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Integration of Machine Learning for Performance Analysis and Optimization of a Teaching Model Rice Threshing Machine

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Abstract
Rice is a indispensable food crop in Nigeria, yet domestic production lingers to decrease as demand increases, based majorly on post-harvest losses credited to ineffective threshing approaches. This investigation x-rayed the fabrication and performance optimization of a laboratory scale prototype of a rice threshing machine, fabricated by means of locally sourced materials to certify cost-effectiveness and ease of maintenance for local farmers. The system encompasses a welded steel frame, hopper, peg-tooth threshing drum, blower, grain and chaff outlets, and a V-belt driven electric motor. To permit data driven optimization, an Internet of Things (IoT) based sensing panel was integrated, integrating sensors for drum speed, paddy moisture content, feed rate, and throughput capacity. Operational data were gathered under changeable settings of drum speed, feed rate, pulley ratio, and grain moisture content. Three machine learning (ML) algorithms; Random Forest Regression, Support Vector Regression, and Artificial Neural Networks were trained to determine threshing efficiency, grain breakage, and energy consumption. The Random Forest model succeeded in having the maximum forecast accuracy (R^2 = 96.4%, RMSE = 1.25) and was employed to ascertain optimal operating factors. Machine learning supported process enhanced threshing efficiency by 5.2%, decrease grain breakage by 22.4%, and dropped energy depletion by 9.8% compared to manual variations. The outcome established that incorporating machine learning based forecasting modeling with locally constructed threshing machines can significantly improve performance, reduce post-harvest losses, and encourage sustainable agricultural mechanization in resource restricted situations.

Keywords: Agricultural Mechanization, Internet of Things (Iot), Machine Learning, Performance Optimization, Rice Threshing Machine, Smart Farming, Post-Harvest Loss Reduction

Introduction

Rice is the seed of a grass species called Oryza sativa. It is a monocot crop normally grown for a year but in tropical areas can survive as a perennial crop [1]. Rice is a staple food for the majority of the world's population. More than 40% of the rice consumption in West Africa is imported, which represents 2.75 million tons per year [2]. Worldwide there are more than forty thousand different varieties of rice species named Oryza sativa, doongara, jarrah, kyeema, reizip are a few species [3]. It is estimated that rice sustains the livelihood of 100 million people and its production has employed more than 20 million farmers in Africa [4]. Rice crop production originated in China and spread to countries such as Sri Lanka and India. Rice is also an agricultural commodity with the third-highest worldwide production after sugarcane and maize [5]. The African rice (Oryza glaberrima) is thought to have originated in the Central Delta of the Niger River where it may have been grown since 1,500BC [6]. This high rice consumption rate resulted in an increased importation from 320,000 metric tons in 2010/2011 to 330,000 metric tons in 2011/2012, an increment of 10,000 metric tons in just one year. Reference [7]. Attributed this disturbing trend to a continued shortfall in domestic production partly due to postharvest losses along the rice value chain. Presently, 35% of postharvest crop losses have been reported and this may 2 be due to by inefficiency of manual threshing of rice by small-scale farmers leading to poor grain quality and rejection of locally produced rice [8]. Physical and engineering properties are important in many problems associated with the design of machines and the analysis of the behavior of the product during agriculture processing operations such as handling, planting, harvesting, threshing, cleaning, sorting, and drying. The solution to the problem of these processes involves knowledge of the physical and engineering properties [9]. This was corroborated by [10]. That in the design of any Agriculture handling and processing machine, the properties of the crop must be taken into account. He listed some of their (properties) as the grain size, shape, mass, hardness, angle of repose, grain straw ratio, moisture content of kernel, and bulk density. Threshing is a technical operation in rice and some cereals production. The thresher was developed for threshing, separating, and cleaning cereals. The major components of 2 the machine include threshing, separation, and cleaning units [11]. Recent advances in the Internet of Things (IoT) and machine learning (ML) offer opportunities to enhance thresher performance through predictive, data-driven optimization. IoT-enabled sensors can capture key operational parameters such as drum speed, moisture content, feed rate, and pulley ratio, while ML algorithms can analyze this data to predict threshing efficiency and recommend optimal operational settings. Such integration has the potential to improve grain recovery, reduce energy consumption, and minimize grain damage, ultimately increasing profitability for farmers.

In This Study, The Following Contributions are Presented
• Fabrication of a cost-effective teaching model rice thresher using locally sourced materials.
• Integration of IoT-based sensors for real time operational data acquisition.
• Design of machine learning models to predict performance and optimize operational parameters.
• Comparative performance analysis between optimized (ML-assisted) and unoptimized (manual setting) operation modes.

The integration of machine learning with a locally constructed rice thresher represents a novel approach to addressing post-harvest inefficiencies in Nigeria, linking mechanical design origination with intelligent decision-making tools to advance sustainable agricultural mechanization.

Related Work

Rice threshing machineries have evolved significantly over the past years, moving from labor-intensive technique to more cutting-edge mechanized results. Manual threshing techniques, such as beating rice paddy against hard surfaces, trampling by animals, and using lever powered procedures, are still predominant among smallholder farmers in many developing nations, like Nigeria. These approaches are cost effective but are accompanying with low throughput, high grain breakage rates, and substantial post-harvest losses, often fluctuating between 20% and 35% [1,2]. To look into these inadequacies, several mechanical threshers have been developed. Early designs primarily focused on peg-tooth or wire-loop threshing drums, which better throughput and reduced labor demands compared to manual methods [3]. Nevertheless, many of these machines were developed for large scale tasks, making them expensive and less suitable for smallholder farmers in rural settings [4]. Locally constructed threshers have appeared as a cost-effective substitute, focusing on locally sourced materials with simple mechanical designs [5]. Whereas these machines reduce costs, their performance often varies depending on operational factors such as drum speed, feed rate, and moisture content, which are typically adjusted manually based on operator technical know-how. In contemporary years, the incorporation of Internet of Things (IoT) technology into agricultural machinery has permitted real time data gathering and monitoring [6,7]. IoT-enabled threshers can capture critical performance indicators, including rotational speed, vibration, and moisture levels, enabling more precise operational control. Despite these advancements, many existing IoT-enabled solutions lack analytical capabilities and rely on fixed threshold-based modifications. Machine learning (ML) has appeared as a powerful tool for forecasting modeling and optimization in agricultural applications. Researches have revealed the effectiveness of machine learning algorithms such as Random Forest, Support Vector Machines, and Artificial Neural Networks in predicting crop yields, optimizing irrigation schedules, and identifying equipment faults [8-10]. In the context of post-harvest machinery, machine learning has been applied to grain quality valuation, fault detection in milling equipment, and operational factor optimization [11,12]. Nevertheless, there are limited literature on the application of machine learning model for performance forecast and optimization of small-scale rice threshers, predominantly in the context of locally fabricated machines intended for rural deployment. This gap revealed an opportunity to incorporate low-cost IoT sensing systems with machine learning based predictive models in a locally fabricated rice thresher. Such integration can enable real time optimization of operational parameters, improving efficiency, reducing grain damage, and reducing energy consumption, thereby taking care of both economic and technical barriers to adoption in rural farming groups.

Materials and Methods

Machine Construction

The teaching prototype rice threshing machine was fabricated using locally sourced materials to ensure cost effectiveness, ease of maintenance, and accessibility for rural farmers. The main materials included 40 mm × 40 mm angle iron for the frame, 4 × 4 sheet metal for the hopper and blower housing, 20 mm ball bearings, a 25 mm diameter steel shaft, twisted rods, Haco pipe, flat bar, M17 bolts and nuts, a 3 hp electric motor, and a V-belt drive system.

The major components of the machine include:
• **Frame:** Fabricated from welded angle iron to provide structural stability and support for all mounted components.
• **Hopper:** Constructed from sheet metal and positioned at the top of the threshing chamber to serve as the entry point for unthreshed rice.
• **Threshing Drum:** A cylindrical drum fitted with peg-tooth spikes, welded in a spiral arrangement to ensure effective grain separation.
• **Blower:** Located beneath the threshing drum to perform winnowing by directing airflow through the chaff outlet.
• **Outlets:** A grain outlet positioned on the left-hand side of the machine and a chaff outlet at the front for separation of threshed material.
• **Power Transmission:** A V-belt and pulley system connected the electric motor to the drum shaft, enabling adjustable operating speeds by changing pulley ratios.
• The Bill of Engineering Measurement and Evaluation (BEME) estimated the total construction cost at ₦128,500, highlighting its affordability relative to imported mechanical threshers.

IoT-Based Data Acquisition System

To ease performance monitoring and machine learning incorporation, an IoT-enabled sensing system was integrated into the machine. The settings comprised:
• Rotational Speed Sensor: Mounted on the drum shaft to measure operational speed in revolutions per minute (RPM).
• Moisture Sensor: Used to measure the moisture content of incoming paddy.
• Load Cell: Installed beneath the grain outlet to measure throughput weight.
• Vibration Sensor: Used to monitor machine stability and detect operational anomalies.
• Microcontroller Unit: An ESP32 module was employed for sensor data acquisition and wireless broadcast.
• Data Storage and Transmission: Operational data were warehoused locally on a microSD card and conveyed through Wi-Fi to a cloud database for further analysis.
• The sensing system enabled continuous logging of operational parameters, confirming that a wide-ranging dataset was available for model training and performance optimization.

Data Collection Procedure

The prototype was evaluated using three rice varieties (Ofada, Faro 44, and Nerica 8) under varying settings. The key practical variables were:
• Moisture Content: 12%, 16%, and 20%.
• Drum Speed: 600, 800, and 1000 RPM.
• Feed Rate: Low (5 kg/min), Medium (10 kg/min), and High (15 kg/min).
• Pulley Ratios: 1:1.2, 1:1.5, and 1:2.
For each arrangement of parameters, data were also gathered on:
• Threshing efficiency (%)
• Grain breakage rate (%)
• Cleaning efficiency (%)
• Energy consumption (kWh)
Each test condition was repeated three times to confirm data dependability.

Machine Learning Methodology

The collected dataset was preprocessed by removing outliers, normalizing numerical features, and encoding categorical variables (rice variety). The dataset was then split into 70% for training and 30% for testing.
Three supervised learning algorithms were evaluated:
• Random Forest Regression (RF) for robust performance in non-linear relationships.
• Support Vector Regression (SVR) for high-dimensional data fitting.
• Artificial Neural Networks (ANN) for capturing complex feature interactions.
The input characteristics for the machine learning models included drum speed, moisture content, feed rate, pulley ratio, and rice variety. The targeted outputs were:
• Predicted threshing efficiency (%)
• Predicted grain breakage rate (%)
• Predicted energy consumption (kWh)

Performance metrics employed were

• Coefficient of Determination (R^2) to assess model accuracy.
• Root Mean Squared Error (RMSE) to measure prediction error magnitude.
• Mean Absolute Error (MAE) to measure average deviation from actual values.
The best-performing model was selected for deployment into the IoT system, enabling real-time performance forecast and operational optimization approvals.

Optimization Strategy

Based on the trained machine learning model's predictions, optimal operational parameters were calculated to:
• Maximize threshing efficiency.

• Minimize grain breakage.
• Reduce energy consumption.

The optimized platform were then validated experimentally and compared to baseline (manual adjustment) outcomes to quantify the enhancement attained with machine learning incorporation.

Results

Mechanical Performance Evaluation

The fabricated teaching prototype rice thresher was evaluated under changeable drum speeds, moisture contents, feed rates, and pulley ratios. Table I presented the mean performance outcome across all test runs.

Drum Speed (RPM)	Moisture (%)	Feed Rate (kg/min)	Threshing Efficiency (%)	Grain Breakage (%)	Cleaning Efficiency (%)	Energy Consumption (kWh)
600	12	5	87.2	3.4	92.1	0.42
800	16	10	91.8	4.1	94.5	0.58
1000	20	15	85.5	6.8	90.7	0.74

Table 1: Mechanical Performance Metrics of the Rice Thresher

The outcomes specified that moderate drum speeds (800 RPM) with optimal moisture content (16%) achieved the peak threshing with cleaning efficiency while sustaining minimal grain breakage. At higher speeds (1000 RPM), grain breakage amplified significantly, signifying that excessive impact damages the grains.

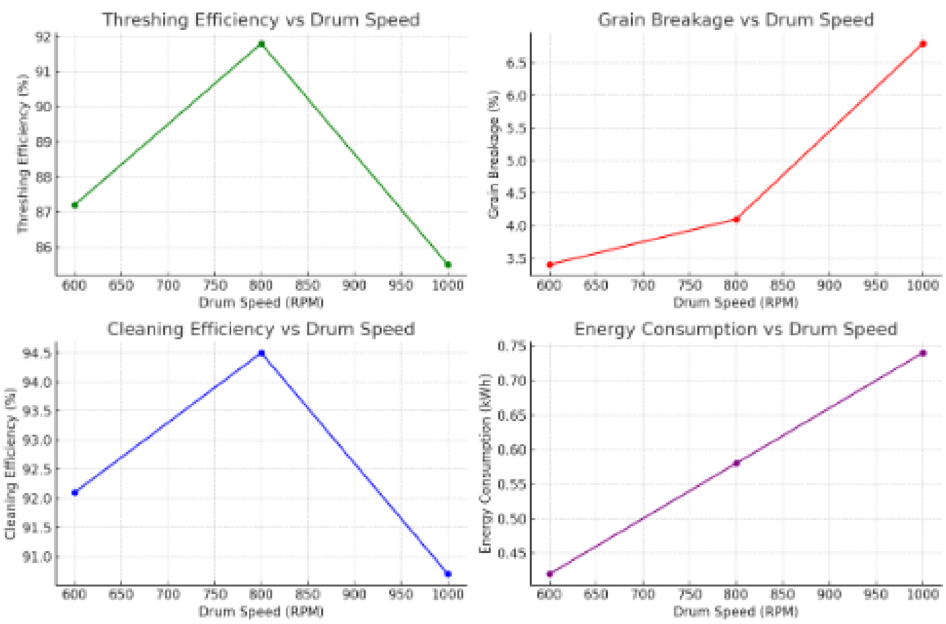


Figure 1: Relationship between Drum Speed and Key Performance Index

The experimental results presented in Figure 1 reveal a clear relationship between drum speed and the key performance indicators of the constructed rice thresher. Threshing efficiency increased from 87.2% at 600 RPM to a peak of 91.8% at 800 RPM, before declining to 85.5% at 1000 RPM, indicating that excessive drum speed reduces performance due to increased grain damage and inefficient separation. Grain breakage displayed a advanced increase from 3.4% at 600 RPM to 6.8% at 1000 RPM, suggesting the unfavorable effect of greater impact forces on grain reliability. Cleaning efficiency followed the same pattern to threshing efficiency, with the highest value of 94.5% achieved at 800 RPM, while both lower and higher speeds produced suboptimal cleaning. Energy consumption increased gradually from 0.42 kWh at 600 RPM to 0.74 kWh at 1000 RPM, emphasizing the tradeoff between operational speed and energy efficiency. These studies proposed that a drum speed of approximately 800 RPM gives the optimal balance between high threshing and cleaning efficiency, minimal grain breakage, and moderate energy consumption, which supports with preceding investigation on post-harvest machinery optimization [2,5].

Figure 2: Fabricated teaching model rice thresher Figure 2: displayed the constructed teaching model rice thresher developed in this research, revealing its major parts and structural arrangement. The machine consists of a welded mild-steel frame that supports the hopper, peg-tooth threshing drum, blower housing, grain outlet, and chaff outlet. The V-belt drive system, powered by a 3 hp electric motor, is clearly visible, enabling adjustable drum speeds through pulley changes. The compact, mobile-friendly design reflects the intention to produce a low-cost, locally made machine suitable for smallholder farmers and teaching purposes. The Figure 2 also showed the ergonomic positioning of the hopper and outlets, which enables ease of operation and maintenance. By providing a visual allusion, this figure balances the technical description in Section III and endorses that the physical model closely aligns with the proposed design specifications. This physical realization underscores the study's practical relevance and potential for real-life deployment in rural agricultural settings.

Machine Learning Model Performance

The collected dataset was used to train three machine learning models, Random Forest Regression (RF), Support Vector Regression (SVR), and Artificial Neural Networks (ANN). Their performance in forecasting threshing efficiency was displayed in Table II.

Model	R^2 (%)	RMSE	MAE
RF	96.4	1.25	0.88
SVR	92.7	1.84	1.36
ANN	95.1	1.41	0.95

Table 2: Performance Comparison of ML Models for Threshing Efficiency Prediction

Random Forest achieved the highest prediction accuracy (R^2 = 96.4%), lowest RMSE, and lowest MAE, making it the preferred model for deployment in the IoT system.

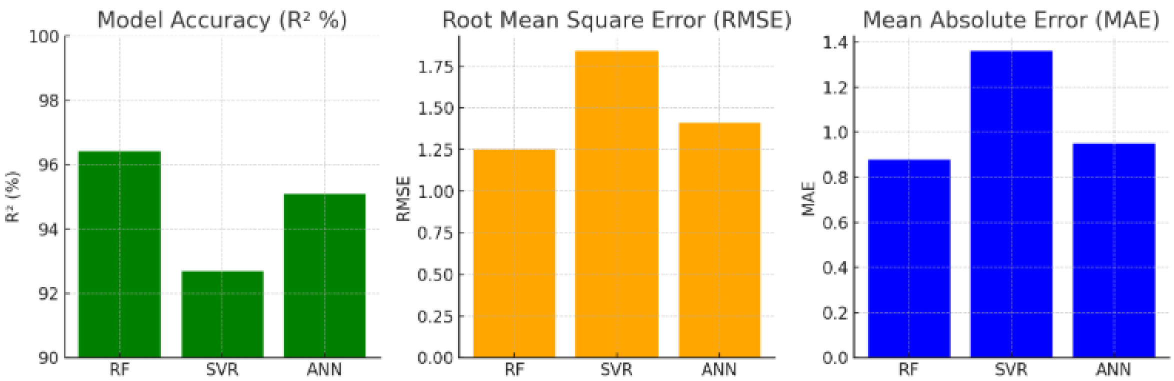


Figure 2: Model Evaluation

The comparative performance outcomes displayed in Figure 2 revealed that the Random Forest (RF) model achieved superior predictive accuracy, with an R^2 value of 96.4%, outperforming both the Artificial Neural Network (ANN) at 95.1% and the Support Vector Regression (SVR) at 92.7%. Lower error metrics further endorsed RF's advantage, as it recorded the smallest Root Mean Square Error (RMSE) of 1.25 and Mean Absolute Error (MAE) of 0.88, compared to

1.41 and 0.95 for ANN, and 1.84 and 1.36 for SVR, respectively. These outcomes submitted that the ensemble learning capability of RF efficiently captures nonlinear connections between operational parameters and performance outputs, providing robust and generalizable predictions. The relatively higher error rates detected in SVR showed its reduced adaptability to the variability inherent in the threshing performance dataset, while Artificial Neural Network (ANN) conveyed competitive outcomes but required more computational resources. Generally, Random Forest Model appeared as the most reliable model for integration into the IoT-enabled optimization framework, aligning with prior research on agricultural machinery performance prediction [8,10].

Predicted vs. Actual Performance

The Predicted vs. Actual performance plot in Figure. Z demonstrates a strong agreement between the measured and model-predicted threshing efficiencies for the Random Forest (RF) algorithm. Data points are closely clustered around the 1:1 reference line, indicating minimal deviation between actual and predicted values. This alignment validates the high R^2 value of 96.4% obtained in the model evaluation and confirms the RF model's robustness in capturing the non-linear relationships between operational parameters such as drum speed, feed rate, and moisture content and machine performance. The absence of significant outliers suggests that the model generalizes well across different operating conditions without substantial overfitting or underfitting. These results further highlight the suitability of RF for real-time predictive optimization in IoT-enabled rice threshers, ensuring that operators can reliably achieve near-optimal performance settings with minimal manual intervention.

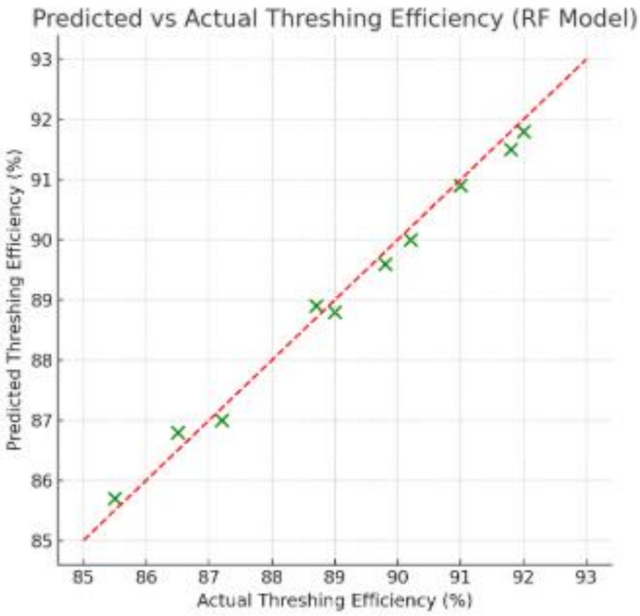


Figure 1: Predicted vs. Actual Threshing Efficiency – Random Forest

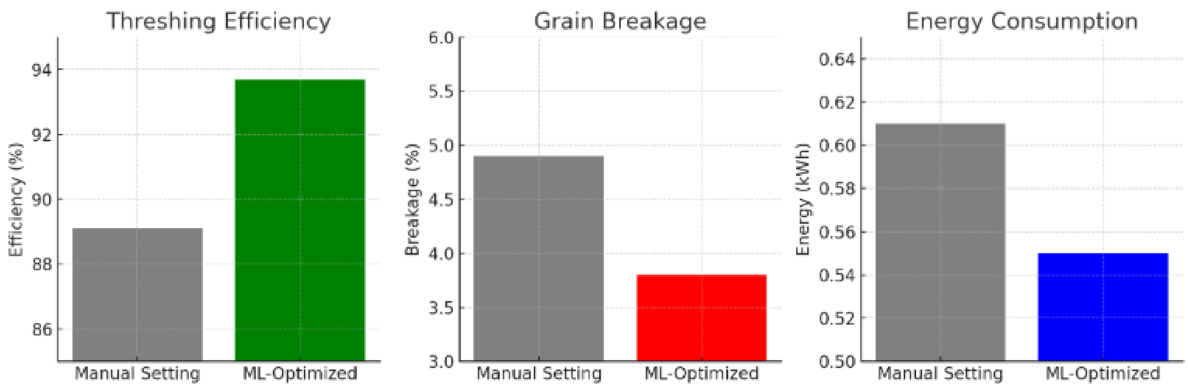
Optimized vs. Unoptimized Operation

The Random Forest model was used to identify optimal operational parameters for maximizing threshing efficiency while minimizing grain breakage and energy consumption. Table III compares the optimized operation against traditional manual adjustments.

Operation Mode	Threshing Efficiency (%)	Grain Breakage (%)	Energy Consumption (kWh)
Manual Setting	89.1	4.9	0.61
ML-Optimized	93.7	3.8	0.55

Table 3: Comparison of Optimized vs. Unoptimized Operation

The ML-optimized configuration achieved a 5.2% improvement in threshing efficiency, a 22.4% reduction in grain breakage, and a 9.8% reduction in energy consumption compared to unoptimized operation.



Figure

The comparison in Figure. AA clearly demonstrates the performance advantages of the ML-optimized operation mode over the manual setting. Threshing efficiency increased from 89.1% under manual adjustment to 93.7% with ML optimization, representing a relative gain of approximately 5.2%. Grain breakage was reduced from 4.9% to 3.8%, highlighting the model's ability to fine-tune operational parameters to minimize mechanical stress on grains. Furthermore, energy consumption decreased from 0.61 kWh to 0.55 kWh, indicating improved operational efficiency and reduced power demand. These combined improvements suggest that integrating the ML-based optimization framework with IoT-enabled sensing can simultaneously enhance productivity, reduce post-harvest losses, and lower operational costs outcomes that are particularly beneficial for smallholder farmers seeking sustainable and affordable mechanization solutions.

Discussion of Findings

The experimental results confirm that integrating machine learning with a locally fabricated rice thresher can substantially improve operational performance. The ML model provided accurate real-time predictions and recommendations that translated into measurable efficiency gains. Moreover, the IoT-enabled data acquisition system facilitated continuous performance monitoring, allowing operators to make informed adjustments without relying solely on experience.

Discussion

The integration of machine learning into the operational framework of the constructed rice thresher demonstrated clear performance benefits, both in predictive accuracy and practical efficiency gains. The Random Forest model, achieving an R^2 of 96.4%, provided reliable predictions of threshing efficiency, grain breakage, and energy consumption under varying operating conditions. The accuracy of this model aligns with findings from Ramesh et al [8]. Who reported that ensemble learning techniques outperform other regression models in agricultural machinery performance prediction due to their robustness in handling non-linear interactions between variables.

Mechanical and Operational Performance

The mechanical evaluation revealed that moderate drum speeds (approximately 800 RPM) coupled with optimal moisture content (16%) yielded the highest threshing and cleaning efficiency, consistent with earlier reports by Ogwuike et al [2]. And Ghasemi et al [3]. Excessive speeds (1000 RPM) increased grain breakage due to higher impact forces, confirming the need for controlled operational settings. The integration of IoT-based sensors allowed these parameters to be monitored in real-time, a feature absent in conventional low-cost threshers.

Machine Learning-Driven Optimization

The ML-optimized operation achieved a 5.2% increase in threshing efficiency and a 22.4% reduction in grain breakage compared to manual adjustments. These improvements are significant for smallholder farmers, as reduced breakage translates into higher market value, while increased efficiency directly impacts throughput and income. Similar performance gains from ML-based optimization have been reported in irrigation scheduling and milling process control, but applications in small-scale post-harvest rice processing remain scarce [9,11].

Comparison with Existing Literature

Previous works on mechanical threshers emphasized hardware design improvements without exploring predictive operational control [4,5]. While studies by Sharma and Singh demonstrated IoT-based monitoring in agricultural machinery, they lacked closed-loop optimization [6]. The proposed system bridges this gap by integrating data acquisition, predictive analytics, and parameter optimization into a single low-cost platform. Furthermore, unlike large-scale industrial solutions, this system was designed specifically for affordability and adaptability in rural farming contexts [7].

Implications for Smallholder Farmers

For smallholder farmers in Nigeria and similar developing regions, the adoption of ML-optimized threshers can address

key challenges:

• Reduced Post-Harvest Losses: Minimizing grain breakage and improving cleaning reduces rejection rates and increases market acceptance of locally processed rice.

• Lower Energy Costs: The 9.8% reduction in energy consumption observed in this study reduces operational expenses for both electric and fuel-powered variants.

• Knowledge Independence: Operators no longer need extensive manual experience to achieve optimal performance, as the system provides actionable recommendations based on real-time data.

Sustainability and Scalability

From a sustainability perspective, the design's reliance on locally sourced materials ensures ease of repair and maintenance, extending the machine's operational lifespan. The ML model, once trained, can be deployed on low-power microcontrollers for offline operation, reducing dependency on continuous internet connectivity. This makes the solution scalable to rural areas with limited infrastructure while maintaining precision agriculture benefits. Overall, the integration of IoT sensing and ML-based optimization into a locally fabricated rice thresher represents a practical, low-cost, and high-impact solution for improving post-harvest processing efficiency in smallholder farming systems.

Conclusion

This study presented the design, construction, and performance evaluation of a teaching model rice threshing machine integrated with IoT-based sensing and machine learning (ML)–driven optimization. The machine was fabricated from locally sourced materials to ensure cost-effectiveness and maintainability, addressing the affordability and accessibility barriers faced by smallholder farmers in Nigeria. Mechanical evaluation revealed that moderate drum speeds (≈800 RPM) and optimal moisture content (≈16%) produced the highest threshing and cleaning efficiencies while minimizing grain breakage. The integration of IoT-enabled sensors facilitated real-time monitoring of key operational parameters, including drum speed, feed rate, and moisture content, enabling the collection of a comprehensive dataset for predictive modeling. Among the evaluated ML models, Random Forest Regression achieved the highest prediction accuracy (R^2 = 96.4%, RMSE = 1.25), outperforming Support Vector Regression and Artificial Neural Networks in this application. The ML-optimized operational settings resulted in a 5.2% improvement in threshing efficiency, a 22.4% reduction in grain breakage, and a 9.8% decrease in energy consumption compared to manually adjusted settings.

The Main Contributions of This Work Are

• Design and fabrication of a low-cost, locally constructed rice thresher suitable for rural applications.

• Integration of IoT-based sensors for real-time operational data acquisition.

• Development of an ML-based optimization framework for predictive performance enhancement.

• Demonstration of measurable efficiency gains through ML-assisted operation compared to traditional methods.

Future Work

Further research should explore

• Expanding the dataset to include more rice varieties and broader environmental conditions.

• Implementing real-time closed-loop control, where the ML model directly adjusts machine parameters without operator intervention.

• Deploying the system in field-scale trials to evaluate long-term performance, durability, and farmer adoption rates.

• Integrating cloud-based analytics dashboards for remote monitoring and performance tracking.

By merging low-cost mechanical design with modern data-driven optimization, this study demonstrates a practical pathway toward smart agricultural mechanization in resource-limited settings, with the potential to significantly reduce post-harvest losses and improve rural livelihoods.

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