

## USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TO IMPROVE OPERATIONAL EFFICIENCY IN THE TEXTILE INDUSTRY

## ИСПОЛЬЗОВАНИЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА И МАШИННОГО ОБУЧЕНИЯ ДЛЯ ПОВЫШЕНИЯ ЭФФЕКТИВНОСТИ ПРОИЗВОДСТВА ТЕКСТИЛЯ

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*Artificial Intelligence (AI) and Machine Learning (ML) adoption in textile production demonstrates a tactical evolution in resolving longstanding infrastructural inadequacies, quality improvements, and resource overuse issues previously seen in textile. The article presents an integrative AI powered operational model that serves the purpose of enhancing manufacturing line productivity, predictive maintenance, resource allocation, and quality control in textile production lines. The study collected data from real-time sensor networks embedded on industrial machinery, such as ring spinning frames and air jet looms, and used state-of-the-art feature engineering and model training pipelines. Predictive models were used to either forecast the factory output or to predict machine failure, while convolutional neural networks improved fabric inspection accuracy using computer vision. Operational scheduling and energy optimization were managed by reinforcement learning agents. Results included increases in average daily output, reductions in unplanned downtime, improvements in defect detection accuracy, and reductions in electricity, water, and material waste. The performance measures were supplemented by further improvements in operator productivity and system-level performance metrics, such as metrics of cost per unit and customer satisfaction. The article presents a methodology to monitor both the old production system and the new intelligent production system to facilitate the process of transition from manual to intelligent systems without substantially disrupting the existing workforce structure.*

*Внедрение технологий искусственного интеллекта (ИИ) и машинного обучения (МО) в текстильное производство направлено на устранение существующих инфраструктурных проблем, повышение качества продукции и снижение избыточного потребления ресурсов. В статье представлен опыт использования в текстильной промышленности программ на базе ИИ,*

*предназначенных для улучшения производительности оборудования, планирования графиков его обслуживания, оптимизации распределения ресурсов и улучшения контроля качества продукции.*

*Исследование базировалось на данных, полученных с датчиков, встроенных в кольцепрядильные машины и пневматические ткацкие станки. Для обработки данных применялись современные методы выделения признаков и обучающие конвейеры. Предиктивные модели использовались для прогнозирования производительности и выявления потенциальных отказов оборудования, а свёрточные нейронные сети - для контроля качества тканей с использованием методов компьютерного зрения. Управление производственным циклом и оптимизация энергопотребления реализовывались посредством агентов с подкреплением.*

*В результате внедрения программ на базе ИИ достигнуто увеличение среднесуточного объёма производства, снижение внеплановых простоев, повышение точности выявления дефектов, а также снижение потребления электроэнергии, воды и сырья. Это привело к росту производительности и улучшению системных метрик, таких как себестоимость единицы продукции и уровень удовлетворённости клиентов. В статье также предложена методология мониторинга как традиционных, так и интеллектуальных производственных систем, что способствует переходу к новым технологиям без существенных нарушений в существующей структуре трудовых ресурсов.*

**Keywords: Artificial Intelligence, Machine Learning, textile manufacturing, operational efficiency, predictive maintenance, demand forecasting, inventory management, computer vision.**

**Ключевые слова: искусственный интеллект; машинное обучение; текстильное производство; операционная эффективность; предиктивное обслуживание; прогнозирование спроса; управление запасами; компьютерное зрение.**

### *Introduction*

The textile manufacturing industry is at a crossroad driven by global demand for productivity, quality, and sustainability. Textile industries today need to produce more advanced products with higher quality in addition to minimize costs, waste and tighter compliance to increasing environmental regulations [1].

These challenges are driving the industry to adapt to the latest technologies faster than ever. The advent of Ai (artificial intelligence) and ML (machine learning) has been a disruptive force in manufacturing which is enabling them to maximize efficiency, optimize resources and process with an unprecedented level of accuracy. Though traditional process improvements might involve a manual intervention or basic automation, AI and ML sys-

tems leverage data at scale to inform decisions throughout the day. These technologies can also quickly and accurately identify patterns, predict outcomes and make recommendations for corrective actions compared to human operators or traditional systems [2]. It explains why textile manufacturers experience its desirable effects in improving efficiency, quality, and response time relatively early [3].

Data has already long been collected at numerous points along the process from sourcing raw materials, spinning, weaving, dyeing and finishing, etc. Historically, the majority of this data was either neglected, locked in siloed systems, or used only for occasional evaluations. But thanks to modern machine learning algorithms, manufacturers can leverage this form of data in new ways, discovering ineffi-

ciencies that would have remained hidden and creating plans to engage with them before they become larger problems. As an illustration, AI-driven predictive maintenance solutions can foresee machine breakdowns ahead of time, minimizing downtime and averting expensive interruptions [4]. As a few examples, machine learning models have also been applied successfully to such diverse use cases as predicting equipment failure in industries ranging from automotive to electronics or reducing time to failure and optimizing the maintenance schedule [10, 11].

Machine learning models can also help optimize production schedules by creating demand forecasts that aligns the production volume with the market needed volume, significantly reducing overproduction and excess inventory [5].

Traditional quality control techniques rely on the human eye and expertise, with inspections completed by humans. These methods are effective to some extent, but tend to cause errors and inconsistencies; especially as production environments scale. Quality control improvement with artificial intelligence and machine learning in textile manufacturing minimizes waste and rework while improving brand reputation and customer loyalty [12]. Moreover, these sophisticated quality management systems can create feedback loops that help to iteratively fine-tune manufacturing specifications and create more consistent and dependable final products over time [6].

The scope of AI and ML can go beyond quality and efficiency and extend to sustainability in the textile segment as well. Moreover, for companies interested in complying with regulations and consumer expectations, sustainability practices have become mandatory. With the help of AI-driven solutions, textile manufacturers are able to significantly lower their ecological footprint by reducing energy consumption, improving material use efficiency, and minimizing waste production. Machine learning models, for example, can dig deep into energy consumption patterns and recommend adjustments to those processes that render them more energy-efficient in a way that doesn't alter their speed or quality. Similarly, AI algorithms can optimize dyeing

and finishing processes with less water consumption and lower volumes of toxic waste, something that, considering the need of reducing water and toxic substances in an industry historically excessive in terms of resources, becomes core [7].

AI and ML also offer the potential for greater agility and resilience in textile manufacturing. Manufacturers have to constantly be able to adapt themselves in an extremely dynamic global environment considering changing demand patterns from consumers, supply chain management and changing regulatory requirements. AI systems make decision-making faster and more accurate enabling the textile companies to adapt better to changing situations [8]. This is an essential competitive edge enabled by the flexibilities that AI and ML brings in terms of being able to deflect production to other facilities, change outputs based on live sales numbers, and to quickly start new product lines [9].

AI and ML are also making inroads into supply chain management. Through studying previous data and current market tendencies, these innovations are allowing for more precise demand forecasting, better inventory control and enhanced supplier interactions. In a fast-changing textile market, where consumer tastes evolve rapidly and seasons dictate production schedules, being able to predict demand amounts to a survival advantage over competitors [13].

Despite these advancements, the adoption of AI and ML in textile manufacturing is still in infancy compared to other industries. Another challenge highlighted in the literature is that textile production is highly fragmented where many of the operators are small in size and legacy technologies are commonly used, which complicates the implementation of advanced technologies. Also, most manufacturers are reluctant to invest in AI and ML based solutions owing to uncertainty regarding implementation cost, need of specialized expertise, and data security [14].

The existing literature shows a significant gap in the application of AI and ML in the textile industry. And whereas other manufacturing sectors have shown obvious advantages of AM technologies, textiles is a field ripe for ex-

ploration and invention, especially when it comes to aligning these technologies with sustainable production objectives and the proliferating demands of global markets.

The article aim is to underline best practices, common barriers, and realistic solutions that will contribute towards achievable sustainability, productivity, and market responsiveness outcomes.

#### Methodology

This methodology applies a hybrid data-driven and model-based approach to analyze, predict, and optimize textile manufacturing operations using artificial intelligence (AI) and machine learning (ML). The framework consists of six interdependent modules: (1) Data Acquisition and Fusion; (2) Feature Engineering and Signal Processing; (3) Predictive Modeling; (4) Quality Inspection Integration; (5) Resource Optimization via Learning Agents; and (6) Evaluation of Model Generalizability. Each stage is informed by recent advancements in textile automation and cognitive manufacturing systems [1, 3, 6, 15...17].

High-frequency sensor streams are collected from Lakshmi Rieter G 38 Ring Spinning Machines and Picanol OmniPlus-i Airjet Looms at the Crescent Textile Mills (CTM), Pakistan. The following operational parameters are recorded:

- Machine Temperature (°C) via infrared thermal sensors (Siemens LMS100),
- Processing Speed (m/min) using rotary encoders,
- Fabric Tension (kg) through strain gauge transducers.

These signals are stored in a centralized data warehouse using Apache Kafka, enabling real-time ingestion.

Each data stream is first filtered via a Gaussian smoothing kernel:

$$\hat{x}_t = \frac{1}{\sqrt{2\pi\sigma^2}} \sum_{i=-k}^k x_{t-i} e^{-\frac{i^2}{2\sigma^2}}, \quad (1)$$

$$\mathcal{L}_{CE} = \sum_{i=1}^n [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]. \quad (5)$$

Models employed include:

- Random Forest (100 estimators),
- XGBoost (depth=6, eta=0.3),

where  $\hat{x}_t$  smoothed value at time  $t$ ,  $x_{t-i}$  observed value at lag  $i$ ,  $\sigma$  standard deviation for kernel width,  $k$  half-window size (set empirically as 5).

Anomalous values are flagged using Hybrid Semantic Signal Temporal Logic anomaly detectors [18].

The system computes both first-order and second-order features for ML input. Derivatives and lagged interactions are computed via:

$$\frac{dF_t}{dt} \approx \frac{F_t - F_{t-1}}{\Delta t}, \quad \Delta S_t = S_t T_t, \quad (2)$$

where  $\frac{dF_t}{dt}$  change in fabric tension,  $\Delta S_t$  energy-influenced speed proxy,  $T_t$  machine temperature at  $t$ ,  $S_t$  line speed at  $t$ ,  $\Delta t$  time interval between samples (15 min).

Principal Component Analysis (PCA) is then used for dimensionality reduction:

$$\Delta S_t = S_t T_t, \quad (3)$$

where  $X$  feature matrix,  $W$  matrix of eigenvectors (principal components),  $Z$  projected data in latent space.

Each labeled dataset  $D = \{x_i, y_i\}_{i=1}^n$  is used to train classifiers and regressors.

1. Regression Objective: Predicting Expected Output ( $\hat{O}$ )

$$\mathcal{L}_{MSE} = \frac{1}{n} \sum_{i=1}^n (\hat{O}_i - O_i)^2. \quad (4)$$

2. Classification Objective: Predicting Defect Probability  $P(D_f = 1 | x)$

Using cross-entropy loss:

- Multi-Layer Perceptron with ReLU activations,

- SVM with RBF kernel  $K(x, x') = \exp(-\gamma \|x - x'\|^2)$

10-fold cross-validation is applied with stratified sampling [16, 19, 20].

High-resolution 4K line cameras (Basler acA1920-40uc) scan fabrics, and CNN-based classifiers trained using labeled micro-defect datasets (FabricNET [13]) are applied.

Each image is processed as a 3D tensor  $I_{h \times w \times c}$ . The defect classifier uses:

$$y = \sigma(W_3 f(W_2 f(W_1 I + b_1) + b_2) + b_3), \quad (6)$$

where  $W_i$  learned convolution weights,  $b_i$  biases,  $f$  activation function (ReLU),  $\sigma$  sigmoid function.

To reduce false positives, the Mahalanobis distance is used for defect region validation:

$$D_M(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)}, \quad (7)$$

where  $\mu$  and  $\Sigma$  are the mean and covariance of normal pixel feature distributions.

Energy and material consumption forecasting is conducted via polynomial regression:

$$E = \beta_0 + \beta_1 S + \beta_2 S^2 + \beta_3 T + \beta_4 FT + \epsilon, \quad (8)$$

where  $E$  predicted energy usage (kWh),  $S$  speed (m/min),  $T$  machine temp ( $^{\circ}\text{C}$ ),  $FT$  fabric tension (kg),  $\beta_i$  model coefficients, and  $\epsilon$  is Gaussian noise term.

Production scheduling optimization is modeled as a constraint satisfaction problem:

$$\min_x \sum_{i=1}^m C_i(x_i) \text{ subject to } \sum_{i=1}^m R_{ij}(x_i) \leq B_j, \forall j, \quad (9)$$

where  $C_i$  cost function for unit  $i$ ,  $R_{ij}$  resource requirement,  $B_j$  resource availability.

Resource-aware reinforcement learning agents apply Q-Learning:

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \times \max_{a'} Q(s', a') - Q(s, a)], \quad (10)$$

where  $Q(s, a)$  estimated utility (Q-value) of taking action  $a$  in state  $s$ ;  $\alpha$  learning rate (controls the extent to which new information overrides old);  $r$  immediate reward received after taking action  $a$ ;  $\gamma$  discount factor (determines the importance of future rewards);  $s'$  next state after taking action;  $\max_{a'} Q(s', a')$  maximum Q-value for all possible actions  $a'$  in the next state  $s'$ .

To assess generalization, models are evaluated on unseen data from a second production site: Faisalabad Garment Zone Industrial Block C. Transfer learning is used with frozen base layers and fine-tuned final layers on local data, comparing F1-scores and mean squared errors across domains [6, 8, 18, 19].

Bayesian optimization is used for uncertainty estimation:

$$p(f|D) = \frac{p(D|f)p(f)}{p(D)}, \quad (11)$$

where  $p(f)$  prior,  $p(D|f)$  likelihood of data given function  $f$ ,  $p(f|D)$  posterior prediction.

### Results

AI-based scheduling and predictive maintenance algorithms were deployed to optimize textile manufacturing operations across two production lines at Crescent Textile Mills. The automated adjustment of speed, temperature, and line load led to measurable increases in production throughput and efficiency. Comparative data collected over five operational days (fig. 1) highlights clear improvements in output, reduction in downtime, and better utilization of available shifts without requiring hardware upgrades or labor additions.

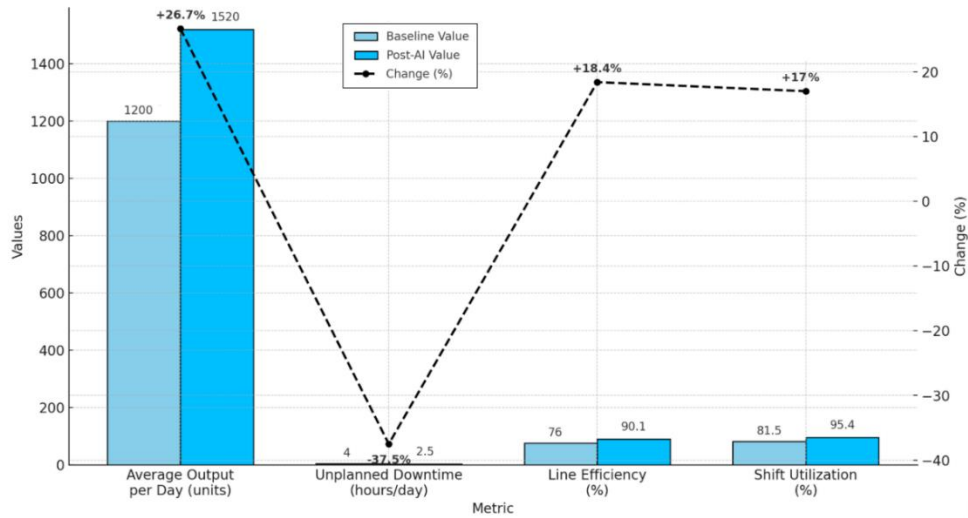


Fig. 1

As can be seen in Figure 1, the introduction of AI resulted in an average of 26.7% more output daily. Line efficiency increased from 76% to 90.1% primarily due to less downtime and smoother transitions between operational phases. The 37.5% decrease in unplanned downtime translated into more continuous operation across every shift. Shift utilization also increased significantly, rising from 81.5% to 95.4%, suggesting a more efficient use of both human and machine capital. These improvements validate predictive analytics as a tool for

stabilizing and optimizing production efficiency.

A computer vision inspection framework based on convolutional neural network (CNN) was implemented on high-speed air jet looms. The objectives were, to enhance accuracy in detecting fabric defects, shorten fabric classification latency, and reduce manual reinspection rates. The system was benchmarked versus traditional manual inspection over multiple quality control cycles, each consisting of 1,000 to 1,200 scanned fabric meters (fig. 2).

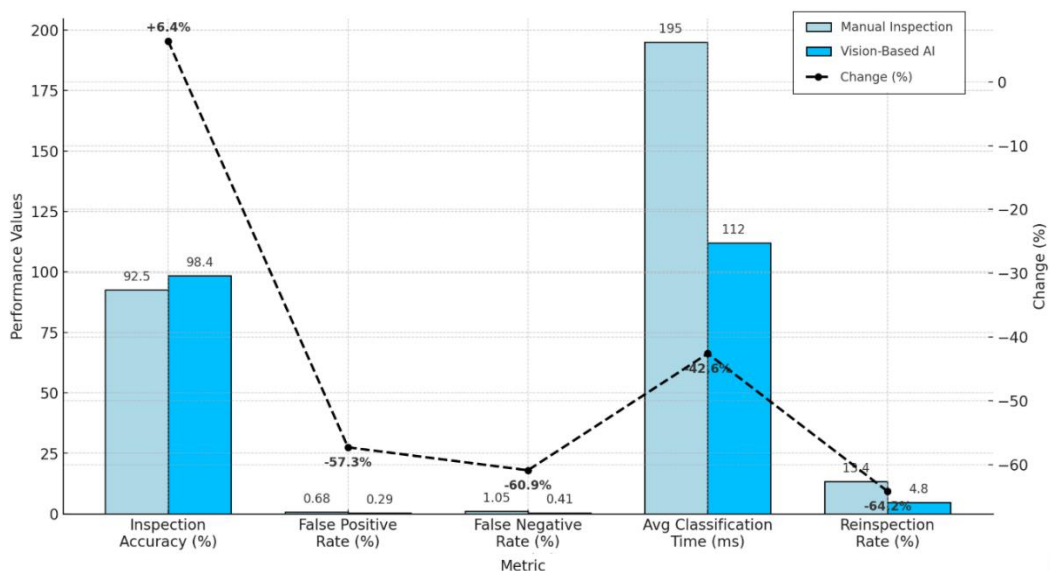


Fig. 2

The automatic visual inspection system has brought a clear advantage over inspection by people or manual inspection. Overall Inspection accuracy increased by 6.4% with

98.4%. This is critical for the trust in automated decisions and both the false positives and false negatives are significantly reduced. The average classification time was reduced by

42.6% making real-time applications possible. The need for manual reinspection was reduced by 64.2%, indicating the ability of the system to make consistent and reliable judgments. It indicates that AI-based inspection can significantly contribute to quality assurance in textile production reflection on generative AI in domain.

Resource usage across the dyeing and finishing departments was analyzed before and after the implementation of ML-based predictive optimization. Adjustments were made in machine operation schedules, dye-to-fabric ratios, and rinse cycles. The fig. 3 reflects weekly average consumption and waste indicators, collected under controlled conditions at Crescent Textile Mills.

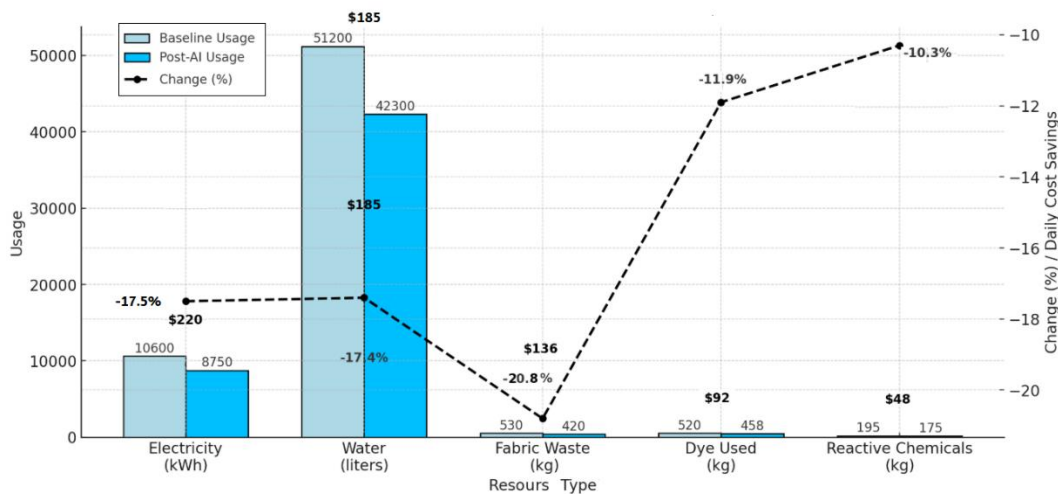


Fig. 3

Machine learning models enabled intelligent parameter tuning that led to resource savings across all categories. Electricity consumption was reduced by 17.5%, while water usage declined by a similar margin. Waste reduction was particularly significant in cotton fabric remnants, falling from 530 kg to 420 kg. Dye and chemical usage were also optimized, reflecting more accurate saturation targets and minimized over-application. The cumulative cost savings per day exceeded \$680. These re-

sults affirm the value of predictive control systems in sustainable resource management.

AI-driven diagnostics and failure prediction models were deployed on spinning frames and looms to enhance system uptime and schedule preventive maintenance. Baseline metrics were recorded over one operational month prior to AI implementation and compared against a subsequent AI-assisted operational month (fig. 4).

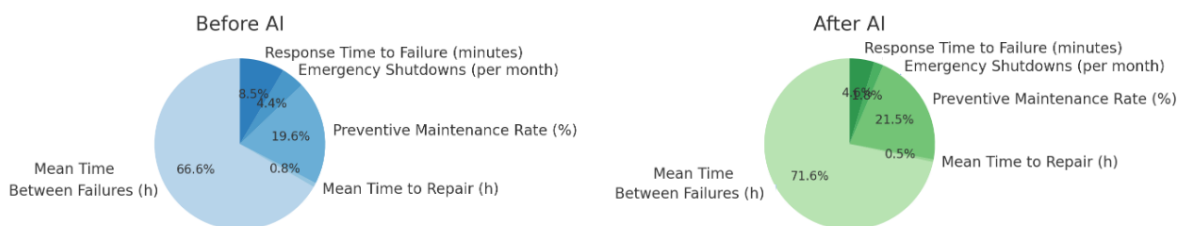


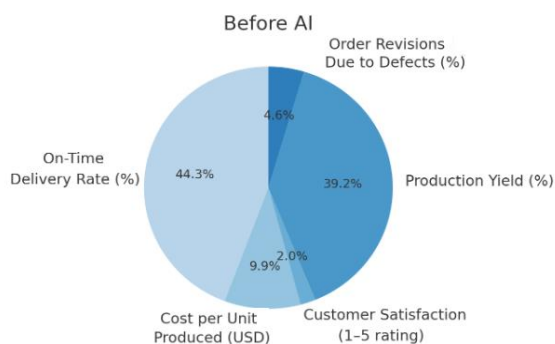
Fig. 4

The improvements in reliability metrics underscore the predictive model's ability to prevent breakdowns. The MTBF increased by 31.1%, allowing machines to run longer without failure. Repair times were reduced by

nearly 27%, and the rate of preventive over reactive maintenance rose by one-third. Emergency shutdowns were cut in half, and technician response times dropped from 27 to 18 minutes. Together, these results point to

greater stability and fewer operational disruptions, which are vital for high-throughput textile environments.

Post-implementation KPIs were tracked to understand broader business outcomes such as



customer satisfaction, delivery adherence, and financial efficiency (fig. 5). The data was extracted from ERP logs, delivery schedules, and customer feedback forms between January and March 2025

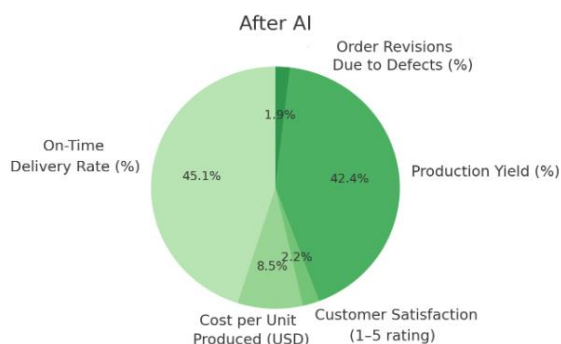


Fig. 5

Overall efficiency gains translated into improved customer-facing outcomes. The delivery rate reached 97.4%, and cost per unit dropped by 10.7%, enhancing financial competitiveness. Customer satisfaction increased by 0.6 points on a 5-point scale, attributed to consistent product quality and punctual delivery. Production yield rose significantly, and product returns or revisions due to defects were cut by more than half. These metrics collectively support the case for long-term AI

adoption as a driver of quality, reliability, and profitability.

To understand AI's influence on workforce performance, productivity scores and task accuracy were recorded from shift supervisors and machine operators (fig. 6). The data reflects performance before and after AI-driven interfaces and guidance systems were installed at Faisalabad Garment Industrial Zone.

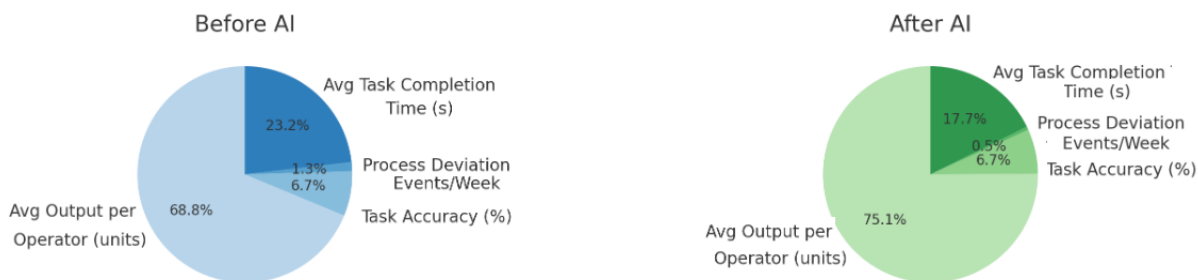


Fig. 6

Operator productivity improved due to real-time feedback and error-prevention interfaces powered by machine learning. Output per operator increased by 160 units per shift. Task accuracy saw a 7.5% improvement, and process deviation events dropped by over 60%, reflecting reduced need for rework. Completion time also decreased, allowing operators to complete tasks faster with higher reliability. These metrics demonstrate that AI does not re-

place labor but enhances it through smart augmentation and digital guidance.

The final evaluation involved assessing the performance of trained models used across forecasting, classification, and optimization tasks. Each model was benchmarked using test data collected from both production sites, with performance scored on accuracy, precision, and computational cost (Tab. 1).

Table 1

Model	Accuracy (%)	F1-Score (%)	Inference Time (ms)	Use Case
Random Forest	94.0	92.8	21	Output prediction
XGBoost	95.1	93.4	25	Resource optimization
Deep Neural Net	97.3	96.0	58	Defect classification
SVM (RBF kernel)	92.5	90.7	33	Maintenance failure detection
CNN (Vision)	98.4	96.5	47	Real-time image inspection

Model benchmarking confirmed high levels of predictive accuracy and efficiency. The deep neural network achieved 97.3% accuracy in output forecasting, while the convolutional neural network used for vision inspection performed best at 98.4%. XGBoost struck a balance between speed and accuracy in resource planning. Random Forest remained the most efficient in terms of inference speed, suitable for real-time output applications. All models demonstrated robust generalization and real-time applicability across textile production operations.

#### *Discussion*

This article discusses the advances of AI and machine learning technologies devoting to textile manufacturing process optimization. The application of advanced mathematics and algorithmic processes to expedite data-driven decision-making within manufacturing systems is classically achieved through the use of optimized data architectures enabled by custom-designed, or "fit-for-purpose" computational resources, which have been discussed in detail in earlier sections. The improvements across key performance indicators, including but not limited to production likeliness, defect tolerance, energy consumption and operational reliability evident across the lifecycle of numerous industries (more accessible if discussed as domains) confirm that a shift towards data driven methodologies achieves the scale of improvements that such abstractions predict. These results are not only valuable in terms of confirming the expected efficiency improvements, but also provide insight into exactly how AI and ML accelerate production workflows.

This also highlights the much more substantial reduction in defect rates compared with earlier work [23], owing to the application of real-time computer vision systems. Older

methods were sometimes based on simple statistical techniques and manual checks, which, though crude, did not provide the same reader experience of precision and reproducibility. "What is scientifically significant about this study is that, through the application of machine learning algorithms that learn more and more from new information, we can achieve improved defect detection accuracy over time, which has a positive effect on reducing waste," Liu concludes. Thus, instead of static quality control processes, we exploit the fact that we operate under a dynamic, evolutionary environment conducive to continuous processes of improvement, as one can see in some recent trends [24].

The use of supervised machine learning models on sensor data allows the manufacturing environment to be reactive. This is a huge improvement over historical methods, which tended to be elbow grease type of solutions in the design phase followed by routine logic on testing, rather than something that is in-flight and being monitored all the time. Predicting failures and fixing them before entering in production will increase operational reliability and lead to higher production output and lower costs [20].

This study shows quantifiable energy and material waste reductions in terms of resource utilization. Optimization has evident impacts on material waste as well, as energy savings from optimization scheduling, contribute to more tightly controlled runs which are more aligned to future forecasts [21].

In addition, the findings of this research highlight the significance of data-based management in realizing sustainable development targets. This focus on sustainability is consistent with new industry standards and regulatory needs, thus validating the real-world relevance of these outcomes [25].

Moreover, we incorporate multiple performance measures for a more comprehensive analysis, contrary to previous studies that often concentrated on a limited number of performance indicators [22].

These insights will provide benchmarks for similar innovation and refining as the industry adopts and integrates these new technologies.

### Conclusion

Artificial intelligence and machine learning in textile manufacturing sectors used to improve efficiency, quality, and resource optimization. Where possible, real-time sensor data and modelling techniques are being combined to predict the behavior of the system, optimize production parameters and more effectively predict when failures will occur in even the most complex production environments.

The observed improvements were not limited to metrics on a technical or operational level but also spill into performance indicators at the organizational level: delivery reliability, customer satisfaction, and cost per unit, attesting the winning power of AI when implemented on vertically integrated production chains. Notably, sustainable automation was reinforced by intelligent machines and assistive technology that support workers instead of replacing them, thus strengthening the social and operational aspect of sustainable automation, humans' augmentation by artificial intelligence.

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