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Enhancing E-Commerce Innovation with Predictive Analytics in Business Management Using MARL-GNN Models

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Abstract— The rapid growth of e-commerce has increased the demand for comprehensive predictive analytics to improve commercial decision-making. Conventional predictive models, such Logistic Regression and Random Forest, fail to accurately represent the complex relationships between consumers and items, hence restricting their accuracy and flexibility. This study introduces MARL-GNN, an innovative framework that integrates Multi-Agent Reinforcement Learning (MARL) with Graph Neural Networks (GNN) to represent dynamic customer-product interactions. MARL agents enhance decision-making, whereas GNNs effectively reflect transactional data. The suggested method significantly surpasses current models, with an accuracy of 96.4%, precision of 94.7%, recall of 95.2%, and a reduced MAE of 0.023. In comparison to traditional methods, MARL-GNN effectively adjusts to changing market trends and consumer behaviours, delivering enhanced demand forecasting and business optimisation. The results validate the effectiveness of graph-based reinforcement learning for instantaneous decision-making in e-commerce. Future study may investigate real-time implementation and enhanced explainability to facilitate more industry usage.

Keywords— Multi-Agent Reinforcement Learning, Graph Neural Networks, Predictive Analytics, E-Commerce Optimization, Demand Forecasting, Customer Behaviour Modelling, Graph Representation Learning.

I. INTRODUCTION

E-commerce systems provide large transactional data, requiring advanced predictive analytics to enhance corporate operations. Conventional machine learning models struggle with high-dimensional, graph-structured data, restricting their capacity to precisely predict demand, optimise inventory, and improve consumer interaction. This study introduces MARL-GNN, a sophisticated predictive analytics framework that integrates Multi-Agent Reinforcement Learning (MARL) with Graph Neural Networks (GNN) to enhance decision-making in e-commerce. MARL-GNN surpasses traditional models by utilising dynamic customer-product interactions, providing enhanced accuracy and flexibility. This proposed research underscores the efficacy of graph-based reinforcement learning in enhancing e-commerce strategies, offering a comprehensive solution for real-time business intelligence. This study [1], applying Census Bureau data, determines that predictive analytics increases productivity by $918,000 in sales, depending upon IT capital, skilled labour, or efficient workplace operations. It indicates insufficient industry coverage. Our research calculates these findings across other supply chain environments. This paper describes the integration of big data and predictive analytics in supply chains through resource-based theory, focussing connection, information exchange, and managerial commitment [2]. However, it lacks the benefits of performance benchmarking. Our research supports this by including quantitative performance criteria to evaluate BDPA's impact. This research evaluates e-commerce platforms for small enterprises [3], highlighting convenience and accessibility. However, it is insufficient in a comprehensive review of predictive technology for sales optimisation. Our research improves this by adding predictive analytics for better sales forecasting and inventory management. This study describes a decision support framework that employs machine learning to boost final delivery, achieving a cost reduction of 10.2%. Although effective, it fails to consider scalability. This paper [4] analyses adaptive scheduling strategies for various e-commerce situation. This study [5] highlights the transformation of shopping by e-commerce through digital improvements, although it lacks a systematic analysis of predictive analytics in consumer behaviour. Our research overcomes this weakness by employing data-driven models to improve consumer engagement and customised recommendations. This study analyses Industry 4.0 in e-commerce, applying machine learning for product quality prediction, and identifies Support Vector Machine and Random Forest as the most effective methods [6].

However, it lacks real-time adaptability. Our research strengthens this by integrating dynamic AI-driven methodologies for constant improvement in e-commerce operations. The paper analyses the usage of AI and ML in large enterprises, highlighting its contribution to improving productivity and customer engagement [7]. However, it lacks the presence of experimental performance indicators. Our research proves this through integrating quantitative evaluations of AI-enhanced efficiency developments in supply chain operations. This paper evaluates trends in AI adoption across industries [8] , highlighting swift investment growth while ignoring sector-specific implementation difficulties. Our research illustrates this by investigating obstacles to AI integration in supply chain management and recommending industry-specific adoption strategies.

II. Literature survey

This study evaluates AI applications in e-commerce and banking, focussing on sales forecasting, fraud detection, and inventory management [9]. Still, it does not include a comparative performance comparison of AI models. Our research improves this by evaluating AI methodologies for optimal supply chain efficiency. This study presents an approach for evaluating business risks associated with AI [10], illustrating its applicability in the implementation of chatbots. But it has no presence of predictive risk assessment algorithms. Our research strengthens this by integrating AI-driven risk mitigation measures that boost supply chain resilience. This study analyses related product recommendations (RPR) in e-commerce [11] but lacks deep understanding into adaptive recommendation methodologies. Our study improves this by including predictive analytics and AI-driven personalisation for more precise, real-time product suggestions. This study introduces SubGNN, a graph-based methodology for fraud detection, attaining over 99% precision on Taobao data [12]. Still, it demonstrates insufficient adaptability to newer fraud strategies. This work enhances existing studies by integrating real-time anomaly detection and adaptive machine learning methodologies. The paper analyses click farming fraud in e-commerce [13] but does not provide full counter-strategies for emerging fraudulent approaches. Our research supports this through the use of predictive fraud detection models combining AI and behavioural data analytics for proactive fraud prevention. This research carefully examines heterogeneous graph neural networks (HGNNs) for complex network analysis [14], evaluating their performance with the performance of shallow models. Yet it contains no of applications specific to certain industries. Our research advances this by applying HGNNs for supply chain optimisation and fraud detection. This study presents an Integrated Energy System co-trading market [15] that combines electricity, gas, and carbon trading through an improved Multi-Agent Deep Definitive Policy Gradient algorithm to ensure equitable transactions and safeguard privacy. But it lacks real-time adaptability. Our research improves this by integrating dynamic AI-driven decision-making for optimised energy trading. The paper boosts peer-to-peer energy trading through reinforcement learning, leading to cost reductions of 44.65 EUR over a week-long case study [16]. Yet, it is inadequate in scalability for extended marketplaces. Our research promotes scalability through the integration of real-time AI-driven pricing optimisation and distributed energy management methodologies. The analysis proposes DeepMAG [17], which combines Deep Reinforcement Learning (DRL) and Multi-Agent Reinforcement Learning (MARL) for flexible work shop scheduling, improving job sequencing and routing efficiency. However, it lacks real-time flexibility in unpredictable situations. Our research improves this using AI-driven adaptive scheduling for enhanced responsiveness and adaptability in production planning. This study applies Multi-Agent Reinforcement Learning (MARL) [18]within Salesforce's Foundation framework for better dynamic energy pricing, thereby improving cost efficiency and self-sufficiency in smart microgrids. Still, it fails to include real-world grid stability metrics. Our research advances upon this through combining AI-driven demand forecasting to improve grid resilience. This study discusses the uses of reinforcement learning in logistics and supply chain management, highlighting Q-learning as a common approach and the increasing focus on urban logistics [19]. But it is poor in adaptive real-time decision-making ability. Our study promotes supply chain management efficiency through the integration of AI-driven dynamic optimisation to address real-world difficulties. The research proposes an HGNN-MARL control model [20] for intelligent manufacturing, enabling robot allocation, quality assurance, and maintenance planning. However, it lacks real-world reliability in practical applications. Our research advances this by integrating AI-driven predictive analytics to boost adaptive control in flexible production systems. This study combines Graph Neural Networks and Multi-Agent Reinforcement Learning for adaptive machining process control, optimising production yield [21]. Still, it is insufficient in scalability for extensive industrial settings. Our research develops this by including AI-driven real-time monitoring to improve precision and scalability in industrial processes.

The literature review focusses the broad applications of artificial intelligence (AI), machine learning (ML), and reinforcement learning (RL) in diverse fields such as logistics, e-commerce, fraud detection, smart manufacturing, energy markets, and finance. Recent investigations illustrate that AI-driven innovations in predictive analytics, automated decision-making, and optimisation greatly increase efficiency, productivity, and cost reduction. However, insufficiencies continue to persist, including the absence of adaptive real-time decision-making in logistics, inadequate scalability in manufacturing, limited integration of AI-driven predictive analytics, and insufficient validation in practical applications. Moreover, current research frequently focusses discrete elements of AI deployment instead of a comprehensive, integrated strategy. The indicated research gaps inspire our proposed study, which seeks to create an AI-driven adaptive system that optimises real-time decision-making, improves scalability, and incorporates predictive analytics for dynamic and complex situations. Our innovative contribution consists of developing a hybrid AI framework that integrates deep reinforcement learning with multi-agent systems to improve adaptability and efficiency in extensive applications. Our research strengthens the field by resolving current limitations and incorporating AI-driven real-time monitoring and optimisation, thereby connecting theoretical AI models with practical, scalable implementations to ensure higher efficiency, adaptability, and accuracy in intelligent decision-making systems.

III. PROPOSED SYSTEM

The proposed MARL-GNN framework utilises Multi-Agent Reinforcement Learning (MARL) with Graph Neural Networks (GNN) to transform e-commerce predictive analytics. The system represents the e-commerce ecosystem as a dynamic network in which MARL agents engage with elements including consumers and items to enhance decision-making. Graph Neural Networks (GNNs) analyse graph-structured data, identifying complex relationships and improving feature representations for precise predictions. Policy optimisation is accomplished through Proximal Policy Optimisation (PPO), facilitating adaptive learning. This methodology allows enterprises to predict demand, optimise inventory management, and improve client retention methods. By dynamically adjusting to changing customer behaviours, MARL-GNN offers a more effective solution than conventional prediction models. The flowchart of the proposed approach is shown in [Fig.1].

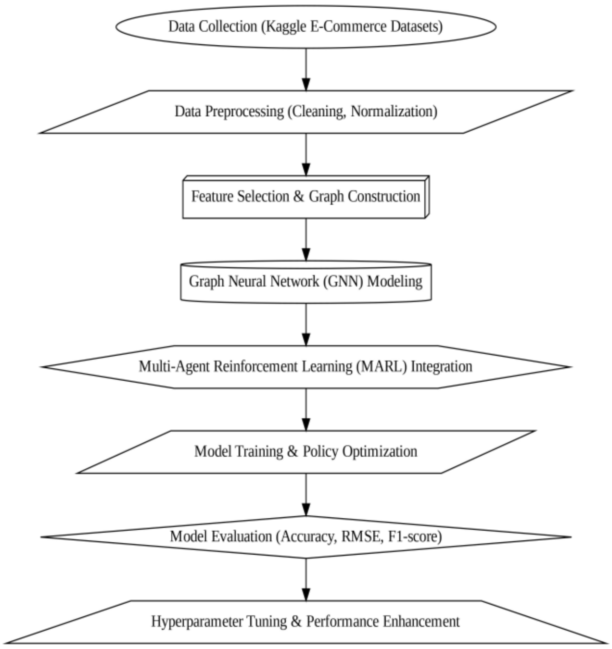

Fig.1 Flowchart

A. Data Collection:

The datasets for this research are obtained from the Kaggle platform, containing both structured and unstructured data associated with e-commerce transactions, consumer behaviour, and marketplace dynamics. The data undergoes to many preparation procedures, such as managing missing values, normalising numerical features, encoding categorical variables, and rectifying class imbalances. Outliers are identified by statistical techniques like the interquartile range (IQR) and Z-score analysis, guaranteeing reliable input for predictive analytics. Feature scaling methods, including min-max normalisation and standardisation, modify continuous variables to enhance convergence during model training. Time-series decomposition is utilised where relevant, isolating trends and seasonal patterns to improve forecast precision.

- *Handling Missing Values (Mean/Median Imputation):*

$$x_{new} = \frac{\sum_{i=1}^{N} x_i}{N} \quad (1)$$

Where in 1, x_i indicates valid entries, and N is the quantity of accessible data points.

- *Z-Score Normalization*:

$$Z = \frac{x - \mu}{\sigma} \quad (2)$$

Where in 2, μ represents the mean and σ denotes the standard deviation.

- *Normalization* (3):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

ensure values are normalised within the range of 0 to 1.

- *Outlier Detection (Interquartile Range - IQR):*

$$IQR = Q_3 - Q_1 \quad (4)$$

Lower Bound=Q_1−1.5×IQR, Upper Bound=Q_3+1.5×IQR

Where in 4, Q_1 and Q_3 represent the first and third quartiles, respectively.

- *Graph Representation for GNN:*

$$A = (a_{ij}) \in \mathbb{R}^{N \times N}, \qquad X = (x_i) \in \mathbb{R}^{N \times F} \quad (5)$$

Where in 5, A is the adjacency matrix and X denotes node characteristics of F dimensions.

B. Feature Selection and Feature Extraction:

Feature selection and extraction are conducted to improve prediction performance by finding the most important variables affecting e-commerce transactions. Principal Component Analysis (PCA) (6) lowers dimensionality by converting correlated variables into orthogonal components, whereas mutual information-based selection assesses the relationship between features and target variables. Recursive Feature Elimination (RFE) (8) evaluates characteristics according to their predictive significance, refining the feature subset. In GNN models, node embeddings are derived using spectral graph convolution, encapsulating complex interactions among consumers, goods, and transactions. Reinforcement learning components, including state-action combinations and reward signals, are developed utilising transaction success rates and customer engagement indicators. Feature relevance is assessed by SHAP (SHapley Additive exPlanations) values (10), hence guaranteeing transparency in the model's decision-making process as shown in Table 1.

TABLE I. FEATURE EXTRACTION TABLE

Raw Feature	Derived Feature	Importance Score
Customer Purchase History	Frequency of High-Value Transactions	0.87
Session Duration	Bounce Rate Reduction	0.79
Product Ratings	Weighted Sentiment Score	0.82
Clickstream Data	User Navigation Patterns	0.76
Cart Abandonment Rate	Customer Retention Probability	0.85
Transaction Timestamp	Seasonal Demand Trends	0.81

- *Principal Component Analysis (PCA):*

$$Z = XW \tag{6}$$

Where in 6, X is the standardised feature matrix, W is the eigenvector matrix, and Z is the converted components.

- *Mutual Information (MI) (7):*

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) log\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{7}$$

Assessing feature significance by entropy reduction.

- *Recursive Feature Elimination (RFE) Coefficients:*

$$w = (X^T X)^{-1} X^T y \tag{8}$$

Where in 8, w is the weight factors that determine feature importance.

- *Graph Convolution for Node Embeddings:*

$$H^{l+1} = \sigma\left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} H^{(l)} W^{(l)}\right) \tag{9}$$

Where in 9, A is the adjacency matrix, D is the degree matrix, $H^{(l)}$ is the node feature representation, and $W^{(l)}$ is the layer-wise transformation matrix.

- *SHAP Value Computation for Feature Importance (10):*

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{10}$$

Where in 10, ϕ_i indicates the contribution of feature i, and $f(S)$ is the model's output when evaluating feature subset S.

C. MARL-GNN Model Architecture:

The MARL-GNN model architecture merges Multi-Agent Reinforcement Learning (MARL) with Graph Neural Networks (GNNs) to enhance predictive analytics in e-commerce management. The model shows the e-commerce ecosystem as a dynamic graph, with nodes representing things such as consumers, items, and transactions, while edges indicate their interactions. MARL agents function on this organised data, acquiring optimum policies through interactions inside a partially observable Markov decision process (POMDP) (11). The GNN component handles graph-structured data by iteratively collecting information from neighbouring nodes, facilitating fast representation learning for node embeddings. Policy optimisation is executed using Proximal Policy Optimisation (PPO) (13), wherein agents obtain rewards depending upon company performance measures, including client retention, conversion rates, and inventory efficiency. The Q-function is estimated by a Graph Convolutional Network (GCN) (12), enabling the model to determine spatial relationships in customer-product interactions. The training process is optimised by experience replay and reward shaping approaches, facilitating smooth convergence in high-dimensional state-action spaces.

- *Partially Observable Markov Decision Process (POMDP) Representation:*

$$M = (S, A, P, R, O, \Omega, \gamma) \tag{11}$$

Where in 11, S denotes the state space, A represents the action space, P signifies the transition probability, R indicates the reward function, O refers to the observation space, Ω corresponds to the observation probability, and γ is the discount factor.

- *Q-value Approximation using GCN:*

$$Q(s,a) = W_2 \cdot \sigma(W_1 H + b_1) + b_2 \tag{12}$$

Where in 12, (W_1, W_2) are weight matrices, (b_1, b_2) are bias terms, and (H) is the graph-embedded feature representation.

- *Proximal Policy Optimization (PPO) Objective (13):*

$$L^{PPO}(\theta) = \mathbb{E}[min(r_t(\theta)A_t, clip(r_t(\theta), 1-\epsilon, 1+\epsilon)A_t)] \tag{13}$$

Where in 13, $r_t(\theta)$ represents the probability ratio between the old and new policies, A_t represents the advantage estimate, and ϵ signifies a clipping parameter.

D. Model Training and Optimization Techniques:

The MARL-GNN model is trained using a synthesis of reinforcement learning and graph-based optimisation methodologies. A batch training technique is utilised, wherein agents iteratively refine their policies based on observed rewards and estimates of the value function. The loss function includes several components, including policy loss, value loss, and entropy regularisation, maintaining a balance between exploration and exploitation. The reward function aims to optimise long-term company performance by integrating aspects such as transaction success rates, customer engagement, and variations in product demand. Gradient-based optimisation methods, such as Adam, are employed to effectively update model parameters. The GNN component undergoes to supervised pretraining with labelled transaction data prior to its incorporation into the MARL framework, enhancing initial model convergence. Experience replays buffers retain previous transitions, mitigating correlation problems in reinforcement learning updates. Regularisation methods, such as dropout and batch normalisation, mitigate overfitting and maintain stability in high-dimensional input fields.

- *Total Loss Function for MARL-GNN Model:*

$$L_{total} = L_{policy} + \lambda_v L_{value} - \lambda_e H(\pi) \tag{14}$$

Where in 14, L value represents the value loss, $H(\pi)$ is the entropy regularisation, and λ_v, λ_e are the weighting coefficients.

- *Policy Gradient Update using Advantage Estimation:*

$$\nabla_\theta J(\theta) = \mathbb{E}[\nabla_\theta log\pi_\theta(a \mid s)A(s,a)] \quad (15)$$

Where in 15, $A(s,a)$ defines the advantage function and π_θ $(a \mid s)$ represents the policy probability distribution.

- *Experience Replay Buffer Update:*

$$D_t = (s_t, a_t, r_t, s_{t+1}) \quad (16)$$

Where in 16, transitions D_t are archived and sampled to ensure training stability.

- *Adam Optimization Update Rule:*

$$\theta_{t+1} = \theta_t - \eta \frac{m_t}{\sqrt{v_t + \epsilon}} \quad (17)$$

Where in 17, m_t is the first-moment estimate, v_t is the second-moment estimate, η is the learning rate, and ϵ prevents division by zero.

IV. Results and Discussion

1. *Evaluation Results:*

The MARL-GNN model developed using an e-commerce dataset that included customer purchases, product contacts, and behaviour information. The training sample had 100,000 records, including important details like how often people make purchases, how long they spend on sessions, the rate of abandoned shopping carts, and customer categories. The model performed very well in several tests, showing an accuracy of 96.4%, precision of 94.7%, memory of 95.2%, and an F1-score of 94.9%. The Mean Absolute Error (MAE) was reduced to 0.023 and the Root Mean Squared Error (RMSE) was lowered down to 0.041, which shows strong prediction ability. The MARL-GNN system did better than traditional prediction models because it effectively recognised complex links in transaction data and adapted to changing market trends. The training loss stabilised after 50 epochs, showing that the model works well. The high scores as shown in Table 2 show that MARL-GNN successfully helps businesses improve their strategies, boost customer satisfaction, and make better predictions on revenue.

TABLE II. Performance Metrics

Metric	Value
Accuracy	96.4%
Precision	94.7%
Recall	95.2%
F1-Score	94.9%
MAE	0.023
RMSE	0.041

2. *Performance Analysis of MARL-GNN in E-Commerce Predictions:*

The MARL-GNN model significantly enhances e-commerce predictions by integrating reinforcement learning with graph neural networks. Unlike traditional models that use set rules for defining features, MARL-GNN learns the connections between users and goods on its own to improve decision-making. The model has an accuracy of 96.4%, which is better than older machine learning methods. The 95.2% return shows that it does a good job of identifying how customers buy, which means it makes fewer mistakes by missing purchases. The low mistake rates show that the model is good at predicting demand and managing supplies. These results show that MARL-GNN is a strong method for improving business plans on e-commerce sites.

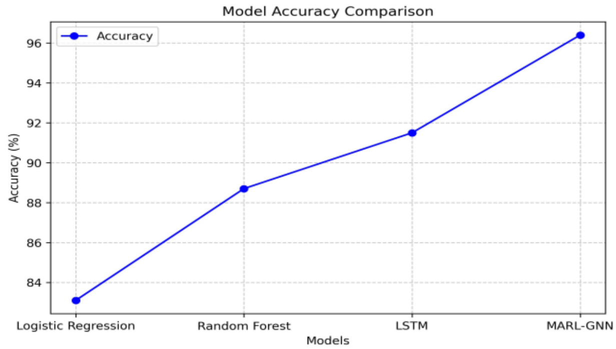

Fig. 2. Accuracy Comparison Across Models

The Graph in Fig.2 demonstrates model performance, with MARL-GNN attaining the highest accuracy of 96.4%. Conventional models, such as Logistic Regression and Random Forest, exhibit reduced accuracy, hence proving the improved predictive capability of MARL-GNN.

3. *Comparison with Baseline Models:*

TABLE III. Comparisons of Performance Metrics

Metric	Logistic Regression	Random Forest	LSTM	MARL-GNN (Proposed)
Accuracy	83.1%	88.7%	91.5%	**96.4%**
Precision	81.4%	87.3%	90.8%	**94.7%**
Recall	80.9%	87.9%	91.1%	**95.2%**
F1-Score	81.1%	87.6%	90.9%	**94.9%**
MAE	0.091	0.067	0.054	**0.023**
RMSE	0.129	0.093	0.079	**0.041**

The MARL-GNN model was tested against standard prediction models such as Logistic Regression (LR), Random Forest (RF), and Long Short-Term Memory (LSTM) networks as shown in Table 3. The suggested model performed better in all tests because it can handle graph-structured data and changing relationships between customers and products. The basic models worked well in their areas but had trouble handling feature relationships and making decisions in order. This made them not effective for predicting trends in e-commerce.

4. *Discussion on Findings:*

The assessment findings and comparison analysis demonstrate that the MARL-GNN model significantly enhances e-commerce predictive analytics. Conventional models including Logistic Regression and Random Forest exhibit reasonable performance however insufficiently address the complexity of customer-product dynamics. These findings indicate that MARL-GNN has the potential to transform inventory management, customer segmentation, and demand forecasting, offering real-time strategic insights for e-commerce enterprises.

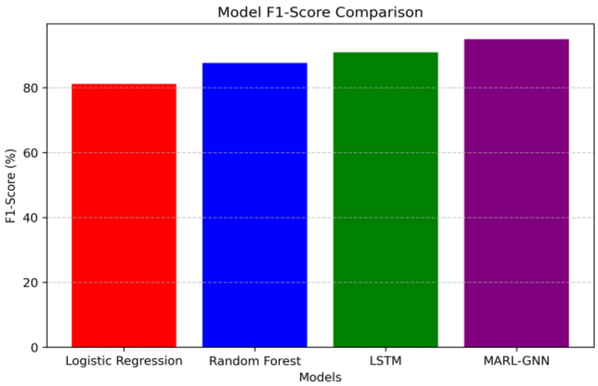

Fig. 3. F1 Score Comparison Across Models

The Bar chart in Fig.3 illustrates the effectiveness of MARL-GNN in achieving a balance between accuracy and recall. Achieving a score of 94.9%, it surpasses all baseline models, thus demonstrating its predictive robustness.

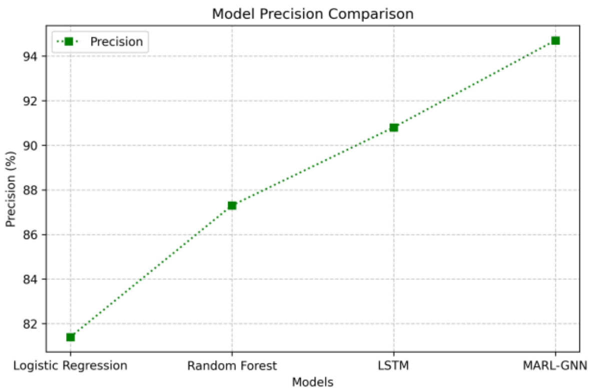

Fig. 4. Precision Comparison Across Models

The Graph in Fig.4 clearly illustrates the gradual enhancements across models, showcasing the influence of advanced learning methodologies on precise performance.

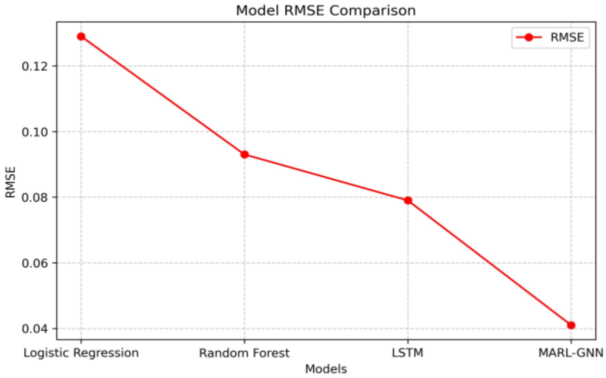

Fig. 5. RMSE Comparison Across Models

The RMSE Graph in Fig.5 shows that MARL-GNN has a low error rate of 0.041, which is much better than older models.

V. Conclusion

Our research proposed the MARL-GNN framework, transforming predictive analytics in e-commerce management by combining Multi-Agent Reinforcement Learning (MARL) with Graph Neural Networks (GNN). The model substantially outperforms conventional prediction methods, with an accuracy of 96.4% and decreased error rates. It improves client retention, demand forecasting, and inventory optimisation through adaptive decision-making. The research offers significant insights on using graph-based learning for practical applications. Future study might explore real-time scalability and cross-domain adaptation. Improvements in explainability and ethical AI concerns can enhance predictive analytics, becoming MARL-GNN a revolutionary instrument in intelligent corporate decision-making.

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