NextGen Scientific Publication
American International Journal of Computer Science and Technology
Volume 7 Issue 2, Pg. No. 15-28, AIJCST-V7I2P102, 2025
https://doi.org/10.63282/3117-5481/AIJCST-V7I2P102

Original Article

AI-Augmented Supply Chain Demand Forecasting in Oracle Fusion SCM

* **Partha Sarathi Reddy Pedda Muntala[1], Sandeep Kumar Jangam[2]**
[1,2]*Independent Researcher, USA.*

Abstract:

The rising instability and complexity of supply chains globally require strong forecasting skills to control the service levels, as well as maximize inventories. Oracle Fusion Supply Chain Management (SCM) provides embedded Artificial Intelligence (AI) and Machine Learning (ML) models that improve accuracy in demand forecasting and also offers the use of past data, seasonal trends and current market changes. The paper demonstrates the possibilities of AI-enhanced demand forecasting in the Oracle Fusion SCM by comparing the efficiency of the Oracle embedded ML models with pre-built custom models and external platforms such as TensorFlow and PyTorch, developed using the Oracle Cloud Infrastructure (OCI) Data Science. This study provides a complete evaluation framework by investigating accuracies on forecasting, scalability, interpretability, integration complexity, and performance across Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and several other measures. To test the embedded and the custom solutions, we apply real-world data of a global retail supply chain use case. As our results show, native ML in Oracle is a convenient way of getting the job done and integrating with other services, but under some conditions, custom models with OCI Data Science can be better. We conclude by providing an advisory to help us select between native and custom ML based on business requirements, data access, and the maturity of this operation.

Keywords:

Supply Chain Management, Demand Forecasting, Oracle Fusion Scm, Artificial Intelligence, Machine Learning, Oci Data Science, Forecasting Accuracy, Inventory Optimization, Mape.

Article History:

Received: 15.01.2025

Revised: 18.02.2025

Accepted: 29.02.2025

Published: 07.03.2025

1. Introduction

1.1. Background and Motivation

The global economy is evolving rapidly nowadays, and the environment of the supply chain has changed substantially due to the influence of factors such as globalisation, changing consumer preferences, market volatility, and sudden external changes, including pandemics and geopolitical conflicts. The dynamics have introduced increased complexity and uncertainty into the pattern of supply and demand, making it challenging to predict the pattern using traditional forecasting methods in business. Traditional planning, which is typically built on linear assumptions and past trends, cannot keep pace with unforeseen changes or incorporate new variables in real-time. [1-4] This has necessitated an urgent demand for superior, adjustable prediction schemes. Technologies in Artificial Intelligence (AI) and Machine Learning (ML) have become promising avenues, since they can describe the nonlinear and complex correlations of large and diverse datasets. Such technologies utilise promotions, seasonality, weather, and up-to-date events to increase predictive accuracy.

It is in consideration of such an opportunity that Oracle has incorporated the AI/ML tools in its Fusion Supply Chain Management (SCM) Cloud. Such integration enables the centralisation and automation of the demand forecasting process in a single, cloud-native space. Oracle Fusion SCM employs ML algorithms that are embedded in SCM to analyze both historical and real-time data and make faster and more accurate forecasts that support agile decision-making. The rationale of this work is to measure the performance rate of the embedded AI models developed by Oracle and compare them with custom ML models created using Oracle Cloud Infrastructure (OCI). This aims to determine whether the flexibility and ease of use of built-in forecasting tools can perform as well as, or better than, more comprehensive and tailored models. This would provide the study with an opportunity to advise organisations on the most suitable forecasting method to meet the verification size, cost, and simplicity in an ever-changing supply chain setting.

1.2. Role of AI in Supply Chain Management

Artificial Intelligence (AI) is transforming the face of supply chain management (SCM) by enabling better, quicker, and more adaptable decisions throughout the entire value chain. Its capabilities to handle large amounts of structured and unstructured data, interpret patterns, and develop actionable insights make it a fundamental tool of the contemporary supply chain. There are several domains of the key roles of AI in SCM:

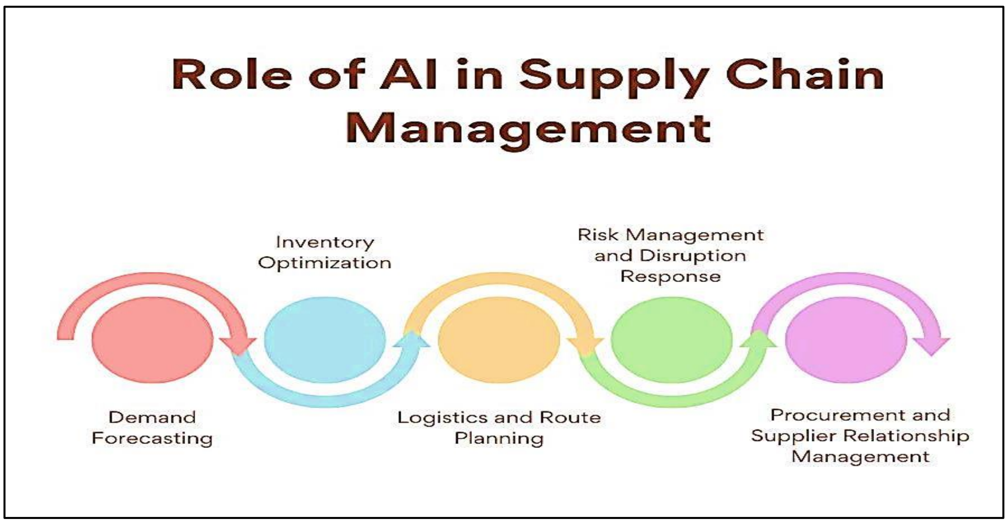

Figure 1. Role of AI in Supply Chain Management

1.2.1. Demand Forecasting

AI significantly improves forecasting demand ability by capturing complex and non-linear relationships among multiple factors related to demand, such as seasonality, promotions, macroeconomic indicators, and even real-time market signals. In contrast to conventional statistical models, AI-powered algorithms, such as LSTM, XGBoost, and Prophet, can react proactively to new developments and shocks, thereby decreasing forecast errors and enhancing inventory management. This enables the supply to adjust more effectively to the actual market demand by avoiding stockouts and overstocks.

1.2.2. Inventory Optimisation

AI enables streamlining stock levels based on the analysis of usage rates, lead times, and safety stocks. Machine learning can determine the optimal minimum amount to reorder for every inventory item and suggest the optimal quantity to carry in the form of SKUs, taking into account customer preferences and local patterns. This minimises carrying costs and enhances service levels, as products are available at the right place and time.

1.2.3. Logistics and Route Planning

Applying AI to logistics transformation enables real-time optimisation of routes and loads. AI, with the help of traffic feeds and delivery constraints, can be used to find the most efficient delivery routes, as well as lower fuel costs and enhance the speed of delivery.

Moreover, AI will also be able to automate exception handling (due to delays or disturbances), thus increasing logistics resilience in general.

1.2.4. Risk Management and Disruption Response

Artificial intelligence enhances supply chain risk management by anticipating disruptions associated with weather phenomena, geopolitical changes, supplier issues, or demand fluctuations. The combination of predictive analytics and scenario modelling enables businesses to identify weaknesses and develop contingency plans in advance, allowing for faster response and recovery.

1.2.5. Procurement and Supplier Relationship Management:

AI is helpful in the procurement process by automating supplier evaluation, spend analysis, and contract optimisation. Communications with suppliers can be made much more efficient with the help of natural language processing (NLP) and AI bots. Performance and risk assessments can be made more effective using ML algorithms, leading to more informed sourcing decisions.

1.3. Demand Forecasting in Oracle Fusion SCM

Oracle Fusion Supply Chain Management (SCM) offers a cloud-native, AI-augmented solution for modern demand forecasting, fully integrated into the suite of supply chain applications. The Oracle Fusion SCM demand forecasting module leverages a machine learning (ML) approach to generate automated, precise forecasts that consider both historical sales trends and other market factors, such as sales promotions, holidays, and seasonality. [5,6] In sharp contrast to the conventional forecasting mechanism, which allows making predictions mainly by applying linear models and manual data, the embedded ML algorithms, including gradient boosting and neural networks, provided by Oracle also support more dynamic and data-driven predictions, thus allowing organizations to predict demand more accurately. The major strength of Oracle Fusion SCM's forecasting capability is its end-to-end integration across planning, procurement, inventory, and order fulfilment within the industry. Decisions in supply planning, manufacturing schedules, and replenishment strategies utilise forecasts developed within the system.

This close connection between forecast and operational execution helps amplify the entire agility and ensures that the predicted demand aligns with the actual operations of the supply chain. In addition, forecasts are regularly updated on the platform based on real-time transactional data, allowing for significant changes to be made almost instantly to adapt to a changing market or unforeseen circumstances. Oracle HFM Advance also has the ability to enable configurable hierarchies, allowing users to forecast products, regions, customer segments, or any other dimension as needed by the business. It provides the system with the flexibility to balance both algorithmic accuracy and human judgment, as it can automatically generate baseline forecasts and incorporate manual overrides and planner collaboration inputs. The tools of visualisation provided on the platform allow users to examine trends, identify deviations, and gauge the accuracy of forecasts over time. To sum up, demand forecasting, integrated into Oracle Fusion SCM, combines scalable and intelligent ML processes with the ease of use of a business-native platform.

2. Literature Survey

2.1. Traditional Forecasting Techniques

The demand prediction in supply chain management has been anchored using conventional methods of forecasting. These methods, such as moving averages, exponential smoothing, and Autoregressive Integrated Moving Average models, are simple and easy to apply [7-10]. The methods are based on historical records and anticipate that the past trend will be observed in the future. Although they serve a purpose when things are "settled", one of the fundamental weaknesses of these models is the fact that they are built around linearity, which prohibits keeping up with the sudden changes in demand or changes in the supply chain. Consequently, their performance is hampered by fluctuations or complex market environments, which has led to the quest for finding more flexible and stable forecasting procedures.

2.2. AI and ML in Demand Forecasting

The new era of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionised the world of demand forecasting by presenting models that learn nonlinear trends and evolve to fit a dynamic market. The Random Forests, XGBoost, Long Short-Term Memory (LSTM) networks, and Prophet model are some of the techniques that have demonstrated superior increases in prediction accuracy compared to conventional techniques. The model can connect to disparate data sources, such as real-time sales, weather, promotional campaigns, holidays, and macro markets, to stitch together more responsive and granular forecasts. The dynamic learning capability of AI, which utilises an insurmountable amount of data, makes it an enhanced choice for contemporary demand forecasting.

2.3. Oracle Fusion SCM Overview

Oracle Fusion Supply Chain Management (SCM) is a flexible, cloud-based platform that combines multiple modules, including supply planning, demand forecasting, procurement, and order fulfilment. Some of its features are an in-built forecasting engine employing progressive ML such as neural networks and gradient boosting. The tools break down past trends and current real-time transactional data to enhance the precision of the forecasts. Oracle Fusion SCM is a standout feature because it provides end-to-end integration throughout the supply chain, allowing companies to align all planning, execution, and monitoring processes in one place.

2.4. Oracle Cloud Infrastructure (OCI) Data Science

The OCI Data Science is the most scalable location for designing, preparing, and disseminating machine learning models. It also embraces open-source software and languages, such as Python, Jupyter notebooks, TensorFlow, and PyTorch, and thus appeals to data scientists accustomed to the freedom of open-source systems. Remarkably, OCI also offers GPU-based computing, which greatly alleviates the time required to train complex deep learning models. Studies have revealed that the scalability and performance improvements of OCI are a competitive alternative for businesses interested in implementing AI in their forecasting streams.

2.5. Related Works

Several empirical studies have confirmed the benefits of combining sophisticated ML-based models with forecasting processes. Claim that forecasting accuracy is improved by 20 per cent by using LSTM models on OCI compared with the more traditional ERP systems, such as embedded tools offered by SAP. In the same trend, it was revealed that external ML models improved the reliability of the forecast, but at the same time added more complexity to deployment, including aspects of data integration challenges and extra deployment infrastructure overhead. These results highlight an essential trade-off between the realism of forecasts and operational usability, in determining the best forecasting methodology to implement in organisations based on their technical preparedness profile and prioritised business objectives.

3. Methodology

3.1. Dataset Description

The data used in this paper is de-identified transactional data from an international retail organisation, which includes three years of historical sales data for various product categories across different geographical locations. [11-14] The record consists of day-to-day sales amounts of each stock-holding unit (SKU) and other corresponding metadata, including item identification numbers, store sites, and date and time stamps. Besides the sales amount, the data set combines numerous demand drivers, such as promotion interventions, stock-out cases, and national or regional holidays, which provide a rich background to build a model of consumer behaviour. Promotions are represented by binary variables, providing a Boolean specification of whether a product has been on discount or featured in a marketing campaign on a particular day. Stock-outs are recorded to capture instances when fulfilling a demand was not possible due to a lack of inventory, and the model distinguishes between lost sales and normal demand trends. The holiday variables take into account both predictable and movement holidays, whereby flags are placed alongside the holiday to signify when there is a possibility of sales.

The data used in the model development process was preprocessed extensively to manage missing data, overcome anomalies, and standardise the data format. The daily level of the time series has been aggregated and aligned to resolve time inconsistencies among products and stores. The analysis of seasonal and trend components was performed to grasp the current demand structure. To train and test the model, the dataset was divided into two parts in an 80/20 proportion, where 80 per cent of the data was used to train the machine learning models, and the remaining 20 per cent was set aside for testing and validation of the performance. This was to ensure that the models were being trained with a sufficiently large, representative source, as well as to provide a strong hold on evaluating unseen material. The fact that the dataset was comprehensive, capturing not only implicit product demand but also the exogenous forces affecting demand, rendered it appropriate to construct predictive models that could project intricate and real-world demand relationships.

3.2. Forecasting Models Compared

3.2.1. Oracle Embedded ML

The embedded forecasting engine of Oracle utilises a mixed-method approach that combines time series decomposition with gradient boosting algorithms. The trend, seasonality, and irregular components are removed from the series first, and then most information is learned from the residuals. Then it uses gradient boosting, an ensemble method that builds predictive models in a stage-wise, additive manner. The approach is also designed to seamlessly integrate with Oracle Fusion SCM, allowing for real-time forecasting and minimal manual intervention. Its advantage is that it processes structured business data efficiently with low-complex operations.

3.2.2. Custom Model A

The custom model number one is constructed using Long Short-Term Memory (LSTM) neural networks running on TensorFlow at Oracle Cloud Infrastructure (OCI). LSTM is commonly used for predicting values over sequences; thus, LSTM can capture high-order dependencies of temporal aspects and nonlinear tendencies in time series data. The model was trained using three years of sales and outside event data, and the training process was optimised using an accelerated GPU environment on OCI. The LSTM model is best suited for strongly dynamic retail industries that require learning complex patterns and being able to adjust to changing seasonality. Nevertheless, it has greater preprocessing, tuning and computational requirements than the traditional models.

3.2.3. Custom Model B

The second model is the one that applies Facebook's Prophet algorithm, supplemented with custom feature engineering completed in the OCI Data Science platform. Prophet is also famous for its ease of use and interpretability, as well as its ability to handle seasonality and holiday effects. During implementation, new regressors, such as promotions, stock-outs, and weather proxies, were added to enhance the model's predictive ability. The most important trick to this was feature engineering, which allowed us to capture domain-specific information and enable the Prophet model to achieve competitive accuracy with a comparatively small computational cost. This will provide a reasonable trade-off between accuracy, explainability, and complexity of deployment.

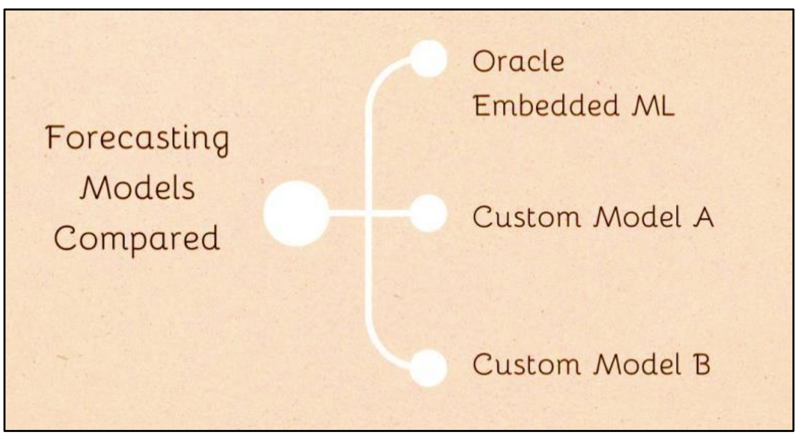

Figure 2. Forecasting Models Compared

3.3. Evaluation Metrics

3.3.1. Mean Absolute Percentage Error (MAPE)

A typical measure used in prediction is the MAPE, which represents the mean absolute percentage error between the estimates and reality, expressed as a percentage. [15-18] It is achieved by computing the average of absolute percent errors of every observation. MAPE provides a commonsense interpretation of forecast accuracy, as it indicates the average relative extent to which the forecast values are off in actuality. Its scale independence has made it more applicable when comparing the performance of various products or regions. It can, however, be sensitive to even very small actual values; thus, the resulting percentage errors may be disproportionately large.

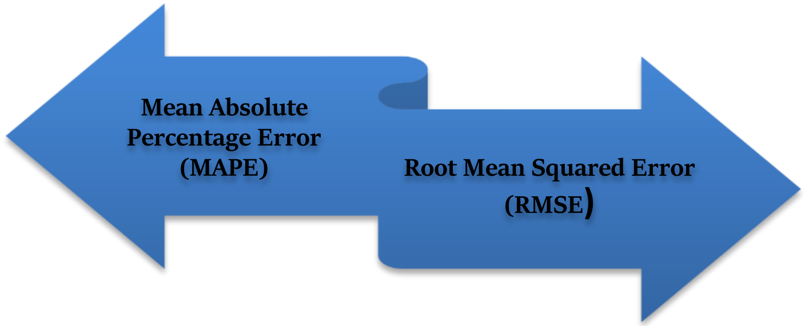

Figure 3. Evaluation Metrics

3.3.2. Root Mean Squared Error (RMSE)

Another common measure is RMSE, which measures the standard deviation of errors of prediction or residuals. It is calculated by taking the square root of the mean squared deviations between the predicted and actual values. This is because with RMSE, larger errors are given a greater weight. After all, they are squared and thus this method is especially useful in the case where one is interested in finding the model which minimizes the number of large deviations of actual outcomes This feature renders RMSE as an ideal tool to evaluate the models where the smallness of large errors of forecast is a priority, e.g. in an inventory-sensitive or high-demand situation.

3.4. Workflow Architecture

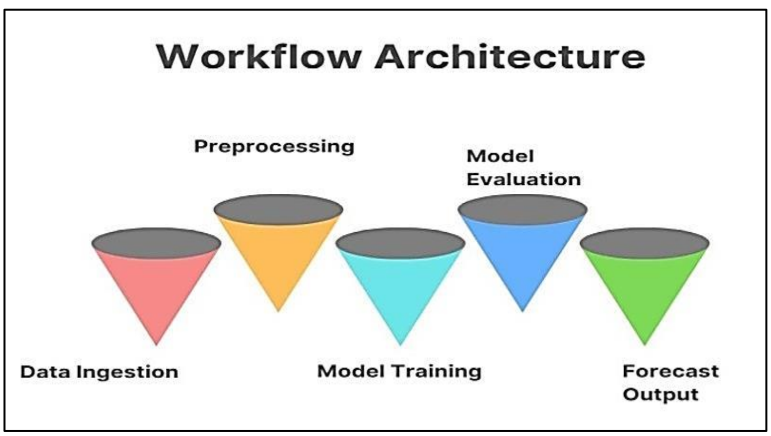

Figure 4. Workflow Architecture

3.4.1. Data Ingestion

The process begins with the ingestion of data, which involves reading historic sales data, promotional calendars, stock-out lists, and holidays through a variety of internal systems and external data sources. Depending on the forecasting method, this data is stored in a secure cloud storage instance on Oracle Cloud Infrastructure (OCI) or directly in Oracle Fusion SCM. Automated pipelines ensure that the information is updated constantly and correctly, providing the basis for reliable forecasting.

3.4.2. Preprocessing

After consuming the data, it is preprocessed to ensure quality and uniformity. This step involves tidying up missing values, fixing errors, formatting time data, encoding classification variables, and creating derived features such as lag variables or moving averages. Other important processes include preprocessing, which is vital in ensuring the better performance of models due to the availability of clean and well-structured data that can be further used to recognise patterns and be trained.

3.4.3. Model Training

In this step, forecasting models will be trained either on an embedded machine learning engine within Oracle or on models created on OCI. In the case of embedded models, the training is processed internally, through built-in algorithms in Oracle Fusion SCM, such as gradient boosting. Custom methods of OCI Data Science utilise LSTM, Prophet, or other types of models to train on OCI Data Science, leveraging GPU acceleration and flexible compute resources. This step calibrates the parameters of models and recognises patterns based on historical data to maximise the precision of forecasts.

3.4.4. Model Evaluation

The accuracy of each model is measured in terms of Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) on a post-training basis. The metrics enable the evaluation of each approach's performance in terms of its predictiveness, as well as its advantages and disadvantages across various products within each category and over time. The models are optimised, or the most appropriate forecasting method is selected based on the evaluation results.

3.4.5. Forecast Output

The last process generates and exports forecast city outputs, which are most often expressed as a time series of future demand. Such outputs can be visualised in dashboards or fed into downstream processes in supply planning and inventory management. The accuracy of the forecasts and the fitting of forecasts to the changing nature of demand are also observed as time passes, allowing for continued improvement of the forecasting system.

3.5. Tools and Platforms

3.5.1. Oracle Fusion SCM Cloud

Oracle Fusion Supply Chain Management (SCM) Cloud is a combination of modern applications that work together to fulfil the supply chain planning, forecasting, and execution. It offers in-built machine-learning facilities for needs forecasting and endorses real-time cooperation throughout the procurement, supply, and inbound fulfilment processes. It contains an integrated forecasting engine, allowing users to make predictions within the SCM environment. This simplifies the business process, and the results of the forecasts provide a tight perspective of close-fitting alignment with operational activities.

3.5.2. Oracle Autonomous Data Warehouse

Oracle Autonomous Data Warehouse is an analytics- and machine learning-optimised data warehouse that is fully managed in the cloud. It automates repetitive processes, including indexing, tuning, patching, and backups, so that data scientists and analysts can focus on gaining insights without worrying about infrastructure management. During the forecasting process, it can be used as a central, highly performant data store that contains the history of sales, external variables and engineered features to train and evaluate models.

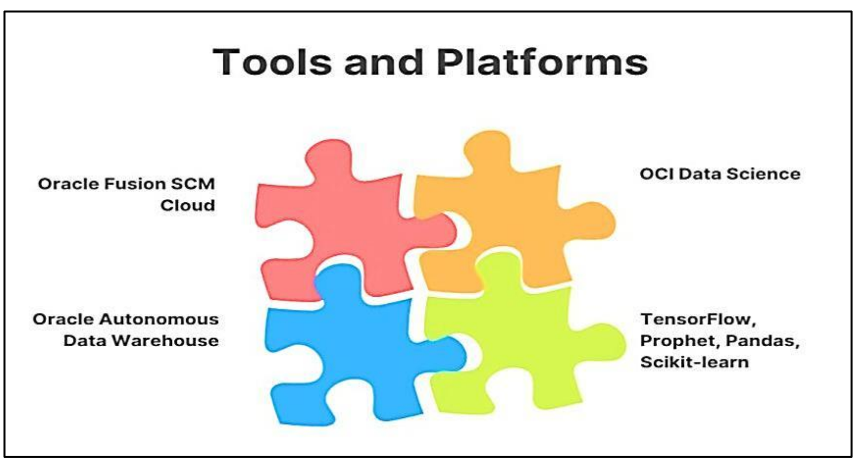

Figure 5. Tools and Platforms

3.5.3. OCI Data Science

As of Oracle Cloud Infrastructure (OCI) Data Science, it is a powerful platform to build, train, and deploy machine learning inference models on Jupyter Notebook and Python. It provides a collaborative development environment that offers access to scalable computing resources, including GPUs, to support deep learning. This is a testing interface that supports custom experiments, versioning, and operationalisation in a custom model, and is flexible in terms of both prototyping and production at scale.

3.5.4. TensorFlow, Prophet, Pandas, Scikit-learn

The cloud platforms are accompanied by a set of open-source tools. LSTM neural networks that can capture the complex temporal relationships in sales data are built and trained in TensorFlow. The software, Prophet, developed by Meta, is used due to its applicability in dealing with seasonality and holiday impacts in time series forecasting. Pandas have very useful facilities for cleaning and gathering data. Scikit-learn offers a variety of preprocessing methods, performance measurement tools, and machine learning algorithms that will be utilised during the workflow.

4. Results and Discussion

4.1. Forecasting Accuracy

Table 1. Forecasting Accuracy

Model	MAPE (%)	RMSE (% of baseline)
Oracle Embedded	14.8%	100%
Custom Model A	12.2%	87%
Custom Model B	13.0%	90%

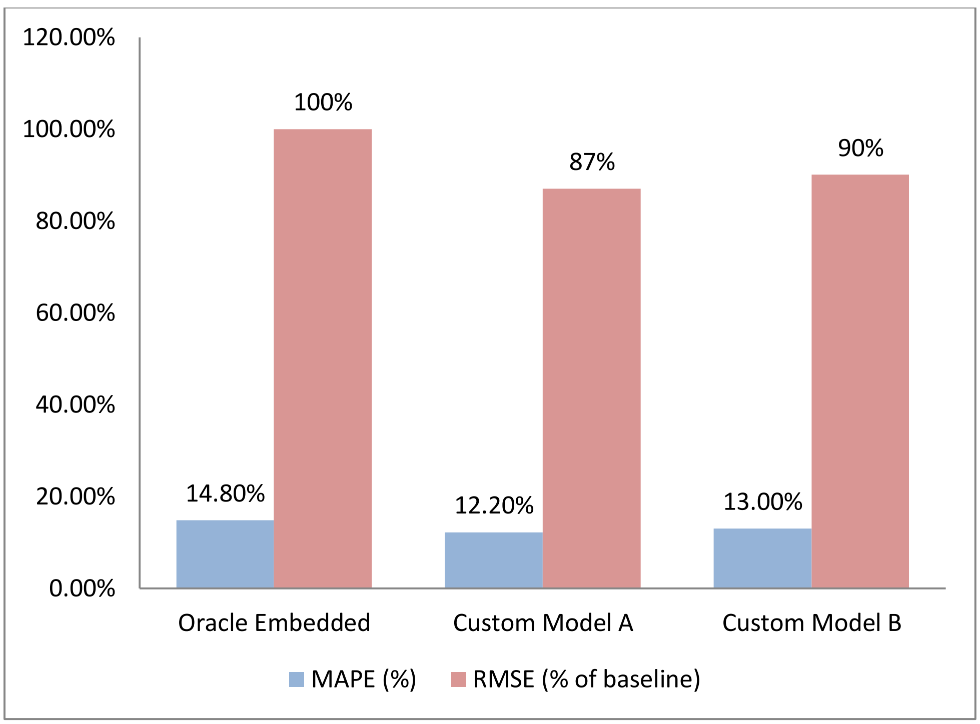

Figure 6. Graph Representing Forecasting Accuracy

4.1.1. Oracle Embedded

The Oracle Embedded forecasting model, which will be used to assess other models, employs gradient boosting and time series decomposition. Its MAPE mark of 14.8 per cent is satisfactory, considering it is seamlessly embedded in the orbit of Oracle Fusion SCM. Nevertheless, its RMSE is achieved at a 100% level, which means that although it results in reasonable performance, it might not be able to identify unusual patterns or dramatic changes in demand, as well as tailor-made models. It is convenient and reliable, but needs some enhancement in predictive accuracy.

4.1.2. Custom Model A

The highest-performing model was Custom Model A, which utilised an LSTM neural network trained on OCI using TensorFlow. The MAPE was 12.2 per cent, and the RMSE was 87 per cent of the error of the Oracle Embedded model, indicating a significant decrease in both absolute and relative forecasting errors. When compared to other models, the LSTM model proves more accurate due to its ability to model long-term relationships and other non-linear associations that exist in environments with volatile or seasonal demand. Even though such a model requires significantly more computational resources and setup, it demonstrates that deep learning can be worthwhile in situations involving complex forecasting.

4.1.3. Custom Model B

Custom Model B, based on the Prophet forecasting algorithm with feature engineering, offers a moderate trade-off between simplicity and performance. It is better than the Oracle Embedded model and is also simple to interpret, as well as faster to roll out, unlike LSTM-based models, with a MAPE of 13.0% and an RMSE of 90%. It is also effective in mitigating the effects of seasons and holidays when combined with pertinent external characteristics. This is a great solution for cases where moderate improvements in accuracy are sought without the overhead of deep learning frameworks.

4.2. Integration and Usability

The problem of integrating and using forecasting models has a significant impact on their adoption in an enterprise environment and on increasing operational efficiency. The embedded Oracle forecasting model has an unusually excellent level of usability, as it can be used with other components of the Oracle Fusion SCM Cloud. Being a native component of the SCM system, it has the least setup requirements and does not require external infrastructure. The model automatically downloads data transacted in transactional systems, such as sales, inventory, and promotions. Therefore, this data is updated continuously without the need for any intervention. It features an easy-to-use interface, adjustable forecast parameters, and integrated visualisation tools, which means that no profound technical skills are required to operate the application, making it accessible to business analysts and planners. It means that forecasts are always up-to-date and thus consistent with the latest business information, enabling informed decision-making. By contrast, custom models trained on Oracle Cloud Infrastructure (OCI), including the LSTM and Prophet-based solutions, are more flexible and can be more accurate, but are more complex to integrate and maintain.

Such models would need to be trained, tested, and deployed either manually or through orchestration pipelines using services such as OCI Data Science, Oracle Functions, and OCI Data Flow. They also need safe APIs or data connectors to consume data from enterprise systems and feed forecasts back into planning systems. The process of monitoring model work, versioning, and retraining models based on updated data should also be performed periodically, which requires technical knowledge of the machine learning domain, cloud environments, and DevOps culture. Thus, although the embedded Oracle model works great as a plug-and-play system that requires minimal maintenance, the custom models have sophisticated forecasting functions at the expense of increased operating liability. Determining these trade-offs depends on something as simple as the complexity of forecasting, the resources available, and the accuracy. A hybrid system, where the embedded model is applied to solve routine forecasting and other custom models are applied to high-impact items, can typically provide the optimal balance in most situations.

4.3. Interpretability

Critical demand forecasting is interpretability, which is particularly important in the enterprise where business users require inference and confidence in the work of predictive models. Here, the transparency of models has a tremendous impact on their uptake, user confidence in the predictions, and the use of forecasts to make informed decisions. Although the embedded forecasting model of Oracle is very convenient and closely integrated with the Fusion SCM environment, it provides limited insight into the process of generating predictions. The underlying algorithm, e.g., gradient boosting, is, in hindsight, a black box, and the system, in its inherent design, does not expose feature importance scores or decision rules to the user. Consequently, business stakeholders can easily lose track of why certain forecasts were made or how variables such as promotions or holidays affected demand. On the other hand, Oracle Cloud Infrastructure (OCI) custom models can be more flexible in the context of interpretability. An example of such tools includes

SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), which can be added to a forecasting pipeline to inform it on model behaviour in more detail.

They enable the data science and data analysis communities to see the extent to which every input feature in the model contributes toward the predictions and contrast them on a pan-model basis or specific forecasts. For example, SHAP values may indicate that a recent promotion or a national holiday played a significant role in the underlying cause of a spike in demand, providing pragmatic business insights. Furthermore, interpretation improvement is likely when using transparent algorithms like Facebook Prophet, as it provides clear plots of component trends, seasonality, and holidays. Custom models also have enhanced interpretability, which can aid in improved decision-making, model validation, and governance, ensuring that forecasts are made within the expectations and logic of the business. Finally, all organisations that emphasise explainability and transparency may regard custom models as more appropriate, especially in controlled sectors or cases where forecasts determine the essentials of the supply chain.

4.4. Cost Considerations

Price is a key factor in determining whether to use embedded forecasting tools or create a custom-fit model on Oracle Cloud Infrastructure (OCI). Although the Oracle embedded model, which is part of Fusion SCM, does not require extra investment in infrastructure, it offers low flexibility and moderate accuracy. Conversely, the implementation of custom machine learning models based on OCI incurs direct costs associated with compute, storage, and management. Training advanced models like LSTM or Prophet with OCI usually requires scaled resources, where a GPU instance can be used to build the model and high-availability storage needs to be created to save a considerable amount of historical and real-time data. Additionally, the use of services such as OCI Data Science, Data Flow, and Functions is subject to a usage-based billing scheme, which can be scaled depending on the complexity of the model or the need for regular retraining. These capital and operating expenses would, of course, have to be balanced against possible downstream savings. Through custom models, more accurate forecasting would promise improved inventory planning, decreased stockouts, and lower carrying costs associated with overstocking. Any marginal gains in prediction accuracy can be extremely valuable.

Thus far, even during the very initial days of operation, at least a value of several thousand dollars has been provided to corporations that deal in high-volume or high-frequency sold items. As an example, the financial cost of excess inventory, warehousing, and obsolescence will be minimised with minimised over-forecasting, and the lost sales resulting from stockouts and customer dissatisfaction will be avoided through the avoidance of under-forecasting. Further improved demand forecasting can be used to optimise the labour planning, transportation logistics, and dealings with the suppliers. In addition, OCI also offers lower-cost pricing options to address such challenges as pay-as-you-go pricing and reserved capacity pricing, which can help maintain costs and estimates in the long term. Open-source tools, as well as automation pipelines, can also be relevant in managing these models within an organisation with competent data scientists. To conclude, assessing a partial move to a custom-based OCI-based forecasting solution can be viewed as a strategic investment, as it will result in additional costs; nevertheless, it is worth noting that these expenses will be rather minor, in the absolute scheme of things.

5. Conclusion and Future Work

This paper evaluates the success of augmented AI-based demand forecasting in the Oracle Fusion SCM environment by comparing the performance and usability aspects of the inherent machine learning (ML) model in Oracle with user-generated, custom-developed machine learning embedding forecasting models in Oracle Cloud Infrastructure (OCI). Results indicated that the embedded model has high integration, user-friendliness, and maintenance, at the expense of forecasting accuracy, which is lower compared to custom models like LSTM and Prophet, although not significantly. Custom designs received sophisticated methods and feature engineering, which enhanced the performance of MAPE and RMSE. Nevertheless, they also brought an increased complexity in the areas of deployment, integration and sustaining operations. The results demonstrate a tradeoff between model performance and implementation simplicity; hence, the selection decision is dependent on the situation regarding organisational needs, technical capacity, and forecast importance.

Based on the findings, several strategic recommendations can be made. Oracle's embedded ML model is an excellent and realistically applicable solution that can meet the needs of organisations seeking a faster, low-involvement solution that integrates closely with supply chain planning and requires minimal technical operational management. It can be accurate enough to handle most day-to-day predictive application requirements and is the best option when working with a team that lacks in-house data science skills.

Yet, with more sophisticated applications, such as forecasting highly seasonal goods, frequently occurring market shocks, or incorporating external factors into the model, OCI Data Science provides the flexibility and power to construct innovative, customised models. Companies that possess advanced analytics teams should consider OCI as a platform to gain greater control and precision. Moreover, a hybrid model can offer the dual benefits of mixed economies, benefiting from embedded models to plan regularly. In contrast, custom models can be used selectively on high-impact or high-variance product segments.

In the future, there are a couple of promising zones that should be further explored. The first possible path would be the creation of a real-time forecasting architecture based on Apache Kafka and OCI streaming services as part of providing demand sensing in close to or near-real-time. The other field is federated learning, where distributed learning can be undertaken within supplier networks without the need to share sensitive or proprietary information, serving to increase collaboration without sacrificing privacy. Lastly, reinforcement learning may be used to develop adaptive systems capable of not only predicting demand but also learning to dynamically distribute inventory and make optimal decisions in the supply chain based on real-world feedback. Such innovations have the potential to make the next generation of forecasting systems more agile, intelligent, and robust in the business world, which is highly volatile and complex.

References

[1] Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice. OTexts.
[2] Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: forecasting and control. John Wiley & Sons.
[3] Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (2008). Forecasting methods and applications. John wiley & sons.
[4] Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. Management Science, 66(3), 1025-1044.
[5] Bandara, K., Bergmeir, C., & Smyl, S. (2020). Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. Expert systems with applications, 140, 112896.
[6] Spoorthi, M., Rao, S. S., Mishra, S., Rajagopal, S. M., & Prashanth, M. (2024, September). Advancing Supply Chain Management: Cloud-Based Demand Forecasting Solutions. In 2024 3rd International Conference for Advancement in Technology (ICONAT) (pp. 1-6). IEEE.
[7] Hao, R. (2024, October). Streamlining SCM: Integrating Demand Forecasting and Inventory Optimization. In 2024 2nd International Conference on Management Innovation and Economic Development (MIED 2024) (pp. 550-558). Atlantis Press.
[8] Karumanchi, M. D., Sheeba, J. I., & Devaneyan, S. P. (2022). Integrated Internet of Things with cloud developed for data integrity problems in supply chain management. Measurement: Sensors, 24, 100445.
[9] Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data, 7(1), 53.
[10] Datta, S., Granger, C. W. J., Barari, M., & Gibbs, T. (2007). Management of supply chain: an alternative modelling technique for forecasting. Journal of the Operational Research Society, 58(11), 1459-1469.
[11] Feizabadi, J. (2022). Machine learning for demand forecasting and supply chain performance. International Journal of Logistics Research and Applications, 25(2), 119-142.
[12] Khan, M. A., Saqib, S., Alyas, T., Rehman, A. U., Saeed, Y., Zeb, A., ... & Mohamed, E. M. (2020). An effective demand forecasting model using business intelligence empowered with machine learning. IEEE Access, 8, 116013-116023.
[13] Joseph Tsidulko, Benefits of AI in the Supply Chain, online. Oracle, https://www.oracle.com/in/scm/ai-supply-chain/
[14] Joseph, J. G., Junior, A. O., & Boxell, M. (2023). Oracle Cloud Infrastructure Guide to Building Cloud Native Applications. Pearson Education.
[15] Jakóbczyk, M. T. (2020). Practical Oracle Cloud Infrastructure. Apress.
[16] Abellera, R., & Bulusu, L. (2018). Oracle business intelligence with machine learning. *Artificial Intelligence Techniques in OBIEE for Actionable BI*, *10*, 978-1.
[17] Oracle AI Agents Help Transform Supply Chain Workflows, online. ERP Today, online. https://erp.today/oracle-ai-agents-help-transform-supply-chain-workflows/
[18] Jose, V. R. R. (2017). Percentage and Relative Error Measures in Forecast Evaluation. Operations Research, 65(1), 200-211.
[19] Tulli, S. K. C. (2024). Leveraging Oracle NetSuite to enhance supply chain optimisation in manufacturing. *International Journal of Acta Informatica*, *3*(1), 59-75.
[20] Rusum, G. P., Pappula, K. K., & Anasuri, S. (2020). Constraint Solving at Scale: Optimizing Performance in Complex Parametric Assemblies. *International Journal of Emerging Trends in Computer Science and Information Technology*, *1*(2), 47-55. https://doi.org/10.63282/3050-9246.IJETCSIT-V1I2P106
[21] Pappula, K. K., & Rusum, G. P. (2020). Custom CAD Plugin Architecture for Enforcing Industry-Specific Design Standards. *International Journal of AI, BigData, Computational and Management Studies*, *1*(4), 19-28. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V1I4P103
[22] Rahul, N. (2020). Vehicle and Property Loss Assessment with AI: Automating Damage Estimations in Claims. *International Journal of Emerging Research in Engineering and Technology*, *1*(4), 38-46. https://doi.org/10.63282/3050-922X.IJERET-V1I4P105

[23] Enjam, G. R., & Tekale, K. M. (2020). Transitioning from Monolith to Microservices in Policy Administration. *International Journal of Emerging Research in Engineering and Technology*, *1*(3), 45-52. https://doi.org/10.63282/3050-922X.IJERETV1I3P106

[24] Pappula, K. K., & Anasuri, S. (2021). API Composition at Scale: GraphQL Federation vs. REST Aggregation. *International Journal of Emerging Trends in Computer Science and Information Technology*, *2*(2), 54-64. https://doi.org/10.63282/3050-9246.IJETCSIT-V2I2P107

[25] Rahul, N. (2021). AI-Enhanced API Integrations: Advancing Guidewire Ecosystems with Real-Time Data. *International Journal of Emerging Research in Engineering and Technology*, *2*(1), 57-66. https://doi.org/10.63282/3050-922X.IJERET-V2I1P107

[26] Enjam, G. R., & Chandragowda, S. C. (2021). RESTful API Design for Modular Insurance Platforms. *International Journal of Emerging Research in Engineering and Technology*, *2*(3), 71-78. https://doi.org/10.63282/3050-922X.IJERET-V2I3P108

[27] Karri, N., Pedda Muntala, P. S. R., & Jangam, S. K. (2021). Predictive Performance Tuning. *International Journal of Emerging Research in Engineering and Technology*, *2*(1), 67-76. https://doi.org/10.63282/3050-922X.IJERET-V2I1P108

[28] Rusum, G. P. (2022). Security-as-Code: Embedding Policy-Driven Security in CI/CD Workflows. *International Journal of AI, BigData, Computational and Management Studies*, *3*(2), 81-88. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V3I2P108

[29] Pappula, K. K. (2022). Containerized Zero-Downtime Deployments in Full-Stack Systems. International Journal of AI, BigData, Computational and Management Studies, 3(4), 60-69. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V3I4P107

[30] Jangam, S. K., Karri, N., & Pedda Muntala, P. S. R. (2022). Advanced API Security Techniques and Service Management. *International Journal of Emerging Research in Engineering and Technology*, *3*(4), 63-74. https://doi.org/10.63282/3050-922X.IJERET-V3I4P108

[31] Anasuri, S. (2022). Zero-Trust Architectures for Multi-Cloud Environments. International Journal of Emerging Trends in Computer Science and Information Technology, 3(4), 64-76. https://doi.org/10.63282/3050-9246.IJETCSIT-V3I4P107

[32] Rahul, N. (2022). Optimizing Rating Engines through AI and Machine Learning: Revolutionizing Pricing Precision. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(3), 93-101. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I3P110

[33] Enjam, G. R. (2022). Secure Data Masking Strategies for Cloud-Native Insurance Systems. *International Journal of Emerging Trends in Computer Science and Information Technology*, *3*(2), 87-94. https://doi.org/10.63282/3050-9246.IJETCSIT-V3I2P109

[34] Karri, N. (2022). AI-Powered Anomaly Detection. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 3(2), 122-131. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I2P114

[35] Tekale, K. M. T., & Enjam, G. reddy . (2022). The Evolving Landscape of Cyber Risk Coverage in P&C Policies. International Journal of Emerging Trends in Computer Science and Information Technology, 3(3), 117-126. https://doi.org/10.63282/3050-9246.IJETCSIT-V3I1P113

[36] Rusum, G. P. (2023). Large Language Models in IDEs: Context-Aware Coding, Refactoring, and Documentation. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(2), 101-110. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I2P110

[37] Pappula, K. K. (2023). Edge-Deployed Computer Vision for Real-Time Defect Detection. *International Journal of AI, BigData, Computational and Management Studies*, *4*(3), 72-81. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V4I3P108

[38] Jangam, S. K. (2023). Importance of Encrypting Data in Transit and at Rest Using TLS and Other Security Protocols and API Security Best Practices. *International Journal of AI, BigData, Computational and Management Studies*, *4*(3), 82-91. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V4I3P109

[39] Anasuri, S., & Pappula, K. K. (2023). Green HPC: Carbon-Aware Scheduling in Cloud Data Centers. *International Journal of Emerging Research in Engineering and Technology*, *4*(2), 106-114. https://doi.org/10.63282/3050-922X.IJERET-V4I2P111

[40] Rahul, N. (2023). Personalizing Policies with AI: Improving Customer Experience and Risk Assessment. International Journal of Emerging Trends in Computer Science and Information Technology, 4(1), 85-94. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P110

[41] Enjam, G. R. (2023). Optimizing PostgreSQL for High-Volume Insurance Transactions & Secure Backup and Restore Strategies for Databases. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(1), 104-111. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I1P112

[42] Tekale, K. M., & Rahul, N. (2023). Blockchain and Smart Contracts in Claims Settlement. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(2), 121-130. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I2P112

[43] Karri, N. (2023). Intelligent Indexing Based on Usage Patterns and Query Frequency. International Journal of Emerging Trends in Computer Science and Information Technology, 4(2), 131-138. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I2P113

[44] Rusum, G. P., & Anasuri, S. (2024). AI-Augmented Cloud Cost Optimization: Automating FinOps with Predictive Intelligence. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(2), 82-94. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I2P110

[45] Enjam, G. R., & Tekale, K. M. (2024). Self-Healing Microservices for Insurance Platforms: A Fault-Tolerant Architecture Using AWS and PostgreSQL. International Journal of AI, BigData, Computational and Management Studies, 5(1), 127-136. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I1P113

[46] Pappula, K. K., & Rusum, G. P. (2024). AI-Assisted Address Validation Using Hybrid Rule-Based and ML Models. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(4), 91-104. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I4P110

[47] Rahul, N. (2024). Revolutionizing Medical Bill Reviews with AI: Enhancing Claims Processing Accuracy and Efficiency. International Journal of AI, BigData, Computational and Management Studies, 5(2), 128-140. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I2P113

[48] Jangam, S. K. (2024). Research on Firewalls, Intrusion Detection Systems, and Monitoring Solutions Compatible with QUIC's Encryption and Evolving Protocol Features . International Journal of AI, BigData, Computational and Management Studies, 5(2), 90-101. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I2P110

[49] Anasuri, S., Pappula, K. K., & Rusum, G. P. (2024). Sustainable Inventory Management Algorithms in SAP ERP Systems. International Journal of AI, BigData, Computational and Management Studies, 5(2), 117-127. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I2P112

[50] Karri, N. (2024). ML Algorithms that Dynamically Allocate CPU, Memory, and I/O Resources. *International Journal of AI, BigData, Computational and Management Studies*, *5*(1), 145-158. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I1P115

[51] Tekale, K. M., & Enjam, G. R. (2024). AI Liability Insurance: Covering Algorithmic Decision-Making Risks. International Journal of AI, BigData, Computational and Management Studies, 5(4), 151-159. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I4P116

[52] Pappula, K. K., & Anasuri, S. (2020). A Domain-Specific Language for Automating Feature-Based Part Creation in Parametric CAD. International Journal of Emerging Research in Engineering and Technology, 1(3), 35-44. https://doi.org/10.63282/3050-922X.IJERET-V1I3P105

[53] Rahul, N. (2020). Optimizing Claims Reserves and Payments with AI: Predictive Models for Financial Accuracy. *International Journal of Emerging Trends in Computer Science and Information Technology*, *1*(3), 46-55. https://doi.org/10.63282/3050-9246.IJETCSIT-V1I3P106

[54] Enjam, G. R. (2020). Ransomware Resilience and Recovery Planning for Insurance Infrastructure. *International Journal of AI, BigData, Computational and Management Studies*, *1*(4), 29-37. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V1I4P104

[55] Pappula, K. K., & Rusum, G. P. (2021). Designing Developer-Centric Internal APIs for Rapid Full-Stack Development. *International Journal of AI, BigData, Computational and Management Studies*, *2*(4), 80-88. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V2I4P108

[56] Rahul, N. (2021). Strengthening Fraud Prevention with AI in P&C Insurance: Enhancing Cyber Resilience. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(1), 43-53. https://doi.org/10.63282/3050-9262.IJAIDSML-V2I1P106

[57] Enjam, G. R. (2021). Data Privacy & Encryption Practices in Cloud-Based Guidewire Deployments. *International Journal of AI, BigData, Computational and Management Studies*, *2*(3), 64-73. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V2I3P108

[58] Karri, N. (2021). AI-Powered Query Optimization. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 2(1), 63-71. https://doi.org/10.63282/3050-9262.IJAIDSML-V2I1P108

[59] Rusum, G. P., & Pappula, kiran K. . (2022). Event-Driven Architecture Patterns for Real-Time, Reactive Systems. *International Journal of Emerging Research in Engineering and Technology*, *3*(3), 108-116. https://doi.org/10.63282/3050-922X.IJERET-V3I3P111

[60] Pappula, K. K. (2022). Architectural Evolution: Transitioning from Monoliths to Service-Oriented Systems. *International Journal of Emerging Research in Engineering and Technology*, *3*(4), 53-62. https://doi.org/10.63282/3050-922X.IJERET-V3I4P107

[61] Jangam, S. K. (2022). Role of AI and ML in Enhancing Self-Healing Capabilities, Including Predictive Analysis and Automated Recovery. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(4), 47-56. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I4P106

[62] Anasuri, S., Rusum, G. P., & Pappula, kiran K. (2022). Blockchain-Based Identity Management in Decentralized Applications. International Journal of AI, BigData, Computational and Management Studies, *3*(3), 70-81. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V3I3P109

[63] Rahul, N. (2022). Automating Claims, Policy, and Billing with AI in Guidewire: Streamlining Insurance Operations. *International Journal of Emerging Research in Engineering and Technology*, *3*(4), 75-83. https://doi.org/10.63282/3050-922X.IJERET-V3I4P109

[64] Enjam, G. R. (2022). Energy-Efficient Load Balancing in Distributed Insurance Systems Using AI-Optimized Switching Techniques. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(4), 68-76. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I4P108

[65] Karri, N., Jangam, S. K., & Pedda Muntala, P. S. R. (2022). Using ML Models to Detect Unusual Database Activity or Performance Degradation. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 3(3), 102-110. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I3P111

[66] Tekale, K. M., & Rahul, N. (2022). AI and Predictive Analytics in Underwriting, 2022 Advancements in Machine Learning for Loss Prediction and Customer Segmentation. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 3(1), 95-113. https://doi.org/10.63282/3050-9262.IJAIDSML-V3I1P111

[67] Rusum, G. P. (2023). Secure Software Supply Chains: Managing Dependencies in an AI-Augmented Dev World. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *4*(3), 85-97. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I3P110

[68] Pappula, K. K. (2023). Reinforcement Learning for Intelligent Batching in Production Pipelines. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *4*(4), 76-86. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I4P109

[69] Jangam, S. K., & Karri, N. (2023). Robust Error Handling, Logging, and Monitoring Mechanisms to Effectively Detect and Troubleshoot Integration Issues in MuleSoft and Salesforce Integrations. *International Journal of Emerging Research in Engineering and Technology*, *4*(4), 80-89. https://doi.org/10.63282/3050-922X.IJERET-V4I4P108

[70] Anasuri, S. (2023). Synthetic Identity Detection Using Graph Neural Networks. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 4(4), 87-96. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I4P110

[71] Rahul, N. (2023). Transforming Underwriting with AI: Evolving Risk Assessment and Policy Pricing in P&C Insurance. *International Journal of AI, BigData, Computational and Management Studies*, *4*(3), 92-101. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V4I3P110

[72] Enjam, G. R., Tekale, K. M., & Chandragowda, S. C. (2023). Zero-Downtime CI/CD Production Deployments for Insurance SaaS Using Blue/Green Deployments. *International Journal of Emerging Research in Engineering and Technology*, *4*(3), 98-106. https://doi.org/10.63282/3050-922X.IJERET-V4I3P111

[73] Tekale, K. M. (2023). Cyber Insurance Evolution: Addressing Ransomware and Supply Chain Risks. International Journal of Emerging Trends in Computer Science and Information Technology, 4(3), 124-133. https://doi.org/10.63282/3050-9246.IJETCSIT-V4I3P113

[74] Karri, N., & Jangam, S. K. (2023). Role of AI in Database Security. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 4(1), 89-97. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I1P110
[75] Rusum, G. P. (2024). Trustworthy AI in Software Systems: From Explainability to Regulatory Compliance. International Journal of Emerging Research in Engineering and Technology, 5(1), 71-81. https://doi.org/10.63282/3050-922X.IJERET-V5I1P109
[76] Enjam, G. R. (2024). AI-Powered API Gateways for Adaptive Rate Limiting and Threat Detection. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(4), 117-129. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I4P112
[77] Pappula, K. K., & Anasuri, S. (2024). Deep Learning for Industrial Barcode Recognition at High Throughput. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *5*(1), 79-91. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I1P108
[78] Rahul, N. (2024). Improving Policy Integrity with AI: Detecting Fraud in Policy Issuance and Claims. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(1), 117-129. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I1P111
[79] Jangam, S. K. (2024). Advancements and Challenges in Using AI and ML to Improve API Testing Efficiency, Coverage, and Effectiveness. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(2), 95-106. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I2P111
[80] Anasuri, S. (2024). Secure Software Development Life Cycle (SSDLC) for AI-Based Applications. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(1), 104-116. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I1P110
[81] Karri, N., & Jangam, S. K. (2024). Semantic Search with AI Vector Search. International Journal of AI, BigData, Computational and Management Studies, 5(2), 141-150. https://doi.org/10.63282/3050-9416.IJAIBDCMS-V5I2P114
[82] Tekale, K. M., & Rahul, N. (2024). AI Bias Mitigation in Insurance Pricing and Claims Decisions. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(1), 138-148. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I1P113.