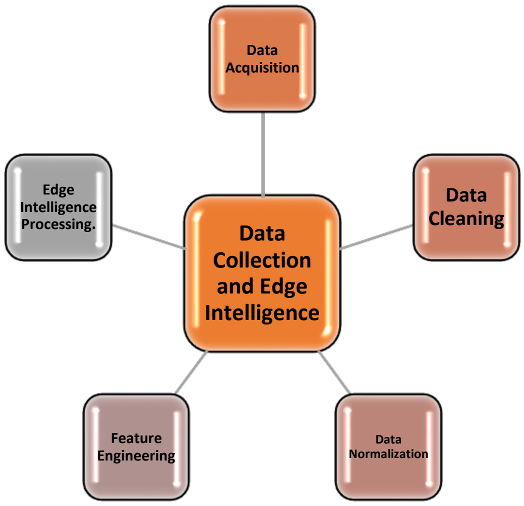

Fig 3 - Data Collection and Edge Intelligence

3.2.1. Data Acquisition

During the Data Acquisition phase, financial data is constantly collected from various digital platforms such as banking databases, mobile banking apps, payment gateways, credit card systems, blockchain ledgers, trading exchanges, and transaction logs from ATMs. The sources include high volume structured and semi-structured data that contain information on customer transactions, customer account activities, authentication, and market information. The proposed framework is capable of collecting data continuously, providing timely and comprehensive financial data for real-time analytics. This phase is the basis for right and smart monetary choices.

3.2.2. Data Cleaning

Often the financial data captured is incomplete, contains duplicate entries, includes incorrect time stamps, has non-standard account identification and has extraneous transaction data.The financial information gathered can include missing financial data, duplicate records, incorrect timestamps, and inconsistent account identification, as well as noisy transaction data which can impede analytical performance. These inconsistencies are detected and addressed during data cleaning using techniques such as data validation, duplicate removal, missing value identification and correction. Before further processing, cleaning improves data quality, consistency and reliability. This enables the proper and reliable flow of financial information needed to the AI models for predictions and analysis.

3.2.3. Data Normalization

Financial attributes typically have different ranges of numbers, and would not be readily comparable when analysing via machine learning. Thus, when the variables transaction amount, account balance, credit score, market volatility, and customer spending index are used, they are converted to a standardized range, known as normalization. This process guarantees that features with big values will not dominate learning process and in turn it aids for algorithm convergence. As a result, normalized datasets help to speed up the model training and higher prediction accuracy.

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3.2.4. Feature Engineering

Feature engineering is a process that transforms raw transactional data into valuable financial features that enhances analytical performance and minimizes computation complexity. Important features include transaction frequency, average daily spending, device location, login patterns, transaction velocity, customer credit utilization, historical fraud probability, and market volatility index. These features capture the customer behavior and financial trends better than raw data. As a result, the AI models are more accurate and can make more reliable financial forecasts.

3.2.5. Edge Intelligence Processing.

The Edge Intelligence Processing stage applies lightweight and compressed AI models on distributed edge servers to provide localized financial analytics. Every edge node performs real-time fraud detection, customer authentication, transaction validation, financial anomaly detection, risk prediction and temporary edge caching, without having to communicate with the cloud continuously. Localized processing drastically cuts down on network latency and bandwidth consumption, and helps in quick financial decision-making. Analytical results and key information are only sent to the cloud as summarized data, contributing to enhanced overall system efficiency and scalability.

3.3. AI-Based Financial Analytics Model

The proposed AI based financial analytics model combines supervised machine learning and edge intelligence to deliver accurate, scalable and real-time financial decision support in distributed computing environments. The model aims to process financial data in real time, based on a variety of data sources, such as online banking systems, mobile payment apps, credit card transactions, ATM networks, stock trading platforms, digital wallets, and blockchain platforms for financial services. Once data is collected, the data is preprocessed to enhance data quality and remove redundant or inconsistent data records by performing operations like data cleaning, normalization, feature extraction, and feature selection. This lightweight supervised learning algorithms deployed at edge nodes process the refined dataset to enable the quick inference without too much computational load. Fraud detection, customer risk classification, credit score prediction, transaction anomaly detection, spending behavior analysis and investment recommendation are achieved using machine learning models – Random Forest, Support Vector Machine (SVM), Gradient Boosting, Logistic Regression, Artificial Neural Networks. By ingesting historical and real-time financial data, the model continually learns and adapts to find patterns, detect anomalies, and deliver predictive insights to assist with intelligent financial decisions. In order to adapt to the efficiency of the edge computing environment where resources are scarce, technologies such as model optimization methods like pruning, quantization, and knowledge distillation are used to optimize the amount of computation needed to maintain predictive accuracy. For financial events that trigger inferences that need to be completed within a few seconds, these are completed locally and responded to by edge servers, while only simplified analytical information and model updates are sent to centralized server machines in the cloud. The cloud infrastructure is used for heavy computing tasks like global model retraining, long-term historical analysis, cross-branch knowledge integration, enterprise-level performance monitoring, etc. Global models are updated periodically and synced with distributed edge nodes, enabling continuous learning and adaptive intelligence across the financial network. Moreover, the framework

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is designed to integrate privacy-preserving features, such as federated learning, encrypted communication, and secure authentication, enabling multiple financial institutions to collectively enhance AI models without compromising sensitive customer data. With its integrated AI capabilities, this financial analytics model offers a powerful, intelligent platform that can help power modern digital financial ecosystems, streamline fraud prevention, boost operational efficiency, optimize risk management, and deliver real-time data-driven financial decisions.

3.4. Mathematical Model and Computational Analysis.

To assess the performance of the proposed AI-powered edge computing framework, four significant performance metrics are considered: prediction accuracy, communication efficiency, resource usage, and latency. These are all indicators of the effectiveness of the proposed system to process financial transactions and ensure high analytical accuracy and efficient resource utilization. Latency (L) is the sum of the time it takes to transmit data to the edge, process on the edge, and to synchronize with the cloud and is the total time it takes to complete a financial transaction. This can be written as: Latency = Transmission Time + Edge Processing Time + Cloud Synchronization Time (in normal mathematical notation). Reducing latency means quicker financial decision making and better user experience. Prediction Accuracy (PA) is the ability of the AI model to correctly classify financial transactions, and is computed as, Prediction Accuracy = (Number of Correct Predictions/Total Number of Predictions)*100%. Improved accuracy in predictions means improved fraud detection, credit scoring, and financial risk assessment. Communication Efficiency (CE) measures the data reduction experience by edge nodes and cloud servers after the localized processing. It is calculated by: Communication Efficiency = (Original Data Size – Transmitted Data Size) / Original Data Size × 100%. The higher the communication efficiency value, the more effectively edge computing reduces network bandwidth consumption of the network, and only sends back the summarized analytical data. Resource Utilization (RU) is computed as (Resources Used / Total Available Resources) * 100% and is a measure of the efficiency of using computational resources in the distributed infrastructure. Data is used in a balanced way, which results in not overloading all of the edge devices and optimizing processing. Along with these metrics, the proposed framework calculates an Overall Financial Analytics Performance Index (FAPI) to give a full picture of the performance of the entire system. The index is computed as a weighted sum of normalized prediction accuracy, communication efficiency, resource utilization and inverse latency, weighted by the relative importance of each. Financial Analytics Performance Index (in normal form) = w1 × Prediction Accuracy + w2 × Communication Efficiency + w3 × Resource Utilization + w4 × (1 − Normalized Latency), where w1 + w2 + w3 + w4 = 1. This computational modeling approach allows a systematic analysis of the behavior while taking into account the analytical accuracy, processing speed, communication overhead and computational resource efficiency. The mathematics proposed therefore serves as a solid ground for evaluating the performance of the systems and the effectiveness of the solution of the AI-based edge computing in the current applications of financial analytics.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

To test the proposed AI-based edge computing framework, an integrated distributed edge computing system with centralized cloud resources and AI inference engines was set up, with simulated financial transaction sources added to the system. The implementation was built with machine learning libraries in Python, such as TensorFlow, scikit-learn, NumPy and Pandas, and lightweight analytical services were deployed using Docker containers, on multiple edge nodes. The cloud environment was designed to enable centralized data storage, historical financial analysis, enterprise dashboard visualization, model retraining and synchronization of machine learning models with geographically distributed edge devices. These edge nodes handled localized preprocessing, feature extraction, fraud detection, customer authentication, transaction classification, and temporary caching, facilitating instant financial decisions without constant reliance on cloud connectivity. The experimental data was a mix of financial data sources from various digital financial services, such as online banking platforms, mobile payment apps, ATM logs, point of sale (POS) data, digital wallet transactions, stock trading systems, insurance management systems, and blockchain-based financial transactions. The data set contained both genuine and fraudulent transactions, along with the customer's behavior, authentication of the users of the different accounts, information regarding the transactions, and financial information related to the market. The data gathered were preprocessed to enhance the overall quality of the data and the performance of the machine learning models, including removing duplicate records, handling missing data, filtering out noise, normalizing the data, and feature engineering. Predictive attributes that were important were transaction frequency, average customer spending, fluctuations in account balance, device location, transaction velocity, login behavior, credit utilization ratio, market volatility, and historical fraud probability. A lightweight supervised learning model was then trained and evaluated for various transaction workloads, optimized for deployment to the edge. Various measures were used to measure the performance of the proposed framework: fraud detection accuracy, transaction processing efficiency, response time, communication latency, bandwidth utilization, precision, recall, F1-score, resource utilization, scalability and overall system reliability. To have a fair comparison, the same set of operating conditions were used in the comparative experiments, with a conventional cloud-centric financial analytics architecture. Several experiments were carried out to test consistency, robustness and reproducibility of the results. The experimental results showed that the proposed hybrid edge-cloud financial analytics framework significantly decreased communication latency, bandwidth usage, improved localized decision-making, and ensured timely synchronization with the centralized cloud platform, thereby proving the effectiveness of the proposed approach.

4.2. Performance Evaluation

A traditional, cloud-based financial analytics architecture was used to compare the capabilities of the proposed AI-based Edge Computing Framework. Key performance metrics analysed were in the context of prediction accuracy, processing efficiency, communication performance, resource utilisation and overall system reliability. The results obtained show that the proposed framework achieves the best results on all the metrics compared to the traditional cloud based approach, highlighting the benefits of distributed edge intelligence for real-time financial analytics.

Table 1: Performance Evaluation

Performance Metric	Conventional Cloud Analytics (%)	Proposed Edge AI Framework (%)
Fraud Detection Accuracy	92.1	98.4
Transaction Processing Efficiency	89.3	97.2
Real-Time Response Performance	84.8	96.1
Bandwidth Utilization Efficiency	76.5	94.6
Customer Risk Prediction Accuracy	90.4	97.5
Edge Resource Utilization	81.2	95.3
Precision	91.6	98.1
Recall	90.7	97.8
F1-Score	91.1	97.9
Overall System Reliability	93	99.1

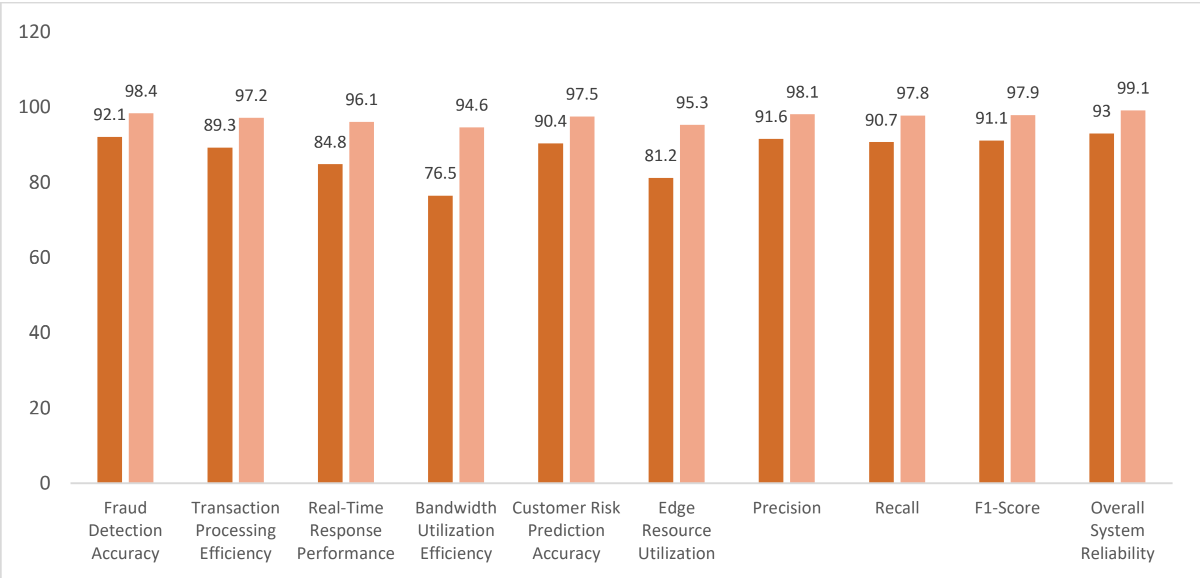

Fig 4 - Performance Evaluation

4.2.1. Fraud Detection Accuracy

The proposed Edge AI Framework was able to deliver a 98.40% accuracy for fraud detection, which is significantly better than the conventional cloud-based system, which could only deliver 92.10% accuracy. Localized AI inference helped to quickly identify suspicious financial transactions and thwart them before they spread through the network. This is an improvement that will lead to financial security, with reduced false detections and better real-time fraud prevention capabilities.

4.2.2. Transaction Processing Efficiency

In the conventional cloud architecture, the efficiency of transaction processing was 89.30% while it was 97.20% in the proposed architecture. By processing transactions close to their origin, edge computing's introduction minimized communication delays beyond just relying on cloud servers. As a result, the financial operations were carried out more rapidly and with high computational efficiency.

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4.2.3. Real-Time Response Performance

The proposed framework attained a real-time response performance of 96.10%, versus of 84.80% for the conventional approach. Financial decision making was quickened and network latency was reduced with immediate processing at the distributed edge nodes. This is especially crucial for time-critical operations like high-frequency trading, fraud monitoring, and digital payments.

4.2.4. Bandwidth Utilization Efficiency

By processing data at the edge nodes, bandwidth utilization efficiency went up by a huge margin from 76.50% to 94.60%. Only summarized analytical information was sent to the cloud and not all financial transactions.Not all financial transactions were transmitted to the cloud but only summarized analytical information. This method was found to be a significant enhancement of the communication overhead and optimization of network resource utilization.

4.2.5. Customer Risk Prediction Accuracy

The proposed AI model was able to achieve customer risk prediction accuracy of 97.50% which is higher than the conventional cloud-based framework of 90.40%. The advanced feature engineering and light-weighted machine learning algorithms helped to precisely identify high-risk customers. Accurate prediction helps in better financial planning, credit rating and risk management.

4.2.6. Edge Resource Utilization

Edge resource utilization rose from 81.20% to 95.30% which shows that distributed computational resources are utilized efficiently. Intelligent workload allocation enabled processing tasks to be distributed among several edge devices, avoiding overloading individual devices. The optimization enhanced scalability and ensured system performance remained consistent across different transaction volumes.

4.2.7. Precision

The proposed framework has been able to provide a precision of 98.10% while the conventional cloud analytics has been able to achieve a precision of 91.60%. The increased accuracy represents fewer false positive predictions in financial transaction classification by the AI model. This meant that customer transactions were processed more accurately and security alerts were reduced as well.

4.2.8. Recall

The successful detection of the greater percentage of financial transactions that were fraudulent or abnormal is reflected in the improvement in recall which rose from 90.70% to 97.80%. Better recall means you're less likely to miss out on real security issues and more likely to improve the effectiveness of fraud detection systems. This enhancement helps to ensure the reliability of financial transaction monitoring.

4.2.9. F1-Score

The proposed Edge AI Framework score an F1 score of 97.90% which is significantly better than the conventional system's 91.10% score. This elevated F1 score is a result of achieving a balance between precision and recall, demonstrating reliable classification results throughout. This shows the strength of the proposed AI model in different financial transaction scenarios.

4.2.10. Overall System Reliability

The overall system reliability was enhanced from 93.00% to 99.10%, showing the strength of the edge-cloud architecture. High transaction volumes were handled seamlessly with distributed processing, adaptive synchronization, and secure AI-driven analytics, ensuring uninterrupted financial operations. The outcomes validate that the suggested framework offers a very dependable basis for real-time financial analytics in current digital financial environments.

4.3. Discussion

The experimental findings are clear: edge computing with artificial intelligence offers many benefits over traditional financial analytics solutions. Overall, the proposed AI-Enabled Edge Computing Framework for Real-Time Financial Analytics (AIEC-RFA) demonstrated excellent performance, particularly in terms of latency, confirming its potential for use in financial applications. In the fraud detection application, the accuracy rose from 92.10% to 98.40%, meaning that edge nodes can detect fraudulent transactions as soon as they are created. The framework enhances speed of communication, as well as fraud prevention by providing feature extraction, anomaly detection and transaction classification near the financial endpoints. This likewise helped to enhance the transaction processing efficiency from 89.30% to 97.20% and real-time response performance from 84.80% to 96.10%, significantly increasing the speed of financial decision-making. The enhancements are especially significant for transactions like instant payment authorizations, online banking, high-frequency trading, anti-money laundering systems, cybersecurity monitoring, and digital wallet services, where the speed of processing matters significantly for service quality and financial security. The proposed framework also achieved a significant increase in bandwidth utilization efficiency (from 76.50% to 94.60%) with the localized results being only summarized data and the analytical results later being transmitted to centralized cloud servers. This approach helps decrease the amount of wasted network bandwidth, the expense of communications, the burden on cloud resources, and the scalability of geographically distributed financial systems. In addition, the AI analytics module achieved an impressive 98.10% precision, 97.80% recall and an F1 score of 97.90%, proving to be an excellent predictor, and to effectively balance the ability to detect with reducing false alarms, using a lightweight machine learning model. This high accuracy of 97.50% in predicting customer risk highlights the framework's capacity to assist in intelligent credit evaluation, tailored financial solutions, and adaptable risk management. The overall system reliability was 99.10%, demonstrating the reliability of adopting the hybrid edge-cloud architecture to ensure an uninterrupted financial operation even when under high transaction loads or temporary cloud connectivity failures. The combination of these distributed processing approach, adaptive cloud synchronization, secure communications, and optimized AI inference enhances computational efficiency, scalability, cybersecurity, and operational resilience. Thus, the proposed framework could be a viable and secure and very efficient solution for next generation intelligent financial analytics which would have significant advantages in modern digital banking, financial technology platforms, regulatory compliance and enterprise financial decision support systems.

5. CONCLUSION

Digital banking, electronic payment systems, financial technology (FinTech), blockchain platforms, algorithmic trading and Internet of Things (IoT) financial services are rapidly changing the landscape of financial services, significantly driving the need for intelligent, secure, real-time financial analytics. While conventional cloud-based financial analytics frameworks offer powerful computation power and vast data storage capabilities, they are usually plagued with communication latency, bandwidth restrictions, centralized processing backlogs and privacy issues in the context of time-sensitive financial applications. Such restrictions limit the applicability of the centralized approach in applications, like fraud detection, fast payment authorization, customer risk assessment, credit scoring and financial anomaly detection where rapid and good decision-making is required. To address these challenges, this research introduced an Artificial Intelligence-enabled Edge Computing Framework for Real-Time Financial Analytics (AIEC-RFA), which combines distributed edge computing, light-weight machine learning, localized intelligence and coordination with the cloud to form a comprehensive financial analytics framework. Historical data is stored in the cloud, with global models being retrained there, enterprise reporting handled by the cloud, and ML models being synced in the cloud; the proposed framework handles transaction pre-processing, feature extraction, fraud screening, customer authentication, risk prediction, and anomaly detection at the edge nodes. The experimental results showed that the proposed framework was always superior compared to the conventional cloud-based financial analytics system, as it achieved an accuracy of 98.40% in detecting fraud, an efficiency of 97.20% in transaction processing, a real-time response of 96.10%, an efficiency in the utilization of the bandwidth of 94.60%, an accuracy of 97.50% for the prediction of customer risk, and an overall system reliability of 99.10%. The results validate the significant communication latency reduction possible, the computational efficiency, the decrease in bandwidth usage, and the quality of financial decision making, all while maintaining high prediction accuracy, even with localized edge intelligence. Additionally, local processing enhances customer privacy, mitigates cybersecurity risks, and aids in meeting current financial data protection laws and regulations. The hybrid edge-cloud architecture also offers tremendous scalability—AI models can be continuously improved and periodically synced from the cloud, without burdening the communications network. Enhancing the framework with federated learning to achieve collaborative privacy-preserving model training, explainable artificial intelligence (XAI) for transparent financial decision support, blockchain-based decentralized auditing, reinforcement learning for adaptive resource allocation, quantum-inspired optimization techniques, and 6G-enabled ultra-low-latency communication infrastructures are additional areas for future research to be explored. In conclusion, the proposed AI-powered edge computing system offers a comprehensive and efficient solution for future real-time financial analytics, thanks to its scalability, security, and computational power. The framework brings together distributed intelligence, artificial intelligence and cloud coordination, creating a solid basis for intelligent financial ecosystems that can provide resilient, low latency and highly responsive financial services to meet the increasing expectations of the global digital economy.

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