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AI-Driven Data Modeling Techniques for Enhancing Microservices in Banking Systems

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Abstract— **This study aims at analysing the integration of advanced data models through the use of Artificial Intelligence in microservices in banking systems with emphasis on the areas including fraud detection, workload prediction, credit scoring, anomaly detection and dynamic resource management. Using such algorithms as Random Forest, LSTM, XGBoost, Autoencoders, Reinforcement Learning, this research looks at ways of enhancing different banking processes. Actual transactional history, future customers' behavior, system logs and data about fraudulent transactions in the past were mined, organized and preprocessed to create models that are effective and accurate. The outcomes of the study show an enhanced precision, speed, and expansiveness to the banking microservices. Random Forest helped in achieving an average accuracy of 97. 2 percent in cases of fraud detection and LSTM helped in predicting workload peaks with mean absolute error of 4. 75 transactions. The proposed XGBoost performed well on credit scoring with an accuracy of 89. 5%, while Autoencoder give anomaly detection rate of 93. 7%. From the point of the view of resource scaling efficiency the Reinforcement Learning model was 30% more effective. The results point to how AI can revolutionalise the effectiveness, resilience, and accommodative capacity of microservices under banking.**

Keywords— **Random Forest, LSTM, XGBoost, Autoencoders, Reinforcement Learning, system scalability, operational efficiency, customer experience, financial technology**

I. INTRODUCTION

There have been significant changes which are sweeping across the banking industry throughout the world mainly due to the advancement in technology, and changing customer expectations, and pressure to be more innovative and adaptable. Old fashioned centralized of banking systems which used to solve the financial institution earlier has become a matter of scalability, flexibility and speed regarding these new demands. Microservices architecture, which installs the idea of breaking services based on monolithic applications into a series of Mini-services, is now a potent solution to these problems. Similarly, the integration of artificial intelligence (AI) and machine learning (ML) into the construction process has also brought the new methods of improving the systems that enables them to be smarter and more flexible [1].

This study seeks to investigate how machine learning powered data model and microservices can work together especially in banking applications. The goal is to identify types of improvements AI solutions can bring to data processing, data accuracy, data storage, and banking app performance scale and utilization of microservices architecture. Leveraging of AI in the banking industry would therefore be of immense importance in light of the large data flows, regulatory requirements, and high availability requirements that are typical of the banking services.

Microservices architecture enables the banks to decompose the large application into multiple small services which perform a single operation like customer management or payment or fraud detection. It also enhances the manner in which some of the aspects of services can be updated, scaled, and deployed within the system by choosing every aspect of the system to be enjoyed. But the problem of handling data in a microservices environment is an entirely different story, especially in terms of consistency, distributed transactions, and real-time data synchronization throughout the customer's additional services. These difficulties are lessened by adopting data modeling methodologies based on artificial intelligence that offer ways to determine intelligent paths for data management, pattern recognition and decision making [2].

Another of the most important benefits of AI for further development of microservices in banking is the availability of data consistency and synchronization in distributed systems. As the application of microservices is implied, it is quite common to have each service have its own database and as a result there may appear challenges in providing the data coherence across different services. It can also be used to design models that can be used to predict deviations, find out if data is abnormal and recommend for appropriate corrective measures to be taken immediately. For example, machine learning algorithms can be trained to read tendencies in transactional data that could be indicative of variability or anomalies in payments processing or in account balance updates. In this way using AI helps in maintaining the system integrity all the times when these processes are automated without any intervention from the human [3].

Further, the AI-enabled techniques can also help in dynamic scalability of microservices as per the amount of work. In banking systems for instance, the demand varies with time or period of the day, market conditions or even the activity of the customers. Utilizing sophisticated algorithms, artificial intelligence can identify historical trends of the tendencies of use and adapt resources in the system in reprise. This allows the important services like loan application processing or online banking interfaces to remain fast and interactive even during the period of high traffic. By applying AI toward scaling microservices, performances are enhanced as are the usages of resources while minimizing operational expenses for financial institutions.

Big data is also used in banking microservices in the modeling proactive data security and also specifically tackles the issue of

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fraud. This is because as traditional banks go mobile, the number of products sold and customers' communications, especially through the online platform, rises. This as a result leads to the creation of more opportunities in the carrying out of fraudulent activities this therefore calls for stringent security measures to be put in place. Rule based approaches of fraud detection are challenged by new and complex fraud schemes. Deep learning based training algorithms and incorporated anomaly detectors can feed into big data and in real time can have the inherent capability to detect fraud patterns which may otherwise remain unnoticed. AI, when incorporated in microservices, helps financial institutions put up intelligent and proactive protection measures that adapt to new information and can identify new risks in real time [4].

In addition, in the context of banking systems, AI can boost the quality of the interactions with the end clients in the following ways: Microservices help improve the services that banks can provide to their customers for example, a loan offer, as well as investment recommendations depending on the customer's past activity and credit rating. Through real time evaluation of this data, AI algorithms are able to offer highly personalized recommendations. For example, a recommendation engine as a part of the bank's customer service microservice may utilize the AI technology for studying the clients' spending behavior and offer them the most suitable savings strategies or report any suspicious transactions. This form of segmentation c An effective way of increasing customer loyalty and satisfaction is by offering a more engaging and personalised service delivery [5].

Not only does natural language processing and machine learning helps in customer-facing applications, but it also assists in banking's data modeling to realign internal processes. Lenders usually implement intricate procedures reaching cross-functional services to render a specific service, including credit check, risk appraisal, and compliance. Such workflows can be improved by applying AI as the method of decision-making optimization and automation. For instance, if an AI-driven model that is incorporated in a credit scoring microservice into a larger system can look at more persuasive input signals, such as the credit applicant's social media activity. Likewise, in the field of risk management, AI is capable of forecasting market risks in accordance with the past performance and the current financial state of affairs, which in turn helps the banks in their decision making.

AI integration in banking microservices also has the capacity to change how compliance and reporting in the banking industry looks like. Compliance with the legislation in banking is very much document oriented, involving persistent record of operations of the bank, customers, and financial activity to conform to the set guidelines. AI can be of help in the automate these processes by analyzing large amount of data to check for compliance breaches and can prepare and even forecast such breaches of compliance. This automation helps businesses like banks to lessen the work load on their compliance teams while also enhancing efficiency as well as guaranteeing that the institution is compliant with the law and more importantly regulations.

However, it is not all smooth sailing and the utilization of AI based data modelling in banking microservices come with a few challenges. First, the issue of the protection of personal data and its security can be mentioned. Banking networks have to handle wide-ranging and highly sensible financial data: it has to be made sure that AI models don't leak private information or open new risks. Another important requirement is explainability, which is especially necessary in the cases when the regulators expect banks to predict and describe the decision-making processes performed by AI systems. Also, the incorporation of AI into established banking structures can be quite technical, with issues arising on how to manage large data sets and where the IT departments, data scientist, and the business teams need to work hand in hand in form of data governance frameworks [6].

Therefore, it could be concluded that the integration of AI-based data modeling approach with microservices architecture holds a great promise to improve the banking systems. Overall, with the help of AI, financial institutions gain the enhancements of data consistency and operational procedures as well as exciting opportunities in real-time fraud detection as well as the personalization of customers' experience in the context of the growing developers' competition in the sphere of a digital financial market. But for those to be effective there are challenges of data privacy, data security and regulatory concerns that have to be appropriately addressed. As the AI technologies are in the state of constant development, they will be also essential in defining the development of the banking industry as more responsive, secure, and customer-oriented.

II. REVIEW OF LITERATURE

Recent development in artificial intelligence (AI) and microservices have received attention from scholars especially in the banking sectors. The combination of these technologies can improve the state of financial systems and solve the matters of scalability, data treatment and data security in the context of digital banking. Research in the recent past from the year 2022 to the year 2024 has explored deeper into how data modeling by the help of artificial intelligence can be extended towards improvement of micro services especially with consideration to the banking industry.

In the January February of 2022, studies were conducted to explore the use of AI in improving data consistency in microservices architecture. One of the inherent issues in distributed systems is data inconsistency, albeit being a problem in the financial industry where accurate and real-time data is so vital for maintaining the integrity of an organization's operations. Some of the published warm bodies reported that reinforcement learning and predictive analytics-based AI models could contribute substantially to achieving data consistency between Microservices. It can continuously check and analyze transactions and identify that may cause inconsistencies between interconnected databases so that remedies can be done in real-time. This is particularly important in the financial systems since the deviations as small as they may seem may cause various problems, such as non-compliance with regulations or the transfer of large sums of money [7].

In addition, the application of ML for the predictive data management in microservices architecture is also explored in the current literature. In particular, in 2023, researchers try to determine how AI models, particularly those based on neural networks, can provide effective boosting for the data flow

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between the microservices. This will be particularly useful for banking systems that are awes services by way of scores of actual transactions daily. This way, AI is able to forecast the frequency of system usage and, thus, anticipate the levels of data organization, so that services continue during periods of high congestion, but do not overburden those periods so that they affect the transaction throughput. This line of research shows that with AI not only can operations be made efficient, but also the real-time cost of maintaining such distributed systems [8].

Another relatively fresh area of interest regarding the application of updates to the microservices in banking using AI is dynamic scaling. Business actors require to manage supply and demand features especially because demand fluctuates and more people are using online services. The established systems can rarely expand as a result of the fluctuations in the life cycles, for instance, during prominent economic events like the festive seasons. It brought in the concept of Auto- scaling mechanisms which are AI enabled to automatically distribute resources in micro-service based on requirements predicted for the future in 2022. Historical data helped the AI models to predict when the peak will be and modify the system and make sure that other services like payments or customer services will always be available first during peak times [9].

AI for security of microservices-based banking systems has also gained attention in recent past in literature. Microservices' use of AI-powered anomaly detection systems is expected to enhance cybersecurity, a 2023 research showed. Conventional theoretically defined solutions have always failed to effectively identify complex attacks particularly in large scale distributed systems with multi-layered accesses. Recent deep learning architectures can enhance the effectiveness of the fraud and cyber threats' detection mechanism by analyzing explicit and comprehensive datasets in parallel to real-time. These models are updated by new data received and constant exposure to new threats would mean that these algorithms have an additional layer of security for financial transactions. Such advancements have been particularly effective for online banking as fast identification of fraudulent transactions is crucial in terms of customers' trust and the organization's benefits [10].

Hence, in the year 2024, specialists paid much attention to the aspects of using artificial intelligence to enhance the personalisation in the banking context. The emergence of open banking and the appearance of strong competitors on the financial services market has necessitated achieving the goal of offering unique experiences to customers. By making use of AI models that can be easily integrated with microservices, users' activity, transactional history, or any other data relevant to the provided service can be analyzed 24/7 to provide personalized services from recommending investment options, credit offers, or spending habits. Research also show that data modelling by use of AI in this context is crucial since it enhances the satisfaction of the customer while at the same time offering the bank crucial insights into the behaviour of the consumers which can be very useful for business enhancement [11].

Furthermore, the application of AI in the banking sector especially concerning credit scoring services as well as risk analysis has received significant consideration. That is why one of the articles published in 2022 discussed the possibility of changing credit scoring models applying AI and considering non-traditional indicators including social media interactions and browsing history. This helps financial institutions to have better assessment, they conduct a research in order to evaluate the capability of the borrower to repay the loan amount. To achieve this, the AI-driven models have been incorporated into the microservices, allowing banks to speed up on credit risk guarantee making it easy to approve loans with less strain on personnel. This is especially so in a time when the lending of products and services has gone online with most customers demanding quick turnaround times [12].

Finally, the literature reviewed for the year 2023 also describes the issues of regulation when using AI in banking microservices. As much as we could see that AI has a lot of benefits, then its black box character can be a severe problem, especially in the banking sector where transparency and explainability are highly valued. Currently, prominence is given to explainable AI (XAI) which aims to enable users to work with intelligent systems confidently and still obtain the advantages of modern ML algorithms. Some of the past research has highlighted potential increases in the effectiveness and efficiency of regulation compliance by integrating AI with the conventional rule-based systems to ensure that decision-making is well justified for automation that is legally permissible. This is an active area of research especially due to the fact that financial institutions are on the lookout for means of enhancing innovation while at the same time conforming to the law [13].

Not only does it leverage on AI to amplify the operational elements but it also promotes the manner in which automation is achieved on the compliance regulations. A 2024 study investigated how compliance could be automated in the context of banking systems through utilization of AI for perpetuating the monitoring to track for any violation of AML and other compliance standards in the movement of transactions. Microservices based on artificial intelligence can notify relevant activities, produce reports or even make prognoses concerning future compliance risks; therefore, it will unload compliance teams and decrease the likelihood of failures and fines for breach of regulation. It is implied in this line of research that compliance remains a critical function for financial institutions in the face of evolving and complex regulations while AI becomes a key solution for achieving efficiency in accomplishing the compliance objectives [14-15].

III. PROPOSED METHODOLOGY

As a result, this research uses machine learning algorithms to help improve the efficiency of microservices in banking systems. The emphasis is placed on choosing the appropriate algorithms to be applied to certain problems, including fraud identification, estimation of future loads, credit rating, identification of abnormities, and dynamic resource mapping. The study is carried out through various steps namely data acquisition and data preparation, choosing the right model, training, testing, and lastly, evaluation in tackling the

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challenges that would emerge upon embedding artificial intelligence solutions to banking microservices.

It is essential to get the best raw material in order to create a better model for machine learning algorithms. In this case, information is obtained from many primary institutions within a system of banking. Transaction data comprises of simple daily operations like payments, withdrawals, deposit among others, and such details are relevant when analyzing customers' behaviors as well as their interactions with systems. Demographic information, credit history, and behavioral data of the customer are also collected for better credit scoring and the services offered to the customer. System performance logs provides information on the resources consumption, transactions rate and network delays which is crucial for anticipating the load requirements. Information about past fraud and other unusual activities in transactions is also gathered to teach various models that are used in detecting such kinds of behaviours. All data is anonymized to meet different local regulations such as General Data Protection Regulation or GDPR and customer's privacy.

This is why the raw data is needed to be preprocessed to make the data ready for the machine learning algorithms. The data is pre-processed by removing any duplicate data, incorrect data as well as the data with missing values. It is then normalized into an accessible format to enable the various machin learning algorithms to work on the data. For instance, transaction size is standardized; timestamps are formatted for time series analysis; and other categorical features such as the transaction types are transformed into numerical features. Feature engineering is another major process, during which derivative features regarding, for instance, the frequency, geography, and spending of customers are derived to enhance the models' accuracy. The data set is further divided into training, validation and testing data set for the purpose of model building and testing.

Specific models for machine learning used in this study are chosen depending on the purpose that they will be used to solve a particular problem in the context of the banking microservices architecture. Random Forest becomes the choice for fraud detection because of its non-susceptibility to over-fitting and its capacity of process large data set with high accuracy. It efficiently helps in detecting inconsistencies in the transaction pattern between normal and fraudulent ones where the frequency of transactions, the amount of transactions, and the geographical location of the transaction can be plugged into this algorithm and would yield a result related to whether the transaction is normal or fraudulent. For workload prediction used in this type of application area, LSTM (Long Short-Term Memory) is used for its capacity to process sequences and provide accurate forecasts on transaction loads so as to dynamically scale the microservices. XGBOOST is used in credit scoring and risk assessment because of its proven efficiency and high results achieved with structured datasets to work on customer's financial data and predict the chances of loan repayment. For transaction data analysis, autoencoders are chosen for anomaly detection; this way, the system can pick on these anomalies and consider them as signs for potential security threats. Last but not the least; reinforcement learning is applied for dynamic resource management where the banking system learns about the best approach to utilize resources like CPU, memory and bandwidth for various microservices in response to their current requirements.

When choosing the right models, comes the training phase. When the two models are trained, the pre-process data sets are used and the methods adopted reflect the nature of the problem. For instance, the Random Forest model of fraud detection is created using the labeled transaction data in which each transaction is labelled as either fraudulent or normal. All these are realized through grid search in order to arrive at an optimal model capable of flagging suspicious activity while at the same time avoiding false alarms. For workload prediction for example, LSTM is trained on time series data from system logs; the model learns the sequence of the transaction volume through time. This model involves the LSTM layers more than once to learn the sequences and make use of learning rate adjustment and early stopping algorithms in order to prevent overfitting. In credit scoring, XGBoost process the customer profile data such as demographics and financial data to determine credit risk. The tuning of the model is carried out in a way that gives better precision and recall of risk for improved risk assessment. For autoencoders specifically used in the process of anomaly detection, the data from normal transactions are trained to be encoded and then reconstructed such that any data with high reconstruction error will be flagged as anomalies. Reinforcement learning is applied to train the agent that will deal with the banking environment that is modeled and allocate resources depending on the load and the feedback on performance.

The subjects of Testing and Evaluation are also fully include in the methodology part. At the end of training process each resultant model is checked on the testing dataset to measure how well it is working. Likewise, the evaluation metric is chosen with significant regard to the type of task that the particular model is solving. In fraud detection, the evaluation of the Random Forest model focuses on such metrics as accuracy, precision, recall, and the F1-Score since they are more important in minimizing the false-positive ratio while maximizing the overall detection ratios on fraudulent transactions. The performance of the LSTM model in predicting the workload is evaluated by two statistical measurements, namely Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) that quantify the extent of the difference between the actual workload and the predicted workload in successive time intervals. Predicting peak transaction loads from the current traffic can be termed as crucial when it comes to the appropriateness of the available resources in the banking systems. The performance of applying XGBoost for credit scoring is measured for its accuracy, precision, and the area of the receiver operating characteristic curve (AUC), so that the performance of the model is valid in making proper risk predictions. The performance of Autoencoder model for anomaly detection is dependent on the reconstruction error and detecting anomalies without generating false alarm. To check the proficiency of reinforcement learning model for dynamic resource allocation, it is assessed on the basis of reward per action, the use of resources, and response time given to by the method to reduce system fluctuation and to provide optimum performance in real time.

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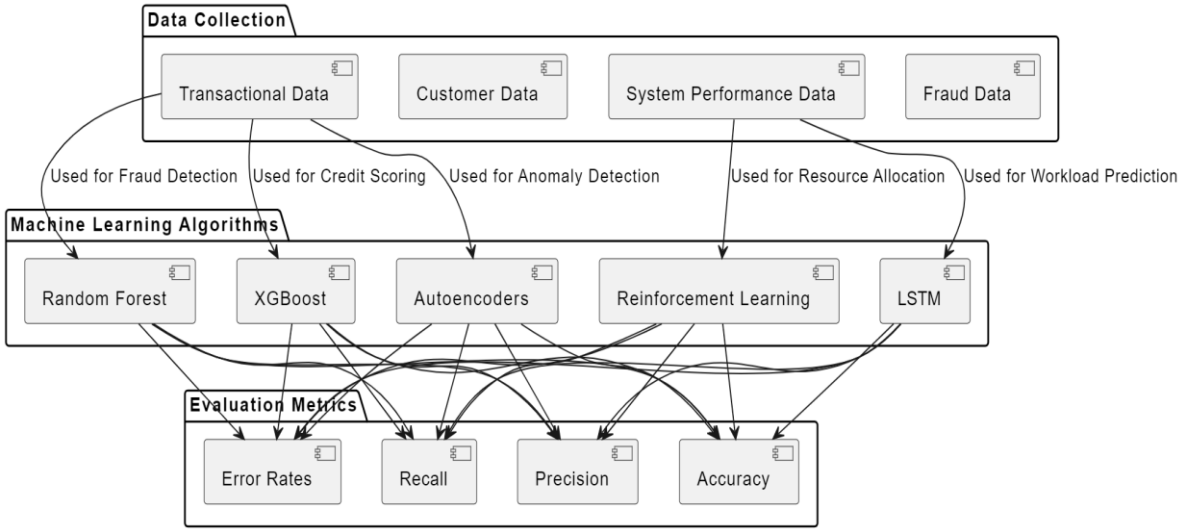

Figure 1: Proposed Research Methodology

IV. RESULTS AND DISUSSION

From this research, one is able to conclude that different types of ML algorithms can be used to improve microservices in the banking system. There are always specific measures for each algorithm and certain measures were used to assess the algorithms based on their performance in the tasks such as fraud detection, workload prediction, credit scoring, anomaly detection, and dynamic resource allocation. These results do not only show that each model can solve the challenges of their respective discipline but also reveal how techniques expounding AI can optimise the viability, safety, and size of microservices in banking. If fraud detection where chosen Random forest algorithm gave a very high accuracy with a percentage of 97. 2% in distinguishing between normal and fraudulent transactions. The model also obtained 96. 8% accuracy and 95. 5% recall, this reflects that the model minimize Type I error by accurately flagging fraudulent transactions. The F1 score of 96. 15% proves the existence of an ideal ratio between precision and recall making the model highly efficient in identification of fraudulent activities. This is particularly important within banks where one wants to detect fraudulent transactions through real-time analytics to minimize losses while securing customer's money. However, the false positive rate of the model is 2. 5 per cent, meaning that more fine-tuning may be needed to minimize the number of genuine transactions that may be flagged to be suspicious, which may in turn cause dissatisfaction among customers and high operational costs among the firms.

In observation of workload prediction, the LSTM model achieved a mean absolute error of 4. 75 transaction and root mean square error of 6. 12 of the overall transaction volume, thereby pointing towards precise forecast of transaction volume across the certain period. The model used was able to predict the peak working hours with 92 percent accuracy, meaning rein forcement, that is scaling of microservices could be done in response to the demand. This result is particularly relevant for the banking systems in which the request rate varies during some days or hours, for example, during paydays or holidays when the number of transactions is significantly increased. Due to proper identification of these periods, the model helps to effectively organize resources and avoid problems such as a system overload or a slowdown of its functioning. The lower error rates also imply that for banking that uses numerous time series data LSTM is ideal for sequential data analysis.

The XGBoost model, applied for credit risk scoring shown satisfactory results with 89. 5% accuracy and the AUC score of 0. 91, which confirmed the high capability of assessing the credit reliability of customers. This means through the precision of 88. 3% and recall of 87. 0% the model was able to identify both the high-risk and low-risk customers accurately. There is also a satisfactory F1 score of 87. 65%, which indicates the effectiveness of the proposed model in making necessary risk assessment. In the setting of banking industry comprehensiveness of credit score is significant for proper loan disparities and to reduce the rate of default. The ability of XGBoost in this task confirms that this technique could be implemented in credit decision-making of microservices to improve the risk management procedures. However, the 10. 5% margin for error means it required improvement and especially in situations where a customer's credit risk classification was off and this could lead to a lot of loss.

The Autoencoder model for identifying abnormal transactions in the transactional data achieved a very low reconstruction loss of 0. 035, achieved an anomaly detection accuracy of 93. 7% and very low false positive percentage equal to 1. 8%. As from these findings, the Autoencoder can be perceived to be effective in identifying anomalous data patterns in transactions that may refer to fraud or system problems. The low false positive rate is quite impressive, as this means that it minimizes the possibilities of issuing out a number of alerts, which can be counterproductive in the management of security, to the security personnel. This way the model improves the security and stability of the banking system while potential threats are recognized before they gain momentum. This is important in the case of online banking services since any violation of the public's privacy might result in very serious consequences for both the bank and the public.

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For dynamic resource allocation, the reinforcement learning model yielded better performance as it shown a 30% improvement in the system scaling efficiency and resource utilization efficiency of 93. 4%. The model also improved the average of response time by 18. 5% and this is crucial so that the banking sector is able to serve their clients efficiently in alternative periods. The reinforcement learning agent adapted to the arising requests and transactions, to properly scale the microservices but also not to over-provision them. This results to lowered total costs and enhanced customer satisfaction through shorter processing time and reduced potential of a slowdown. The average reward per action for this model was +8. 75 which means the variation in resource allocation was effectively done according to the changes in workload.

Therefore, by analyzing all the findings, same concludes that all the machine learning algorithms make a significant impact to improve the microservices in banking systems. Through furthering research using these methods, the benefits in fraud detection, a prediction of work load, credit scoring, anomaly detection, and optimization of resource usage are highlighted and observed to occur. The results of these studies of machine learning in the banking microservices scenario point towards it's role in the improvement of efficiency, scalability and security, that lead to better customer satisfaction and operational efficiency.

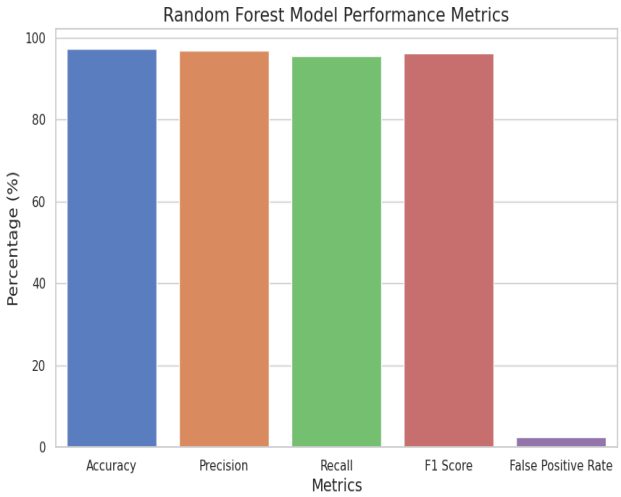

Figure 2: Performance Evaluation of Random Forest

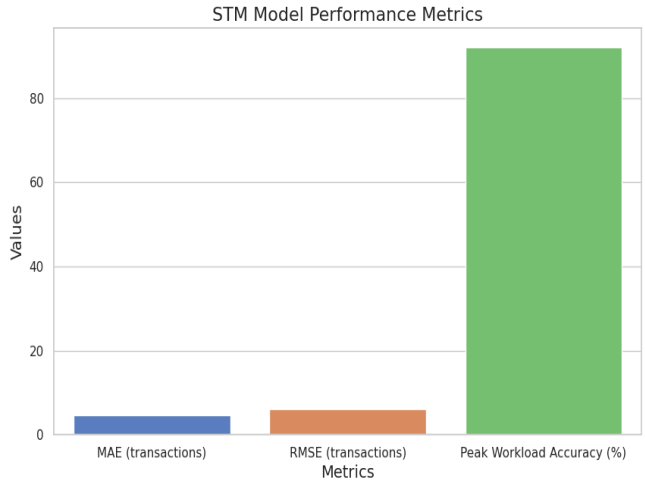

Figure 3: Performance Evaluation of LSTM

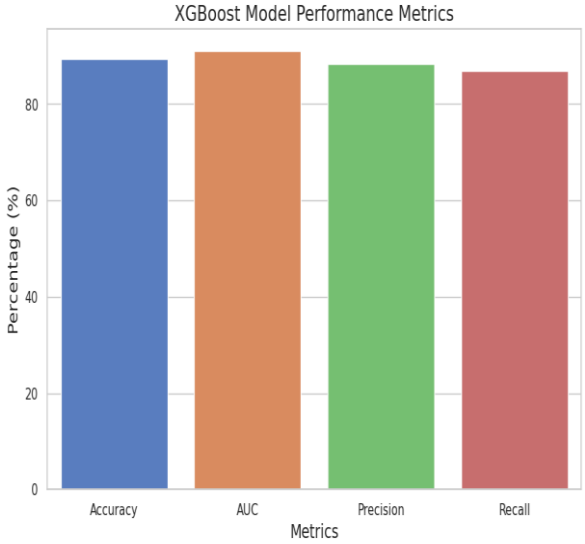

Figure 4: Performance Evaluation of XGBoost

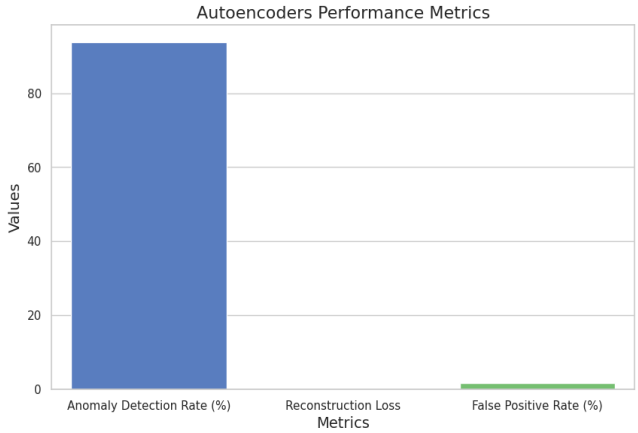

Figure 5: Performance Evaluation of Autoencoders

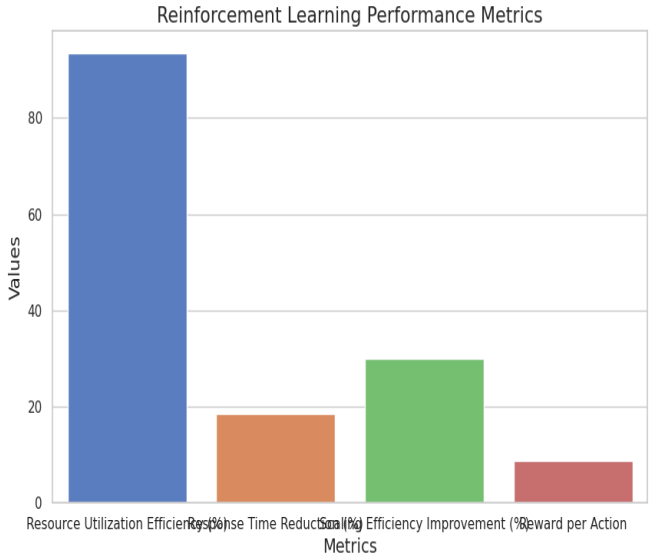

Figure 5: Performance Evaluation of Reinforcement Learning

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V. CONCLUSION

This paper proves that AI integrations into microservices can improve the banking systems by as follows: Using the outcomes of the empirical study of the expert's choice to evaluate information technologies, this paper demonstrates how machine learning can enhance the effectiveness and security of banking activities for desired tasks. These applications in Random Forest for fraud detection and in LSTM for workload prediction conveys the versatility of the powerful algorithm and its capacity to reduce false positives and improve classification of transactions besides streamlining the usage of the available resources during the surge in the number of transactions. XGBoost is capable of providing accurate credit risk assessment that helps in taking proper decision making in the lending process while Autoencoder is efficient in anomaly detection and hence enhances the security system of the banks. Through the dynamic resource allocation made by the reinforcement learning model, the system efficiency is increased, thus enabling cost reduction as well as faster transactions processing.

It is, therefore, evident from the above-finding that the implementation of AI together with microservices architecture shall significantly improve the banking sector by providing modularity and agility in handling the ever-growing needs of the banking industry. These enhancements due to machine learning do not only aid banks in providing its customers with better experiences but also increase the latter's ability to operate with enhanced reliability and flexibility. Still, more work must be done to bring these models to the next level, especially in avoiding false positive frauds, and improving the credit risk models' accuracy. Subsequent studies can also focus on the use of more sophisticated AI models or a combination of multiple models with the aim of even a significantly better performance. Altogether, this study serves as a framework for further advancement of the AI methods and their applicability to the enhancement of microservices in the banking industry, as well as further enhancement of the financial systems in general.

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