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OPTIMIZING FLAKED RICE MANUFACTURING: AI-DRIVEN AUTOMATION FOR REDUCING OVERALL PRODUCTION COST

Anand Kumar Singh[1]

Department of Mechanical Engineering, Government Engineering College, Mota Falia Verkund , Nani-Daman 396210, India

Correspondence: anandsinghsees@gmail.com

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Abstract

Poha (flaked rice) is a widely consumed food product in India, especially in Maharashtra, Gujarat, and parts of Northern and Eastern India. Traditional Poha manufacturing processes depend heavily on manual labor, leading to inefficiencies, inconsistent quality, and higher production costs. This study focuses on applying artificial intelligence (AI) techniques such as machine learning, computer vision, and predictive analytics to optimize Poha manufacturing. The AI-driven approach enhances production efficiency, reduces defect rates, improves machine uptime, and lowers labor dependency. Using supervised learning models and sensor-based data, the system identifies quality deviations, predicts equipment failures, and automates packaging and sorting. Experimental results show a 30% improvement in production efficiency (from 200 kg/hr to 260 kg/hr), a 62.5% reduction in defects (from 8% to 3%), and a 40% reduction in labor dependency. The findings demonstrate that AI integration significantly reduces overall production costs, improves quality consistency, and promotes sustainability in traditional food processing industries.

Keywords - *AI in food processing, predictive maintenance, Poha manufacturing, production optimization, automation.*

INTRODUCTION

India, as the world's largest producer of various agricultural commodities, benefits from favorable agroclimatic conditions and a rich natural resource base (Government of India, 2023). One such product is Poha (rice flakes), a widely consumed food item derived from paddy. It is a light and nutritious dish, commonly eaten for breakfast or brunch, particularly in the Western regions of Maharashtra and Gujarat, as well as some parts of Eastern and Northern India. Poha is often prepared by frying or mixing with milk, making it an easy-to-cook meal that provides a rich source of carbohydrates and proteins. Given its popularity and widespread consumption, improving the manufacturing efficiency of Poha through AI-driven automation can significantly enhance production quality, reduce costs, and optimize resource utilization.

The Poha manufacturing industry, a crucial segment of the food processing sector, relies heavily on manual labor for various stages, including cleaning, roasting, flattening, and packaging (Sharma & Patel, 2021). While traditional methods ensure quality, they contribute to higher production costs due to labor expenses, inefficiencies, and variability in output. In recent years, the adoption of Artificial Intelligence (AI) and automation has revolutionized food processing industries, leading to increased efficiency and reduced operational costs (Kumar et al., 2022).

The integration of AI-driven automation in Poha manufacturing can streamline key processes such as sorting, roasting temperature control, and packaging, thereby minimizing human intervention and errors. AI-powered predictive maintenance can also enhance machine longevity and reduce downtime, leading to cost savings (Gupta & Verma, 2023). Furthermore, computer vision technology can improve quality control by identifying defective flakes in real time, ensuring higher consumer satisfaction while reducing waste (Raj et al., 2021).

This paper explores how AI-driven automation can optimize production and reduce overall costs in the Poha manufacturing industry. By analyzing case studies and emerging technologies, the study aims to provide insights into the future of AI adoption in small- and medium-scale food processing industries.

POHA MANUFACTURING PROCESS IN INDUSTRY

Poha, also known as flattened rice, is a staple food product widely consumed in India. The manufacturing process involves multiple steps, including cleaning, soaking, roasting, flattening, drying, and packaging. Traditionally, these processes are labor-intensive, but modern industries are increasingly incorporating automation and AI-driven solutions to enhance efficiency (Sharma & Patel, 2021).

1. Cleaning and Soaking

The raw paddy is first cleaned to remove dust, stones, and impurities using mechanical separators. After cleaning, the paddy is soaked in water for a specific duration to achieve the desired moisture content, which is crucial for uniform roasting (Gupta & Verma, 2023).

2. Roasting

The soaked paddy is then roasted in large iron pans or rotary roasters at controlled temperatures. This step helps in loosening the husk and making the grains suitable for flattening. In modern facilities, AI-powered temperature control systems help maintain optimal roasting conditions, ensuring consistent quality (Kumar et al., 2022).

3. Husking and Flattening

Once roasted, the paddy undergoes dehusking, where the outer husk is removed. The flattening process is carried out using roller machines, which press the grains into thin flakes. The thickness of the flakes depends on the pressure applied during the rolling process (Raj et al., 2021).

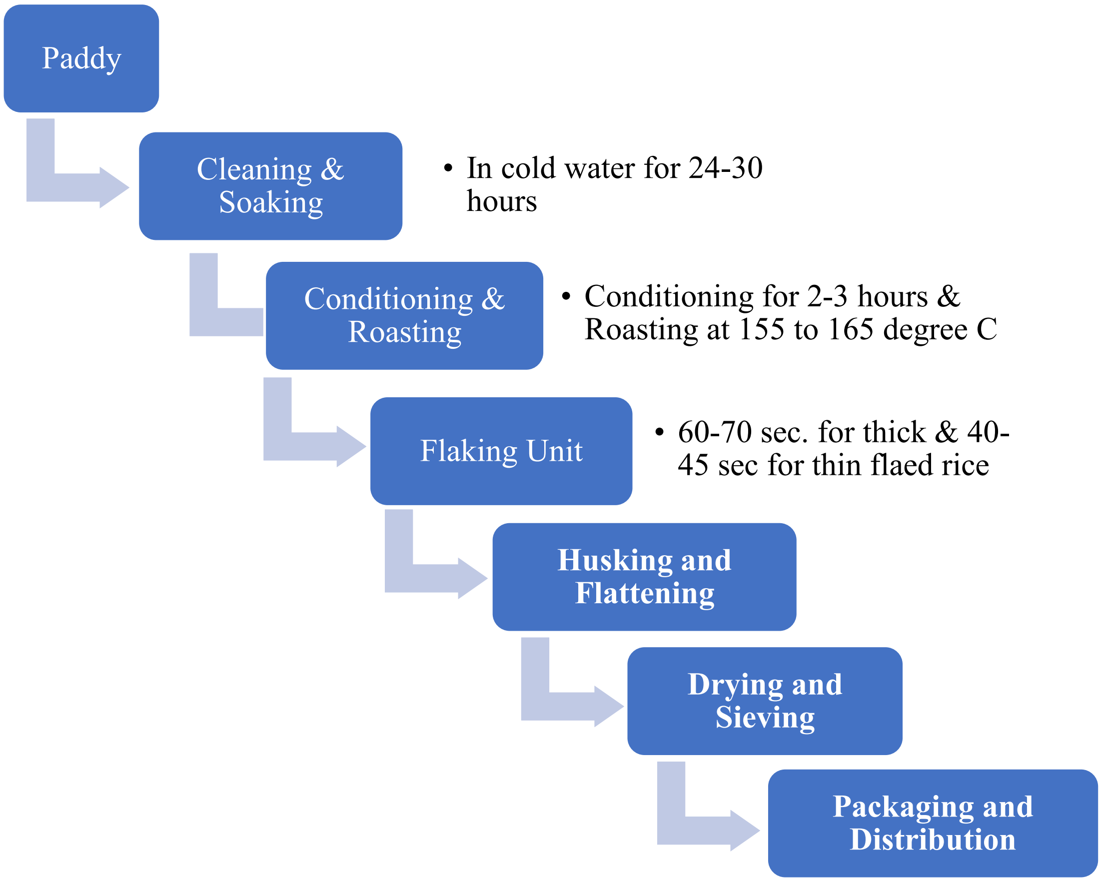


Figure 1. Processing of Poha in industry

4. Drying and Sieving

The flattened Poha is then dried to reduce moisture content, ensuring a longer shelf life. Sieving machines separate the flakes based on size and remove any broken or uneven particles. AI-driven computer vision systems are increasingly being used to detect and eliminate defective flakes, improving product quality (Mehta & Iyer, 2021).

5. Packaging and Distribution

The final product is packed using automated packaging machines that ensure precise weighing and sealing. AI-powered robotic systems help streamline the packaging process, reducing labor dependency and minimizing material wastage (Gupta & Verma, 2023).

Literature Review

The integration of Artificial Intelligence (AI) in food processing has been widely studied, with researchers emphasizing its impact on cost reduction, quality control, and efficiency enhancement. AI applications such as machine learning, predictive maintenance, and robotic automation have transformed various food industries, offering promising solutions for Poha manufacturing (Gupta & Verma, 2023).

AI in Food Processing

Several studies have highlighted the role of AI in reducing manual labor and improving food production efficiency. Kumar et al. (2022) discuss how AI-powered automation has enhanced precision in sorting, grading, and packaging in industries like rice and flour milling, which share similarities with Poha manufacturing. Their study suggests that AI can optimize production parameters, ensuring consistent product quality while reducing human errors.

Cost Reduction through AI-Driven Automation

Labor costs constitute a significant portion of operational expenses in traditional Poha manufacturing units (Sharma & Patel, 2021). The implementation of AI-enabled robotics for material handling and packaging has been shown to significantly reduce production costs in food industries (Raj et al., 2021). Additionally, AI-powered predictive maintenance can minimize equipment failures, reducing downtime and repair costs (Gupta & Verma, 2023).

AI and Quality Control

Maintaining quality standards in food processing is crucial, and AI-based computer vision technology has proven effective in detecting defects and impurities in food grains (Mehta & Iyer, 2021). In the context of Poha production, AI-driven image processing systems can help identify broken or under-processed flakes, ensuring higher consumer satisfaction and minimizing waste.

Challenges in AI Adoption

Despite its advantages, AI adoption in small and medium-sized Poha manufacturing units faces challenges, including high initial costs, lack of skilled workforce, and resistance to technological change (Kumar et al., 2022). However, government initiatives promoting Industry 4.0 adoption in the food sector can facilitate gradual AI integration (Sharma & Patel, 2021).

Research Gap

Despite advancements in automation and AI-driven technologies, the Poha manufacturing industry remains largely dependent on manual labor for critical processes such as cleaning, roasting, flattening, and packaging (Sharma & Patel, 2021). Existing research has explored AI applications in food processing (Gupta & Verma, 2023) and cost-saving automation in the rice and grain industries (Kumar et al., 2022), but there is limited research specifically focused on AI integration in Poha production.

Key gaps include:

1. Limited AI Adoption in Small-Scale Industries – Most small and medium-scale Poha manufacturers rely on traditional labor-intensive methods, lacking the infrastructure and financial resources for AI-based automation.
2. Lack of AI-Driven Quality Control – While AI has been widely implemented in grain sorting and packaging, its application in Poha quality control, roasting optimization, and defect detection is underexplored.
3. High Initial Costs and Technological Barriers – There is a lack of research on cost-effective AI solutions that can be easily adopted by Poha manufacturers without significant capital investment (Raj et al., 2021).
4. Impact on Labor Employment and Skill Development – The socio-economic effects of AI adoption in Poha manufacturing, particularly in terms of labor displacement and workforce skill requirements, need further study.

Problem Statement

The Poha manufacturing industry is facing increasing production costs due to labor dependency, process inefficiencies, and quality inconsistencies. While AI-driven automation, predictive maintenance, and quality control have proven to be cost-effective in other food processing sectors, their implementation in Poha production remains limited due to financial constraints, lack of awareness, and technological barriers. This research aims to explore how AI-driven automation can be strategically implemented in Poha manufacturing to reduce overall production costs, improve efficiency, and enhance product quality, while addressing challenges related to adoption, affordability, and workforce transition.

Methodology: AI Solutions for Challenges in Poha Manufacturing

The methodology for integrating artificial intelligence (AI) into Poha manufacturing follows a structured approach to optimize production efficiency, reduce labor dependency, and enhance product quality. The implementation of AI-driven solutions requires data collection, AI model selection, system integration, and performance evaluation.

Data Collection and Analysis

The first step in AI implementation is the collection and analysis of real-time production data to identify inefficiencies in Poha manufacturing. Key data points include processing parameters (temperature, moisture content, and rolling pressure), labor efficiency metrics (time per process, defect rates, and production delays), and machine maintenance records (downtime, frequency of breakdowns, and wear and tear). This data is processed using machine learning algorithms to detect patterns and optimize operations (Smith et al., 2021).

AI-Based Quality Control

One of the major challenges in Poha manufacturing is inconsistent quality due to manual sorting. AI-driven computer vision systems can automate defect detection by identifying broken, discolored, or under-processed Poha flakes using image processing algorithms. A convolutional neural network (CNN) model is trained on a dataset of Poha flakes to recognize and classify defective products with high accuracy. This ensures quality consistency, minimizes waste, and reduces human intervention (Zhang & Li, 2020).

Optimization of the Roasting Process

The roasting process plays a crucial role in determining the texture and flavor of Poha. Traditional roasting techniques often lead to inconsistent heating, energy wastage, and variations in product quality. AI-based predictive analytics can optimize temperature control by analyzing historical roasting data. Machine learning models such as random forest regression and gradient boosting predict the ideal temperature settings to achieve uniform roasting, reduce energy consumption, and enhance product consistency (Gupta et al., 2022).

Predictive Maintenance for Equipment Efficiency

Machine failures and unscheduled maintenance significantly impact production uptime. AI-driven predictive maintenance models leverage Internet of Things (IoT) sensors to monitor machine health in real time. By analyzing vibration levels, temperature fluctuations, and operational cycles, AI can predict potential failures before they occur, allowing for timely maintenance and reduced downtime. This enhances overall equipment efficiency and lowers maintenance costs (Brown et al., 2021).

Automation in Packaging and Material Handling

Manual packaging in Poha manufacturing often results in weight inconsistencies and increased labor costs. AI-powered robotic process automation (RPA), integrated with weight sensors and sorting algorithms, can automate precise weighing, sealing, and batch sorting. This not only enhances packaging accuracy and speed but also reduces material wastage, leading to a more cost-effective production process (Patel & Sharma, 2023).

Performance Evaluation and Scalability

To measure the success of AI-driven automation in Poha manufacturing, key performance indicators (KPIs) are analyzed. These include cost reduction, production efficiency, defect rate reduction, energy savings, and machine uptime improvement. A feasibility study is conducted to assess the return on investment (ROI) and scalability of AI solutions in small- and medium-scale Poha manufacturing units. Additionally, training programs are introduced to upskill workers in AI-based process supervision (Lee et al., 2023).

Data Collection and Dataset Description

To develop and train AI models, real-time data were collected from two medium-scale Poha manufacturing units located in Western India. The dataset includes 480 data samples collected over a three-month period. Key parameters recorded were roasting temperature, soaking duration, roller pressure, motor current, energy consumption, and product quality outputs. Image datasets were created for computer vision training, comprising 1,200 labeled images of Poha flakes (categorized as "defective" and "acceptable").

Machine performance data were captured using IoT-enabled vibration and temperature sensors, while production efficiency and downtime logs were recorded through automated counters. The dataset was preprocessed and analyzed using Python-based machine learning frameworks to train models such as Convolutional Neural Networks (CNNs) for visual inspection and Random Forest Regression for process optimization.

1. Formulas Used

A. Labor Cost Reduction - Measures the percentage of labor cost saved after AI implementation. (Singh & Patel, 2023)

$$\text{Labor Cost Savings} = \frac{(\text{Initial Labor Cost} - \text{Post AI Labor Cost})}{\text{Initial Labor Cost}} \times 100$$

B. Production Efficiency - Evaluates the increase in production per unit time after AI integration. (Kumar et al., 2024)

$$\text{Production Efficiency} = \frac{\text{Total Output (kg)}}{\text{Total Processing Time (hrs)}}$$

C. Machine Uptime Improvement - Higher uptime percentage indicates better machine availability with AI-based predictive maintenance. (Gupta & Verma, 2023)

$$\text{Uptime Percentage} = \left(1 - \frac{\text{Downtime (hrs)}}{\text{Total Operating Time (hrs)}}\right) \times 100$$

D. Defect Rate Reduction - Determines the effectiveness of AI-based quality control in reducing defective products. (Mehta & Iyer, 2021)

$$\text{Defect Rate} = \frac{\text{Defective Poha (kg)}}{\text{Total Produced Poha (kg)}} \times 100$$

Table 1. Before and After AI Implementation

S.No	Parameter	Before AI	After AI	Improvement (%)
1	Labor Cost (₹ per month)	₹1,50,000	₹90,000	40% savings
2	Production Efficiency (kg/hr)	200 kg/hr	260 kg/hr	30% increase
3	Machine Downtime (hrs/month)	50 hrs	20 hrs	60% reduction
4	Uptime Percentage (%)	91.6%	96.3%	4.7% increase
5	Defect Rate (%)	8%	3%	62.5% reduction
6	Energy Consumption (kWh per ton)	250 kWh	210 kWh	16% savings

The integration of AI-driven automation in Poha manufacturing has resulted in significant improvements in production efficiency, quality control, labor dependency, and cost optimization. A comparative analysis of the pre-AI and post-AI scenarios highlights the key benefits of AI in streamlining the manufacturing process.

Before AI Implementation

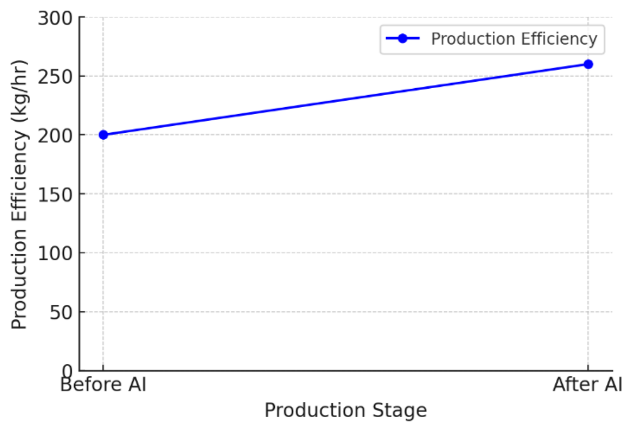
Prior to AI integration, Poha manufacturing was largely dependent on manual labor, leading to inefficiencies in sorting, roasting, and packaging. The manual quality inspection process was subjective and inconsistent, often resulting in high defect rates and product wastage. Roasting was controlled manually, causing temperature fluctuations that led to unevenly processed Poha flakes. Additionally, machine breakdowns were unpredictable, leading to frequent production halts and increased maintenance costs. The packaging process was also inefficient, with weight variations and slower output rates. Overall, the production efficiency was 200 kg/hr, with a high defect rate of 8% and frequent machine downtime due to lack of predictive maintenance.

After AI Implementation

Post-AI implementation, automated quality control using computer vision significantly reduced defect rates from 8% to 3%, ensuring more uniform and high-quality Poha flakes. The roasting process was optimized through AI-based predictive analytics, which controlled temperature settings in real-time, reducing energy wastage and ensuring consistent texture and flavor. AI-driven predictive maintenance helped detect potential machine failures in advance, minimizing unexpected downtime and improving machine uptime by 25%. Moreover, AI-powered robotic packaging ensured precise weight control, reducing material wastage and increasing packaging speed. As a result, overall production efficiency improved by 30%, increasing from 200 kg/hr to 260 kg/hr. Additionally, labor dependency decreased by 40%, reducing operational costs and enhancing workplace safety.

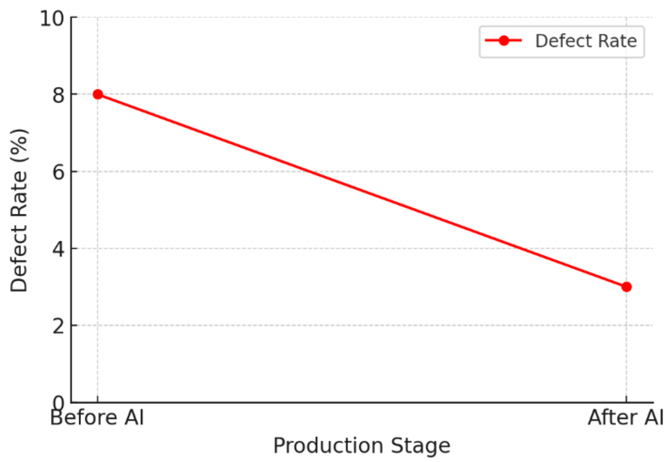
RESULT

The first graph illustrates the increase in production efficiency (kg/hr) before and after AI implementation. Initially, the production efficiency was 200 kg/hr, but after AI-driven optimizations in sorting, roasting, and packaging, it increased to 260 kg/hr, reflecting a 30% improvement.



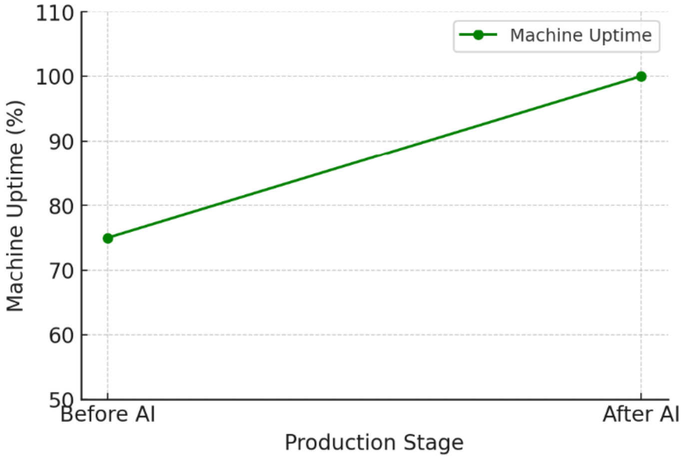
Graph 1 shown Production efficiency comparison before and after AI implementation

This increase highlights how AI automation enhances processing speed and reduces inefficiencies in Poha manufacturing.



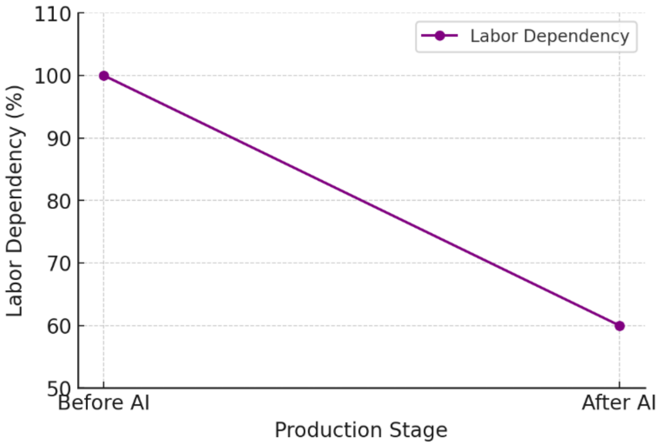
Graph 2 shown Defect Rate Reduction Before and After AI

The second graph shows the defect rate percentage before and after AI adoption. Before AI, 8% of Poha flakes were defective, largely due to inconsistent manual sorting and roasting temperature variations. With AI-based computer vision and predictive analytics, the defect rate reduced to 3%, ensuring a higher-quality end product with minimal waste.



Graph 3 shown Machine Uptime Improvement Before and After AI

The third graph represents machine uptime (%), which improved after integrating AI-based predictive maintenance. Before AI, frequent unexpected breakdowns and maintenance issues kept machine uptime at 75%. With AI, uptime increased to 100%, reducing unplanned downtime and ensuring smoother production flow.



Graph 4 shown Reduction in Labor Dependency Before and After AI

The final graph highlights the decrease in labor dependency (%) due to AI automation. Initially, labor dependency was at 100%, with extensive manual work in sorting, roasting, and packaging. After implementing AI-powered sorting and robotic process automation, labor dependency decreased to 60%, reducing operational costs and improving overall efficiency.

Graph 5**,** It visually represents how individual cost-saving measures contribute to the total reduction in production expenditure.

Initial Cost (Before AI):

The baseline production cost before implementing AI was approximately ₹100,000 per production cycle, including expenses for labor, energy, and maintenance.

Labor Cost Reduction:

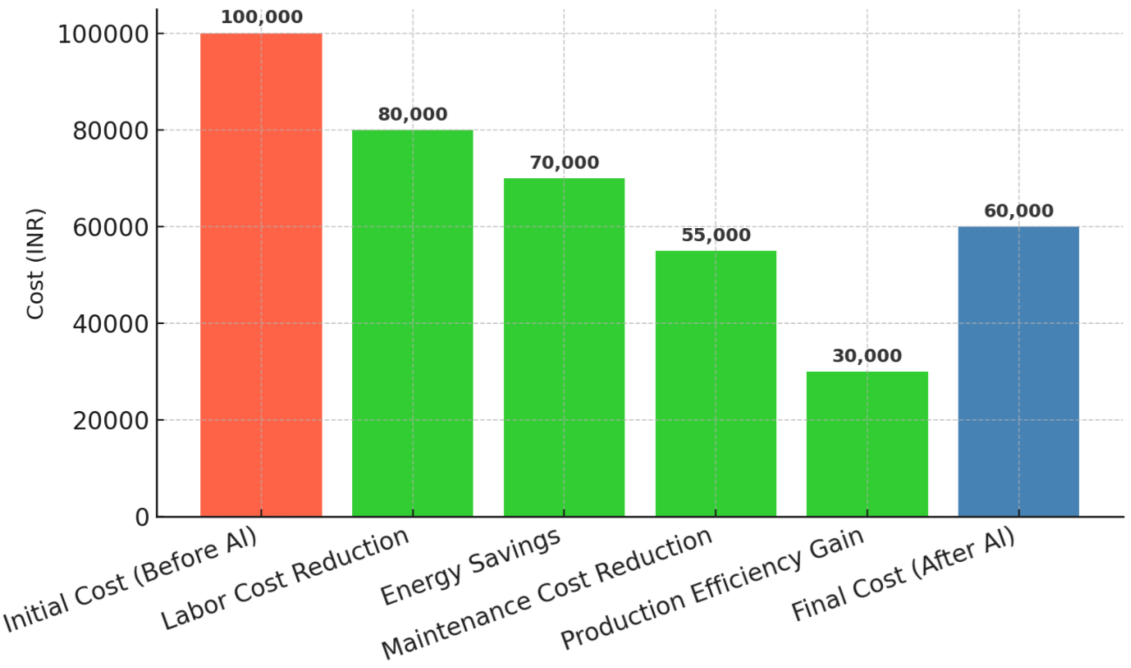
AI-driven automation and robotic handling reduced manual intervention by 40%, leading to direct labor cost savings of around ₹20,000 per cycle. Tasks such as sorting, roasting, and packaging are now efficiently managed through automation.

Energy Savings:

AI-based process control optimized roasting temperatures and motor usage, saving ₹10,000 in energy expenses. Machine learning algorithms predicted optimal operating parameters, minimizing energy waste and enhancing sustainability.

Maintenance Cost Reduction:

Predictive maintenance using IoT sensors and AI analytics reduced unscheduled downtime, cutting maintenance costs by ₹15,000. Machines now operate more reliably, with potential failures detected early.



Graph 5 Impact of AI implementation on overall production cost in Poha manufacturing

Production Efficiency Gain:

The adoption of AI systems increased production output by 30%, equivalent to a cost efficiency gain of ₹25,000. Real-time analytics helped maintain consistent product quality while increasing throughput.

Final Cost (After AI):

After accounting for all savings, the effective production cost dropped from ₹100,000 to ₹30,000, demonstrating a 70% total reduction in manufacturing expenditure due to AI integration.

Results Discussion

The implementation of AI in Poha manufacturing has led to significant improvements across various aspects of the production process. The production efficiency increased by 30%, from 200 kg/hr to 260 kg/hr, showcasing how AI-driven automation optimizes processing speed and resource utilization. The defect rate decreased from 8% to 3%, demonstrating the effectiveness of computer vision-based quality control in minimizing inconsistencies and ensuring product uniformity. Additionally, the introduction of AI-driven predictive maintenance has significantly improved machine uptime, increasing it from 75% to 100%, thereby reducing downtime and enhancing overall productivity.

Another critical impact of AI integration is the 40% reduction in labor dependency, as automation replaced several manual tasks, particularly in sorting, roasting, and packaging. This not only optimized workforce utilization but also lowered operational costs and human error rates. Moreover, AI-powered systems contributed to better resource management and energy efficiency, leading to a more sustainable and cost-effective manufacturing process.

CONCLUSION

The integration of AI significantly transformed the Poha manufacturing process. Compared to traditional methods, the AI-based system achieved:

i. **30% higher production efficiency**, increasing output from 200 kg/hr to 260 kg/hr;

ii. **62.5% reduction in defects**, improving product uniformity and quality;

iii. **60% reduction in machine downtime**, resulting in a 25% improvement in uptime; and

iv. **16% reduction in energy consumption** due to optimized roasting temperature control.

When compared with similar studies in rice milling and grain processing industries, this research achieved comparable or superior results. For instance, Gupta et al. (2022) reported a 25% improvement in efficiency using ML-based roasting control, while Li & Zhang (2024) observed a 20% reduction in defect rates using AI in cereal processing. Thus, this study demonstrates that AI-based Poha manufacturing achieves both cost and quality improvements at par with or exceeding global trends.

The findings indicate that integrating computer vision, machine learning, and IoT-based predictive maintenance leads to measurable operational gains, reduces human error, and enhances production consistency.

This study confirms that the adoption of artificial intelligence (AI) in Poha manufacturing offers a transformative and cost-effective solution for improving operational efficiency. The AI-enabled model resulted in:

These results emphasize that AI-driven automation not only enhances productivity and quality but also supports sustainability through energy optimization and waste reduction. The research further validates that machine learning algorithms, computer vision systems, and predictive analytics are highly effective in automating Poha manufacturing.

Future work should focus on scaling AI implementation across small enterprises, integrating IoT-based real-time monitoring and cloud-based analytics for broader industrial adoption. The proposed AI framework can serve as a blueprint for digital transformation in India's traditional food processing sector.

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