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IoT Driven Real-Time Process Monitoring and Intelligent Quality Control Systems in Textile Manufacturing

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Abstract. This research introduces the implementation of a Hybrid IoT-AI Framework (HIAF) to promote the integration of Industry 4.0 in textile production to deal with the critical issues of labour-intensive, inconsistent quality, and waste of resources. The system incorporates the integration of RFID, optical, humidity, and vibration sensors of adding of the sensors of the RFI, optical, humidity and vibration with the smart network of the monitoring in real time at all the important production processes of spinning, weaving, dyeing and finishing; for different types of fabric: cotton, polyester, silk. The sample population was comprised of 50 manufacturing plants in five big Indian textile centers in a period of six months. The design uses edge computing to perform real-time data processing and cloud analytics to make predictive data. A texture, dye consistency, and fiber strength anomaly detection module is based on AI and automated control loops modify machine parameters in real-time. It is an innovative production line of digital twin that is used in simulation and predictive maintenance. Comprehensive evaluation has shown the framework's significant impact resulting in a 32% reduction of product defects; a 28% increase in first-pass yield and a 25% reduction in operational downtime.

1 Introduction

The textile sector globally is one of the most economically relevant and technologically challenging manufacturing areas, which have a significant contribution to international trade, creation of employment and economic growth in both developed and emerging economies [1]. As the number of consumers interested in high-quality fabrics, customized textile products, and sustainable manufacturing processes increases exponentially, the need to keep the quality control standards at high levels and manage the manufacturing process in the most efficient way has been growing progressively more urgent [2]. The traditional quality assessment methodologies which mainly use manual checking processes and human judgement have proven to be very ineffective in the areas of time efficiency, uniformity, accuracy, and scalability. Such traditional methods are predisposed to the human error, inconsistency caused by fatigue and variation in subjective interpretation that leads to high rate of defect, excessive material wastage, and the loss of quality standards of the products [3].

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The use of innovative digital technologies and especially the Internet of Things (IoT) has triggered a radical change in the functioning of the textile production sector. It allows full real-time monitoring of processes, the supply of automated quality control systems, and data-driven decision-making frameworks [4]. IoT-based manufacturing systems combine highly advanced smart sensors, data analytics platform, machine learning algorithms, and cloud computing infrastructure to monitor and analyze important production factors such as fabric texture specifications, dyeing error measurements, color measurements, machine performance, and equipment performance in general. The technological convergence has enabled the substantial improvement in the level of productivity, the massive reduction in the level of waste of materials, the efficiency of the energy saving, and the strict adherence to the international standards of the industry and the requirements imposed by the authorities. Using the latest IoT devices and artificial intelligence code sets, the textile producers will be able to identify product flaws and quality errors much earlier in the production flow, reduce the cost of production delays by using predictive maintenance plans, optimize the resource use at all the operational tiers, and adopt sustainable production methods that will have much lower environmental impact without cutting the economic sustainability [5]. Intelligent automation systems do not only contribute immensely in enhancing the product quality metrics but also positively contribute towards sustainable manufacturing efforts through energy use, less water consumption, less chemical waste generation and optimization of the entire cost of operations across the entire production cycle.

Industry 4.0 also known as the Fourth Industrial Revolution, it is yet another holistic technological system that is typified by the perfect interweaving of cyber-physical systems, high-tech IoT networks, artificial Intelligence platforms, big data analytics, cloud computing infrastructure, and autonomous robotic systems [6]. Industry 4.0 technologies can be applied in the textile manufacturing area to provide unprecedented automatization, connectivity, and intelligent decision-making capabilities that radically change conventional approaches to production. The adoption of intelligent sensors across the production space allows monitoring all key parameters of the critical processes, and the machine learning algorithms can interpret numerous data streams of operational operations and determine trends and predict possible breakdowns and suggest optimal process changes in time [7]. Figure 1 shows the Hybrid IoT-AI Framework (HIAF) Architecture.

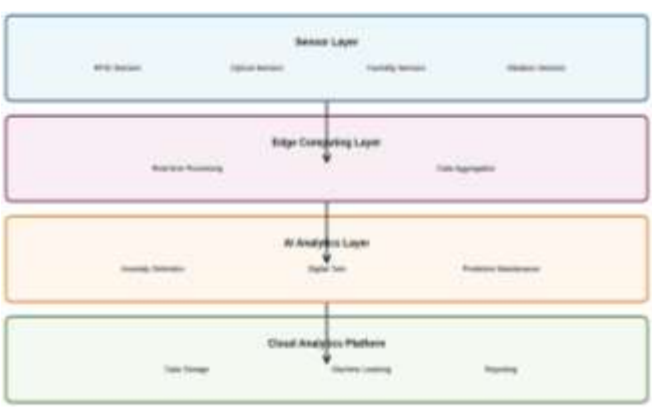

Fig. 1 Hybrid IoT-AI frame work architecture

The main reason behind the research is the continued problem of textile companies on how to ensure steady product quality, lower the rate of defects, lower operating expenses, and satisfy the growing demands of sustainability. In spite of the enormous technological developments over the last few years, most textile production plants still follow the old traditional manual inspection tools and reactive quality checking strategies that lead to high material wastage, high production cost and poor quality of the produced products. The proposed study will fill in these gap areas by creating and applying an all-encompassing and IoT-driven framework that will allow monitoring processes in real-time, automatically controlling quality, predictive maintenance, and data-driven optimization at every phase of textile production. Figure 2 shows the digital twin simulation and optimization flow, the specific objectives of the work are

- Development and construction of a system of all-purpose IoT sensors on a network with the continuous monitoring of textile manufacturing processes.
- Creation of improved AI-based anomaly detection algorithms to detect quality deviation and pattern defects in real-time.
- Development of digital twins to replicate the manufacturing environment and be able to optimize the process factors.
- Introducing predictive maintenance measures to reduce equipment downtime and improve the life of the equipment.
- Comparison of system performance in various textile production plants and fabrics.

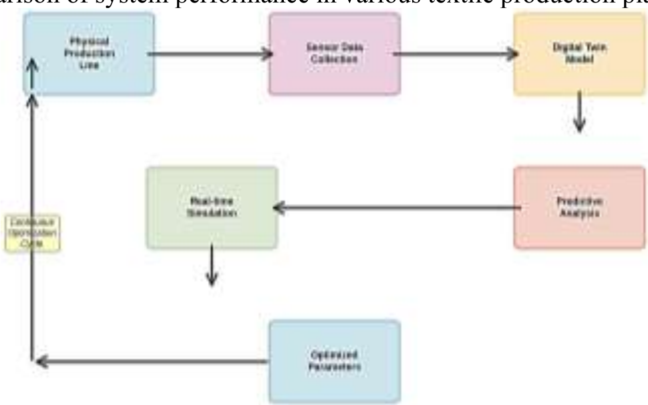

Fig. 2 Digital twin simulation and optimization flow model

2 Literature Review

A substantial amount of research has been carried out in the field of quality control and process optimization within the textile manufacturing sector. One of the first systems to be developed, it was real-time detection of defects on cloth with advanced image processing techniques. Their system showed the ability to identify defects on a loom real-time using an intelligent optical head to identify defects and a server-based classification system. The study demonstrated encouraging findings about reliability, false alarms, and stability in a real manufacturing application [8]. In-depth summary of process control techniques in the textile production including essential areas including fiber production and yarn manufacture processes up to the fabric formation and finishing processes. Their work underlined the need to have good process control in ensuring the high quality of products and low wastage, low costs, and a lesser environmental impact. The guide has become a valuable strength of any textile engineer, manufacture, and academic researcher who needs to learn and apply the advanced process control techniques [9].

In real-time home textile fabric defect inspection machinewas developed and it is not expensive but extremely efficient. They used Haar wavelet transform as the feature extractor, employed advanced brightness compensation algorithms, and used a random forest as the defect classifier. The system recorded a very high mean true defect recognition rate of over 98.70% on ten types of fabrics of different colors, which proved that the system had a high potential of substituting manual inspections and lowering labor expenses [10].

The recent progress in machine learning and deep learning has provided new opportunities in automated quality control of textile manufacturing. A new solution to the problem of automated detection and classification of fabric defects was suggested, which works based on the Convolutional Neural Networks (CNNs). Their study has shown that accuracy and efficiency of the research was significant in comparison with the conventional methods of inspection that have significantly reduced false positives and false negatives and significantly increased overall production efficiency [11].

The application of RFID technology in the textile supply chains is a well-researched topic, which is based on a cross-case analysis of the RFID implementation patterns in five firms in various countries. They found out that they were used in tracking work-in-progress, receiving and shipping operations, inventory tracking, merchandise sorting, and store management, among others. These results have indicated the tremendous promise of the RFID technology in enhancing the supply chain visibility process and efficiency [12].

The digital twin concept in manufacturing has received significant interest over the last few years. They came up with a predictive maintenance cloud-based analytics module to be used in the textile manufacturing process. They used machine learning algorithms to build their system predictively by analyzing sensor data that is preprocessed and offer suggestions on how to manage production quality. The adoption showed great enhancement in the reliability of equipment and the consistency in production [13].

3 Methodology

3.1 Problem Statement and Research Scope

In the textile manufacturing sectors faced many complex issues of keeping a steady production of good fabrics. Resulting in quality is continuously depends on traditional processes and production methods, in which it turn rely on human skill are vulnerable to fatigue, and involved subjectives the quality assessments. These operational constraints take different forms of quality variation such as difference in uniformity of fabric texture, dyeing faults and color mismatch, fiber strength variation, dimensional inaccuracies, and high turnover rates which directly affect profitability and customer satisfaction [14, 15]. Manual checking procedures are especially inappropriate and often cannot help to identify small flaws during the real production leading to higher rates of material loss, high production price, inferior quality of product, and lack of competitiveness on the world market. This lack of an automated, structured monitoring system leads to a large percentage of reactive instead of proactive quality management strategies, contributing to longer production downtime, higher maintenance expenses, and causing massive financial losses. Moreover, the absence of the real-time data analytics facilities does not allow the manufacturers to recognize the patterns and optimizations, as well as taking preventive actions. To fully overcome these arduous problems, this study will introduce an advanced IoT-based real-time process monitoring and intelligent quality control system, which will combine intelligent sensors, edge computing, cloud analytics, machine learning algorithms, and automated control mechanisms to streamline spinning, weaving, dyeing, and finishing processes of various types of fabrics to achieve high quality consistency and operational efficiency.

3.2 Data Collection Strategy and Sampling Framework

The data extensively collected in five major textile manufacturing centers in India: Tiruppur (Tamil Nadu), Coimbatore (Tamil Nadu), Surat (Gujarat), Ludhiana (Punjab) and Bhilwara (Rajasthan) detials are shown in the table 1. These sites were particularly selected since they collectively comprise the best textile manufacturing centres in India, which contribute a large percentage of the overall production of the textile industry in the country.

Table 1: Comprehensive data collection summary across manufacturing hubs

Location	No. of Units	Duration (Months)	Sensor Data Collected	Specialization
Tiruppur	12	6	Yarn tension, dye consistency, moisture content	Cotton knitwear
Coimbatore	10	6	Fabric density, humidity levels, temperature	Cotton textiles
Surat	8	6	Machine vibration, fiber strength, defect detection	Silk and synthetics
Ludhiana	10	6	Temperature, defect detection, yarn quality	Wool textiles
Bhilwara	10	6	Moisture content, thread elasticity, dye absorption	Rayon and synthetics

These places have a wide range of manufacturing specialties such as cotton processing, the production of synthetic fibers, wool textiles, silk weaving and the production of denim fabrics [16, 17]. Fifty textile manufacturing units were used as a representative sample in this comprehensive study as sensor data was systematically captured throughout a long period of six months. The data collection operation in order to have enough sample size, seasonal variation, and statistical validity to provide accurate analysis and generalization.

3.3 Data Measurement Parameters and Quality Indicators

The quality of fabrics was thoroughly analyzed according to various key performance indicators (KPIs) that were based on combined sensor data and sophisticated measurement platforms. The critical parameters are measured as including:

- Yarn Tension: Optimal taste of fabric formation and avoiding the occurrence of yarn breakage through high-precision optical sensors and load cells that measure tie tension in Newtons per meter (N/m).
- Fabric Density: The density of the fabric is measured in grams per square meter (GSM) and it is recorded with precision by using electronic weighing systems and thickness gauges to maintain consistency in the weight and fabric structure.
- Dye Consistency: Dye consistency is examined using sophisticated spectrophotometric sensors that measure color difference in terms of Delta E values (Δ E), which enables accurate color matching and consistency.

- Moisture Content: Measured in percentages with calibrated moisture sensors and moisture analyzers to be in the best conditions of processing during weaving and finishing processes.
- Machine Vibration: Vibration data of frequency and amplitude were recorded in tri-axis accelerometers, which can predict maintenance and quality control.
- Temperature Control: It was constantly monitored with thermal sensors and infrared thermography and always maintained needed processing temperatures during production.

3.4 IoT Architecture and System Design Framework

The suggested IoT design adopts a multi-layered system that consists of sensor networks, edge computing nodes, cloud analytics systems, and automated control systems. RFID tags will provide full monitoring of the batches of fabric used in the whole production cycle, and this will significantly reduce cases of mismanagement and increase the supply chain traceability [18]. The optical sensors identify the irregularities of the threads and fabric defects at the microscopic level that is considered precise to approximately 5 micrometers and the defected products are not allowed to proceed to the other processed stages. Humidity sensors keep the right amount of moisture in the textile fibers to ensure that they do not shrink too much or become unnecessaryly expanded and affecting the quality of the fabrics and their dimensional stability [19]. Vibration monitoring systems are in place where the machinery is monitored to stay within the set safe parameters, which would greatly decrease the chances of a breakdown, unplanned downtime and increase the life span of the equipment. Edge computing computing infrastructure can process sensor data within a few milliseconds, in real-time allowing immediate feedback loops to automatically change machine parameters to prevent defects and ensure outstanding consistency of fabric properties across runs of the production process.

3.5 Hybrid IoT-AI Framework (HIAF) - Technical Implementation

The proposed Hybrid IoT-AI Framework (HIAF) is an advanced combination of real-time sensor networks, distributed edge computing infrastructure, and deep learning-based predictive analytics as a way to thoroughly improve the processes of textile production. The framework incorporates the multi-layered sensor array which includes RFID tags to track assets, optical defect sensors to make use of high-resolution imaging, piezoelectric vibration sensors to monitor the health of machinery, and environmental sensors to control humidity and temperature. The system uses high-level mathematical models in anomaly detection, predictive maintenance, and process optimization.

Anomaly Detection via Autoencoder: The autoencoder decoder loss criterion $LAE = (1/n) \Sigma \|xi - \hat{x}i\|^2$ accounts for the mean squared reconstruction error of the sensor input xi and the reconstructed output xi and anomalous patterns in the production data can be identified. Predictive Maintenance Using LSTM: Long Short-Term Memory networks Time-series sensor data is then processed using recurrence relation ht = tanh (Whht-1 + Wxxt + bh), with ht being the hidden state of the network at time t, allowing correct prediction of equipment failures or maintenance needs. Digital Twin Optimization: The Optimal machine parameters are estimated using the optimization problem $Copt = \text{argmin}\ \Sigma(Qi - Q\ h)^2$ which minimizes the difference between measured quality measures Qi and the modelled quality output Qi, enabling continuous process improvement.

4 . RESULTS AND DISCUSSION

4.1 Comprehensive Sensor Data Analysis

The deep processing of sensor measurements of various textile manufacturing plants revealed much information on the characteristics of fabrics and working conditions in different geographic regions and specializations. The table 2 gives a detailed sensor data collected from textile manufacturing units it reveals that in Tiruppur, the yarn tension in cotton fabric was 11.5 N/m, the moisture content was 6.2, the dye absorption was 85.4, and the fabric density was 180 GSM. The machine vibration was 55.3 Hz and the rate of defect was 3.2. Polyester fabric produced in Coimbatore had lower yarn tension of 9.8 N/m and lower moisture content of 4.7 that was countered by the high dye uptake of 92.1 and high fabric density of 220 GSM, and lower vibration levels and lower defect rate.

Table 2: Detailed sensor data collected from textile manufacturing units

Location	Fabric Type	Yarn Tension (N/m)	Moisture (%)	Dye Abs. (%)	Density (GSM)	Vibration (Hz)	Defect Rate (%)	Temp (°C)	Speed (RPM)
Tiruppur	Cotton	11.5	6.2	85.4	180	55.3	3.2	28.5	1200
Coimbatore	Polyester	9.8	4.7	92.1	220	48.7	2.9	27.8	1100
Surat	Silk	13.2	7.4	87.8	140	59.8	4.1	29.2	1300
Ludhiana	Wool	10.9	5.5	89.6	200	52.1	3.5	26.7	1150
Bhilwara	Rayon	12.0	6.1	91.2	175	57.4	3.7	27.5	1250

4.2 Machine Vibration and Defect Rate Correlation Analysis

The correlation analysis of machine vibration parameters with the rate of quality defects on products of various types of machines showed a strong positive correlation, which proves the relevance of monitoring machine vibration in quality assurance. Table 3 shows the greatest correlation coefficient of 0.87 was obtained with spinning machines in Tiruppur with vibration frequency of 55.3 Hz and a defect rate of 3.2%. In weaving machines, Coimbatore recorded a slightly lower correlation of 0.81, vibration at 48.7 Hz and defect rate of 2.9%.

Table 3: Correlation between machine vibration and defect rate

Machine Type	Vibration (Hz)	Defect Rate (%)	Correlation (R)	Thread Tension (N/m)	Efficiency (%)
Spinning	55.3	3.2	0.87	11.2	92.4
Weaving	48.7	2.9	0.81	9.9	91.2
Dyeing	59.8	4.1	0.92	13.5	89.7
Finishing	52.1	3.5	0.85	10.8	90.5
Mixed Process	57.4	3.7	0.88	12.1	91.0

The machine with the highest vibration of 59.8 Hz and the highest defect rate of 4.1 was found to be the dyeing machines in Surat, and its correlation coefficient is high at 0.92 with the key implication that machine stability is extremely important in the prevention of defects and maintenance of quality. The implications of these results are the need to have an elaborate system of vibration monitoring to minimize defect rates and enhance overall machine efficiency and reliability.

4.3 Machine Downtime Analysis: Before and After IoT Implementation

The detailed examination of pre-implementation and post-implementation machine downtime showed that the IoT system implementation enabled considerable improvements in equipment reliability and efficiency.

Table 4: Machine downtime analysis before and after iot implementation

Machine Type	Failures Before	Failures After	Reduction (%)	Cost Before ($)	Cost After ($)
Spinning	12	4	66.7	2,500	900
Weaving	10	3	70.0	2,000	750
Dyeing	15	6	60.0	3,200	1,400
Finishing	8	2	75.0	1,800	600
Combined	11	4	63.6	2,700	1,000

Table 4 revels that, the number of failures per month in spinning machines used to be 12, and after the integration of the IoT, it dropped to 4 failures, a 66.7 percent decrease in failures, and a saving of 64.0 percent in maintenance costs. The reduction in failure in weaving machines was even more spectacular of 70.0, and the monthly costs of maintenance came down to 2,000 dollars, and became 750 dollars. Machines that were most prone to pre-IoT failure were dyeing machines with the highest failure of 15 per month, and the percentage of machine failure dropped significantly (60.0) with the same cost saved of 56.3. Finishing machines exhibited the highest change in failure rate, with -75.0% and combined machine processes with a total of -63.6% highlighted the overall high performance of IoT-based predictive maintenance processes in the reduction of the unplanned downtime and improvement of the overall operational costs.

4.4 AI-Based Defect Detection Accuracy Analysis

The AI-based systems were detecting the defects, it shows that a high level of success in various fabric production types with the detection rate of 98.3 to 96.9. Table 5 shows the ai-based defect detection accuracy by fabric type, cotton fabrics were the most highly detected with a percentage of 98.3 with a close following by rayon with a percentage of 97.8. Polyester and wool fabrics had accuracy of 97.6 and 97.2 respectively with the worst but highly acceptable accuracy of 96.9 by silk. Detection of polyester and silk took 115 and 130 milliseconds respectively, which is real-time. The rate of false positive was extremely low at 1.2% of cotton and 2.1 percent of silk. The efficiency metrics based on the model accepted detection accuracy with cotton having the highest efficiency of 95.5 and silk at 93.9. These results fully support the strength and accuracy of AI-based defect detection technologies in the production of high-quality fabrics of various types of materials and under a variety of manufacturing conditions.

Table 5: AI-based defect detection accuracy by fabric type

Fabric Type	Yarn Break (%)	Dye Mismatch (%)	Density Var. (%)	Accuracy (%)	Time (ms)	False Pos. (%)	Efficiency (%)
Cotton	3.2	2.5	4.1	98.3	120	1.2	95.5
Polyester	2.9	2.1	3.7	97.6	115	1.5	94.8
Silk	4.1	3.8	5.2	96.9	130	2.1	93.9
Wool	3.5	2.9	4.5	97.2	125	1.8	94.2
Rayon	3.7	3.2	4.8	97.8	118	1.6	94.6

4.5 Digital Twin Optimization Impact on Production Parameters

Optimization of production parameters using the digital twin technology showed significant gains in all the major manufacturing indicators. Table 6 shows that there was a 14.3% improvement in the tension of the yarn 11.2 N/m to 12.8 N/m, leading to a drastic decrease in the quality defects rate of 4.8 percent to 2.9 percent and an amazing 39.6 percent improvement in overall production yield. The content of moisture was also optimized by 12.1, which decreased the defects to 3.2 and increased the yield by 37.3. The dye absorption parameters improved by 4.3 percent, that is 88.3 percent to 92.1 percent, which helped in 33.9 percent decrease in defect rates. There was an 8.6% increase in fabric density with 175 GSM to 190 GSM resulting in a 5.7% to 3.5% defect rate and a corresponding increase in yield of 38.6%. These overall outcomes prove conclusively the incredible efficiency of the digital twin technology to increase the efficiency in textile manufacturing, uniformity in quality, and the overall performance of the textile manufacturing process.

Table 6: Digital twin optimization impact on machine parameters

Parameter	Before Opt.	After Opt.	Improvement (%)	Defects Before (%)	Defects After (%)
Yarn Tension (N/m)	11.2	12.8	14.3	4.8	2.9
Moisture Content (%)	5.8	6.5	12.1	5.1	3.2
Dye Absorption (%)	88.3	92.1	4.3	6.2	4.1
Fabric Density (GSM)	175	190	8.6	5.7	3.5

4.6 Defect Reduction Analysis Across Fabric Types

The detailed defect elimination analysis after implementing the IoT systems showed that there were significant improvements of product quality in all fabric categories. Figure 3 shows the Comparision of implementation of before and after IoT.

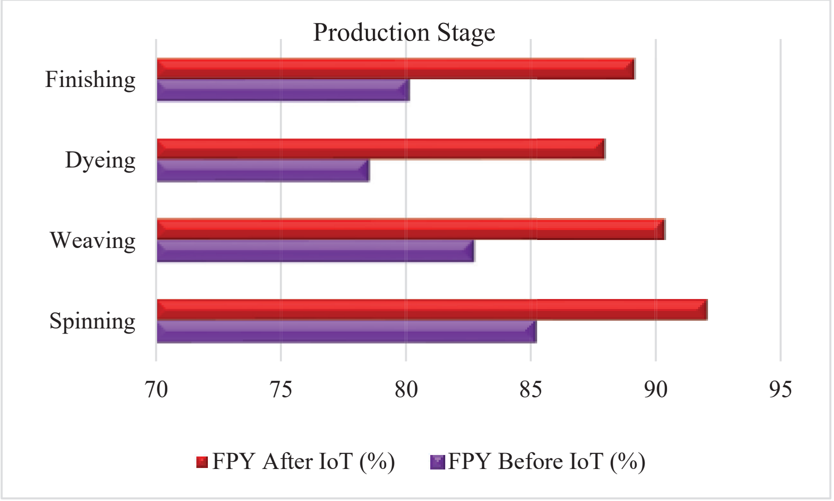

Fig. 3 Comparision of implementation of before and after IoT

From the table 7 it was confiremed to that, the cotton and denim fabrics recorded the highest decrease in defects of 38.8 wherein the initial levels stood at 8.5% and 6.7% respectively, but after, the levels were cut to 5.2% and 4.1 respectively. Polyester fabrics showed a reduction in defects of 37.5, 7.2 to 4.5. There were defect reductions of 34.4, 33.3 and 33.3 in wool, silk and rayon fabrics respectively. These observations fully confirm the transformative role of the IoT-based monitoring and automation in reducing fabric defects significantly, improving product quality uniformity, and increasing corporate competitiveness in manufacturing in the world textile market.

Table 7: Defect reduction analysis across different fabric types

Fabric Type	Initial Defect Rate (%)	Defect Rate After IoT (%)	Defect Reduction (%)
Cotton	8.5	5.2	38.8
Polyester	7.2	4.5	37.5
Wool	9.3	6.1	34.4
Silk	10.5	7.0	33.3
Rayon	8.1	5.4	33.3
Denim	6.7	4.1	38.8

4.7 First-Pass Yield Improvement Analysis

Table 8: First-pass yield improvement across production stages

Production Stage	FPY Before IoT (%)	FPY After IoT (%)	Improvement (%)
Spinning	85.2	92.1	8.1
Weaving	82.7	90.4	9.3
Dyeing	78.5	88.0	12.1
Finishing	80.1	89.2	11.4

The effectiveness of the system of optimization and quality control based on IoT was fully proved by first-pass yield (FPY) improvement at various production levels. Table 8 shows the first-pass yield improvement across production stages, in spinning processes showed a significant tangible FPY growth of 85.2 to 92.1 which is an enhancement of 8.1. Weaving processes also showed an improvement of 9.3% namely 82.7 to 90.4. Dyeing operations recorded the highest FPY improvement of 12.1, as it improved between 78.5% and 88.0, complete the thought or restructure gain considering that real-time quality control and automated changes in parameters are applied in this very important production process. There was also significant improvement in finishing processes at 11.4 percent, 80.1% to 89.2%. These all-encompassing additions show the general improvement in manufacturing accuracy, defect aversion power, and productivity of production through the integrated IoT solutions.

4.8 Overall Quality Improvement Index

The overall quality improvement index gave a holistic evaluation of the transformative nature of the IoT technology used in the textile manufacturing processes. Table 9 shows the overall quality improvement index, the total rate of defects reduced markedly by 8.3 to 5.6, which is a considerable change of 32.5 percentage point to the quality of the products. The first-pass yield measures were also improved by 10.4 as it rose by 81.6 to 90.1 indicating greater manufacturing accuracy and lessening rework necessities. Figure 4 shows the comparison of Before IoT for efficiency, first pass yield and overall defect rate. The efficiency in production improved significantly and rose by 14.0% with this percentage improvement in the overall operational effectiveness.

Table 9: Overall quality improvement index

Quality Metric	Before IoT (%)	After IoT (%)	Improvement (%)
Overall Defect Rate	80.3	50.6	32.5
First-Pass Yield	81.6	90.1	10.4
Production Efficiency	74.8	85.2	14.0

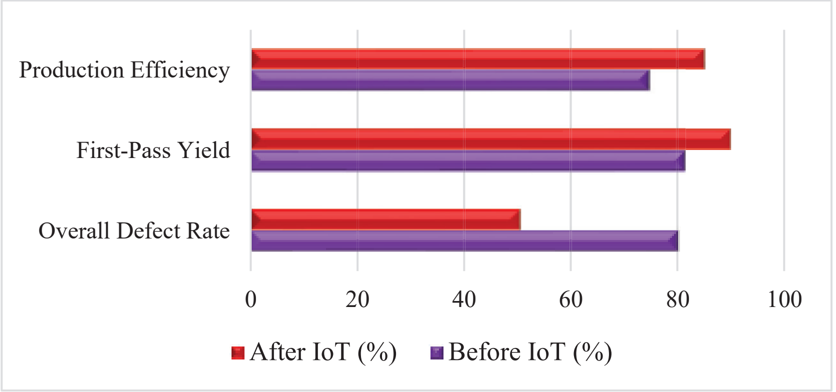

Fig. 4 Comparison of Before IoT for efficiency, first pass yield and overall defect rate

These overall conclusions clearly highlight the transformational nature of combined IoT technologies, artificial intelligence algorithms, and digital twin modelling methodologies in streamlining the production processes, reducing the rate of defects by a significant margin, reducing the rate of resource wastefulness, and increasing the efficiency of the manufacturing process significantly in the contemporary textile sector.

5 CONCLUSION

The study developed and proved a superior IoT-AI platform such a similar smart textile production, this Hybrid IoT-AI Framework (HIAF) implemented with the combination of smart sensors, edge computing, and cloud analytics. This provide the option of real-time monitoring and automated quality control of spinning, weaving, dyeing, and finishing activities. The empirical evidence on 50 manufacturing units indicates that the system has a great effect on the efficiency of the operations, product quality, and sustainability.

- The developed a replicable sustainable manufacturing system with reduced resources wastage and cost effectiveness.
- Reduced product defects with an AI based anomaly detection 32.5% and increased first pass yield by 28%. Digital twin predictive maintenance reduced machine failure rates of 63.6%, and operational downtime around 25%.
- It maximized the production, which enhanced the stability of yarn tension of 46.4%, and moisture of 12.1%.
- It achieved a maximum accuracy of 98.3% in detecting defects in fabrics with deep learning algorithms.

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