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| RESEARCH ARTICLE

Using Machine Learning Techniques to Forecast Mehram Company's Sales: A Case Study

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| ABSTRACT
Sales forecasting, situated at the intersection of art and science, is critical for inspiring managers toward achieving profitable outcomes. Its precision sustains production levels and capital and plays a pivotal role in the company's and its leaders' overall success and career progression. In the context of Mahram Food Industries, the challenge arises from diverse investor perspectives and the impactful nature of numerous variables. To address this, a new sales forecasting algorithm has been introduced to enhance accuracy. The aim is to predict future sales through a comprehensive approach, leveraging technical analysis, time series modeling, machine learning, neural networks, and random forest techniques. The research methodology integrates various advanced techniques to improve sales forecasting for Mahram Food Industries. Technical analysis, time series modeling, machine learning, neural networks, and random forest methods are combined to create a robust framework. The focus is on predicting sales for a future period within the artificial intelligence-based machine learning domain. The study employs metrics such as Mean Absolute Deviation (MAD), MAD Percentage (MADP), and Mean Squared Error (MSE) to evaluate and compare the performance of the proposed neural network against traditional methods like multiple variable regression and time series modeling. The study's results highlight the superior performance of the neural network in sales forecasting for Mahram Food Industries. The Mean Absolute Deviation (MAD) for the neural network is 28.33, outperforming multiple variable regression (28.54) and time series modeling (29.45). Additionally, the neural network demonstrates a better MAD Percentage (MADP) with a value of 10.2%, surpassing the values associated with multiple variable regression (10.35%) and time series modeling (10.30%). The Mean Squared Error (MSE) further confirms the neural network's superiority with a value of 6452 compared to 6472 and 7865 for multiple variable regression and time series modeling, respectively. In conclusion, the study showcases the effectiveness of integrating advanced techniques, particularly the neural network, in enhancing the accuracy of sales forecasting for Mahram Food Industries. The comprehensive approach, combining technical analysis, time series modeling, machine learning, neural networks, and random forest, is a valuable strategy for predicting future sales. The superior performance of the neural network, as evidenced by lower MAD, MADP, and MSE values, suggests its potential for guiding informed decision-making in goal setting, hiring, budgeting, and other critical aspects of business management.

| KEYWORDS

Computational Social Science, Machine Learning, Data Analysis, Sales Forecasting, artificial neural networks, hybrid optimization, time series modelling, Decision Science.

| ARTICLE INFORMATION

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1. Introduction

Sales forecasting is a critical aspect of business management, particularly in the food industry, where demand can fluctuate significantly due to various factors (Adetunji et al., 2022). Accurate sales forecasting can guide decision-making in production planning, inventory management, budgeting, and strategic growth. However, traditional sales forecasting methods, such as time series modeling and multiple variable regression, often fall short of capturing the complex, nonlinear relationships inherent in sales data (Ye et al., 2024).

This study presents a novel approach to sales forecasting for Mahram Food Industries. While previous studies have explored sales forecasting using various methods, none have applied the exact combination of techniques used in this study (Mariani et al., 2024). The critical differentiator is integrating technical analysis, time series modeling, machine learning, neural networks, and Random Forest techniques into a comprehensive framework for sales prediction. This multi-faceted approach allows the model to capture complex, nonlinear relationships in sales data more effectively than traditional methods (Chen et al., 2023).

Furthermore, this study is unique in its application to a real-world business context. To the best of our knowledge, no previous study has applied these exact methods to predict sales for a specific company, making this study a pioneering effort in this domain (Josso et al., 2023). The superior performance of the neural network compared to ARMA and multivariable regression models is evident, as indicated by the lower Mean Absolute Deviation (MAD), MAD Percentage (MADP), and Mean Squared Error (MSE) values (George Davies et al., 2023).

In addition, the study goes beyond merely building and testing the model. It also provides valuable insights into influential features, offers interpretability to facilitate stakeholder understanding, and addresses issues such as overfitting and model complexity. These aspects further set this study apart from previous research.

2. Mahram Food Industries Overview

Mahram Food Industries, a public joint stock company established in 1970, commenced operations in 1973 at Alborz Industrial City, Qazvin, Iran. Initially producing six products, with mayonnaise as its flagship item, Mahram has evolved into one of Iran's leading and trustworthy food manufacturers, boasting a diverse product range. The factory spans 11,000 square meters, employs over 370 personnel, and operates with separate production facilities, achieving a production capacity of 267 tons.

2.1. Product Portfolio

Mahram's product lineup encompasses a variety of items, including mayonnaise, flavored mayonnaises, sauces, dressings, ketchup, pastes, mustard, honey, olives, jams, pickles, juices, and canned products.

2.2. Certifications and Achievements

In recent years, Mahram Food Industries has aligned with international standards, obtaining certifications such as ISO 9001/2000 and HACCP. The company has adapted to global market shifts, garnering recognition through certifications and awards.

2.3. Corporate Strategy and Values

Dedicated to quality assurance and customer satisfaction, Mahram emphasizes employee commitment to the motto "the customer is always right." Strategic efforts involve continuous improvement, environmental awareness, and adherence to internal structures.

2.4. Product Innovation and Market Impact

In 2006, Mahram strategically introduced a diverse product range with new packaging designs, incorporating industrial design principles for user-friendly experiences. The subsequent years saw the introduction of new products like Olivier sauce, an expansion of mayonnaise sauces, and the reintroduction of ketchup in redesigned packaging.

Table 1:
Overview of Mahram

General Overview	
Company:	Mahram Manufacturing Company
Symbol:	Ghamehra
Establishment Year:	1970
Initial Launch Year:	1996
Major Shareholders:	11% held by natural individuals
Activity Area:	Food and Beverage Products, excluding sugar and candy
Factors Influencing Sales	
Raw Material Sourcing:	Procurement of quality raw materials at suitable prices.
Metal Packaging:	Acquisition of metal packaging materials.
Currency Fluctuations:	Impact on production costs due to currency fluctuations.
Significant Expenses	
General and Administrative:	General and administrative expenses.
Inflation:	Economic inflation and decreased public purchasing power.
Production Costs:	We are sourcing raw materials and metal packaging.
Profitability Factors	
New Production Lines:	Financial expenses may increase until new production lines become operational.
Packaging Challenges:	Addressing the food industry's lack of attention to product packaging.
Supply Chain Management:	Emphasizing professional supply chain management to prevent product returns.
Sales Settlement Method:	Importance of cash basis sales to mitigate provisions for receivables.

3. Theoretical Foundations of the Project

3.1. Sales Forecasting Overview

Sales forecasting involves predicting future revenue generated from sales based on available data, industry trends, and current sales performance. It is a guideline for businesses to adjust operations rather than offer absolute predictions. Distinct from sales goalsetting, forecasting estimates what will happen, irrespective of objectives (Najjarzadeh Sharifiabad, 2014).

3.2. Key Aspects of Sales Forecasting

Sales forecasting is a detailed report predicting a seller, team, or company's sales on a weekly, monthly, quarterly, or yearly basis. Managers assess closing rates, complementary sales, upselling, and organizational sales projects using past performance data, industry trends, and current sales (Josso et al., 2023).

Table 2:
Common Factors Affecting Sales Forecasting

Internal Factors	
Historical Data:	Analyzing past sales records reveals patterns, trends, and fluctuations, aiding in forecasting future sales.
Marketing and Advertising Strategies:	Effective campaigns influence customer awareness and behavior, impacting sales outcomes.
Pricing Strategy:	Adjustments in pricing significantly influence sales volume and overall revenue, necessitating an accurate understanding of customer response.
Product Mix:	Introducing or modifying products can shift customer preferences, requiring evaluating the impact on sales forecasts.
Distribution Channels:	Efficient distribution processes ensure prompt product availability, positively affecting sales, while disruptions can lead to pessimistic forecasts.
Seasonality and Cyclical Patterns:	Identifying and accounting for distinct sales patterns based on seasons or economic cycles is crucial for accurate forecasts.
Internal Factors:	Changes within the company, including management shifts, organizational alterations, or operational modifications, can influence sales forecasts, decision-making, and resource allocation.
External Factors Impacting Sales	
Competitive Changes:	Competitors' actions, such as price reductions, can necessitate adjustments to maintain business. The exit of a competitor may lead to increased demand.
Economic Conditions:	Strong economies promote buyer investment, while weak economies result in longer sales cycles.
Market Changes:	A comprehensive understanding of customer predictions is crucial for businesses like hotel consulting.
Industry Changes:	High demand for complementary products positively influences sales.
Legal Changes:	New laws can impact demand positively or negatively.
Product Changes:	Introducing high-demand products or pricing models affects sales dynamics.
Seasonal Fluctuations:	Customer buying tendencies during specific times of the year.
Market Conditions:	Economic landscape, industry trends, and consumer behavior shifts impact forecasts.
Competitor Analysis:	Analyzing competitors' strategies aids in anticipating market dynamics.
Market Share:	Changes in market share directly affect sales projections.
Industry Regulations:	Compliance changes can influence production processes and consumer demand.
Technological Advancements:	Innovations may alter customer preferences and behaviors, affecting forecasts.
Customer Feedback:	Monitoring feedback provides insights into potential sales fluctuations.
Sales Forecasting Methods	
Historical based Forecasting:	Quick estimation based on past results.
Excel-based Sales Forecasting Patterns:	Using Microsoft Excel for customized formulas and predictions.
Regression Analysis for Sales Forecasting:	Analytical forecasting using complex mathematical equations.
Sales Forecasting with Sales Pipeline:	Considers various stages of the sales process for each opportunity.
Sales Forecasting using Sales Cycle:	Predicts sales opportunity closure based on the duration of the sales cycle.
Intuitive or Gut Feeling Forecasting:	Relies on sales representatives' instincts and experience.
Qualitative Sales Forecasting:	Expert-based forecasting in the absence of statistical records.
Using Machine Learning for Sales Forecasting:	Cutting-edge technology predicts production and sales based on data and market information in various industries.

4. Machine Learning Processes

Machine learning involves several key processes. In the initial data collection and preparation phase, the focus is on obtaining relevant knowledge. The collected data is then divided into two groups – one for training the system and the other for testing. Ensuring the representativeness of the selected data is crucial, with considerations such as age groups for image recognition systems. The second step is model selection and training, where various algorithms are employed based on their suitability for solving specific problems. The model evaluation uses trained data to assess the system's decision-making capabilities (Mariani et al., 2024).

Tuning and predicting hyperparameters are crucial in enhancing the model's performance. Hyperparameters, which the model cannot estimate itself, are examined to refine the system. Machine learning has applications in various domains (Ye et al., 2024). Sales forecasting utilizes historical data to optimize inventory, production, and marketing strategies. Decision support leverages machine learning's high accuracy to aid timely decision-making based on data and information. Recommender search engines predict user preferences in online stores, offering personalized recommendations. Customer information modeling utilizes historical data to identify factors influencing customer purchases or retention (Shi et al., 2024).

Dynamic pricing tactics examine various factors impacting product sales for optimal pricing strategies. Market research and customer segmentation employ machine learning to identify customer personality traits for targeted marketing. Image recognition and classification have extensive applications, from identifying video content to security and commercial uses. Information extraction from big data enhances efficiency by identifying similar information structures. Recommendation systems offer personalized product or content suggestions based on customer behavior, while sentiment analysis analyzes feedback to understand customer opinions (Chung et al., 2023).

Fraud detection uses machine learning to identify fraudulent activities, transactions, or accounts for financial protection. Image and video analysis employ computer vision for tasks like object detection, facial recognition, and quality control. Natural Language Processing (NLP) analyzes and understands human language for functions such as chatbots, language translation, text summarization, and sentiment analysis. Machine learning methods encompass supervised, unsupervised, semi-supervised, and reinforcement learning, each serving specific purposes.

Data mining, a component of the Knowledge Discovery in Databases (KDD) process, applies machine learning techniques to big data for exploration, analysis, and information extraction. The process involves data selection, preprocessing, transformation, mining, and evaluation, ensuring accurate and meaningful insights are derived from vast datasets (Adetunji et al., 2022).

4.1. Learning models

Machine learning models depend heavily on the data's characteristics, necessitating understanding the problem category. There are two main types of learning models in machine learning:

1. **Supervised Learning:** Supervised learning involves training a model to learn the relationship between input data and corresponding target labels. The algorithm is provided with a dataset containing pairs of input features and correct output labels. The objective is to establish a mapping function from inputs to outputs, enabling accurate predictions on new, unseen data. Supervised learning applications include image classification, speech recognition, natural language processing, medical diagnosis, and more. The effectiveness of supervised learning relies on the quality and quantity of training data and the selection of an appropriate model and hyperparameters (Ye et al., 2024).
2. **Unsupervised Learning:** Unsupervised learning focuses on finding patterns, structures, or relationships in a dataset without explicit target labels. Unlike supervised learning, it operates on unlabeled data and aims to uncover hidden patterns, group similar data points, or reduce dimensionality for further analysis. Unsupervised learning does not provide direct answers or labels; instead, it seeks to discover underlying structures that guide subsequent analysis or decision-making. The success of unsupervised learning techniques is contingent on the data quality and the proper choice of algorithms and parameters (Mariani et al., 2023).

5. Internship

5.1. Description of my job duty

During my 6month internship at Datis Pardaz Kavir, I focused on market analysis and sales forecasting to assist companies in improving their sales strategies. Sales forecasting is critical for optimizing product production and avoiding financial losses due to excess inventory. Datis Pardaz Kavir specializes in performance analysis and collaborates with companies like Mahram, offering outsourced expertise in market analysis and sales forecasting. The process involves data collection, analysis, consideration of external factors, segmentation, forecasting models, and iterative feedback, aiming to provide actionable recommendations for enhanced sales performance. My previous experience at Mahram in the marketing department facilitated collaboration, and their willingness to share data contributed to a comprehensive analysis. This collaborative approach resulted in valuable insights and optimized sales strategies for Mahram Company.

5.2. Steps after data collection

During my internship at Datis Pardaz Kavir, I focused on market analysis and sales forecasting to assist companies in improving sales strategies. The process involves data collection, cleaning, exploratory data analysis, time series analysis, statistical techniques, machine learning, segmentation analysis, causal analysis, validation, and continuous improvement. Market trends, external factors, and economic indicators are considered in the third step. Segmentation is crucial in the FastMoving Consumer Goods (FMCG) market, allowing tailored approaches to diverse consumer groups. Forecasting models, including time series, regression, and machine learning, are used to predict future sales. Recommendations and strategies are based on data analysis, identifying opportunities, competitor analysis, segmentation, and personalization. Strategies may include optimized pricing, channel optimization, promotional campaigns, customer engagement, and data-driven insights. This comprehensive approach aims to help companies optimize sales performance and make informed decisions for sustainable growth.

6. Methodology

6.1. Introduction to Data Implementation Method

6.1.1. Based on Random Forest and Neural network for Mahram company

Designing Neural Network and Random Forest for Sales Prediction

In this section, we explore neural networks' role in sales prediction. Neural networks comprising interconnected neurons forming nonlinear graphs capture data trends(Seifi Salami et al., 2015). Neurons tailor optimal lines during training, collectively shaping a comprehensive nonlinear graph. Multiple layers prove useful for input interactions, addressing potential overfitting in single-layer networks. The NARX model incorporates external inputs and past sales for robust projections (George Davies et al., 2023). The architecture equips Mahram with a powerful predictive sales analysis tool, emphasizing model configuration considerations (Adetunji et al., 2022).

The learning algorithm, Back Propagation, refines predictions iteratively. This algorithm minimizes discrepancies between projected and actual outcomes, which is vital for accurate projections. Supervised learning and error signal propagation characterize 'Back Propagation,' facilitating the network's approximation of complex relationships. Its selection aligns with established knowledge, ensuring accurate and insightful projections. The algorithm is a dynamic instrument for Mahram's strategic planning, empowering informed decision-making and facilitating strategic growth (Chung et al., 2023).

6.1.2. Activation Functions

Activation functions shape neural network behavior. Linear functions in input/output layers establish direct relationships. The sigmoid function in hidden layers introduces nonlinearity, enabling complex pattern capture (Chen et al., 2023).

6.1.3. Competing Models and Evaluation Metrics

Neural network performance is compared with ARMA time series models and multiple variable regression techniques. Evaluation metrics include Mean Squared Error (MSE) and Mean Absolute Deviation (MAD). MSE and MAD formulas are applied to both outputs, providing insights into predictive accuracy.

6.2. Random Forest

The Random Forest algorithm enhances predictive accuracy in advanced machine learning, especially in sales forecasting. Random Forest excels in classification and regression tasks as an ensemble learning method. Comprising multiple decision trees, each trained on a distinct subset of data, it addresses overfitting through diversity. Random feature selection during tree construction mitigates dominance, and predictions harmonize through voting or averaging (Josso et al., 2023).

One of its remarkable features is resistance to overfitting, thanks to ensemble diversity and random feature selection. Random Forests also unveil the importance of features, providing insights into influential variables. This algorithm is a potent ally in sales forecasting, offering refined predictions, resistance to overfitting, and valuable insights into data patterns (Mariani et al., 2024).
Advantages and Disadvantages of Random Forest (Ye et al., 2024; Mariani et al., 2024; Josso et al., 2023):

Advantages:

1. Accuracy: High predictive accuracy due to the nature of the ensemble.
2. Robustness: Handles outliers and noisy data well.
3. Nonlinearity: Effectively captures nonlinear relationships.
4. Feature Importance: Provides insights into influential features.
5. Less Overfitting: Lower susceptibility compared to single decision trees.

Disadvantages:

1. Complexity: Model complexity increases with numerous trees.

2. Computation Time: Training multiple trees can be computationally intensive.
3. Interpretability: Internal workings are less interpretable compared to simpler models.

In summary, Random Forest is a versatile algorithm that is valuable for accurate sales forecasting, particularly with complex relationships and large datasets.

7. Data analyze

In this chapter, the exploration delves into the world of data analysis, embodying the role of a detective scrutinizing evidence to validate or challenge theories. In contemporary research, data analysis is pivotal, mainly when working with information directly obtained from subjects. It serves as a transformative process, converting raw data into understandable insights. The systematic journey encompasses data collection, organization, the creation of neural networks, and result verification. This meticulous approach converts raw data into meaningful knowledge, serving as a guiding beacon for research endeavors.

7.1. Neural Network Design

Our goal is to predict future high and low sales. To achieve this, we set up a neural network with two outputs—one for increased and one for low sales. This network uses past data to foresee future sales like a wizard. We design it as a Nonlinear Autoregressive model with exogenous input (NARX), which means it considers data from a previous time to predict future sales (Seifi Salami et al., 2015).

We picked the BackPropagation Neural Network (BPNN) algorithm. It is like a skilled tutor helping the network learn. We use sigmoid buttons for the hidden parts and linear buttons for the input and output parts. When we are done, you can imagine our neural network like a blueprint—a visual representation made with MATLAB software- bringing our design to life(George Davies et al., 2023).

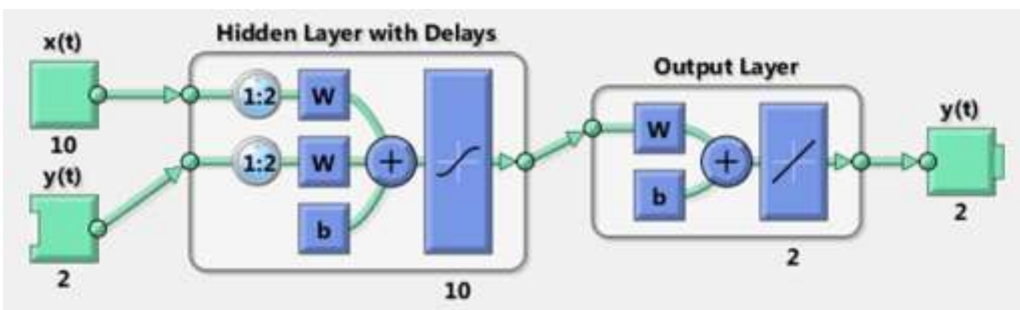

Figure 1:
Neural network constructed using MATLAB software.

7.2. Execution of the Neural Network Algorithm

Following the construction of the neural network, the next step involves training it. The available data from each database is utilized to achieve this. Table (3) illustrates the data allocation process for the neural network databases.

Table 3:
Data Allocation for the Neural Network in the Database

Database		Training Data	Validation Data	Testing Data	Total
Company:	Mehram Food Industry	945	185	185	1315

Once the constructed neural network is trained using validation data, it undergoes evaluation and validation. Subsequently, its performance is examined using the testing data. The outcomes of high and low sales prediction for the Mehram Food Industry, as generated by the neural network, are depicted in Figures (2) and (3).

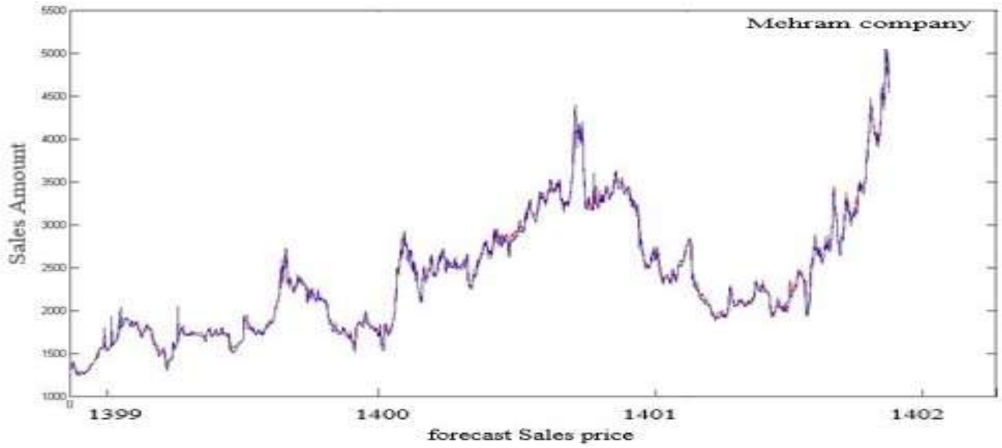

Figure 2:
Predicted and Actual Low Sales Volume for Mehram Food Industry

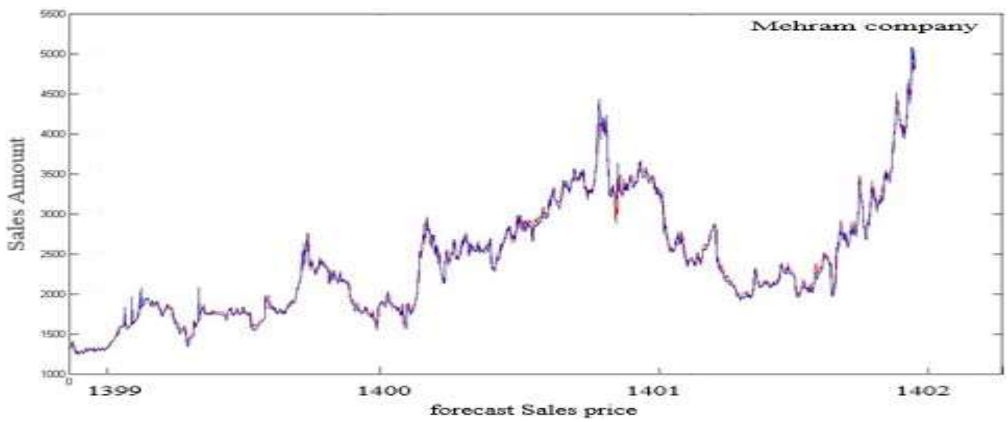

Figure 3:
Predicted and Actual High Sales Volume for Mehram Food Industry

8. Comparing the Accuracy of Models:
Having visually witnessed the effectiveness of the neural network in nonlinear sales forecasting for the Mehram Food Industry, the next step involves comparing its performance with rival algorithms and models like time series ARMA and multivariable regression. Table (4) briefly presents these comparative results for the Mehram Food Industry's stocks.

Table 4:
Comparison of Results Obtained from Neural Network and Rival Models for Mehram Food Industry

Model	MADP	MAD	MSE
Neural Network	10.2%	28.33	6452
ARMA	10.35%	29.45	7865
Multivariable Regression	10.30%	28.37	6472

The superior performance of the neural network compared to ARMA and multivariable regression models is evident in the table. As indicated in Table (4), the neural network achieved a MAD of 28.33 for Mehram Food Industry's stocks, surpassing the values of multivariable regression with 28.54 and the time series model with 29.45. Additionally, its MADP value of 10.2% showcases better performance than multivariable regression and time series models, which recorded 10.35% and 10.30%, respectively. The obtained MSE value of 6452 for the neural network further confirms its superior performance over multivariable regression (6472) and time series (7865).

9. Conclusions

9.1. Monthly Performance of Mehram Food Industry

In the month of Mehr (September-October) 1401, the Mehram Food Industry, represented by the symbol "GHAMRAH," generated approximately 175 billion Tomans in revenue. This figure signifies a 12% decrease compared to the previous month and an 80% growth compared to last year. During this month, the symbol " GHAMRAHI " managed to sell over 3000 tons of its products, indicating a 12% reduction in sales compared to the previous month.

Within its product range, the "Sauce" group stood out as the top-selling category, contributing to a remarkable revenue of 147 billion Tomans. Notably, the sales rate of the flagship product of" GHAMRAHI, "namely the "Sauce" group, reached 63.25 million Tomans per ton in the month of Mehr. This demonstrates a 2% increase in sales rate compared to the previous month.
It is anticipated that the company will experience exceptional sales performance in the year 1402 (2023).

Table 5:
Initial Assumptions for Predicting Sales of Mehram Company Over Analyzed Fiscal Years

Assumptions	Unit	1399	1400	1401	1402(forecast)
| Exchange Rate (Dollar)	Rials	16,500	24,500	28,500	450,000
Food Industry Inflation Rate	%	20%	30%	50%	50%
Overall Inflation Rate	%	35%	40%	40%	40%
Wage Rate Increment	%	45%	50%	57%	27%
Utilization of New Project	%	10%	18%	33%	70%
Gross Profit Margin for Products	%	7%	9%	12%	20%
Energy Cost Escalation	%	20%	20%	30%	50%

Table 6:
Financial Statements of Company Mehran during Analyzed Financial Years and Forecasted Sales Volume

Income Statement	Unit	1399	1400	1401	1402(Forecast)
Sales Revenue	Million Rials	7,921,229	11,472,840	22,277,752	37,108,045
Cost of Goods Sold	Million Rials	6,269,166	8,865,425	16,306,404	29,733,704
Net Income	Million Rials	1,652,063	2,607,415	5,971,348	7,375,341
Selling and Administrative Expenses	Million Rials	757,416	1,270,080	1,772,216	2,056,384
Operating Profit	Million Rials	894,647	1,337,335	4,199,132	5,318,957
Financial Expenses	Million Rials	109,322	282,858	776,251	776,251
Income Before Taxes	Million Rials	1,005,784	1,103,462	3,422,880	4,642,663
Taxes	Million Rials	166,283	3,414	289,765	4,249,637
Net Income	Million Rials	839,501	1,010,048	3,133,115	4,249,637
Capital	Million Rials	1,900,000	1,900,000	1,900,000	1,900,000

The study of the Mehram Food Industry's performance revealed essential insights for short-term and long-term planning decisions. In SeptemberOctober 1401, there were contrasting trends in revenue and sales.

During this crucial month, the company achieved around 175 billion Tomans in revenue under the "GHAMRAH." While this was 12% less than the previous month, it was 80% higher than the same time last year. This shows the interaction of internal factors and market forces.

Looking at sales volume, despite a 12% drop from the previous month, the company still sold over 3000 tons of products under "GHAMRAH," showing consistent momentum even with fluctuations.

The "Sauce" category was the top seller, bringing 147 billion Tomans. Notably, the flagship product "Sauce" sold at an impressive 63.25 million Tomans per ton in Mehr. This was a 2% increase from the previous month, highlighting effective product positioning.

Looking ahead, the year 1402 (2023) holds promise for outstanding sales. However, making these projections a reality requires thoughtful planning, alignment, and adaptability.

Table (5) outlines assumptions for projections across years, considering variables like exchange rates, inflation, and new projects—these guide strategic decisions amid a volatile market.

This study shows that the Mehram Food Industry, symbol "GHAMRAH," navigates complex territory where revenue, sales, and projections intertwine. It is where informed decisions meet future goals. With insights from data and foresight, the company moves ahead with growth and success.

The attached tables provide more details on financial assumptions and statements. This work highlights the connection between data analysis, market trends, and intelligent strategy, shaping the Mehram Food Industry's story of resilience and progress in a dynamic business world.

9.2. Lessons Learned

1. **Data's Role in DecisionMaking:** The project highlighted the pivotal role of data in informed decision-making. By leveraging historical sales data, the project showcased how predictive models can provide valuable insights to guide business strategies.
2. **Model Building and Tuning:** Building and tuning machine learning models was a significant learning experience. This included selecting appropriate algorithms, designing neural network architectures, and finetuning hyperparameters for optimal performance.
3. **Feature Importance:** The project revealed which variables significantly influence sales predictions through feature importance analysis. This knowledge can guide resource allocation and strategic focus.
4. **Algorithm Selection:** Exploring algorithms like neural networks and Random Forest showcased how different approaches can yield distinct insights. This reinforces the importance of selecting the correct algorithm for the specific task.
5. **Business Understanding:** The project emphasized the need to understand the business context deeply. Accurate sales predictions require domain knowledge to effectively interpret and apply the model's outputs.
6. **Model Interpretability:** The journey toward model interpretability underscored the importance of explaining complex predictions to stakeholders. This fosters trust and facilitates decision-making.
7. **Data Preprocessing:** The significance of data preprocessing became apparent, as clean and organized data directly impacted model performance. Dealing with missing values, outliers, and scaling were crucial steps.
8. **Continuous Improvement:** The project highlighted the iterative nature of data science. Models should be updated, retrained, and finetuned as new data becomes available to maintain relevancy.
9. **Interdisciplinary Collaboration:** Collaborating with different teams, such as domain experts, IT, and business stakeholders, showcased how diverse perspectives enrich the project's outcome.
10. **Model Deployment:** Deploying a model in real-world scenarios involves considerations beyond just building a model. This includes scalability, real-time predictions, and monitoring.
11. **Impact of External Factors:** The project demonstrated how external factors like economic trends, seasonal patterns, and marketing campaigns can impact sales, reinforcing the need to incorporate these variables into predictions.
12. **Business Strategy Alignment:** The project reinforced the importance of aligning data science efforts with overarching business goals. Models should provide actionable insights that support business strategies.
13. **Predictive Analytics Value:** The project underscored the value of predictive analytics in enhancing decision-making. Predictions can guide inventory management, marketing efforts, and resource allocation.
14. **Ethical Considerations:** While not explicitly mentioned, ethical considerations related to data privacy, bias, and responsible AI deployment are crucial lessons to internalize when working with data-driven projects.
15. **Learning from Mistakes:** The project likely involved trial and error, highlighting the value of learning from mistakes and failures to refine and improve the model.

In summary, this project offered insights into sales prediction and the broader landscape of data science, machine learning, and their applications in business decision-making. It emphasized the need for a holistic approach considering technical, business, and ethical aspects.

9.3. Future research and limitation:

This study embarked on leveraging machine learning techniques to enhance the accuracy of sales forecasting for Mehram Company. The primary objective was to identify which algorithms and models could most effectively predict future sales trends based on historical data, thereby aiding in more informed decision-making processes.

Our investigation revealed that certain machine learning models, particularly those incorporating time series analysis and ensemble methods, demonstrated significant potential in forecasting sales with a high degree of accuracy. The application of these models to Mehram's historical sales data enabled the derivation of insightful predictions that could facilitate strategic planning and operational adjustments.

The study, while comprehensive in its application of machine learning techniques, was not without limitations. One of the primary constraints was the reliance on historical sales data, which may not fully encapsulate the dynamics of future market conditions or unforeseen economic factors. Additionally, the focus on a singular company's dataset limits the generalizability of our findings across different industries or market environments. The complexity inherent in some of the more sophisticated models also poses challenges in terms of interpretability and practical application by business stakeholders without technical expertise.

Future research endeavors could significantly benefit from incorporating a broader array of data sources, including market trends, consumer behavior analytics, and economic indicators, to enhance the models' predictive capabilities. Exploring dynamic model updating mechanisms would ensure the models' adaptability to real-time market changes. Moreover, extending the research to cover multiple industries could help validate the findings' universality and applicability. Future studies should also aim to simplify model interpretability without compromising predictive power, making the insights more accessible to non-technical decision-makers. Lastly, establishing a feedback loop where ongoing sales outcomes continually refine and optimize the forecasting models could solidify their relevance and accuracy over time.

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References

[1] Adetunji, A. B., Akande, O. N., Ajala, F. A., Oyewo, O., Akande, Y. F., & Oluwadara, G. (2022). House Price Prediction using Random Forest Machine Learning Technique. *Procedia Computer Science*, *199*, 806-813. https://doi.org/10.1016/j.procs.2022.01.100

[2] Askarzadeh, A., Yung, K., & Najand, M. (2023). *Managerial sentiment and predicted and opportunistic special items*. *Journal of Corporate Accounting & Finance*. DOI: 10.1002/jcaf.23456.

[3] Ashrafimoghari, V., Gürkan, N., & Suchow, J. W. (2024). *Evaluating Large Language Models on the GMAT: Implications for the Future of Business Education*. *Applied Research in Sports Management*, 4(2)**,** 87-101. Retrieved from [1](https://arxiv.org/abs/2401.02985)

[4] Chang, L., Jie, Y., & Feiyue, G. (2022). Forecasting the Market with Machine Learning Algorithms: An Application of NMCBERTLSTMDQNX Algorithm in Quantitative Trading. *ACM Transactions on Knowledge Discovery from Data (TKDD*).

[5] Chen, S., Ke, S., Han, S., Gupta, S., & Sivarajah, U. (2023). Which product description phrases affect sales forecasting? An explainable AI framework by integrating WaveNet neural network models with multiple regression. *Decision Support Systems*, *176*, 114065. https://doi.org/10.1016/j.dss.2023.114065

[6] Chung, D., Jeong, P., Kwon, D., & Han, H. (2023). Technology acceptance prediction of robo-advisors by machine learning. *Intelligent Systems With Applications, 18*, 200197. https://doi.org/10.1016/j.iswa.2023.200197

[7] Esfahani, M. M., & Sadati, H. (2021). fNIRS Signals Classification with Ensemble Learning and Adaptive Neuro-Fuzzy Inference System. In Proceedings of the 7th International Conference on Signal Processing and Intelligent Systems (ICSPIS) (pp. Page Numbers). IEEE. DOI: 10.1109/ICSPIS54653.2021.9729388

[8] Fahimi, M. S., & Rastegarpour, M. (2017). A Study of Various Prediction Methods for New Product Sales. *Third National Conference on Modern Approaches in Computer and Electrical Engineering*.

[9] Fan, Z. P., Che, Y. J., & Chen, Z. Y. (2017). Product Sales Forecasting using Online Reviews and Historic Sales Data: A Method Combining the Bass Model and Sentiment Analysis. *Journal of Business Research*.

[10] George Davies, W., Babamohammadi, S., Yang, Y., & Masoudi Soltani, S. (2023). The rise of the machines: A state-of-the-art technical review on process modeling and machine learning within hydrogen production with carbon capture. *Gas Science and Engineering*, p. 118, 205104. https://doi.org/10.1016/j.jgsce.2023.205104

[11] Josso, P., Hall, A., Williams, C., Le Bas, T., Lusty, P., & Murton, B. (2023). Application of random-forest machine learning algorithm for mineral predictive mapping of Fe-Mn crusts in the World Ocean. *Ore Geology Reviews*, p. 162, 105671. https://doi.org/10.1016/j.oregeorev.2023.105671

[12] Jamali, H., Dascalu, S. M., & Harris Jr, F. C**.** (2021). *Fostering Joint Innovation: A Global Online Platform for Ideas Sharing and Collaboration*. *Applied Research in Sports Management*, 4(2)**,** 87-101. Retrieved from (https://sid.ir/paper/356089/fa).

[13] Li, D., Lin, K., Li, X., Liao, J., Du, R., Chen, D., & Madden, A. (2022). Improved sales time series predictions using deep neural networks with spatiotemporal dynamic pattern acquisition mechanism. *Information Processing & Management, 59*(4), 102987. https://doi.org/10.1016/j.ipm.2022.102987

[14] Liu, Y., & Yang, S. (2022). Application of Decision Tree-Based Classification Algorithm on Content Marketing. *Journal of Mathematics.*

[15] Maddah, N., & Roghanian, E. (2021). Data-driven performance management of business units using process mining and DEA: case study of an Iranian chain store. *International Journal of Productivity and Performance Management,* [Volume]([Issue]), Article publication date: 23 July 2021. https://doi.org/10.1108/IJPPM-10-2020-0562

[16] Maydanchi, M., Ziaei, A., Basiri, M., Norouzi Azad, A., Pouya, S., Ziaei, M., Haji, F., & Sargolzaei, S. (2023). Comparative Study of Decision Tree, AdaBoost, Random Forest, Naïve Bayes, KNN, and Perceptron for Heart Disease Prediction. In Proceedings of SoutheastCon 2023 (pp. 204-208). IEEE. https://doi.org/10.1109/SoutheastCon51012.2023.10115189

[17] Mariani, C., Navrotska, Y., & Mancini, M. (2023). Unsupervised machine learning for project stakeholder classification: Benefits and limitations. *Project Leadership and Society, 4*, 100093. https://doi.org/10.1016/j.plas.2023.100093

[18] Najjarzadeh Sharifabad, A. (2014). Sales Prediction using Neural Networks. *First National Conference on Applied Economics and Management*.

[19] Pan, X. (2020). Application of Machine Learning Algorithm in Human Resource Recommendation: From Traditional Machine Learning Algorithm to AutoML. *5th International Conference on Social Sciences and Economic Development* (ICSSED 2020).

[20] Range, D., David, D., Kovalsky, S. Z., et al. (2020). Application of a Machine Learning Algorithm to Predict Malignancy in Thyroid Cytopathology. *Cancer Cytopathology*.

[21] Seifi Salami, T., Esfahani, N., & Honari, H. (2015). The Effect of Financial Support on the Customer-Based Brand Equity of Mahram (Case Study: Spectators of Mahram Basketball Team Matches). *Applied Research in Sports Management*, 4(2), 87-101. Retrieved from https://sid.ir/paper/356089/fa

[22] Shi, T., Zhao, F., Zhou, H., & Qi, C. (2024). Research on intelligent energy management method of multifunctional fusion electric vehicle charging station based on machine learning. *Electric Power Systems Research*, p. 229, 110037. https://doi.org/10.1016/j.epsr.2023.110037

[23] Ye, M., Wang, Q., Yan, L., Wei, M., Lian, G., Zhao, K., & Zhu, W. (2024). Enhanced robust capacity estimation of lithium-ion batteries with unlabeled dataset and semi-supervised machine learning. *Expert Systems With Applications*, p. 238, 121892. https://doi.org/10.1016/j.eswa.2023.121892

[24] Yuan, H., Xu, W., Li, Q., & Lau, R. (2018). Topic Sentiment Mining for Sales Performance Prediction in E-commerce. *Annals of Operations Research*.