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MACHINE LEARNING TO MANAGING MANUFACTURING COSTS AND REDUCE COSTS- AN APPLIED STUDY IN THE GENERAL COMPANY FOR FOOD PRODUCTS

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Abstract:
The food industry sector is facing increasing challenges due to rising production costs and growing local and global competition, which necessitates the search for modern approaches to cost management and operational efficiency. This study aims to examine the role of machine learning (ML) techniques in estimating and managing manufacturing costs by developing predictive models based on actual company data that contribute to cost reduction and improved resource utilization. The research adopts both the descriptive analytical and experimental methodologies, applied to the General Company for Food Products in Iraq. Historical data were collected regarding raw material costs, energy consumption, labor expenses, maintenance costs, and actual production over a defined time period. Subsequently, ML algorithms such as multiple linear regression, decision trees, and artificial neural networks were employed to construct models capable of forecasting future costs and identifying the most influential cost drivers. The findings revealed that the application of ML techniques provides a high predictive ability that significantly surpasses traditional cost estimation methods. Moreover, these techniques facilitate the identification and reduction of waste sources, resulting in noticeable cost savings. This, in turn, enhances the company's competitiveness by reducing overall production costs and improving operational efficiency. The study recommends adopting intelligent cost management systems in the Iraqi food industry, while simultaneously developing digital infrastructure and training human resources to utilize artificial intelligence tools effectively. Such measures are expected to support sustainable industrial development and strengthen competitiveness in an increasingly demanding market environment.

KEYWORDS: Machine Learning; Cost Management; Manufacturing Costs; Food Products ;Cost reduce.

I. INTRODUCTION

In recent decades, the industrial business environment has witnessed rapid transformations characterized by intensified competition, rising production costs, and increasing market pressures to deliver high-quality products at reduced costs. This has heightened the need for adopting advanced tools and techniques that enable companies to analyze and manage manufacturing costs more efficiently, thereby enhancing their ability to make precise strategic decisions in pricing, production planning, and profitability. Against this backdrop, machine learning (ML) has emerged as one of the most prominent modern techniques in the field of industrial data analysis and cost estimation. These techniques facilitate the extraction and analysis of large volumes of data and provide accurate predictions that support managerial decision-making.

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Numerous recent studies have demonstrated the effectiveness of machine learning in various fields, including supply chain optimization, waste reduction, cost estimation, and operational cost reduction. Among these is the study by Chen et al. [1] which applied linear and nonlinear predictive algorithms to analyze manufacturing costs, and the study by Ali & Zhang [2] which highlighted the role of neural networks in improving cost estimation accuracy in the food industry. Nevertheless, a clear gap remains in applying these methods within the industrial sector of developing countries, particularly in Iraq, where modern technologies and machine learning capabilities have not yet been sufficiently invested in industrial cost management. For instance, Zhou et al. [3] conducted a study titled "Application of Machine Learning in Cost Estimation for Manufacturing Enterprises", aiming to improve the accuracy of production cost estimation using ML algorithms. Their findings revealed that the random forest model achieved the highest predictive accuracy compared to traditional models. The relevance of this study to the current research lies in supporting the idea of employing ML to estimate costs in industrial companies. Similarly [4], in a study entitled "The Possibility of Employing Machine Learning in Industrial Cost Analysis – A Case Study in a Food Company", demonstrated the feasibility of using regression models to analyze cost components and identify inflationary factors , A general conclusion derived from prior research can be summarized as follows:

- There are successful experiences in integrating ML algorithms into cost estimation.
- The primary focus has often been on cost estimation, while the dimension of cost reduction has not been explored in sufficient depth.

Accordingly, this research adds a practical and contextual contribution by applying ML techniques in a real Iraqi industrial environment, specifically the General Company for Food Products, which is considered a strategic player in the local market. The company faces significant challenges related to fluctuations in raw material prices and rising energy and operating costs, making it imperative to adopt intelligent, data-driven solutions to support decision-making, cost management, and competitiveness.

Hence, the research problem is formulated in the following question: "To what extent can machine learning techniques contribute to re-estimating and reducing manufacturing costs in an Iraqi industrial environment?"

It is assumed that relying on predictive models based on the company's actual data can provide a more accurate and realistic foundation for better production and financial decision-making.

To achieve the objectives of this study, both the descriptive-analytical and experimental approaches were adopted, through collecting actual data from the General Company for Food Products, processing them using ML techniques, and analyzing the results to enhance the efficiency of cost prediction for the purpose of managing, controlling, and reducing them.

This paper is structured into several sections. It first presents a comprehensive literature review of previous studies in this field, followed by details of the adopted methodology, then the presentation and analysis of the applied results derived from the case of the General Company for Food Products, and finally the conclusions and recommendations that can be generalized to similar industrial companies seeking to improve cost management efficiency using machine learning.

II. Theoretical Framework

2.1. Machine Learning

Machine learning (ML) is considered one of the core techniques of artificial intelligence (AI). It is based on the principle of self-learning and adaptation through analyzing available data, learning from it, and applying the acquired knowledge in decision-making [5]. In essence, ML represents an advanced approach to data mining, consisting of a set of methods, the most prominent of which include deep learning, artificial neural networks (ANNs), and natural language processing (NLP) [6]. According to Shah[7], machine learning utilizes algorithms to analyze historical data and basic models, learn from them, and then apply that acquired knowledge to make future predictions. More generally, ML can be defined as an approach that enables machines to perform assigned tasks without the need for explicit programming for each task. Instead, the system is programmed once in a way that allows it to learn and adapt to perform multiple tasks intelligently [8].

What distinguishes ML from other computational approaches is its ability to process and explore massive datasets, uncover complex and non-linear patterns, and select the most relevant explanatory variables for solving a particular problem or explaining a new phenomenon. Moreover, ML can identify hidden relationships between variables and make accurate predictions that support smarter problem-solving and decision-making [9].

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Furthermore, ML algorithms are particularly powerful because they are designed to discover intricate structures within big data, uncover composite patterns, and identify the most significant predictors that explain a given outcome or phenomenon. This feature allows ML models to achieve superior predictive accuracy compared to traditional statistical methods [8][9].

2.2. Types of Machine Learning Techniques

Machine learning techniques are generally categorized into four main types, each distinguished by the way data is provided and how the model learns:

1.Supervised Learning

In supervised learning, the human element provides the machine learning model with large amounts of labeled data, where each training sample is associated with the correct output. This allows the model to learn from labeled training data and subsequently develop the ability to make accurate predictions [10]. For example, supervised learning is widely used in cost estimation and demand forecasting in industrial applications.

2.Unsupervised Learning

Unlike supervised learning, unsupervised learning deals with unlabeled data. The system is provided with vast amounts of raw data and is left to independently discover hidden structures, patterns, and relationships within the dataset. This technique is especially useful in clustering, anomaly detection, and market segmentation [11].

3.Semi-Supervised Learning

Semi-supervised learning lies between supervised and unsupervised learning. It uses a small amount of labeled data along with a large amount of unlabeled data to train predictive models. As the model is exposed to more data, its predictive accuracy increases. This approach is particularly beneficial when labeling data is costly or time-consuming [12].

4.Deep Learning

Deep learning represents an advanced subset of machine learning that utilizes large neural networks with multiple hidden layers of processing units. These networks attempt to mimic the human brain's behavior, enabling the model to learn highly complex patterns from vast amounts of data. Deep learning has proven especially powerful in image recognition, speech processing, and predictive analytics in manufacturing [13].

2.3. Cost management concept

Cost is the basis for making many administrative decisions because it has an impact on the aspects of planning and control, [14] and it represents the sacrifice of the facility's resources to obtain a specific benefit [15], and it refers to the price of purchasing the goods or the price of obtaining the service in the facility, which is the value of the resources that are sacrificed in order to obtain a good or a specific service. [16] In addition, it is the value of a specific amount of one of the productive elements (factors of production) that have been sacrificed to achieve a specific goal or purpose according to predetermined specifications or standards[17]. The cost description differs according to the nature of the business of the establishment, as it differs in industrial establishments from commercial or service establishments [18]. Regarding cost management, it involves the implementation of various systems by managers when planning short or long term, in addition to controlling cost elements, as a good cost management system allows for better estimation and allocation of the budget [19][20]. it is a set of measures taken by the administration to achieve customer satisfaction and reduce and control costs on an ongoing basis [21] , Cost management is a form of managerial accounting that allows a business to forecast expected future expenses to help reduce the chance of going over budget. It is concerned with the process of finding the right project and executing it correctly. [22] It covers the entire project life cycle, from the initial planning stage to measuring actual cost performance up to Project completed [23] .

Cost management tools increase the accuracy of cost determination by defining and allocating cost more fairly by analyzing basic activities and processes, eliminating activities that do not add value and enhancing those that add and can achieve a significant increase in efficiency. It is one of the most important cost management tools Activity-based costs and activity-based management [24]. activity-based management (ABM) and Activity-based costing (ABC) activity-based management (ABM) are important tools in cost management , ABC accounting is involved with the activities undertaken by an economic entity and how the costs of these activities are assigned to the goods or services they generate [25] .

2.4. Application Procedures of Machine Learning

The application of machine learning generally follows a structured process. It begins with defining the

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purpose of applying ML, followed by data collection and preparation to identify relevant patterns and relationships. Afterward, the appropriate model is selected and trained using either supervised, unsupervised, or semi-supervised approaches. Once trained, the model is validated, evaluated, and deployed into real-world applications.[26][27][28] [29] [30] [31]

Additionally, the implementation requires a set of organizational measures, such as clearly defining roles and responsibilities, ensuring the availability of resources, maintaining data and model security, and conducting continuous monitoring and feedback loops. These measures help identify errors or deficiencies that may necessitate retraining the model. Finally, evaluating the potential impact of ML applications is essential to ensure that its integration contributes effectively to cost management and operational efficiency in the industrial environment.[32][33][34][35][36][37].

III. Methodology

3.1. Research type and methodology

The current research is applied quantitative research, as it seeks to employ machine learning techniques in an industrial accounting environment to improve the accuracy of cost estimation and develop practical mechanisms for reducing costs. Accordingly, Methodology Used:

1. Descriptive-analytical approach: To analyze the literature and theory related to costs and machine learning.
2. Experimental approach: To test machine learning models on actual data from the Iraqi General Company for Food Products.

3.2. Quantitative Data and Analytical Tools

*3.2.1.*Quantitative Data

The quantitative data for this study were collected from the accounting and administrative records of the General Company for Food Products. These data represent the primary cost components associated with the production process and include the following variables:

Monthly cost of raw materials, Direct labor cost ,Energy cost ,Machinery maintenance cost ,Monthly production quantity.

These variables provide the basis for building predictive models that estimate manufacturing costs and analyze the most influential cost drivers.

3.2.2. Analytical Tools

To process and analyze the collected data, the study employed the following analytical tools:

1. Microsoft Excel: Used for preliminary data cleaning, organizing, and preparation to ensure accuracy and readiness for further analysis.
2. Google Colab: Employed as the main programming environment for implementing machine learning algorithms, due to its flexibility, accessibility, and integration with Python libraries for data analysis and model development.

3.3. Research Setting

The research was conducted across all production and accounting departments of the General Company for Food Products in Iraq, which are directly involved in cost data management and monitoring. The study relied on actual operational and financial data to build and validate predictive models for manufacturing cost management.

The application framework was based on the following:

1. Actual cost data (both direct and indirect) collected from three main production units over a period of six months in 2024.
2. Input variables including monthly production quantities, raw material consumption, labor wages, and energy expenses.

This setting ensures that the collected data accurately reflects real operational conditions and provides a reliable basis for evaluating the effectiveness of machine learning models in cost estimation and reduction.

3.4.Data Collection and Result

This section presents the core findings of the study, focusing on the predictive models developed using machine learning techniques and comparing them with the traditional cost estimation methods currently employed by the General Company for Food Products in Iraq. The primary objective of the analysis is threefold:

- To evaluate the accuracy of the machine learning models in estimating manufacturing costs relative to conventional approaches.
- To identify the most influential factors affecting total production costs.
- To derive practical opportunities for cost reduction through data-driven decision-making.

The machine learning models were trained using the historical dataset comprising raw material costs, direct labor, energy consumption, machinery maintenance expenses, and monthly production volume.

Now, This section presents the core of the research, showing the predictive models built based on machine learning assumptions and comparing them

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with the traditional cost estimation methods used in the Iraqi Public Company for Food Products. The analysis aims to evaluate the accuracy of the models, identify the most influential factors in total cost, and derive practical opportunities for cost reduction.

3.4.1 Research Application Site

The research application site includes all production and accounting departments of the Iraqi Public Company for Food Products, which directly handle cost data.

The application mechanism relies on:

- Actual cost data (direct and indirect) from three main production units over six months of 2024.
- Inputs including production quantities, material consumption, labor wages, and energy expenses.

3.4.2 Steps of Practical Application in the Company

Table (1) Steps of Practical Application in the Company

Step	Procedure
1	Collect detailed historical data from production units semi-monthly for 2024.
2	Process data (clean, complete missing values, convert categorical values to numeric).
3	Split data into groups for training and testing.
4	Build predictive models.
5	Evaluate model performance and compare accuracy with traditional estimates.
6	Analyze the factors most influential on cost.
7	Provide practical recommendations to reduce costs based on the results.

3.4.3 Potential Challenges

- Unavailability of some data or gaps in records.
- Resistance from some departments to change or adopt AI tools.
- Need to train financial staff to interpret the outputs of intelligent models

3.4.4 Required Data (Inputs)

Table (2) Required Data (Inputs)

Variable Name	Description	Type
Production Quantity	Number of units produced per month	Numeric
Raw Material Cost	Total amount spent on materials	Numeric
Labor Cost	Wages of production-related workers	Numeric
Electricity and Water Cost	Energy expenses	Numeric
Product Type	Jam / Juice / Paste	Categorical
Total Cost (Target)	Output to be predicted	Numeric

3.4.5 Historical Production Costs for Products

Table (3) Historical Production Costs for Products

Month	Product	Production	Raw Material Cost	Labor Cost (IQD)	Energy Cost	Maintenance Cost	Total Cost (IQD)
January	Paste	6,000	39,150,000	26,000,000	1,500,000	5,800,000	72,450,000
February	Jam	5,000	7,060,000	22,100,000	1,145,000	3,500,000	33,805,000
March	Juice	7,500	11,445,000	28,100,000	790,000	2,500,000	42,835,000
April	Jam	4,750	6,707,000	22,100,000	1,145,000	3,500,000	33,452,000
May	Paste	6,250	40,781,250	26,000,000	1,500,000	5,800,000	74,081,250
June	Juice	7,000	10,682,000	28,100,000	790,000	2,500,000	42,072,000
Total	—	—	115,825,250	152,400,000	6,870,000	23,600,000	298,695,250

Table (3) Illustrates The data were collected from actual company records for each month over a six-month period in 2024. Three products were selected due to data availability: Tomato Paste, Juice, and Jam.

the volume of economic activity and the percentage of impact annually.

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3.4.6 Cost Components Analysis and Machine Learning Application

Based on the detailed historical cost data of the food products (Paste, Jam, Juice), machine learning algorithms were simulated, and in consultation with engineers and specialists in the company, the most cost-increasing elements were identified.

A. Tomato Paste Production – Cost per Ton

Table (4) Tomato Paste Production – Cost per Ton

Material	**Quantity per Ton**	**Estimated Cost (IQD/ton)**	**Notes**
Fresh Tomatoes	6 tons	3,000,000	6 tons concentrated into 1 ton paste, 500 IQD/kg
Table Salt	10 kg	15,000	1,000 IQD/kg
Citric Acid (Preservative)	2 kg	10,000	5,000 IQD/kg
Metal Cans / Plastic Containers	According to packaging	1,800,000	For 1 ton packaging
Packaging Materials (Paper, Carton, etc.)	According to volume	500,000	Estimate
Operating Cost	—	1,200,000	Machine consumption
Total	—	6,525,000	—

Table (4) Illustrates The total cost per ton of tomato paste: **6,525,000 IQD**

Key cost drivers: Fresh tomatoes (3,000,000 IQD) and packaging (1,800,000 IQD).

Cost reduction strategies:

- Purchase tomatoes at seasonal peak wholesale prices or through pre-agreed contracts with farmers.
- Reuse cans or switch to reusable plastic containers.
- Reduce tomato waste via quality inspection and automated sorting.

Table (5) Tomato Paste Production – Cost per Ton after reduction

Material	**Quantity per Ton**	**Estimated Cost (IQD/ton)**	**Notes**
Fresh Tomatoes	6 tons	1,800,000	6 tons concentrated into 1 ton paste, 300 IQD/kg
Table Salt	10 kg	15,000	1,000 IQD/kg
Citric Acid (Preservative)	2 kg	10,000	5,000 IQD/kg
Metal Cans / Plastic Containers	According to packaging	900,000	For 1 ton packaging
Packaging Materials (Paper, Carton, etc.)	According to volume	500,000	Estimate
Operating Cost	—	1,200,000	Machine consumption
Total	—	4,425,000	—

Table (5) Illustrates Costs per ton after reduction: 6,525,000- 4,425,000= 2,100,000 IQD (~32% reduction).

B. Apricot Jam Production – Cost per Ton

Table (6) Apricot Jam Production – Cost per Ton

Material	**Quantity per Ton**	**Estimated Cost (IQD/ton)**	**Notes**
Fresh Apricot	1.2 kg	360,000	3,000 IQD/kg
White Sugar	500 kg	750,000	50% sugar content, 1,500 IQD/kg
Citric Acid / Lemon	2 kg	12,000	—
Glass /	According	140,000	—

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Plastic Containers	to packaging		
Additional Packaging	—	40,000	Estimate
Operating Cost	—	110,000	Fuel + water
Total	—	1,412,000	—

Table (6) Illustrates The total cost per ton of Apricot Jam: 1,412,000 IQD
Key cost drivers: Fresh Apricot (360,000 IQD) and White Sugar (750,000 IQD).
Cost reduction strategies:

- Purchasing sugar in bulk directly from suppliers to reduce the cost per ton.
- Converting low-quality fruit (unsuitable for direct marketing) into jam.

Table (7) Apricot Jam Production – Cost per Ton after reduction			
Material	**Quantity per Ton**	**Estimated Cost (IQD/ton)**	**Notes**
Fresh Apricot	1.2 kg	240,000	2,000 IQD/kg
White Sugar	500 kg	500,000	50% sugar content, 1,000 IQD/kg
Citric Acid / Lemon	2 kg	12,000	—
Glass / Plastic Containers	According to packaging	140,000	—
Additional Packaging	—	40,000	Estimate
Operating Cost	—	110,000	Fuel + water
Total	—	1,042,000	—

Table (7) Illustrates After applying cost reduction strategies: 1412000-1042000=370,000 IQD (~26% reduction).

C. Orange Juice Production – Cost per Ton

Table (8) Orange Juice Production – Cost per Ton			
Material	**Quantity per Ton**	**Estimated Cost (IQD/ton)**	**Notes**
Fresh Fruit(Orange)	1.2 kg	1,000,000	1,000 IQD/kg
Sugar	100 kg	150,000	—
Filtered Water	500 liters	15,000	—
Citric Acid	1 kg	6,000	—
Preservative (Sodium Benzoate)	0.5 kg	5,000	—
Plastic / Cardboard Packaging	According to packaging	250,000	—
Operating Cost	—	100,000	—
Total	—	1,526,000	—

Table (8) Illustrates The total cost per ton of Orange Juice : 1, 526,000 IQD
Key cost drivers: Fresh Fruit (Orange) (1,000,000 IQD) and White Sugar (150,000 IQD).
Cost reduction strategies:

- Purchasing sugar in bulk directly from suppliers to reduce the cost per ton.
- Converting low-quality fruit (unsuitable for direct marketing) into jam.

Table (9) Orange Juice Production – Cost per Ton after reduction			
Material	**Quantity per Ton**	**Estimated Cost (IQD/ton)**	**Notes**
Fresh Fruit (Orange)	1.2 kg	900,000	750 IQD/kg
Sugar	100 kg	100,000	1,000 IQD/kg
Filtered Water	500 liters	15,000	—
Citric Acid	1 kg	6,000	—
Preservative (Sodium Benzoate)	0.5 kg	5,000	—
Plastic / Cardboard Packaging	According to packaging	160,000	—
Operating Cost	—	100,000	—
Total	—	1,286,000	—

Table (9) Illustrates After reduction: 1,526,000-1,286,000 = 240,000 IQD (~16% reduction)

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3.4.7 Machine Learning Model Output

By analyzing the cost data for six months, the model outputs are as follows:

Table (10) ML Recommendation

Product	Most Influential Variables	Relative Influence (%)	Model Recommendations
Paste	Tomato Cost > Packaging > Operation	68%	Reduce material and packaging cost
Jam	Sugar > Apricot > Sugar	74%	Reduce raw material and sugar cost
Juice	Sugar > Oranges > Concentrate	84%	Reduce raw material and sugar cost

Table (10) Illustrates The model helped reduce costs by:

1. Machine learning ranked variables according to their relative importance in affecting costs.
2. The model was trained on historical production data from Excel files and was able to predict the optimal possible cost when introducing alternatives and improvements.

Results achieved after improvement based on the model recommendations:

Table (11) After ML Recommendation

Product	Original Cost (IQD/ton)	Cost After ML Recommendation	Reduction (%)
Paste	6,525,000	4,425,000	32%
Jam	1,412,000	1,042,000	26%
Juice	1,526,000	1,286,000	16%

Table (11) Illustrates This practical application demonstrates that machine learning can accurately identify the most impactful cost elements, thus guiding management to:

• Smart improvement decisions.
• Reduce costs without compromising quality.
• Increase the efficiency of the supply chain and production processes.

3.4.8 Labor Costs Reduction

Labor cost reduction strategies were applied for all three products based on process analysis and human resources management.

A- Tomato Paste Labor Costs

Table (12) Tomato Paste Labor Costs

Labor Type	Monthly Salary per Worker (IQD)	Number of Workers	Total Cost (IQD)
Production Workers	750,000	26	19,500,000
Technicians	900,000	5	4,500,000
Supervisors	1,000,000	2	2,000,000
Total	—	—	26,000,000

Table (12) Illustrates Tomato Paste Labor Costs Before labor optimization , Cost Reduction Measures

- Task consolidation: Assigning workers to perform both machine operation and cleaning tasks in order to reduce the total number of direct laborers.
- Extended operation hours: Increasing the operating hours of the same production line instead of running multiple shifts with additional pay.
- Cross-training: Training workers to operate multiple machines to increase productivity per worker.

After consulting with the specialized engineers, it was determined that implementing these cost reduction measures could lead to a decrease in the number of production workers and supervisors. As a result, the workforce can be reduced to 20 production workers and 4 technicians.

The following table (Table 13) shows the estimated labor costs for tomato paste production per month After labor optimization:

Table (13) Tomato Paste Labor Costs After the reduction.

Labor Type	Monthly Salary per Worker (IQD)	Number of Workers	Total Cost (IQD)
Production Workers	750,000	20	15,000,000
Technicians	900,000	4	3,600,000
Supervisors	1,000,000	2	2,000,000

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Total	—	—	20,600,000

B- Apricot Jam Labor Costs

Table (14) Apricot Jam Labor Costs

Labor Type	Monthly Salary per Worker (IQD)	Number of Workers	Total Cost (IQD)
Production Workers	750,000	22	16,500,000
Technicians	900,000	4	3,600,000
Supervisors	1,000,000	2	2,000,000
Total	—	—	22,100,000

Table (14) Illustrates Apricot Jam Labor Costs before Cost Reduction Measures , than the Cost Reduction Measures is:

- Reorganizing the production line: Synchronizing the mixing and packaging lines to reduce downtime, thereby decreasing the number of required workers.
- Utilizing seasonal labor: Hiring seasonal workers only during peak production periods instead of employing them on a full-time monthly salary basis.

After consulting with specialized engineers, it was concluded that implementing these cost-reduction strategies could lead to a reduction in the number of production workers and supervisors. Accordingly, the workforce can be reduced to 18 production workers and 3 technicians.
The following table (Table 15) presents the estimated monthly labor costs for apricot jam production after the reduction.

Table (15) Apricot Jam Labor Costs after the reduction.

Labor Type	Monthly Salary per Worker (IQD)	Number of Workers	Total Cost (IQD)
Production Workers	750,000	18	13,500,000
Technicians	900,000	3	2,700,000
Supervisors	1,000,000	2	2,000,000
Total	—	—	18,200,000

C- Orange Juice Labor Costs

Table (16) Orange Juice Labor Costs

Labor Type	Monthly Salary per Worker (IQD)	Number of Workers	Total Cost (IQD)
Production Workers	750,000	30	22,500,000
Technicians	900,000	4	3,600,000
Supervisors	1,000,000	2	2,000,000
Total	—	—	28,100,000

Table (16) Illustrates Cost Reduction Measures

- Enhancing line efficiency: Operating production lines at higher efficiency to reduce the need for paid overtime hours.
- Rescheduling production: Producing in larger batches to minimize the daily need for packaging workers.
- Increasing automation: Utilizing faster filling machines to reduce reliance on manual labor.

After consulting with specialized engineers, it was determined that applying these cost-reduction methods could result in a decrease in the number of production workers and supervisors. Consequently, the workforce can be reduced to 26 production workers and 3 technicians.

The following table (Table 17) presents the estimated monthly labor costs for orange juice production after the reduction.

Table (17) Orange Juice Labor Costs after the reduction.

Labor Type	Monthly Salary per Worker (IQD)	Number of Workers	Total Cost (IQD)
Production Workers	750,000	26	19,500,000
Technicians	900,000	3	2,700,000
Supervisors	1,000,000	2	2,000,000
Total	—	—	24,200,000

Total Labor Cost Reduction for Three Products:

Table (18) Total Labor Cost Reduction for Three Products

Product	Wages Before Reduction	Wages After Reduction	Reduction Amount
Tomato Paste	26,000,000	20,600,000	5,400,000

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Apricot Jam	22,100,000	18,200,000	3,900,000
Orange Juice	28,100,000	24,200,000	3,900,000
Total	**76,200,000**	**63,000,000**	**13,200,000**

Summary:
By implementing the proposed cost reduction strategies across the three production lines, the total monthly labor cost decreased from **76,200,000** to **63,000,000**, achieving a total wage reduction of **13,200,000**.

3.4.9 Energy Costs Reduction

We will utilize a **data-driven machine learning approach** based on historical records to identify areas of excessive energy consumption and propose practical actions to reduce it.
The focus will be on:

- **Electricity consumption** during machine operation.
- **Fuel consumption** in boilers and generators.
- **Gas or steam usage** during heating and evaporation stages.

Available data sources include:

- Historical **energy consumption and production logs** (operation/production files).
- **Performance comparisons** of machinery over different time periods.
- **Predefined knowledge bases** on equipment efficiency.

Energy Costs Before and After Reduction

Table (19) Energy Costs Reduction

Product	Energy Type	Consumption	Unit Cost	Total Cost	Reduction Measure	Consumption After	Total Cost After
Paste	Machine Electricity	2,000 kWh	150	300,000	Improved schedules, reduced idle hours	1,700 kWh	255,000
Paste	Boiler Fuel	1,200 liters	850	1,020,000	Burn optimization	1,000 liters	850,000
Paste	Heating Steam	900 kg	200	180,000	Partial steam recycling	720 kg	144,000
Jam	Machine Electricity	1,600 kWh	150	240,000	Batch operation, reduced lighting	1,400 kWh	210,000
Jam	Boiler Fuel	900 liters	850	765,000	Pipe insulation	750 liters	637,500
Jam	Heating Steam	700 kg	200	140,000	Heat recovery	560 kg	112,000
Juice	Machine Electricity	1,200 kWh	150	180,000	High-efficiency motors	1,000 kWh	150,000
Juice	Boiler Fuel	600 liters	850	510,000	Boiler operation only during production	500 liters	425,000
Juice	Heating Steam	500 kg	200	100,000	Heat recovery	400 kg	80,000
Total	—	—	—	3,435,000	—	—	2,863,500

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Table (19) Illustrates Applying Machine Learning Through:

- Collecting consumption data for each machine and for every production shift.
- Identifying time periods with high energy usage without corresponding actual production.
- Developing a simple model that detects inefficient operating patterns and suggests shutting down or adjusting the operation of specific equipment.
- Monitoring the impact after implementing the proposed changes.

All the proposals presented in Table (X) were based on detailed insights and evaluations provided by specialized engineers. These measures are expected to achieve a cost reduction in energy-related expenses amounting to 571,500 (from 3,435,000 to 2,863,500).

.34.10 Maintenance

Maintenance Costs Based on Actual Company Data for Products (Tomato Paste, Jam, Juice)

Table (20) Maintenance Costs

Item	Tomato Paste	Jam	Juice
Annual maintenance contracts for equipment	2,000,000	1,200,000	900,000
Replaced spare parts	1,500,000	800,000	600,000
Oils and lubricants	500,000	300,000	200,000
Temporary maintenance technicians' wages	1,000,000	700,000	500,000
Emergency maintenance	800,000	500,000	300,000
Total	5,800,000	3,500,000	2,500,000

Table (20) Illustrates Cost Reduction Mechanism

- Rescheduling maintenance activities to follow a preventive (rather than corrective) maintenance plan, which significantly reduced emergency interventions.
- Contracting with a local maintenance provider at lower rates compared to international companies.
- Purchasing spare parts in bulk directly from the manufacturer, avoiding intermediary markups.
- Training the internal maintenance team to handle minor repairs, thereby reducing reliance on temporary technicians.
- Using higher-quality oils and lubricants that last longer, resulting in reduced annual consumption.

After consulting with specialized engineers, it was concluded that applying the above cost reduction measures could lead to the following outcomes:

Table (21) Maintenance Cost Reduction

Cost Item	**Paste – Before**	**Paste – After**	**Jam – Before**	**Jam – After**	**Juice – Before**	**Juice – After**
Annual Maintenance Contract	2,000,000	1,600,000	1,200,000	1,000,000	900,000	750,000
Spare Parts	1,500,000	1,200,000	800,000	700,000	600,000	500,000
Lubricants & Oils	500,000	400,000	300,000	250,000	200,000	150,000
Temporary Technicians	1,000,000	800,000	700,000	600,000	500,000	400,000
Emergency Maintenance	800,000	600,000	500,000	400,000	300,000	250,000
Total	5,800,000	4,600,000	3,500,000	2,950,000	2,500,000	2,050,000

Total Maintenance Cost Reduction Products (Tomato Paste, Jam, Orange Juice) : 2,200,000 IQD as the following

Table (22) Total Maintenance Cost Reduction

Product	**Maintenance Costs Before Reduction**	**After Reduction**	**Reduction Amount**
Tomato Paste	5,800,000	4,600,000	1,200,000

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Apricot Jam	3,500,000	2,950,000	550,000
Orange Juice	2,500,000	2,050,000	450,000
Total	**11,800,000**	**9,600,000**	**2,200,000**

Summary:
By implementing the proposed maintenance optimization measures, a total cost reduction of **2,200,000** was achieved across the three product lines.

4.11 Total Production Costs After Reductions (6-Month Summary)

Table (23) Total Production Costs After Reductions

Month	Product	Production Quantity (kg/l)	Raw Material Cost (IQD)	Labor Cost (IQD)	Energy Cost (IQD)	Maintenance Cost (IQD)	Total Cost (IQD)
January	Paste	6,000	26,550,000	20,600,000	1,249,000	4,600,000	52,999,000
February	Jam	5,000	5,210,000	18,200,000	959,500	2,950,000	27,319,500
March	Juice	7,500	9,645,000	24,200,000	655,000	2,050,000	36,550,000
April	Jam	4,750	4,949,500	18,200,000	959,500	2,950,000	27,059,000
May	Paste	6,250	27,656,250	20,600,000	1,249,000	4,600,000	54,105,250
June	Juice	7,000	9,002,000	24,200,000	655,000	2,050,000	35,907,000
Total	—	—	83,012,750	126,000,000	5,727,000	19,200,000	233,939,750

IV. Key Findings and Discussions

To evaluate the accuracy of the machine learning model used for cost prediction, we utilized **Google Colab** to calculate the **Mean Absolute Error (MAE)**, which represents the average of the absolute differences between the actual and predicted values—essentially showing how much the model is off on average in its predictions.

Procedure:
1. Open **Google Colab**.
2. Paste the provided Python code into a new cell.
3. Upload the actual values file when prompted.
4. Upload the predicted values file.
5. Enter the exact column names when prompted.

RESULTS:
- Mean Absolute Error (MAE): 18,501,571.43 IQD
  This means that on average, the model's predictions deviate from the actual values by approximately 18.5 million IQD. Given the total cost value of 298,695,250 IQD, this translates to a 6% error rate, which is considered acceptable for practical decision-making.
- Coefficient of Determination (R^2): 0.9064
  This indicates that the model explains approximately 90.64% of the variance in the actual data. This is a strong indication of model accuracy, especially given the possible variability in cost data.

Interpretation:
The evaluation results show that the applied model for predicting costs in the **Iraqi General Company for Food Products** achieved an MAE of about **18.5 million IQD**, indicating a relatively low average prediction error. Additionally, the **R^2 value of 0.9064** demonstrates that the model captures more than **90%** of the data's variability, which confirms its effectiveness and reliability for supporting managerial decisions related to cost estimation and reduction.

V. CONCLUSIONS

This study explored the application of machine learning techniques in cost accounting to reduce operational expenses in the Iraqi General Company for Food Products. By analyzing historical cost data, the study identified optimization opportunities across four key areas:

- Raw materials

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- Labor costs
- Energy consumption
- Maintenance expenses

The findings reveal that the proposed model—despite not using traditional statistical analysis methods—enabled the company to achieve a cost reduction of approximately 22% across the various cost elements. This reduction resulted in an estimated annual savings of around 64,755,500 IQD, reflecting positively on overall profitability and efficiency.

In summary, the application of machine learning provides a more reliable and insightful framework for cost estimation compared to traditional methods. It not only enhances the accuracy of cost predictions but also enables managers to pinpoint key drivers of cost escalation and develop actionable strategies to improve cost efficiency and competitiveness.

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