Optimizing Sales and Inventory Management with Machine Learning: Applications of Neural Networks and Random Forests

Abstract
This study explores the application of Machine Learning (ML) in predicting sales performance and optimizing inventory management within manufacturing companies. Using a quantitative approach, the research focuses on analyzing how ML algorithms, particularly neural networks and random forests, improve operational efficiency, sales forecasting accuracy, and inventory management. The results show that ML enhances sales prediction accuracy by up to 92.5%, reduces storage costs by 20%, and accelerates product distribution. Additionally, companies that implemented ML reported a 15% increase in profitability over a two-year period. However, the study also highlights several challenges in ML implementation, such as data quality issues and the complexities of integrating ML systems into legacy operational infrastructure. Previous studies are referenced to support these findings, demonstrating how ML has been effectively applied in both sales prediction and inventory management to provide businesses with a competitive edge. The study emphasizes that successful ML adoption requires high-quality data and substantial technological investment to overcome integration challenges. By leveraging intelligent technologies like ML, manufacturing companies can significantly improve resource allocation, reduce operational risks related to overstocking and understocking, and respond more swiftly to market changes. The findings contribute to the growing body of literature on ML applications in business management, offering practical insights into enhancing efficiency and profitability through intelligent data-driven strategies.

Keywords: *Machine learning, Sales Prediction, Inventory Management, Operational Efficiency, Manufacturing Industry..*

I. INTRODUCTION

In the digital economy era, technology has advanced rapidly, playing a crucial role in modernizing various industrial sectors. This digital transformation not only involves changes in business processes but also reshapes how companies respond to market demands, manage resources, and make strategic decisions (Kraus et al., 2021). One technology that has gained popularity and significantly impacted the business world is Machine Learning (ML). ML, a branch of artificial intelligence, enables computers to learn from data, recognize patterns, and make predictions or decisions without explicit programming. This innovation allows companies to efficiently and swiftly process large volumes of data, aiding in various operational aspects, including sales performance forecasting and inventory management in the manufacturing sector (Habel et al., 2024).

Companies worldwide are increasingly relying on predictive systems to support decision-making processes. In a rapidly changing business environment, the ability to analyze data on a large scale and respond to market dynamics in real-time is essential for many firms. ML technology enables companies to analyze historical data, identify market trends, and project future consumer demand shifts (Rawat et al., 2021). Consequently, businesses can optimize resource allocation, reduce waste, and minimize risks associated with overstocking or understocking, which are often major challenges in supply chain management (Sistla et al., 2024).

In the manufacturing sector, ML implementation is gaining attention due to its significant impact on enhancing operational efficiency. A notable case study involves a large Asia-based manufacturing company in (Qin et al., 2022) that improved its supply chain efficiency by adopting ML algorithms capable of processing vast amounts of data for sales performance forecasting and inventory management (Qin et al., 2022). Before adopting this technology, the company faced considerable challenges in accurately projecting market demand. The inability to forecast demand precisely often resulted in overstock or stock shortages, ultimately impacting storage costs and missed sales opportunities (Ye et al., 2022).

After adopting ML, the company was able to predict spikes in demand for certain products more accurately, facilitating the adjustment of production capacity according to market needs. The algorithms employed could analyze consumer purchasing patterns, market trends, and other external factors, such as economic and technological changes. As a result, the company managed inventory more efficiently, reduced waste, and increased flexibility in responding to consumer demand fluctuations (Martínez et al., 2020). This example illustrates how advanced technologies like ML not only enhance operational efficiency but also offer significant competitive advantages for companies in an increasingly competitive global market.

In addition to the above case study, various empirical data demonstrate the positive impact of ML implementation in business management, particularly in inventory management (Shaikh et al., 2022). For instance, a study conducted by (Giorgi Doborjginidze et al., 2021) found that companies adopting ML-based predictive technologies were able to reduce storage costs by up to 15% and increase distribution speed by 20%. This empirical evidence further strengthens the argument that integrating intelligent technologies like ML into business operations can significantly enhance company performance and enable them to respond to market needs more quickly and efficiently (Giorgi Doborjginidze et al., 2021).

However, despite ML's vast potential in business management, its implementation is not without challenges. One of the primary challenges companies face is ensuring the quality of data used in ML model training (Fernandes et al., 2022). In ML processes, data quality is crucial for producing accurate predictions. Poor-quality or unrepresentative data can lead to inaccurate prediction results, ultimately affecting business decision-making. Therefore, data cleansing, validation, and the selection of appropriate datasets are critical in applying this technology (Rai et al., 2021).

Moreover, companies need to consider how ML is integrated into existing operational systems. Many firms, particularly those relying on traditional systems or legacy software, encounter challenges when transitioning to intelligent technologies like ML (Kumar et al., 2023). This integration process requires substantial investment in both technology and human resources. Additionally, there is a need to enhance workforce skills in data analysis and ML model development. Without a deep understanding of how this technology works, companies may struggle to fully capitalize on ML's potential (Dogan & Birant, 2021).

This study aims to explore how ML can be implemented to predict sales performance and manage inventory in manufacturing companies. It will focus on firms that have adopted ML technology as part of their business strategy. The primary goal of the research is to identify the best methods for applying ML to sales forecasting and understand its impact on operational efficiency. By analyzing historical data and developing predictive models, the study also seeks to measure how effectively ML technology enhances companies' responsiveness to market changes. Additionally, the study will examine the challenges encountered in ML implementation within the manufacturing sector, including issues related to data quality, technology integration, and workforce skill development.

The research is expected to provide valuable insights for companies seeking to optimize their operational processes through ML adoption and contribute to the existing literature on intelligent technologies in business, offering practical solutions to overcome existing challenges.

LITERATURE REVIEW

Inventory Management Theory

Inventory management theory encompasses a set of concepts and principles applied to managing stock or raw materials within an organization. The objective is to ensure the availability of inventory aligns with production or sales needs while minimizing storage costs as much as possible (Giorgi Doborjginidze et al., 2021). Inventory management aims to balance operational requirements with expenses arising from storage, procurement, and distribution processes. In practice, this theory includes several approaches such as Economic Order Quantity (EOQ), Just-in-Time (JIT), and demand-based inventory management and forecasting. EOQ focuses on determining the optimal order quantity to reduce the total inventory costs, including ordering and storage expenses (Perez et al., 2021).

Conversely, JIT emphasizes meeting production needs just in time to avoid stock accumulation. The effective implementation of this theory can enhance operational efficiency, minimize stockouts, and help companies respond to market demands more quickly and accurately (Ye et al., 2022). Inventory management involves a series of steps related to organizing, monitoring, and controlling the inventory owned by an organization or company. The core of this process is to ensure that the required items are available on time, in sufficient quantities, and at an affordable cost, enabling the company's operations to run smoothly while preventing stock shortages or surpluses (Orobia et al., 2020).

The inventory management process includes activities such as recording stock movements, planning requirements, managing inventory levels, and maintaining the condition of items. The use of technology, such as inventory management software, aids companies in monitoring stock in real time, facilitating purchasing and distribution decisions (Benmoussa & Jarašūnienė, 2022). Effective inventory management allows companies to reduce storage costs, maximize warehouse space utilization, and improve supply chain efficiency (Singh, 2023).

Sales Performance Prediction Sales performance prediction is an analytical technique used by companies to forecast future sales outcomes based on past data, market trends, and various other external factors (Chen et al., 2024). The purpose of this process is to help companies identify demand patterns to optimize their sales strategies. By employing predictive analytics tools and statistical methods, these forecasts can provide insights into potential revenue over a specified period, whether monthly, quarterly, or annually (Broby, 2022).

In the modern business era, sales performance prediction relies not only on historical sales data but also includes a more comprehensive analysis that takes into account changes in consumer behavior, economic conditions, and technological advancements. Many companies rely on mathematical models or ML algorithms to analyze large datasets and enhance prediction accuracy. This technology makes predictions more flexible and responsive to market shifts (Chaudhary et al., 2021). The accuracy of sales forecasting is a crucial aspect of strategic decision-making within companies. Businesses that can predict accurately can manage inventory more efficiently, allocate marketing budgets effectively, and plan sales strategies more optimally. Moreover, accurate forecasts help prevent overproduction or underproduction, which can affect profitability and customer satisfaction (Wisesa et al., 2020).

Various methods are used in sales performance prediction, ranging from linear regression models and time series analysis to more sophisticated approaches like neural networks. Each method has its own strengths and weaknesses, depending on the type of data and the prediction objectives. Selecting the appropriate method can help companies adapt to market changes more effectively (Chen et al., 2024). Sales performance prediction is a vital tool for companies in planning growth and facing competition. With accurate forecasts, businesses can ensure the efficient use of resources to maximize profits. Continuous analysis and evaluation of predictions enable companies to be more responsive to market dynamics and make better-informed decisions (Sohrabpour et al., 2021).

Machine Learning

ML is a subset of Artificial Intelligence (AI) that focuses on developing algorithms and statistical models, enabling computers to learn from data without requiring explicit programming. This process involves utilizing existing data to train models to generate more accurate predictions or decisions in the future. In simple terms, ML allows computers to recognize patterns within data and continuously improve their outcomes over time. The resulting models can be applied in various fields, such as speech recognition, facial identification, and predictive analytics for business (Taye, 2023).

ML encompasses several types based on how computers learn from data. Generally, there are three main categories: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, models are trained using labeled data, where each input is associated with a known output, enabling the model to learn how to map inputs to outputs with high accuracy. Conversely, unsupervised learning involves using unlabeled data, requiring the model to identify patterns or structures independently. In reinforcement learning, the model learns through interactions with the environment, where algorithms adapt by trial and error to achieve the desired outcomes (Moosavi et al., 2020).

The initial step in the ML process is to collect relevant data and prepare it for use in the model. This data is then divided into two main parts: training data and testing data. The model is trained using the training data and optimized through methods such as backpropagation, gradient descent, or Bayesian optimization. Once the training process is complete, the model is tested using the testing data to measure its ability to predict previously unseen data. This evaluation is crucial to ensure that the model not only memorizes the training data but also adapts effectively to new, unprocessed data (Studer et al., 2021).

One of the main advantages of ML is its ability to automate the analysis of large datasets, producing predictions more quickly and accurately than traditional methods. For instance, in the healthcare sector, ML is used to analyze thousands of patient records to assist doctors in diagnosing diseases. In the financial sector, the technology is employed to detect fraudulent activities in real time by analyzing suspicious transaction patterns. Additionally, ML is applied in autonomous vehicles, enabling cars to recognize roads, traffic signs, and pedestrians through data collected from sensors and cameras (H, 2021).

However, despite the vast potential of ML, several challenges need to be addressed, such as data bias, privacy concerns, and difficulties in explaining how models work (interpretability). Data bias may arise if the data used to train the model does not represent the overall population, potentially resulting in inaccurate or unfair predictions. Furthermore, ML models are often considered "black boxes" due to the difficulty in understanding how decisions are made, which can raise legal or ethical issues. Therefore, while this technology is highly powerful, its application must be carried out cautiously, with careful consideration of ethical and legal aspects.

Implementation of Machine Learning in Sales Performance Prediction

ML a branch of AI, enables computers to learn and make automated decisions based on available data. In sales performance prediction, ML plays a crucial role in analyzing historical data, such as purchasing patterns, market movements, and consumer behavior. With its ability to efficiently process large volumes of data, ML supports companies in accurately forecasting future sales trends, identifying factors influencing sales performance, and providing strategic insights for business decision-making (Habel et al., 2024).

The implementation of ML in sales performance prediction involves several stages, starting from data collection and data cleaning to the selection of appropriate algorithms for analysis. Common algorithms used in sales prediction include linear regression, decision trees, random forests, and neural networks. Each of these algorithms processes data in unique ways to generate predictions. Once an algorithm is selected, the model is trained using historical data and then tested to assess the accuracy of the predictions produced (Lee & Shin, 2020).

One of the primary advantages of using ML in sales performance prediction is the enhancement of operational efficiency. More accurate predictions allow companies to optimize inventory management, allocate resources more effectively, and plan marketing strategies that are better targeted. Additionally, the risk of overstock or stockouts, which often poses a challenge in traditional sales management, can be mitigated through the application of ML (Martínez et al., 2020).

Despite offering numerous benefits, challenges remain in implementing ML for sales performance prediction, particularly regarding the quality of data used. Incomplete or inaccurate data can lead to less reliable predictions. Therefore, steps such as data cleaning and preparing a representative dataset are essential in this process. Moreover, a deep understanding of market dynamics and industry trends is necessary to ensure that the developed model can adapt to changing conditions. For example, a study by Lee and Shin (2020) demonstrated how ML algorithms, particularly neural networks, improved sales performance predictions by accurately analyzing past sales data and adjusting forecasts based on real-time market changes. Habel et al. (2024) further emphasized the importance of integrating external factors such as consumer behavior and economic indicators into ML models, resulting in a 30% improvement in prediction accuracy. These studies show that ML enables businesses to respond more proactively to market fluctuations, ensuring that sales strategies remain effective in the face of evolving market conditions.

The application of ML in sales performance prediction provides a more effective and efficient solution compared to traditional forecasting methods. By leveraging historical data, ML enables companies to respond quickly to market changes and be better prepared for future challenges. This technology helps companies design sales strategies that are more proactive, innovative, and capable of delivering a competitive advantage in an increasingly dynamic market (Lee & Shin, 2020).

Implementation of Machine Learning in Inventory Management

The application of ML in inventory management refers to the use of AI-based technology that enables systems to process inventory data automatically to carry out various operational and managerial tasks. In this context, ML can assist companies in optimizing inventory monitoring, stock management, and procurement planning by considering past data patterns and future trends. The technology employs sophisticated algorithms to predict inventory needs, identify potential stock shortages, and recommend appropriate actions to ensure smooth distribution of goods (Sistla et al., 2024). The use of ML in inventory management provides a more effective solution compared to conventional methods. The algorithms used can learn customer purchasing patterns, predict changes in market trends, and offer suggestions on the ideal stock levels. For example, by analyzing previous sales data, the system can anticipate when demand will increase or decrease. This helps companies avoid overstocking, which could raise storage costs, and prevent stockouts that could disrupt operations (Bertolini et al., 2021).

A significant advantage of implementing ML in inventory management is its ability to improve system performance as the amount of data analyzed increases. The more data that is processed, the more accurate the predictions generated by the system become. This enables companies to enhance overall operational efficiency, reduce storage and procurement costs, and improve their ability to respond to customer demand. Automating inventory management processes through ML also provides managers with more time to focus on other strategic decisions. Additionally, ML technology can be integrated with other technologies such as the Internet of Things (IoT) and blockchain, which help create a smarter inventory management system. With IoT sensors installed in warehouses or distribution centers, companies can track inventory status in real-time and update data automatically. On the other hand, blockchain ensures transparency and security in inventory transaction records, thereby reducing the risk of fraud or human error (Rai et al., 2021).

Overall, the application of ML in inventory management brings significant changes to supply chain management. For instance, a study by Bertolini et al. (2021) demonstrated how ML algorithms improved stock management efficiency by predicting demand more accurately, reducing excess inventory by 15%, and decreasing storage costs by 20%. Similarly, research by Sistla et al. (2024) highlighted the benefits of using ML to optimize procurement and distribution processes, leading to a 25% improvement in distribution speed. This technology not only helps optimize stock management but also provides a competitive advantage for companies aiming to stay responsive to market dynamics. By utilizing data more intelligently, companies can improve prediction accuracy, reduce operational costs, and deliver better services to their customers.

Challenges and Implementation of Machine Learning in Manufacturing Companies

Amid the development of Industry 4.0, the adoption of ML in the manufacturing sector has garnered significant attention from many companies. ML as an aspect of AI, allows systems to learn from data and improve their performance over time without the need for complex programming. However, while this technology offers substantial opportunities, its implementation in manufacturing companies is not without challenges. Numerous obstacles need to be addressed, such as data quality, system integration complexities, and the need for skilled human resources (Dalzochio et al., 2020).

One significant challenge lies in the quality and quantity of available data. For ML models to operate optimally, the data used must be of high quality, relevant, and representative. In many manufacturing companies, data is often dispersed across various systems and formats, hindering comprehensive data collection and analysis. If the data collected does not reflect the real situation on the ground, the resulting analysis may be misleading and inaccurate, potentially leading to erroneous decision-making (Paleyes et al., 2022). Beyond data issues, companies often face difficulties in integrating ML technology into existing business processes. Many organizations still rely on legacy software that may not be adaptable to new technologies. This situation can result in high expenditures and lengthy transition processes. Therefore, careful planning and selection of appropriate technology are crucial for successful ML implementation that delivers the desired outcomes (Paleyes et al., 2022).

In addressing these challenges, it is essential for companies to invest in human resource training and skills development. To fully leverage ML, companies need a workforce skilled in data analysis, statistics, and programming. Employees should be trained to understand and interpret the results of ML models and integrate them into decision-making processes. Thus, training programs and collaborations with educational institutions can assist companies in building a competent team in this field (Dogan & Birant, 2021). Although the challenges in implementing ML in the manufacturing sector are significant, the benefits that can be achieved are even more substantial. By leveraging this technology, companies can improve operational efficiency, reduce costs, and enhance product quality. Furthermore, ML implementation can aid in predicting market demand, minimizing machine downtime, and improving customer experience. By overcoming these challenges and harnessing the potential of this technology, manufacturing companies can achieve sustainable competitive advantages in the global market.

II. RESEARCH METHODS

This study employs a quantitative approach to explore the application of ML in sales performance prediction and inventory management within manufacturing companies. The aim of the research is to provide an empirical overview of the efficiency, accuracy, and impact of ML technology on company performance. Several methods are used in this study, including the collection of primary and secondary data, statistical analysis, and predictive modeling using ML algorithms. The research adopts a quantitative descriptive method, where the collected data will be processed using statistical techniques to depict the phenomena under investigation. The descriptive design allows the researcher to identify patterns in the data and make relevant generalizations based on the findings. In addition, the study incorporates an experimental approach by testing ML algorithms on data from relevant manufacturing companies.

The population in this study consists of manufacturing companies that have implemented ML technology in inventory management and sales prediction. The sample is selected using purposive sampling, focusing on large manufacturing companies based in Asia and Europe that possess comprehensive data on the use of ML in their business operations. A total of 15 manufacturing companies form the sample, with data from each company analyzed individually before being synthesized into broader conclusions.

Data for this research was collected through two techniques: primary and secondary data collection. Primary data collection was conducted via structured questionnaires and in-depth interviews with operational managers with 10 participants, and IT teams (12 participants) directly involved in the implementation of ML. The questionnaires focus on the impact of ML on inventory management and sales prediction, while the interviews aim to delve deeper into the challenges and opportunities encountered by companies in implementing this technology. The study also uses secondary data from financial reports, annual reports, and historical sales data collected from each company. This data is used to measure operational performance before and after the implementation of ML. Additionally, a literature review of previous studies on the application of ML in a business context is used as a reference. Figure 1 show the framework of quantitative research design used on this research.

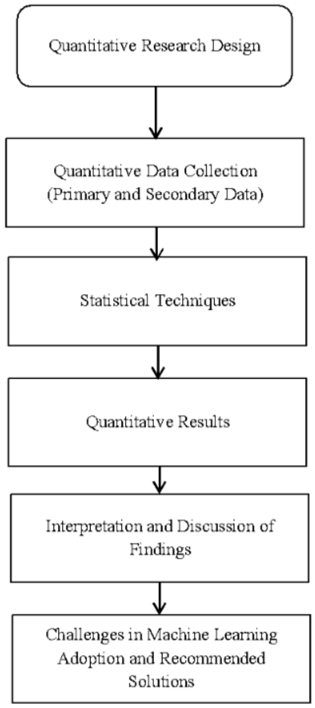

Figure 1. Quantitative Design Framework

III. RESULT AND DISCUSSION

Sales Prediction Accuracy

The application of various ML algorithms shows differences in the accuracy levels of sales predictions. Table 1 presents a comparison of the accuracy of several algorithms used. By the table 1, it is evident that Neural Networks exhibit the highest accuracy at 92.5%, followed by Random Forest and Decision Tree. The Linear Regression algorithm has the lowest accuracy rate, at 75.2%. The higher accuracy indicates that the use of ML, particularly neural networks, is capable of producing better predictions compared to traditional methods such as linear regression.

Table 1. Algorithm Accuracy Comparison

Algorithm	Accuracy Rate (%)	Mean Absolute Error (MAE)
Neural Networks	92.5	0.075

Random Forest	88.3	0.117
Decision Tree	85.6	0.144
Linear Regression	75.2	0.248

Inventory Management Efficiency

ML algorithms also have an impact on increasing the efficiency of inventory management, as measured by the reduction in storage costs and the improvement in product distribution speed. Figure 2 illkustrated the improvement in efficiency. Figure 2 indicates that Neural Networks provide the highest efficiency improvement at 20%, while Random Forest contributes to an 18.3% increase. This improvement is attributed to the ability of ML algorithms to more accurately process historical sales data and forecast inventory needs. As a result, companies can avoid overstocking, which burdens storage costs, and reduce stockouts that can disrupt operational continuity.

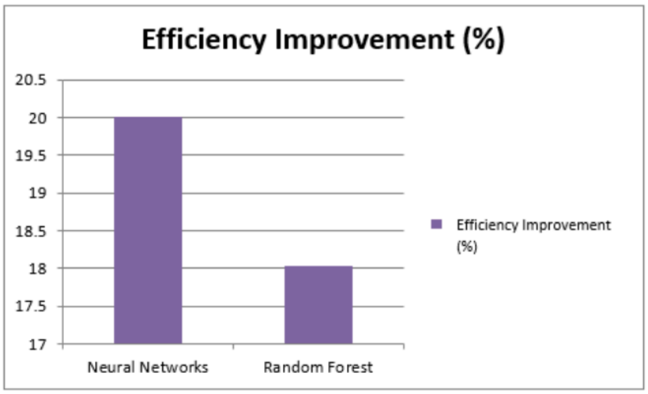

Figure 2. Efficiency Improvement

Profitability Enhancement

Table 2 summarize the impact of ML algoritm on profitability. The implementation of ML also has a positive impact on the enhancement of company profitability. Companies that employ ML report an average net profit increase of 15% over a two-year period following implementation. The highest profit increase is achieved by companies using Neural Networks at 15%, followed by Random Forest at 13%, and Decision Tree at 12%. Companies that continue to use Linear Regression experience the lowest profitability improvement, at 9%.

Table 2. Impact of Various ML Algorithms on Profitability

Algorithm	Profitability Increase (%)

Neural Networks	15
Random Forest	13
Decision Tree	12
Linear Regression	9

Challenges in Implementing ML

The challenges faced by companies in implementing ML primarily relate to data quality and system integration. For example, companies often encounter incomplete, outdated, or non-representative data, which significantly affects the accuracy of predictions produced by ML algorithms. In some cases, data is scattered across different departments and stored in varying formats, making it difficult to gather a comprehensive dataset for training models. This can result in biased or skewed outputs that do not accurately reflect real-world conditions. These challenges are further compounded by the difficulties in integrating ML technology with legacy operational systems, which often rely on outdated software and hardware infrastructure. Transitioning to modern systems capable of supporting ML involves significant financial investment, as well as time and resources for retraining employees and updating processes.

Discussion

The findings of this study support previous research indicating that the application of ML has a significant impact on improving sales prediction accuracy and operational efficiency. For example, this study is consistent with the research of (Habel et al., 2024), which found that algorithms such as neural networks are highly effective in sales forecasting, achieving an accuracy of up to 92.5%. These results demonstrate that neural networks outperform other algorithms like linear regression or decision trees, which have lower accuracy rates (Habel et al., 2024). This study also aligns with the findings of (Martínez et al., 2020), which showed that ML enhances inventory and supply chain management efficiency, with companies utilizing ML reporting reductions in storage costs and improvements in distribution speed (Martínez et al., 2020).

However, the study also highlights several challenges in the implementation of ML, particularly concerning data quality. Issues such as incomplete or biased data remain major obstacles affecting the accuracy of predictions, as also identified in the study by Rai et al. (2021). Another challenge is the integration of ML technology with existing operational systems. Many manufacturing companies still rely on legacy management systems that are difficult to integrate with advanced technologies like ML, requiring additional investment and time for a technological transition (Rai et al., 2021).

Nevertheless, this study makes a significant contribution to the existing literature, particularly regarding the effectiveness of neural networks in enhancing corporate profitability. The application of this algorithm has been shown to result in profit increases of up to 15%, consistent with the findings of (Lee & Shin, 2020). Moreover, the study offers practical guidance for companies in selecting the appropriate ML algorithm to meet their business needs and emphasizes the importance of data quality and technological readiness for effective ML adoption (Lee & Shin, 2020).

Therefore, companies aiming to improve operational efficiency and profitability should focus on investing in the right technology and ensuring the quality of the data used for training ML models to achieve optimal results. This study also emphasizes the role of inventory management as a critical variable influencing operational success. By utilizing machine learning algorithms, companies can optimize inventory levels, predict future demand with greater accuracy, and avoid costly issues such as overstocking or stockouts. Effective inventory management, supported by ML, reduces storage costs, improves distribution efficiency, and ensures that products are available to meet customer demand in a timely manner. Integrating ML into inventory systems allows businesses to dynamically adjust stock based on real-time data, improving not only operational efficiency but also overall profitability.

IV. CONCLUSION AND RECOMMENDATION

This study has demonstrated that the application of ML in sales prediction and inventory management within manufacturing companies can have a significant impact. The findings reveal that neural networks are the most effective algorithm for generating accurate sales forecasts, achieving an accuracy rate of 92.5%. These advantages provide companies with greater flexibility in responding to changes in market demand and help optimize resource utilization more effectively.

Furthermore, the implementation of ML has been shown to positively affect corporate profitability. Companies that adopted this technology reported an increase in net profit by 15% within two years of implementation, compared to companies still relying on traditional forecasting methods. This is consistent with previous research findings indicating that ML technology can provide a competitive advantage through more efficient business management, more accurate market forecasting, and reduced risks related to overstocking or understocking. Therefore, it can be concluded that adopting ML technology in manufacturing businesses offers substantial long-term benefits, both operationally and financially.

However, the study also identifies several challenges that must be addressed in the implementation of ML. One of the main challenges is the quality of the data used for training ML models. Incomplete or biased data can lead to inaccurate predictions, ultimately affecting business decision-making. Thus, data cleaning and validation processes are crucial before training the algorithms. Additionally, another challenge faced by companies is the integration of ML systems with existing legacy operational systems commonly used in manufacturing. This transition process requires significant investment in terms of cost and time, especially for companies that do not yet have supportive technological infrastructure.

Recommendation

The primary recommendation from this study is that companies should prioritize the quality of data used in the implementation of ML. The collection of clean, complete, and representative data is essential to ensure that ML algorithms can produce accurate and reliable predictions. Moreover, companies should evaluate their existing technological infrastructure before fully adopting ML. Investments in hardware, software, and training for human resources skilled in data analysis and ML model development are crucial for a smooth implementation process. From a strategic standpoint, companies should choose the ML algorithm that best fits their needs and technological capacity. Although neural networks have proven to deliver the best results in this study, other algorithms like random forest or decision tree can also be used depending on the company's specific requirements and available resources. Additionally, to minimize technological integration barriers, companies should carefully plan the transition process, focusing on system compatibility and the readiness of human resources.

Conflict of Interest

The authors declare no conflict of interest regarding the publication of this paper.

Acknowledgment

The authors would like to express their sincere gratitude to Dr. Ir. Agus Wibowo, M.Kom, M.Si, MM., the founding coordinator, for his invaluable guidance and support throughout this research. We also extend our appreciation to Universitas STEKOM for providing the necessary facilities and resources that made this study possible

REFERENCES

Benmoussa, O., & Jarašūnienė, A. (2022). Towards an Integrated Inventory Management Process. *Journal of Operations Management, Optimization and Decision Support (JOMODS)*, *2*(1), 36–48. https://doi.org/10.34874/imist.prsm/jomods-v2i1.32539

Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F. (2021). Machine Learning for Industrial Applications: A Comprehensive Literature Review. *Expert Systems with Applications*, *175*(1), 114820. https://doi.org/10.1016/j.eswa.2021.114820

Broby, D. (2022). The Use of Predictive Analytics in Finance. *The Journal of Finance and Data Science*, *8*, 145–161. https://doi.org/10.1016/j.jfds.2022.05.003

Chaudhary, K., Alam, M., Al-Rakhami, M. S., & Gumaei, A. (2021). Machine Learning-Based Mathematical Modelling for Prediction of Social Media Consumer Behavior Using Big Data Analytics. *Journal of Big Data*, *8*(1), 1–20. https://doi.org/10.1186/s40537-021-00466-2

Chen, G., Huang, L., Xiao, S., Zhang, C., & Zhao, H. (2024). Attending to Customer Attention: A Novel Deep Learning Method for Leveraging Multimodal Online Reviews to Enhance Sales Prediction. *Information Systems Research*, *35*(2), 829–849. https://doi.org/10.1287/isre.2021.0292

Dalzochio, J., Kunst, R., Pignaton, E., Binotto, A., Sanyal, S., Favilla, J., & Barbosa, J. (2020). Machine Learning and Reasoning for Predictive Maintenance in Industry 4.0: Current Status and Challenges. *Computers in Industry*, *123*(1), 103298.

https://doi.org/10.1016/j.compind.2020.103298

Dogan, A., & Birant, D. (2021). Machine Learning and Data Mining in Manufacturing. *Expert Systems with Applications*, *166*(1), 114060. https://doi.org/10.1016/j.eswa.2020.114060

Fernandes, M., Corchado, J. M., & Marreiros, G. (2022). Machine Learning Techniques Applied to Mechanical Fault Diagnosis and Fault Prognosis in the Context of Real Industrial Manufacturing Use-Cases: A Systematic Literature Review. *Applied Intelligence*, *52*(12), 14246–14280. https://doi.org/10.1007/s10489-022-03344-3

Giorgi Doborjginidze, Lily Petriashvili, & Mariam Inaishvili. (2021). Optimization of Inventory Management in the Supply Chain. *Journal of Communication and Computer*, *16*(1), 1–5.

https://doi.org/10.17265/1548-7709/2021.01.001

H, S. I. (2021). Machine learning: Algorithms, Real-World Applications and Research Directions. *SN Computer. Science*, *2*(3), 1–21. https://doi.org/10.1007/s42979-021-00592-x

Habel, J., Alavi, S., & Heinitz, N. (2024). Effective Implementation of Predictive Sales Analytics. *Journal of Marketing Research*, *61*(4), 718–741. https://doi.org/10.1177/00222437221151039

Kumar, S., Gopi, T., Harikeerthana, N., Gupta, M. K., Gaur, V., Krolczyk, G. M., & Wu, C. S. (2023). Machine Learning Techniques in Additive Manufacturing: A State of the Art Review on Design, Processes and Production Control. *Journal of Intelligent Manufacturing*, *34*(1), 21–55. https://doi.org/10.1007/s10845-022-02029-5

Lee, I., & Shin, Y. J. (2020). Machine Learning for Enterprises: Applications, Algorithm Selection, and Challenges. *Business Horizons*, *63*(2), 157–170.

https://doi.org/10.1016/j.bushor.2019.10.005

Martínez, A., Schmuck, C., Pereverzyev, S., Pirker, C., & Haltmeier, M. (2020). A Machine Learning Framework for Customer Purchase Prediction in the Non-Contractual Setting. *European Journal of Operational Research*, *281*(3), 588–596. https://doi.org/10.1016/j.ejor.2018.04.034

Moosavi, S. M., Jablonka, K. M., & Smit, B. (2020). The Role of Machine Learning in the Understanding and Design of Materials. *Journal of the American Chemical Society*, *142*(48), 20273–20287. https://doi.org/10.1021/jacs.0c09105

Orobia, L. A., Nakibuuka, J., Bananuka, J., & Akisimire, R. (2020). Inventory Management, Managerial Competence and Financial Performance of Small Businesses. *Journal of Accounting in Emerging Economies*, *10*(3), 379–398. https://doi.org/10.1108/jaee-07-2019-0147

Paleyes, A., Urma, R. G., & Lawrence, N. D. (2022). Challenges in Deploying Machine Learning: A Survey of Case Studies. *ACM Computing Surveys*, *55*(6), 1–29. https://doi.org/10.1145/3533378

Perez, H. D., Hubbs, C. D., Li, C., & Grossmann, I. E. (2021). Algorithmic Approaches to Inventory Management Optimization. *Processes*, *9*(1), 1–17. https://doi.org/10.3390/pr9010102

Qin, J., Hu, F., Liu, Y., Witherell, P., Wang, C. C. L., Rosen, D. W., Simpson, T. W., Lu, Y., & Tang, Q. (2022). Research and Application of Machine Learning for Additive Manufacturing. *Additive Manufacturing*, *52*(1), 102691. https://doi.org/10.1016/j.addma.2022.102691

Rai, R., Tiwari, M. K., Ivanov, D., & Dolgui, A. (2021). Machine Learning in Manufacturing and Industry 4.0 Applications. *International Journal of Production Research*, *59*(16), 4773–4778. https://doi.org/10.1080/00207543.2021.1956675

Rawat, S., Rawat, A., Kumar, D., & Sabitha, A. S. (2021). Application of Machine Learning and Data Visualization Techniques for Decision Support in the Insurance Sector. *International Journal of Information Management Data Insights*, *1*(2), 100012. https://doi.org/10.1016/j.jjimei.2021.100012

Shaikh, A. A., Lakshmi, K. S., Tongkachok, K., Alanya-Beltran, J., Ramirez-Asis, E., & Perez-Falcon, J. (2022). Empirical Analysis in Analysing the Major Factors of Machine Learning in Enhancing the E-Business through Structural Equation Modelling (SEM) Approach. *International Journal of System Assurance Engineering and Management*, *13*(1), 681–689. https://doi.org/10.1007/s13198-021-01590-1

Singh, N. (2023). AI in Inventory Management: Applications, Challenges, and Opportunities. *International Journal for Research in Applied Science and Engineering Technology*, *11*(11), 2049–2053. https://doi.org/10.22214/ijraset.2023.57010

Sistla, S. M. K., Krishnamoorthy, G., Jeyaraman, J., & Konidena, B. K. (2024). Machine Learning for Demand Forecasting in Manufacturing. *International Journal For Multidisciplinary Research*, *6*(1), 1–115. https://doi.org/10.36948/ijfmr.2024.v06i01.14204

Sohrabpour, V., Oghazi, P., Toorajipour, R., & Nazarpour, A. (2021). Export Sales Forecasting Using Artificial Intelligence. *Technological Forecasting and Social Change*, *163*(120480), 1–10. https://doi.org/10.1016/j.techfore.2020.120480

Studer, S., Bui, T. B., Drescher, C., Hanuschkin, A., Winkler, L., Peters, S., & Müller, K. R. (2021). Towards CRISP-ML(Q): A Machine Learning Process Model with Quality Assurance Methodology. *Machine Learning and Knowledge Extraction*, *3*(2), 392–413. https://doi.org/10.3390/make3020020

Taye, M. M. (2023). Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. *Computers*, *12*(5), 91. https://doi.org/10.3390/computers12050091

Wisesa, O., Adriansyah, A., & Khalaf, O. I. (2020). Prediction Analysis for Business To Business (B2B) Sales of Telecommunication Services Using Machine Learning Techniques. *Majlesi Journal of Electrical Engineering*, *14*(4), 145–153. https://doi.org/10.29252/mjee.14.4.145

Ye, Y., Suleiman, M. A., & Huo, B. (2022). Impact of Just-In-Time (JIT) on Supply Chain Disruption Risk: The Moderating Role of Supply Chain Centralization. *Industrial Management and Data Systems*, *122*(7), 1665–1685. https://doi.org/10.1108/imds-09-2021-0552

galley jmi 0909.docx

ORIGINALITY REPORT

5%	3%	4%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	P. S. Venkateswaran, Sriramkumar Mm. "chapter 19 Predictive Analytics", IGI Global, 2025 Publication	1%
2	Submitted to Nexford Learning Solutions Student Paper	1%
3	jmi.stekom.ac.id Internet Source	1%
4	so16.tci-thaijo.org Internet Source	1%
5	Rashmi Ranjan Panigrahi, Avinash K. Shrivastava, Sai Sudhakar Nudurupati. "Impact of inventory management on SME performance: asystematic review", International Journal of Productivity and Performance Management, 2024 Publication	1%
6	da Fonseca, Inês Maria Mendes. "The Analize and Optimization of Stock Management at a Portuguese Company in the Wholesale Sector: A Case Study", Universidade de Lisboa (Portugal), 2024 Publication	1%
7	ebin.pub Internet Source	1%