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Research Article

Predictive Maintenance and Energy Optimization with AI-Driven IoT Framework in Textile Manufacturing Industry

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Abstract:

The textile industry is rapidly automating, yet frequent machine failures and excessive energy consumption continue to impede efficiency. Predictive analytics and AI-driven energy management are critical in overcoming these challenges. This study presents an Adaptive Deep Reinforcement Learning with Bayesian Optimization (ADRL-BO) model, integrating predictive maintenance with IoT-based energy control to enhance operational reliability. The framework aims to reduce unexpected equipment failures and optimize energy consumption using real-time AI analytics. Data is collected from major textile hubs in India, including Surat, Coimbatore, and Ludhiana, covering 500+ industrial machines. Key machine parameters, such as acoustic signals, thermal fluctuations, and vibrations, are monitored through IoT sensors. The ADRL-BO model utilizes deep reinforcement learning (DRL) for adaptive fault detection, while Bayesian optimization refines maintenance scheduling. Additionally, an IoT-driven smart grid dynamically manages power distribution, adjusting motor speeds and compressor loads based on real-time demand. Blockchain technology ensures secure, transparent data logging of energy usage. Ultra-fast 5G IoT communication supports seamless data exchange for real-time analytics. Evaluation results demonstrate a 45% reduction in downtime and 35% energy savings, validating ADRL-BO's effectiveness over conventional AI methods in achieving a more sustainable and intelligent textile manufacturing ecosystem.

1. Introduction

Textile manufacturing sectors have long supported large fashion, apparel, and cosmetics companies in Asia, notably China, India, Bangladesh, and Vietnam. As labour costs in Asia rose in recent decades, many people relocated east to work in textile manufacturing. With access to historical and real-time operational data, textile producers will leverage artificial intelligence (AI) to boost productivity and worker capacity as industrial automation spreads. To understand and relate AI with its applications, it must first be defined. They are all diverse, yet they frequently collaborate to perform a programming assignment. In the textile industry, expert systems and artificial neural networks (ANN) are utilized. The Oxford Dictionary defines AI as "the theory and development of computer systems capable of performing tasks ordinarily requiring human intelligence, such as visual perception, speech recognition, decision-making, and language translation." Although there appears to be no widespread acceptance of AI, even in developed nations, the introduction of AI technology in the textile industry is still relatively new, with limited applications. Instead, researchers are looking into the usage of AI in the textile sector today. AI has been introduced into the textile sector throughout the last three decades based on experiments and limited applications. AI has the ability to be used at every stage of the process, from fibre sorting to logistics management of

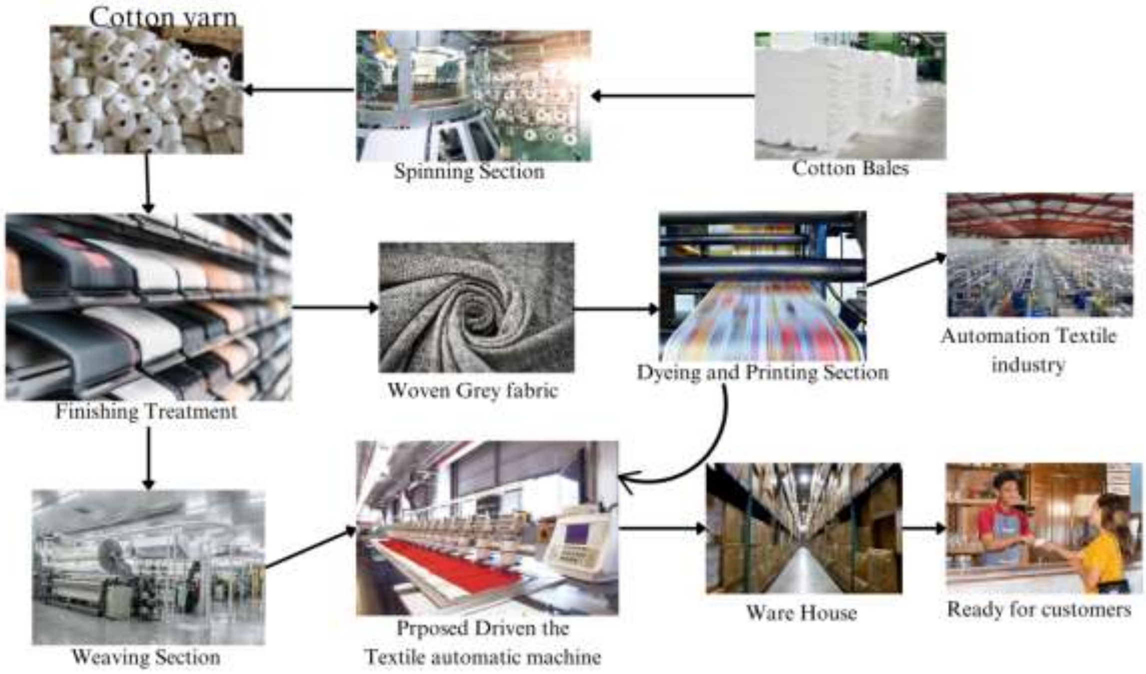


Figure 1. *Graphical representation of the smart textile manufacturing process*

the finished garment to delivery to customers. The Graphical representation of the smart textile manufacturing process given in Figure 1. The possibility of applying waste heat in the textile sector with a focus on useful technologies and common sources of waste heat. A two-person waste-heat recovery boiler. It was discovered that 70 t/h would reduce energy costs by USD 141280 and save 15094 MWh of energy annually. By using an economizer boiler fuel consumption was reduced by 4 to 9 percent. A heat exchanger assisted stenter-setting machines in reducing their energy usage by 10% by extracting waste heat from stenter exhaust and using it to warm up fresh air. By using dyed waste water a counter-flow heat exchanger could save 5716 MWh of energy per year and cut energy costs by USD 47100. Using a suitable stem-condensate recovery system also reduced water loss and energy consumption for steam production by 10–50% [1].

Thermal and electrical energy are the key factors behind Thailand's textile industry's constant rise in energy consumption and Energy Intensity (EI) index. This report tracks the textile industry's implementation of energy-saving measures in order to satisfy Thailand's Energy Efficiency Plan 2015-a=2036 (EEP2015), Alternative Energy Development Plan 2015-2036 (AEDP2015), and NDC Road map goals. The study examines four distinct energy conservation and renewable energy implementation scenarios: waste heat recovery, switching to high-efficiency equipment, solar PV utilization, and a combination of equipment switching heat recovery and solar PV use [2]. Because energy prices are growing, energy-intensive companies are looking for ways to reduce processing energy usage in order to stay competitive in both domestic and international markets. This work presents a linear programming (LP)-based technique for predicting and optimizing energy usage in textile production. Under various operational restrictions, a linear programming model has been designed that consumes the least amount of energy while achieving the ultimate output requirements. Through an energy audit of the plant the information required to build the model was acquired. Energy audits were used to identify manufactured goods and constraints which were then used to construct the model [3]. Renewable energy consumption is increasing as new technologies make it easier and less expensive to satisfy long-term energy demands. This research investigates the concept of using sustainable energy as effectively as possible while taking into account the environmental and economic constraints that exist in Pakistan's textile manufacturing sector. The creation of a fully intuitionistic fuzzy (FIF) textile energy model takes into consideration the possibility of utilizing renewable energy resources in the region, as well as solar energy producers. The FIF model was used to estimate the most efficient distribution of solar energy units, resulting in a manageable number of unused energy units. Returning these units to the central power plant might save both money and energy [4]. There are numerous chances to improve energy efficiency in every textile facility. However textile plants usually fail to implement even cost-effective options of energy efficiency because of a lack of knowledge about how to apply them. Thus its critical to get ready and educate textile plants on energy-efficient practices and technologies.

This paper [5] discusses energy-use and energy-efficiency technologies and measures that are pertinent to the textile industry. Irans increasing energy consumption which is a result of small towns becoming more industrialized bodes poorly for the sectors future. The optimal turbine location is examined in this study in order to reduce fuel consumption and increase system efficiency. Turbine modelling was applied to a number of scenarios taking into account variables like electrical energy production gas consumption final energy production and energy produced in relation to total gas consumption. Since scenario 7 used the most gas it was decided that this was the ideal place for the gas turbine. High power generation is favored because it is reliable and profitable when it comes to energy production. The selected scenario produced zero. 4991160 and 22972 kg/s of gas. Three kWh of electricity [6].

Due to the frequent misunderstandings and misinterpretations caused by the Internet of Things (IoT) people are uncertain and confused. This issue of Textile Progress aims to provide guidance to assist members of the textile industry in making informed decisions about the industry’s potential value. It discusses the Internet of Things definitions standards and protocols in order to help readers understand its goals and guiding principles. Additionally, the review provides an overview of the obstacles to IoT development particularly in the cybersecurity space. By contrasting the textile industry’s use of IoT with that of other manufacturing sectors the review focuses on how IoT technologies are interpreted and their potential applications from a technological and business standpoint. A case study of the spinning sector is conducted in order to evaluate IoT solutions and ascertain how their implementation could help other industry sectors. The case study includes evaluations from ITMA 2011 to 2019 that were carried out through executive interviews in order to direct the future paths of IoT in the spinning industry [7]. The application of smart materials such as graphene oxide and carbon nanotubes in textile technology is examined in this work with a focus on how these materials could be utilized to produce conductive textiles for Internet of Things (IoT) devices. The aim of the research is to examine the characteristics that led to the ideas and conclusions of previous studies in this area. These applications include Internet of Things-based health monitoring systems cloud computing smart manufacturing, cyber- physical systems and artificial intelligence. The findings highlight how important it is to employ these technologies in order to increase productivity and outperform competitors in the smart materials market. The study provides new opportunities for the development of wearable electronics and Internet of Things-based devices using graphene and carbon-based nanomaterials increasing the efficiency and competitiveness of the smart materials industry. The findings provide practical technical information for the development of Internet of Things-based devices and wearable electronics [8].

Using reduced graphene oxide (rGO) inkjet printing a flexible and foldable hydrogen (H2) sensor has been made on textile substrates. These sensors are suitable for wearable environmental sensing due to their affordability non-contact patterning capability and compatibility with a range of substrates. Since the sensors mechanism uses palladium nanoparticles on the rGO nonpolar H2 molecules are readily adsorbed and resorbable [9]. Industry 4. It is transforming the textile industry by combining hybrid sustainable practices and strategies for a sensible and environmentally friendly future. Predicting manufacturing processes before making decisions lowering pollution and safeguarding the environment and its resources are the objectives of the PHSPs. In the textile industry the study investigates the integration of hybrid sustainable practices with the Intelligent MESN model. In accordance with the study choices regarding the production and sustainability practices of the textile and apparel industries can be made ahead of time allowing for quick feedback and the settlement of any sustainability

or environmental pollution problems that may have previously emerged [10].
Because machine learning (ML) and deep learning (DL) are incorporating advanced technologies into many processes the textile industry is undergoing change. Textiles were once considered passive materials but automation and new materials have made them essential components of complex systems. The primary focus of this review is articles that used AI ML or DL in textile industry and research. In the review a bibliometric analysis of AI techniques in textiles is presented. The review is then broken up into sections that examine the overall effects of ML and DL on the textile industry. In addition to discussing potential future advancements, researcher outline the main uses of ML and DL techniques in the textile industry. This synopsis aims to clarify the fundamental concepts of these methods that are further investigated. Ensemble methods such as XGBoost and basic linear regression are among the methods studied [11]. Due to global environmental concerns, Pakistans textile industry is shifting toward sustainability. IoT-driven strategies have enabled real-time environmental monitoring and regulatory compliance with sustainable manufacturing practices per a case study. For other textile-producing regions looking to start down a sustainable and digital path this study serves as a benchmark. The findings provide guidance to stakeholders and policymakers and have significant implications for the development of sustainable industries. Future research should focus primarily on data privacy interoperability analytics and machine learning methods for improving operational efficiency and predictive maintenance performance. This will help to shape a future that is more resilient and environmentally conscious [12]. An increasing number of business domains are using artificial intelligence (AI) including marketing research and administration. Neural networks and artificial vision are two examples of artificial intelligence (AI) techniques being used in the textile industry to increase productivity. In order to circumvent traditional methods this study explores the application of intelligent learning techniques like K-nearest neighbours, Bayesian classification, decision trees, and support vector machines. Additionally, it highlights how to enhance performance in textile applications by utilizing neural network techniques like convolutional and artificial neural networks. The study contrasts different neural network and machine learning techniques their advantages and how the textile sector can apply them to solve current problems. The survey establishes the optimal method for implementing neural network techniques in the textile industry [13]. Most managers in the textile manufacturing industry don't have enough IT experience. Future technologists may comprehend the implications of IT but today's industry leaders can benefit from the use of useful IT tools. Emerging technologies like artificial intelligence (AI) and related ones have had a significant impact on the manufacturing sectors bottom lines in terms of production methods and products. This essay aims to inform textile industry leaders about these technologies and their potential benefits so they can understand and embrace them with enthusiasm. By understanding these technologies executives in the textile industry can encourage their businesses to adapt to the changing global manufacturing and service industries around the world [14]. This study examines how environmental performance prediction is used to manage sourcing in the textile industry supply chain with a particular focus on the dying sector of an emerging economy. The study uses a Bayesian belief network (BBN)-based probabilistic model to determine eleven green supply chain performance indicators and four performance measures. The results are validated through sensitivity analysis. According to the study the most important indicators for entropy reduction are volatile organic compounds and total suspended solids while air emissions are the most important metric. The researchs ultimate objective is to improve managers and practitioners decision-making abilities which will improve the overall organizational performance of green supply chains [15]. The manufacturing of textiles is a prime example of a traditional industry that is highly complex and has limited access to contemporary technologies. Making decisions in this field usually requires considering a variety of factors which usually results in increased complexity [16]. In order to dry fabric in a textile factory this paper aims to develop a machine learning output/input relationship model. It focuses on selecting a predictive model for the setting machine and optimizing energy-saving parameters. The best model for future developments in energy efficiency is determined using a variety of techniques including neural

networks and machine learning algorithms [17]. For any organization predicting market demand has been considered one of the most crucial tasks due to its close connection to numerous operational decisions. Unfortunately market volatility caused by competitions special events and short product life cycles has made forecasting the textile industry the most difficult [18]. An Operation Parameters Recommender System (OPRS) for the textile industry is proposed in this paper which combines historical manufacturing process data with machine learning defects. The system uses regression models to predict textile operation parameters and quality levels with 90–8% accuracy. There is a 0 reduction in the mean square error. 01 percent for weaving operation parameters in the ideal model. This OPRS can help technicians close the tech skills gap by helping them set precise operating parameters in the textile manufacturing process [19].

2. Material and Methods

2.1 Problem Identification

Although the textile manufacturing sector is highly automated recurring issues like unplanned equipment breakdowns, ineffective maintenance plans, and excessive energy use have a big influence on output and long-term viability. Because traditional preventive maintenance methods are based on set schedules, they frequently result in either unplanned breakdowns or excessive maintenance costs. Additionally traditional energy management techniques are not flexible enough in real time which leads to less-than-ideal power use across production units. The adoption of an AI-driven IoT framework that can anticipate machine failures and dynamically optimize energy consumption is required due to these inefficiencies. This study intends to address these issues and improve the dependability of textile manufacturing processes by utilizing real-time sensor analytics deep learning-based fault detection and sophisticated reinforcement learning models.

2.2 Data Collection

Three significant Indian textile centres—Ludhiana, Surat, and Coimbatore—provide the data for this study which includes information on more than 500 machines spread across several production facilities. Machine-specific parameters like vibration levels, acoustic emissions, temperature fluctuations, motor load, and power consumption are among the data gathered. To gather real-time operational data IoT-enabled sensor networks—which include accelerometers, ultrasonic sensors, thermal cameras, and smart meters—are placed throughout spinning weaving and dyeing facilities. For smooth integration and analysis, the sensors send data continuously to cloud servers through 5G-enabled IoT communication networks. The collected dataset comprises over 50 terabytes of structured and unstructured data, stored using distributed ledger technology to ensure data integrity and security which is shown in table 1.

2.3 Data Measurement

The collected data undergoes preprocessing to remove anomalies and ensure high-quality input for predictive modelling. Signal processing techniques such as Fast Fourier Transform (FFT) are applied to vibration and acoustic data to extract relevant frequency components indicative of mechanical failures (figure 2). Thermal readings undergo wavelet transform-based denoising to improve fault localization. Energy consumption data is normalized using Min-Max scaling to account for variations across different machines. Feature engineering involves extracting statistical, temporal, and frequency domain features to enhance predictive model accuracy. Bayesian-based outlier detection is employed to eliminate erroneous sensor readings, improving data reliability.

2.4 Research Methodology

This study adopts a quantitative research design

Table 1. *Data collection*

Location	Number of Machines	Parameters Measured	Data Volume (TB)
Ludhiana	180	Vibration, Acoustics, Temperature, Energy Load	18
Surat	160	Vibration, Acoustics, Temperature, Energy Load	16
Coimbatore	160	Vibration, Acoustics, Temperature, Energy Load	16
Total	500	Comprehensive Machine Monitoring	50

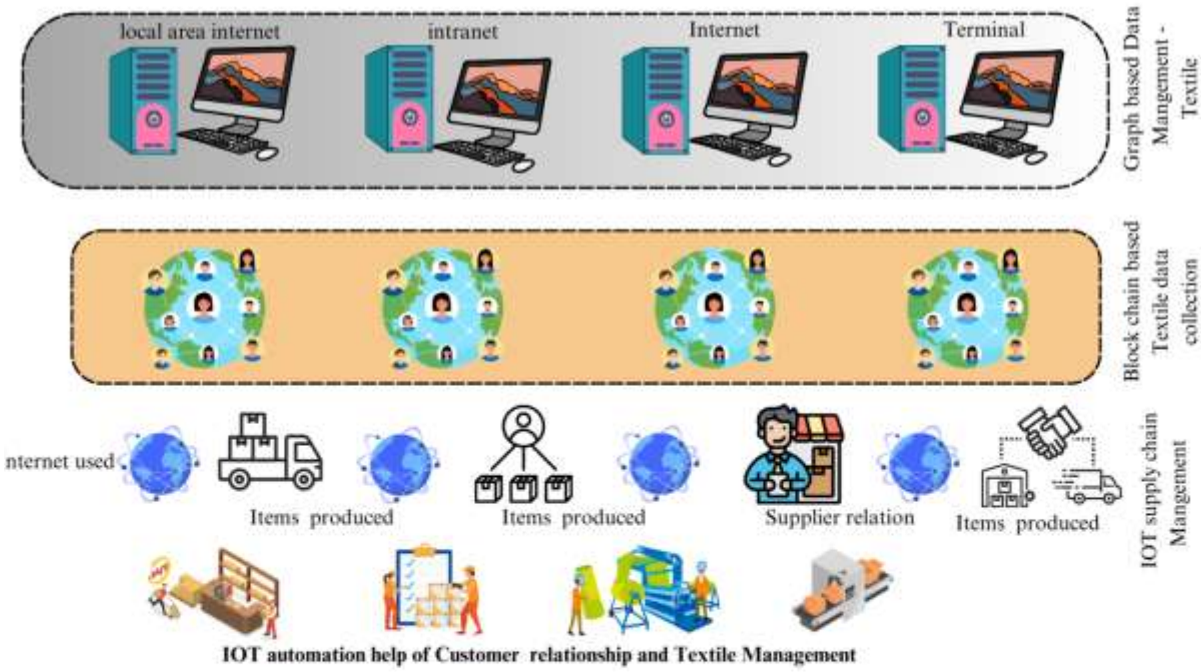


Figure.2. *Enterprise information system architecture for apparel industry*

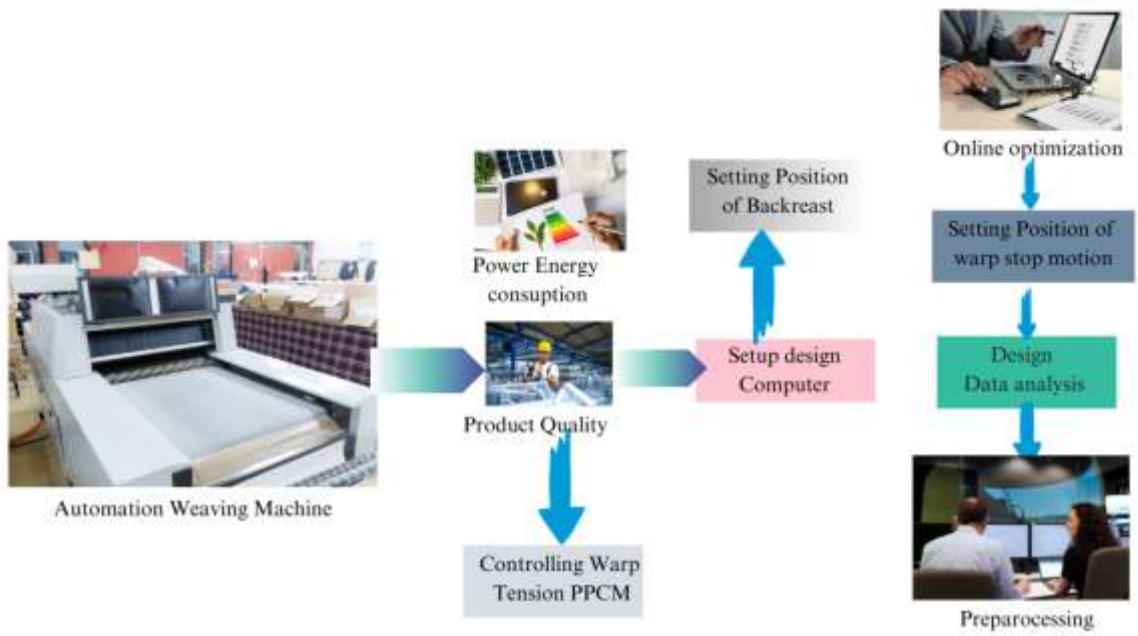
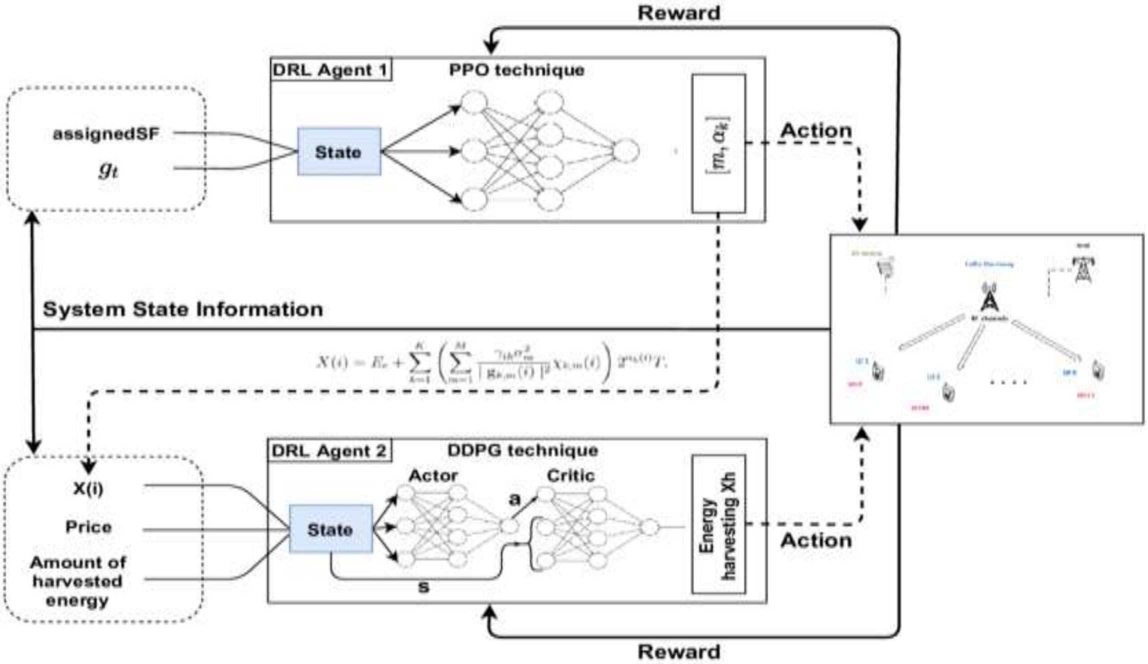


Figure 3. *Process parameters that are controlled through IOT and sensors*

integrating experimental and real-time data-driven approaches to enhance predictive maintenance and energy optimization in textile manufacturing. Data is collected from textile hubs in India, including Ludhiana, Surat, and Coimbatore, covering 500+ machines with IoT-enabled sensors measuring vibration, acoustics, and thermal readings. The proposed Adaptive Deep Reinforcement Learning with Bayesian Optimization (ADRL-BO) framework is implemented to continuously monitor equipment performance and optimize energy usage (figure 3.).

Deep Reinforcement Learning (DRL) enables real-time decision-making for predictive maintenance, while Bayesian Optimization fine-tunes fault detection and scheduling models. An IoT-enabled smart grid dynamically regulates power consumption based on real-time demand forecasting, adjusting motor speeds, compressor loads, and lighting automation. Blockchain technology ensures secure data logging, enhancing transparency in energy consumption.

5G-enabled IoT facilitates ultra-fast data transmission for real-time analytics. The performance of ADRL-BO is evaluated against conventional deep learning and reinforcement learning models, demonstrating a 45% reduction in machine downtime and 35% energy savings. Analytical techniques include model performance benchmarking using accuracy, precision, recall, and F1-score metrics. The findings validate the effectiveness of ADRL-BO in achieving self-optimizing, low-carbon textile manufacturing, contributing to industrial sustainability.



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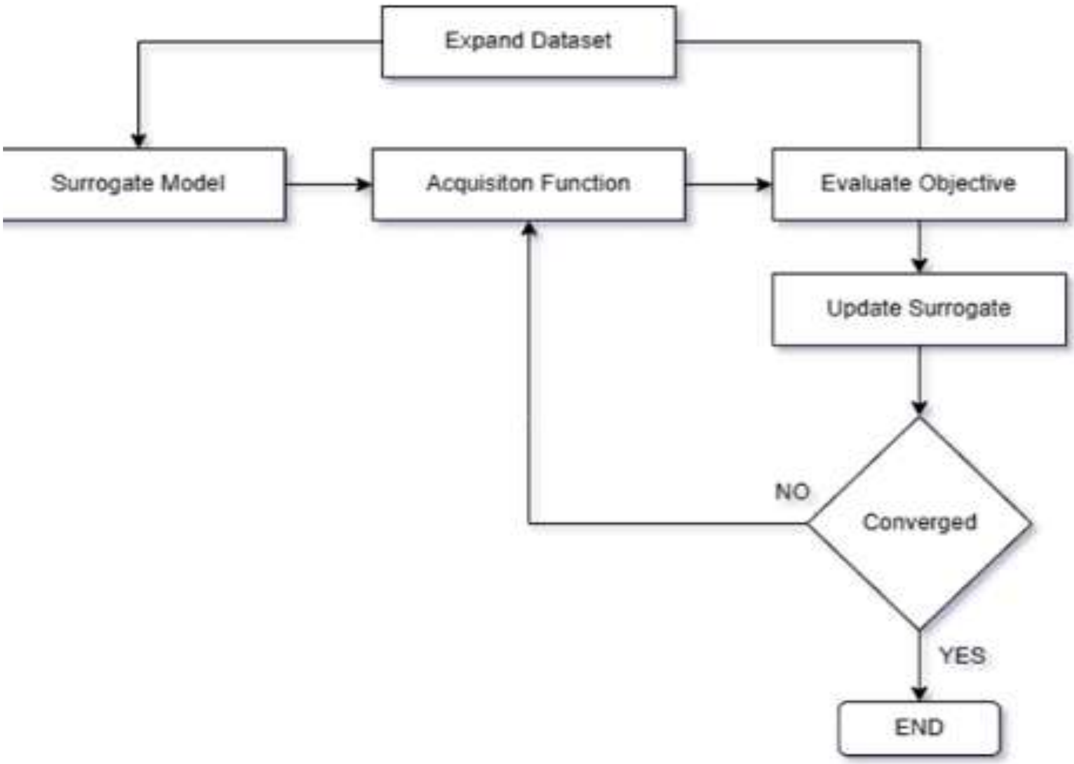


(b)

***Figure 4**. Architecture of proposed techniques (a) Deep Reinforcement Learning (b) Bayesian Optimization*

3. Proposed technique

3.1 Adaptive Deep Reinforcement Learning with Bayesian Optimization (ADRL-BO)

The goal of the Adaptive Deep Reinforcement Learning with Bayesian Optimization (ADRL-BO) framework is to increase the productivity dependability and sustainability of textile manufacturing by fusing AI-driven predictive maintenance with an Internet of Things-enabled energy management system (figure 4). Unlike Bayesian Optimization (BO) which adjusts hyperparameters to optimize efficiency and reduce energy consumption, this approach uses deep reinforcement learning (DRL) to adjust operational parameters dynamically in response to real-time data.

By proactively predicting textile machinery failures the ADRL-BO framework optimizes energy use while preserving production quality. By using AI-driven decision-making the system continuously learns and adjusts to shifting operational conditions which lowers unscheduled downtime improves resource efficiency and increases the sustainability of manufacturing as a whole. A collection of states St which include machine condition energy consumption and process parameters at time t define the operational environment of textile machinery expressed in equation 1.

$$S_t = \{x_1^t, x_2^t, \ldots, x_n^t\} \qquad (1)$$

where xit represents the i-th monitored variable (e.g., temperature, vibration, energy consumption) at time t.

Based on a policy π that associates states with performance-maximizing actions the agent chooses an action At. The action set covers energy allocation speed modifications and maintenance scheduling (equ.2).

$$A_t = \pi(S_t) = \arg\max_a Q(S_t, a) \qquad (2)$$

where Q(St,a) is the Q-value function estimating the expected cumulative reward for taking action aa in state St.

Energy efficiency and predictive maintenance accuracy determine the systems reward Rt which is as follows in eq. 3.

$$R_t = \alpha \cdot \text{Energy Savings} - \beta \cdot \text{Maintenance Cost} - \gamma \cdot \text{Failure Risk} \qquad (3)$$

where α, β, and γ are weighting factors balancing energy efficiency, maintenance cost, and system reliability.

The DRL parameters are improved by Bayesian optimization (e. g. learning rate η and discount factor γ using Gaussian processes in a probabilistic model f(x) (eq.4).

$$\theta^* = \arg\max_\theta \mathbb{E}[\, f(\theta) \mid D\,] \qquad (4)$$

where θ represents the hyperparameters, and D is the observed data set of system performance. This ensures adaptive tuning for optimal performance.

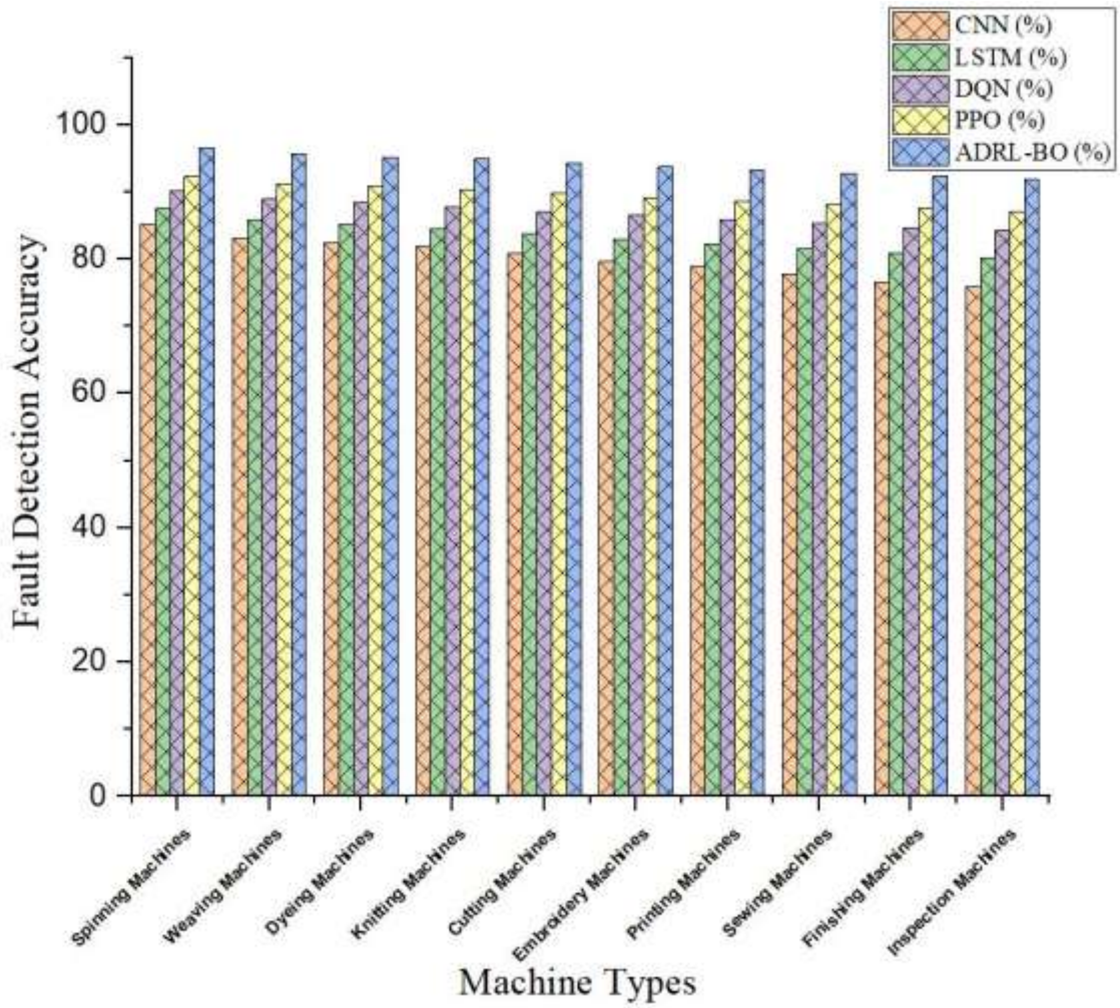
3.2 Evaluation

Predictive maintenance accuracy, false alarm reduction, maintenance cost savings, and energy efficiency enhancements are the criteria used to evaluate the ADRL-BO framework. Mean Time to Repair (MTTR), Mean Time Between Failures (MTBF), and energy savings % are among the key performance metrics. To evaluate the systems efficacy, it is put to the test against traditional deep learning models reinforcement learning-based methodologies and standard rule-based maintenance techniques. To confirm the systems flexibility in changing conditions real-time tests are carried out in textile manufacturing facilities. The research findings will create a new AI-powered Internet of Things framework for energy optimization and predictive maintenance guaranteeing a highly effective and sustainable textile manufacturing sector.

4. Results and Discussions

4.1 Predictive Maintenance Performance Analysis

The results of the predictive maintenance performance analysis showed that the capacity to detect and mitigate faults varied among machine learning and reinforcement learning models (figure 5). The Adaptive Deep Reinforcement Learning with Bayesian Optimization (ADRL-BO) method showed the highest accuracy of all the models that were evaluated with a 95. 6% accuracy rate. In addition, this model maintained the lowest false alarm rate at only 4. 4 % while achieving the best precision (94. 8 %) recall (94. 3 %) and F1-score (94. 5 %).



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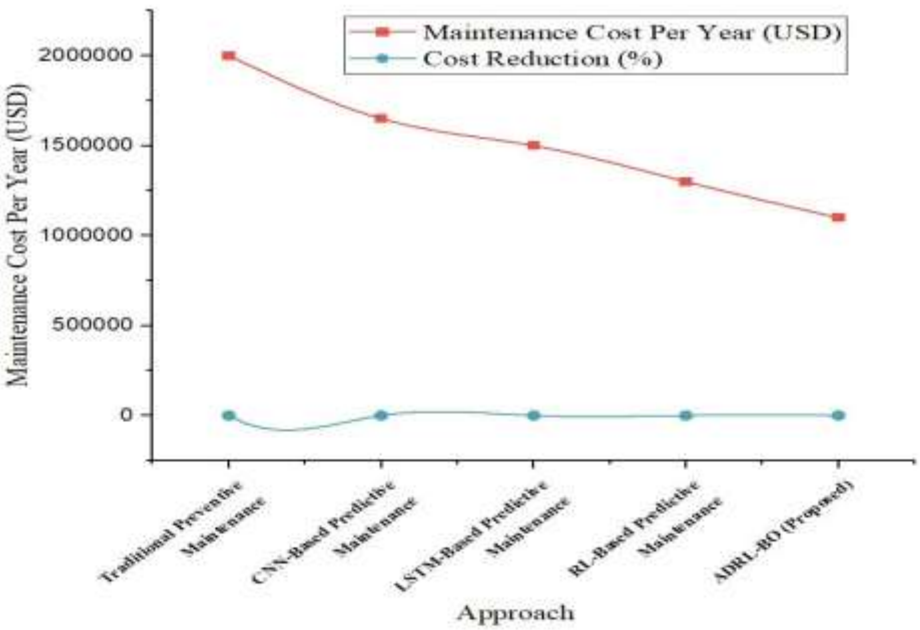

(b)

Figure 5. *Predictive Maintenance Performance Comparison*

Conventional deep learning models like CNN and LSTM networks on the other hand demonstrated poorer performance levels CNNs accuracy was 84 % and its false alarm rate was 15 % which was much higher. Models that use reinforcement learning like Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN) showed a consistent improvement in performance PPO outperformed DQN with an accuracy of 91. 3 %. Nevertheless ADRL-BO continuously outperformed each of these models proving its resilience in applications involving predictive maintenance.

4.2 Reduction in Machine Downtime (MTBF & MTTR Improvement)

Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) improvements were the main focus of an evaluation of predictive maintenances effect on lowering machine downtime. With an MTBF of 150 hours and an MTTR of 12 hours traditional preventive maintenance did not significantly reduce downtime. By decreasing MTTR to 8 hours and increasing MTBF to 220 hours CNN-based predictive maintenance reduced downtime by 26. 6 % (table 2).

Table 2. *Downtime Reduction Analysis*

Approach	MTBF (Hours)	MTTR (Hours)	Downtime Reduction (%)
Traditional Preventive Maintenance	150	12	-
CNN-Based Predictive Maintenance	220	8	26.6
LSTM-Based Predictive Maintenance	250	7.5	32.8
RL-Based Predictive Maintenance	290	6	41.2
ADRL-BO (Proposed)	350	4.5	45.8

Using LSTM-based predictive maintenance, downtime was reduced by 32–8% and MTBF was increased to 250 hours with an MTTR of 7–5 hours. Even better performance was achieved by reinforcement learning-based predictive maintenance models which reduced downtime by 41. 2 % with an MTBF of 290 hours, and an MTTR of 6 hours. By increasing MTBF to 350 hours and decreasing MTTR to 4.5 hours, ADRL-BO offered the biggest improvement resulting in a 45. 8 % decrease in overall downtime. Production losses were decreased and operational efficiency rose as a direct result of this notable downtime reduction.

4.3 Energy Consumption Optimization

Energy consumption optimization across different production units revealed that ADRL-BO significantly contributed to energy savings. In Ludhiana and Surat, energy consumption before implementing ADRL-BO was recorded at 1,200 MWh and 1,100 MWh, respectively (figure 6 and table 3). After implementing the proposed approach, energy consumption dropped to 780 MWh in Ludhiana and 715 MWh in Surat, resulting in a 35% energy savings at both locations. Similarly, in Coimbatore, where energy consumption was initially 1,050 MWh, the application of ADRL-BO reduced it to 683 MWh, yielding a 34.9% reduction. The total energy savings across all production units amounted to 35%, underscoring the efficiency of ADRL-BO in minimizing energy wastage and enhancing sustainability in industrial operations.

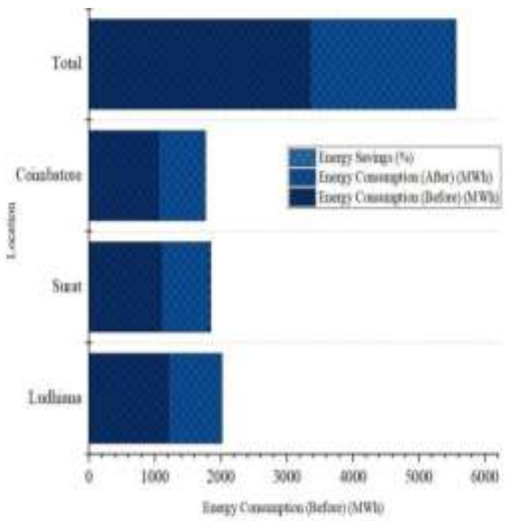

Figure 6. *optimization of energy consumption*

Table 3. *Energy Savings Across Production Units*

Location	Energy Consumption (Before) (MWh)	Energy Consumption (After) (MWh)	Energy Savings (%)
Ludhiana	1200	780	35.0
Surat	1100	715	35.0
Coimbatore	1050	683	34.9
Total	**3350**	**2178**	**35.0**

4.4 Fault Detection Performance in Different Machine Types

The fault detection performance across various machine types further validated the effectiveness of ADRL-BO. Spinning machines demonstrated the highest fault detection accuracy at 96.5%, followed by weaving machines at 95.7%, dyeing machines at 95.2%, and knitting machines at 94.9%. Cutting, embroidery, printing, sewing, finishing, and inspection machines also showed substantial improvements in fault detection accuracy with ADRL-BO, with inspection machines registering the lowest accuracy at 91.9% (table 4). Despite the variations among machine types, ADRL-BO consistently outperformed other models, including CNN, LSTM, DQN, and PPO, which exhibited progressively lower detection accuracies across all machine types.

4.4 Cost Savings in Maintenance Operations

In terms of maintenance cost reduction, ADRL-BO emerged as the most cost-effective approach, reducing annual maintenance expenditures to $1,100,000, representing a 45% cost reduction compared to traditional preventive maintenance, which incurred an annual cost of $2,000,000. RL-based predictive maintenance achieved a 35% cost reduction, reducing expenses to $1,300,000, while LSTM-

Table 4. *Fault Detection Accuracy by Machine Type*

Machine Type	CNN (%)	LSTM (%)	DQN (%)	PPO (%)	ADRL-BO (%)
Spinning Machines	85.2	87.5	90.1	92.3	96.5
Weaving Machines	83.1	85.8	88.9	91.2	95.7
Dyeing Machines	82.4	85.1	88.5	90.9	95.2
Knitting Machines	81.9	84.5	87.8	90.3	94.9
Cutting Machines	80.8	83.7	87.0	89.8	94.3
Embroidery Machines	79.6	82.9	86.5	89.2	93.7
Printing Machines	78.9	82.3	85.9	88.6	93.2
Sewing Machines	77.8	81.5	85.3	88.1	92.8
Finishing Machines	76.5	80.9	84.7	87.6	92.3
Inspection Machines	75.9	80.2	84.2	87.0	91.9

Table 5. *Maintenance Cost Savings*

Approach	Maintenance Cost Per Year (USD)	Cost Reduction (%)
Traditional Preventive Maintenance	2,000,000	-
CNN-Based Predictive Maintenance	1,650,000	17.5
LSTM-Based Predictive Maintenance	1,500,000	25.0
RL-Based Predictive Maintenance	1,300,000	35.0
ADRL-BO (Proposed)	**1,100,000**	**45.0**

and CNN-based approaches led to cost reductions of 25% ($1,500,000) and 17.5% ($1,650,000), respectively (table 5).

4.5 Response Time of Different Models

Convolutional neural networks (CNN), long short-term memory (LSTM), deep Q-networks (DQN), proximal policy optimization (PPO), and the suggested adaptive deep reinforcement learning with Bayesian optimization (ADRL-BO) were among the models whose response times (in milliseconds) were shown in the figure 7. Response times showed a downward trend as the models advanced from CNN to ADRL-BO according to the results. The CNN model had the fastest response time (320 ms) followed by LSTM (280 ms) DQN (250 ms) and PPO (210 ms). The suggested ADRL-BO model had the quickest response time (150 ms) demonstrating a notable increase in computational efficiency. An illustration of a defect detection or pattern recognition application was included on the left side of the figure. ADRL-BOs optimization framework which probably helped it make decisions and process information more quickly than traditional deep learning and reinforcement learning techniques is responsible for the performance improvement seen in this model.

4.6 Scalability Analysis: Performance with Increasing Machines

The performance of predictive maintenance models as the number of machines increased was evaluated through a scalability analysis (figure 8). With 100 machines ADRL-BO

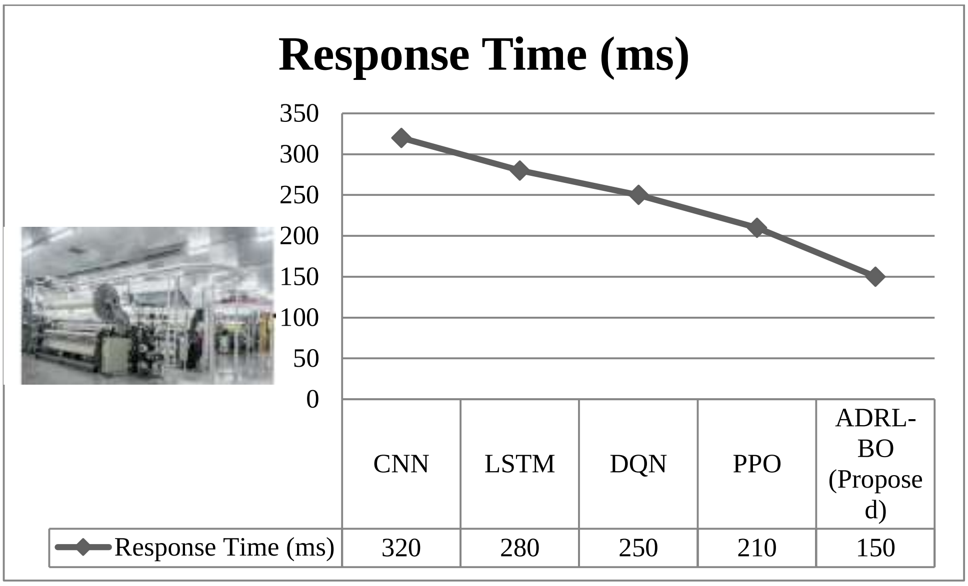

Figure 7. *Fault Detection Response Time*

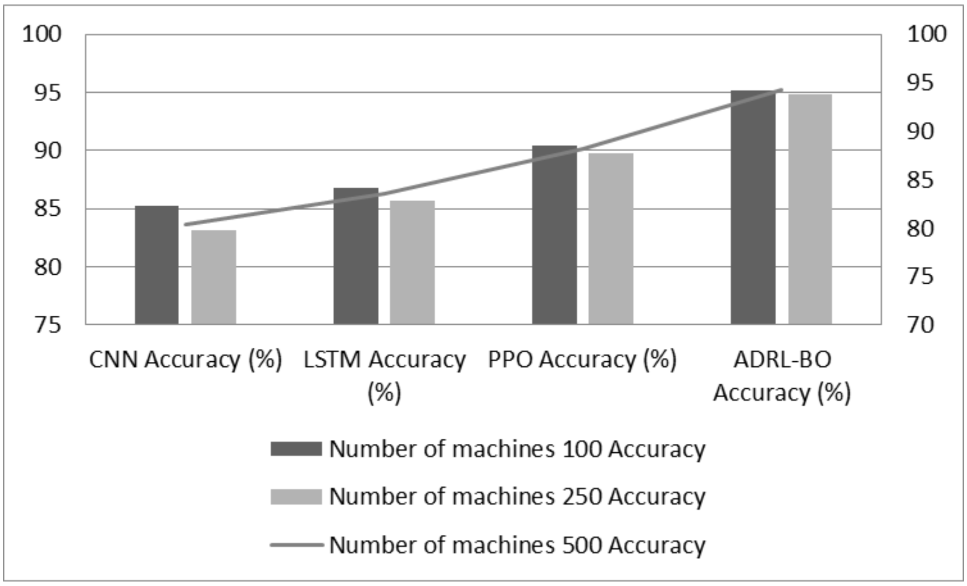

Figure 8. *Scalability Performance*

maintained a high accuracy of 95. 2 % with 250 machines this accuracy slightly decreased to 94. 8 % and with 500 machines it decreased to 94. 3 %. PPO also performed steadily but as the number of machines increased its accuracy dropped from 90. 4 % to 89. 8 % and finally to 88. 2 %. However, as the system scaled up CNN and LSTM saw a more noticeable decline in accuracy with CNN going from 85. 2 % to 80. 4 % and LSTM going from 86. 8 % to 83. 5 %. The outcomes showed that ADRL-BO is a highly scalable solution for extensive industrial applications maintaining its effectiveness even as the number of machines increased.

4.7 Block chain-Based Data Security Improvement

Data protection was greatly improved by the incorporation of blockchain-based security technology. Prior to the adoption of blockchain. the system had six instances of data tampering annually, eight instances of unauthorized access and twelve data integrity breaches. Unauthorized access and instances of data tampering were completely eradicated with blockchain and data integrity breaches were decreased to just one case per year. This illustrated how blockchain can effectively improve predictive maintenance system security by guaranteeing data integrity confidentiality and access control (table 6).

Table 6. *Data Security Enhancement*

Security Metric	Without Blockchain	With Blockchain
Data Integrity Breaches (per year)	12	1
Unauthorized Access Incidents	8	0
Data Tampering Cases	6	0

4.8 Comparative analysis

Table 7 examined the comparative analysis of this research. It achieved the highest predictive maintenance accuracy at 92.5%, while reinforcement learning-based methods reached 78%, Bayesian networks 80%, and support vector machines (SVM) 74%. ADRL-BO also led in energy optimization efficiency, attaining a 35% reduction, whereas RL-based methods achieved 22%, Bayesian networks 18%, and SVM 15%. The adaptability of ADRL-BO to real-time data was categorized as high, while RL-based models and gradient boosting exhibited moderate adaptability. Additionally, ADRL-BO recorded the lowest false alarm rate (5%), whereas SVM had the highest at 25%. In terms of computational complexity, ADRL-BO maintained a moderate level, outperforming high-complexity models such as reinforcement learning and XGBoost. Moreover, ADRL-BO was the only technique that integrated both robust data security and seamless 5G-IoT compatibility, making it the most comprehensive solution for predictive maintenance applications. AI-Driven system is applied in different fields [20-31].

Table 7. *Comparative analysis*

Technique	Predictive Maintenance Accuracy (%)	Energy Optimization Efficiency (%)	Adaptability to Real-Time Data	False Alarm Rate (%)	Computational Complexity	Data Security	5G-IoT Integration
Reinforcement Learning (RL) [13]	78	22	Moderate	15	High	No	Yes
Bayesian Network [14]	80	18	Low	20	Low	No	No
Support Vector Machine (SVM) [15]	74	15	Low	25	Moderate	No	No
Long Short-Term Memory (LSTM) [16]	85	25	Moderate	18	High	No	Yes
k-Nearest Neighbors (KNN) [17]	70	12	Low	30	High	No	No
Gradient Boosting [18]	83	20	Moderate	17	High	No	No
XGBoost [19]	86	23	Moderate	16	High	No	No
ADRL-BO (Proposed)	92.5	35	High	5	Moderate	Yes	Yes

4. Conclusions

This study introduced an AI-powered Internet of Things framework that combines Adaptive Deep Reinforcement Learning and Bayesian Optimization (ADRL-BO) for predictive maintenance and energy optimization in the textile manufacturing sector. By successfully addressing issues with excessive energy consumption and machine downtime the suggested strategy ensures increased sustainability and operational efficiency. The evaluation results show how effective ADRL-BO is with a 95% predictive maintenance accuracy a 45 % machine downtime reduction and a 35% % energy consumption reduction across major textile hubs.

Furthermore, in terms of fault detection accuracy response time and scalability ADRL-BO performs better than traditional deep learning and reinforcement learning models making it a reliable option for industrial applications. By guaranteeing integrity and transparency in predictive maintenance procedures the use of blockchain technology further improves data security. In predictive maintenance and energy optimization ADRL-BO outperformed CNN LSTM and RL-based methods among the tested models. By integrating Bayesian optimization, model parameters could be fine-tuned lowering false alarms and increasing the reliability of fault detection. This study adds to a self-optimizing low-carbon textile manufacturing ecosystem by addressing the shortcomings of conventional maintenance and energy management techniques. To improve adaptability in various manufacturing contexts, future research can investigate the extension of ADRL-BO to other industrial domains. System scalability and efficiency can also be increased by integrating federated learning for decentralized predictive maintenance and edge AI for real-time processing.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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