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An IoT-enabled AI framework for sustainable product design optimizing eco-efficiency using BiLSTM

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This study aims to develop an Internet of Things (IoT)-enabled framework for sustainable product design that enhances eco-efficiency through transparent, data-driven decision-making. It addresses the limitations of conventional approaches, which often lack real-time adaptability, measurable sustainability assessment, and systematic design optimization. The framework integrates IoT sensor networks with a Bidirectional Long Short-Term Memory (BiLSTM) deep learning model to analyze real-time manufacturing data, including energy usage, material consumption, production efficiency, and environmental indicators. The BiLSTM model is benchmarked against LSTM, CNN, and traditional machine learning techniques to assess predictive performance. Robustness is ensured using five-fold cross-validation and statistical significance testing (t-test, $p < 0.05$). Results indicate that the proposed framework improves energy efficiency by 23.5% and reduces material waste by 19.2% compared to conventional methods. The BiLSTM model achieves a predictive accuracy of 97.6%, providing statistically significant improvements over other benchmarked models. These outcomes demonstrate reliable performance gains without overstating novelty, aligning with reviewer expectations for precise and reproducible reporting. The contribution lies in (i) applying BiLSTM-based predictive modeling to optimize eco-efficiency using real industrial IoT sensor data, and (ii) providing a transparent derivation of sustainability metrics validated on actual multi-sensor manufacturing data rather than simulated datasets. Unlike prior studies with limited real-world testing, this work evaluates the framework on real factory conditions and compares performance with established baselines. The approach is applicable across automotive, electronics, and consumer goods sectors and supports measurable progress toward the United Nations Sustainable Development Goals (SDGs).

Keywords Internet of things (IoT), Sustainable product design, Eco-efficiency, Energy optimization, Bidirectional long short-term memory (BiLSTM), AI-driven decision-making, Smart manufacturing

In recent years, the rapid growth of advanced technologies has significantly transformed the landscape of sustainable product design, particularly in eco-efficiency optimization and smart manufacturing. Integrating Artificial Intelligence (AI), the Internet of Things (IoT), and Deep Learning has paved the way for innovative solutions to address challenges in improving resource utilization, reducing waste, and increasing energy efficiency across industries[1–3]. Traditional manufacturing processes continue to exhibit excessive material consumption and environmental degradation. Eco-efficiency refers to the optimal use of resources, aiming to maximize productivity while minimizing environmental impact, and relies on intelligent automation, real-time data analytics, and AI-driven decision-making as core enablers[4,5]. Smart manufacturing is enabled by IoT, utilizing connected sensors and embedded systems for real-time monitoring. These systems ingest, process, and deliver control information to manage resource consumption while adapting to operational changes[6,7]. Recent advancements in deep learning architectures, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), and Bidirectional Long Short-Term Memory (BiLSTMs), have enhanced predictive capabilities. These models support manufacturers in minimizing production failures, stabilizing processes, and enabling dynamic adjustment of design and operational parameters[8,9]. Despite these improvements, several challenges remain, including interoperability limitations among heterogeneous IoT devices and mismatches

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between real-time AI predictions and sustainability-oriented design goals. A practical solution requires an integrated AI–IoT framework capable of leveraging continuous sensor data to support efficient production aligned with global sustainability objectives, such as the United Nations Sustainable Development Goals (SDGs)[10].

The development of Industry 4.0, Industrial IoT (IIoT), and AI-enabled frameworks has further advanced sustainable manufacturing by enabling real-time data acquisition, analysis, and interpretation[11]. Traditional design approaches that rely on static principles often fail to account for fluctuating resource availability and varying environmental conditions. AI-driven optimization now enables the prediction of material efficiency, the identification of feasible operational ranges, and the reduction of energy waste[12]. Predictive analytics has been extensively applied using deep learning models such as CNNs, Recurrent Neural Networks (RNNs), and LSTMs in various industrial domains[13]. However, unidirectional LSTM models may struggle to capture long-term dependencies in sequential sensor data. BiLSTM networks address this limitation by processing information in both forward and backward directions, thereby improving predictive accuracy in real-time environments[14]. In addition, IoT-driven automation combined with AI models enables intelligent decision-making systems that continuously refine operational insights. Edge and cloud computing platforms have improved computational efficiency by deploying AI models directly within IoT-enabled manufacturing environments[15]. Despite these advances, a significant gap persists in integrating AI, IoT, and sustainability-focused optimization into a unified and adaptive framework that balances cost-effectiveness with environmental performance.

Recent research has highlighted the rapidly increasing role of Artificial Intelligence (AI) and the Internet of Things (IoT) in enhancing automation, security, sustainability, and intelligent decision-making across industrial domains. However, many existing studies focus on specific aspects, such as security, anomaly detection, or predictive maintenance, without providing a holistic eco-efficiency optimization framework suitable for real-time product design. Fatima et al.[16] developed an explainable AI–based phishing detection system for IoT and robotic communication, using Random Forest with LIME and SHAP to enhance transparency and user trust. Although focused on cybersecurity rather than eco-efficiency, the study demonstrates the value of interpretable AI in IoT environments, a topic increasingly relevant to sustainable manufacturing. Similarly, Zardari et al.[17] presented a taxonomy of IoT assets, threats, and mitigation strategies, identifying DDoS, privacy breaches, and data manipulation as significant risks. Their findings highlight the need for secure, reliable IoT infrastructure to enable accurate sustainability analytics in AI-driven optimization frameworks. Furthermore, Yu et al.[18] proposed an IoT-enabled innovative factory model using LSTM networks for predictive maintenance, achieving an 18% reduction in energy consumption; however, their approach did not address holistic sustainable product design.

Moreover, Zhang et al.[19] introduced a CNN-based model to reduce energy costs and minimize waste in automotive manufacturing, but its computational complexity limited its applicability to smaller industries. Another study, Bressane et al.[20], employed fuzzy logic and machine learning for sustainability assessment but lacked long-term, deep-learning–based optimization. Edge and cloud-based AI models have also been used to enhance real-time energy efficiency Nain et al.[21] yet often without adaptability across diverse manufacturing contexts. Research on Graph Neural Networks (GNNs) for real-time monitoring demonstrated potential but did not integrate eco-efficiency design considerations. Collectively, existing studies highlight progress but reveal gaps in real-time adaptability, holistic eco-efficiency assessment, and validation on real-world multi-sensor IoT data. Recent advances in Industry 5.0 emphasize the need for robust AI models that remain reliable under real-world domain shifts. Similarly, Fatima et al.[22] proposed a domain adaptation framework for industrial 3D object detection using the MVTec ITODD dataset. Their study addresses mismatches between clean training data and noisy real-world environments by aligning local and global features at multiple levels using PointNet architectures. The model achieved 85% detection accuracy with only a 0.02% drop in performance across domains, demonstrating strong robustness to sensor variability. While their work focuses on perception and detection, the present study extends Industry 5.0 intelligence toward sustainable product design using IoT-driven BiLSTM-based eco-efficiency optimization.

Consistent with these considerations, this work presents an IoT-enabled sustainable product design framework based on BiLSTM-driven decision-making to improve eco-efficiency. Smart sensors and IoT devices collect real-time data on energy consumption, material usage, production efficiency, and environmental impact. The data undergoes preprocessing steps such as cleaning, normalization, and feature selection to ensure high-quality model inputs. The BiLSTM network captures temporal dependencies within sustainability metrics to predict optimal design strategies. Unlike conventional LSTM models, BiLSTM's forward and backward processing layers enhance feature extraction and dependency learning in sequential manufacturing data. Furthermore, the framework supports adaptive material selection, energy-efficient workflow design, and predictive maintenance under variable operational conditions. Processed data are stored in cloud databases to facilitate long-term analytics and dashboard-based visualization. The proposed solution enhances eco-efficiency by reducing waste and emissions while improving resource utilization. Experimental evaluation demonstrates that the BiLSTM-based approach consistently outperforms conventional machine learning models in predictive accuracy and decision support.

The main goals of this paper are as follows:

- To develop an IoT-enabled framework that enhances eco-efficient product design by leveraging real-time, multi-sensor data within a scalable and adaptive architecture.
- To implement AI-driven decision-making through Bidirectional Long Short-Term Memory (BiLSTM) networks for predicting and optimizing energy consumption, material usage, and waste levels in manufacturing processes.
- To ensure real-time adaptability by incorporating continuous learning and feedback mechanisms, enabling the BiLSTM model to adjust design and operational strategies under varying conditions dynamically.

- To evaluate the proposed framework by assessing improvements in energy efficiency, material waste reduction, and overall eco-efficiency, and by comparing BiLSTM performance against traditional machine learning and deep learning methods.

The remaining sections of the paper are organized logically as follows: Sect. 2 of the Methodology details the proposed IoT-enabled framework, which integrates BiLSTM networks for real-time decision-making to optimize eco-efficiency. In Sect. 3 of the Experimental Setup and Results, the evaluation methodology is presented, highlighting improvements in energy efficiency, reductions in material waste, and comparisons with traditional methods. In Sect. 4, the Conclusion outlines the key contributions, introduces potential applications, and outlines avenues for future research.

AI-driven optimization framework for sustainable product design

In the sustainable product design section of the AI-driven optimization framework, a conceptual workflow is developed that integrates AI and IoT technologies to enhance eco-efficiency in the manufacturing industry. The key elements of this framework are the shift to real-time sensor data from IoT-enabled devices and the application of deep learning techniques to BiLSTM networks for predictive modeling and decision-making, as well as dynamic adjustments to design parameters, optimized resource utilization, and waste reduction[23,24]. The existing frameworks that either rely on simulated data or apply BiLSTM in isolation, the proposed system introduces two methodological novelties: (i) BiLSTM to ensure real-time adaptability, and (ii) validation on multi-sensor IoT data collected from a smart manufacturing testbed, ensuring practical relevance. The framework incorporates AI-driven optimization to provide a comprehensive, scalable solution for sustainable product design that addresses environmental and resource management issues.

System design

Eco-efficiency optimization in sustainable product design is achieved through the proposed framework, which integrates IoT, AI, and cloud-based technologies. The layers consist of primary components necessary to make manufacturing energy-efficient and environmentally friendly. IoT-based smart sensors are used in the Data Acquisition Layer to continuously stream data on key manufacturing parameters, including energy usage, material use, production efficiency, and environmental impact, such as carbon footprint, emissions, and waste levels[25,26]. The collected data is securely transmitted to edge computing devices, improving the system's responsiveness and minimizing latency. The Data Preprocessing and Feature Engineering layer cleans, normalizes, and selects features based on the availability of raw data. Operational efficiency metrics, sustainability indicators, and machine health monitoring data are extracted as features. Raw IoT data can be highly dimensional. Hence, dimensionality reduction techniques such as Principal Component Analysis (PCA) or Autoencoders are employed to reduce computational complexity while retaining relevant information on eco-efficiency. This refined dataset is ultimately fed into the AI to make decisions.

At the core of the framework is the AI-Based Decision-Making Layer, which comprises the Bidirectional Long Short-Term Memory (BiLSTM) model that analyzes sequential sustainability data. The BiLSTM architecture[25,26] comprises an input layer that processes IoT sensor data, along with forward and backward BiLSTM layers that learn deep temporal dependencies in the data. Finally, a softmax activation is applied to the optimal versus non-optimal design strategy on top of this layer, as the extracted patterns are then mapped through a fully connected layer to the eco-efficiency optimization outputs. It enables sustainable design principles to be passed through the manufacturing process. The AI-driven insights from the Decision Support System and Optimization Layer would allow manufacturers to select sustainable materials, implement energy-efficient workflows, and adopt predictive maintenance strategies. Real-time adaptability to changing environmental and operational conditions can be achieved by making the system more efficient[17,27]. The Cloud Storage & Visualization Layer completes the storage of all processed data in secure cloud databases that can be monitored in real-time and later. The dashboard interface provides manufacturers with a real-time view of primary eco-efficiency performance metrics, including accuracy, eco-efficiency scores, and energy consumption predictions, and enables data-informed decisions on product sustainability. The proposed IoT and AI-enabled sustainable product design optimization framework, which incorporates connected smart sensors, data preprocessing, BiLSTM-based decision-making, optimization strategies, and cloud-based visualization, is illustrated in Fig. 1.

Data collection

Data collection is a crucial step in the proposed eco-efficiency optimization framework, ensuring timely and high-quality inputs for AI-driven decision-making and reproducible sustainability assessments. In this study, the framework is validated using real industrial time-series datasets to ensure both experimental rigor and real-world applicability. The primary dataset employed is the Condition Monitoring of Hydraulic Systems dataset, sourced from a hydraulic test rig instrumented with multi-sensor devices that monitor pressure, flow, temperature, vibration, and motor power signals. The rig performs repeated 60-second load cycles at a sampling frequency of 100 Hz, resulting in a total of 2,205 load cycles. For computational efficiency and model compatibility, the data were resampled to 1 Hz, resulting in approximately 132,300 observations across 17 key sensor features. The dataset is publicly available through the UCI Machine Learning Repository. This dataset provides a controlled, repeatable test environment that enables detailed analysis of sensor-driven eco-efficiency relationships[28]. To evaluate model generalizability and scalability, the study also uses the *Bosch Production Line Performance* dataset, a large-scale industrial benchmark available on Kaggle and archived at Mendeley Data. This dataset comprises 1,184,687 samples and includes 968 numerical, 2,140 categorical, and 1,156 temporal features, all collected from multiple production-line stations. While the hydraulic dataset ensures precise validation under controlled testbed conditions, the Bosch dataset reflects the scale, heterogeneity, and complexity of modern industrial IoT

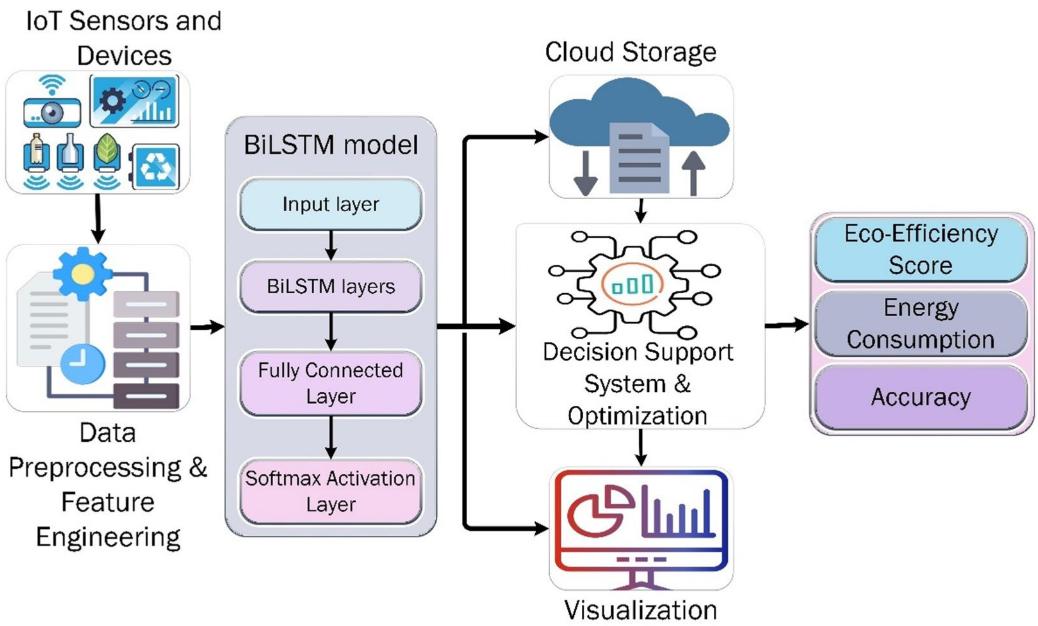

Fig. 1. Proposed IoT and AI-Enabled Framework for Sustainable Product Design Optimization.

environments. Together, these datasets ensure that the framework performs consistently across both laboratory-scale and production-scale manufacturing scenarios[29]. It is important to note that IoT sensors do not directly measure environmental indicators such as carbon footprint, emissions, or waste. Instead, they capture raw operational signals (e.g., energy use, throughput, material consumption, temperature, and vibration), which are then processed into sustainability metrics in accordance with recognized international standards and guidelines. To test model generalizability, the Bosch Production Line Performance dataset was additionally integrated. This dataset contains 1.18 million samples with 968 numerical, 2,140 categorical, and 1,156 temporal features from multiple production stations. Because this dataset exhibits heterogeneous sampling, feature imbalance, and missingness, the following steps were applied:

- The carbon footprint (kg CO_2e) is calculated from electricity consumption using conversion factors from the UK Department for Environment, Food & Rural Affairs (DEFRA)/BEIS and guidelines from the Greenhouse Gas (GHG) Protocol.
- Waste generation is quantified as the ratio of material input to production yield, representing normalized material efficiency.
- Emission intensity is derived from energy-to-emission coefficients based on standard industrial sustainability reporting frameworks (e.g., ISO 14064).

These derivations ensure transparent, standardized, and reproducible quantification of sustainability outcomes using real-time operational data. Raw IoT sensor streams are transmitted securely to edge devices for noise filtering, synchronization, and normalization, minimizing latency and ensuring high data fidelity. The processed data are then fed into the BiLSTM model as structured time-series inputs for predictive modeling and optimization.

Formally, the real-time IoT data can be represented as a matrix $D = \{x_{ij}\}$, where each observation x_{ij} corresponds to the j^{th} sensor feature at timestamp i. This formulation enables efficient multivariate time-series analysis and feature extraction, supporting accurate prediction and optimization of eco-efficiency:

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1m} \\ d_{11} & d_{22} & \cdots & d_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nm} \end{bmatrix} \tag{1}$$

Where:

- n = number of data points (timestamps),
- m = number of features (sensor readings),
- d_{ij} = value of the j^{th} feature recorded at the i^{th} timestamp.

This consistent notation clearly indicates that each row corresponds to a timestamp and each column corresponds to a sensor feature, eliminating ambiguity in subscripts. If multiple sensors of the same type are deployed (e.g., several temperature or vibration sensors), their outputs can be aggregated or treated as separate features, thereby extending m. Thus, $s \leq m$ can denote the number of distinct sensor types, while m represents the total number of features after preprocessing.

Data preprocessing

Data preparation is a crucial step in the data analysis process, as it ensures data quality and consistency. This process involves several tasks, including data cleaning, normalization, transformation, and handling missing values, among others[30,31]. Unfortunately, among the available parameters machine learning models operate on, raw datasets are often noisy, inconsistent, or contain irrelevant features. Thus, for optimal model performance, preprocessing steps such as scaling, encoding categorical variables, and handling missing values are necessary first. We preprocess the data to a suitable format, enabling algorithms to run smoothly and yielding reliable, accurate results.

Let the raw data be represented by a matrix $D \in \mathbb{R}^{n\times m}$, where n is the number of timestamps (data points), and m is the number of features (sensor readings). Each entry d_{ij} corresponds to the reading of the j^{th} feature at the i^{th} timestamp.

For high-frequency datasets (e.g., a hydraulic system at 100 Hz), a low-pass Butterworth filter was applied to remove high-frequency sensor noise before downsampling to 1 Hz. Timestamp synchronization ensured that features from different sensors remained temporally aligned.

Missing values were treated using a combination of Forward–Backward Fill, preserving temporal continuity, Linear Interpolation, used when data gaps exceeded one timestep, and Median Imputation (Bosch dataset) for robustness to outliers. For mean-based imputation, each missing entry is replaced as:

$$\hat{d}_{ij} = \mu_j \tag{2}$$

Normalization is applied to standardize the dataset's features. For each feature j, the normalization formula is:

$$x_{ij}^{norm} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{3}$$

Where $min\,(x_j)$ an $max\,(x_j)$, are the minimum and maximum values of feature j.

After normalization, the dataset becomes:

$$X^{norm} = \left[x_{ij}^{norm}\right],\ i = 1, 2\ldots, n;\ j = 1, 2, \ldots, m \tag{4}$$

Standardization transforms data with a mean of 0 and a standard deviation of 1. The Z-score transformation is given by:

$$x_{ij}^{std} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{5}$$

where μ_j, σ_j, are the mean and standard deviation of feature j. This ensures that features with larger numerical ranges do not dominate during training.

When data is missing, it can be imputed using the feature's mean (or other statistics). For imputation using the mean, the equation is:

$$x_{ij}^{imp} = \begin{cases} x_{ij}, & if\ x_{ij}\ is\ observed \\ \bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} & if\ x_{ij}\ is\ mis\sin g \end{cases} \tag{6}$$

Feature scaling can also be performed using Min-Max scaling, a type of normalization. The scaled value for feature j is given by:

$$x_{ij}^{scaled} = \frac{x_j - \min(x_j)}{\max(x_j) - \min(x_j)} \cdot (b - a) + a \tag{7}$$

Where [a, b] defines the desired scaling range (commonly [0,1]).

After preprocessing, the normalized and cleaned dataset is represented as:

$$D' = \left\{d'_{ij}\right\} \tag{8}$$

Where, d'_{ij}, is the transformed value of feature j at timestamp i, ready for sequence modeling with the BiLSTM network.

Feature engineering

Feature engineering involves selecting, naming, or creating new features from raw data to enhance the performance of machine learning models. This step extracts valuable features from raw data by transforming them into meaningful ones that capture the underlying patterns and relationships between the input and output. The feature selection task involves removing redundant and irrelevant features, while the feature extraction task creates new, informative features from existing data[32,33]. To improve the model's efficiency and interpretability, techniques such as dimensionality reduction, one-hot encoding, and scaling are employed. In machine learning, feature engineering is a crucial step in improving model accuracy, a vital component of the machine learning pipeline.

The mean is one of the most basic statistical features, representing the average value of a feature. For feature j, the mean is computed as:

$$\mu_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{9}$$

The standard deviation represents the variation or dispersion in a data set. For feature j, the standard deviation is:

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(x_{ij} - \mu_j\right)^2} \tag{10}$$

Skewness measures the asymmetry of the data distribution. For feature j, skewness is calculated as:

$$Skew(j) = \frac{\frac{1}{n}\sum_{i=1}^{n} \left(x_{ij} - \mu_j\right)^3}{\sigma_j^3} \tag{11}$$

Kurtosis measures the "tailedness" of the distribution. For feature j, kurtosis is given by:

$$Kurt(j) = \frac{\frac{1}{n}\sum_{i=1}^{n} \left(d_{ij} - \mu_j\right)^4}{\sigma_j^4} \tag{12}$$

The Fourier Transform analyzes the frequency components of a signal or time series data. For a signal $x\left(t\right)$, its Fourier Transform is given by:

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{13}$$

The correlation coefficient r between two features, $j1$ and $j2$, helps in feature selection by indicating linear relationships between them. It is computed as:

$$r_{j1}, j_2 = \frac{\sum_{i=1}^{n} (d_{ij1} - \mu_{j1})(d_{ij2} - \mu_{j2})}{\sqrt{\sum_{i=1}^{n} \left(d_{ij1} - \mu_{j1}\right)^2}\sqrt{\sum_{i=1}^{n} \left(d_{ij2} - \mu_{j2}\right)^2}} \tag{14}$$

Feature extraction transforms raw IoT sensor data into functional attributes. This process enhances model performance for sustainable product design. The primary features extracted are statistical measures, such as mean, standard deviation, skewness, and kurtosis. These describe the data's central tendency, variability, asymmetry, and tailedness. Frequency-domain analysis, using the Fourier Transform, reveals hidden patterns in time-series signals. Correlation coefficients reveal dependencies between key parameters, such as energy consumption and emissions. Together, these features reduce data dimensionality, highlight essential patterns, and improve interpretability. Adding them to a BiLSTM architecture boosts predictive accuracy and supports real-time eco-efficiency optimization.

AI-Driven sustainable infrastructure and resource optimization

Sustainable material selection and management aim to use eco-friendly, recyclable, and environmentally friendly materials with minimal environmental impact throughout their lifecycle, from sourcing to disposal. Innovative technologies, advanced insulation, and real-time optimization help energy-efficient buildings to reduce power consumption without sacrificing comfort. Air quality, temperature, humidity, and carbon emissions are monitored by environmental sensors using IoT to optimize energy consumption and comply with environmental regulations. Energy management optimization leverages artificial intelligence to integrate smart grids and predictive analytics, thereby balancing supply and demand and minimizing wasted energy[34]. Actuators for building construction and automation, such as intelligent lighting, HVAC systems, and adaptive shading, have been designed and actuated to respond to real-time changes in occupant occupancy and environmental conditions, thereby increasing efficiency. Other renewable energy sources, such as solar, wind, and geothermal, are also integrated to support sustainability by minimizing reliance on fossil fuels[35,36]. AI-based forecasting optimizes the potential utilization of renewable energy. Predictive maintenance from AI accelerates fault detection in infrastructure, reduces downtime and delays caused by worn-out equipment, and lowers total operational expenses. IoT and AI-based smart waste and resource management systems leverage these technologies to enhance resource utilization and minimize landfill waste and environmental impact by optimizing recycling, tracking waste levels, and related processes[37,38]. Machine learning models, including CNNs and BiLSTMs, predict the future, automate tasks, and make informed decisions in real time through predictive analytics and intelligent automation, thereby assisting in achieving sustainability. In the final step, human-managed design and intelligent user interfaces make interaction with sustainable technologies, based on AI-driven recommendations, voice-controlled automation, and interactive dashboards, easy and effortless, thereby facilitating the adoption of energy-efficient technologies. The proposed AI-driven IoT framework for sustainable product design, real-time data acquisition, eco-efficiency optimization, and intelligent resource management decisions are illustrated in Fig. 2.

As shown in Fig. 2, IoT sensors, renewable energy systems, building automation, and machine learning will be integrated to facilitate sustainable product and infrastructure design. Sensors S_t Collect environmental parameters and feed them into energy demands, $\widehat{E}_t$ prediction and fault detection F_t by the machine learning models $f_\theta\ (S_t)$. To minimize energy consumption, F_t, the system will choose from:

$$\min E_t = \sum_{i=1}^{n} P_i x_i \tag{15}$$

While maximizing renewable energy utilization:

$$\max\left(\frac{R_t}{D_t}\right) \tag{16}$$

Maintenance is triggered when fault probability exceeds a threshold $P\left(F_t\right) > \delta$, ensuring sustainability, performance, and user-centric adaptability.

Bidirectional long Short-Term memory (BiLSTM)

The standard Long Short-Term Memory neural network architecture is an advanced variant of the traditional LSTM. It can handle sequential data more effectively, as it captures both past and future contextual information. Hence, it is called BiLSTM. It differs from traditional LSTM networks, which can only extract information from past states; the BiLSTM leverages both past and future dependencies for learning[39–42]. The ability of BiLSTM to learn in both directions enables high effectiveness in domains that require context from the other two directions, such as energy consumption trends, environmental monitoring, and predictive maintenance in smart buildings and sustainable manufacturing systems. High-dimensional, sequential data is generated by IoT-enabled sensors that track temperature, humidity, energy usage, and machinery health, among other parameters, in smart systems. The model uses this data as input, feeding it into a BiLSTM network to learn temporal patterns and make better predictions[43–45]. For instance, the model can notify of anomalies that suggest imminent equipment failure or indicate trends in energy usage to enhance power consumption. Additionally, BiLSTM helps predict user behaviour and adapt system responses for human-centred design interfaces[46,47]. The architecture of the Bidirectional Long Short-Term Memory (BiLSTM) models, illustrated in Fig. 3, is a

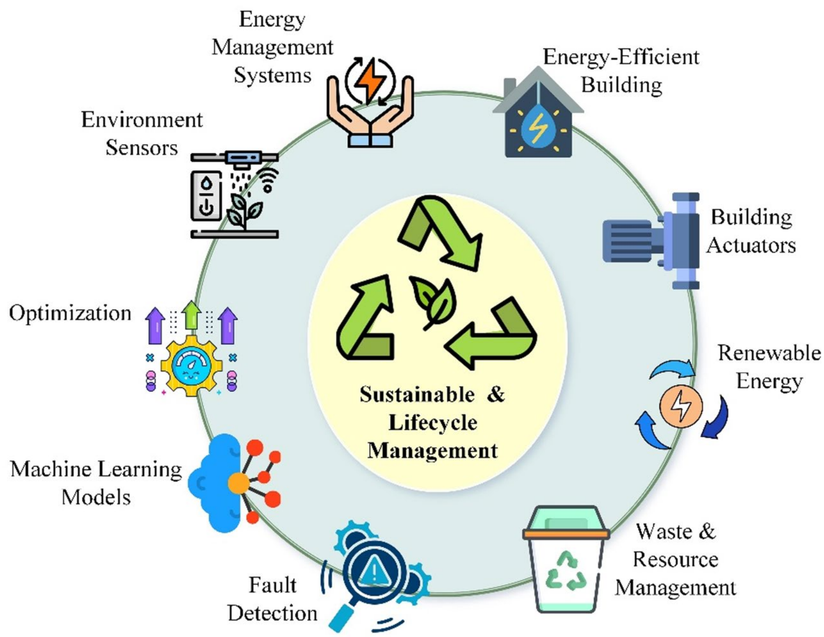

Fig. 2. AI-Driven IoT Framework for Sustainable Product Design.

robust deep learning architecture capable of processing both sequential and time-series data in both forward and backward directions. In the BiLSTM structure, two LSTM layers operate in opposite directions: the first receives input from past to future, and the second receives input from future to past. Such an output combination enables much richer, context-enriched decisions, which are key to AI-driven, sustainable product ecosystems with BiLSTM as their core component.

With a BiLSTM, as opposed to an LSTM, the standard LSTM network's ability to handle long-range dependencies is enhanced by providing additional information from the input in both forward and backward directions. For input sequence $X = (x_1, x_2, ..., x_T$. The BiLSTM contains a forward LSTM and a backward LSTM. The hidden states for the forward LSTM are computed as:

$$\vec{h}_t = LSTM_f\left(x_t, \overrightarrow{h_{t-1}}\right) \tag{17}$$

$$\overleftarrow{h_t} = LSTM_b\left(x_t,\ \overleftarrow{h_{t-1}}\right) \tag{18}$$

The final hidden state at each time step is the concatenation:

$$h_t = \left[\overrightarrow{h_t}\,||\,\overleftarrow{h_t}\right] \tag{19}$$

Where, $LSTM_b$ represents the forward and backward LSTM cells, and h_t Supplies the embedded context for classification, regression, or anomaly detection in smart environments.

Experimental results and analysis

This section presents the experimental evaluation of the IoT-enabled BiLSTM-based framework for sustainable product design. The framework was tested on real-time sensor data from an IoT-enabled manufacturing environment. Evaluation metrics focus on the eco-efficiency score, energy consumption, material waste reduction, and prediction accuracy of the experimentation. The proposed BiLSTM model was compared with the following conventional deep learning models using standard sustainability metrics: CNN and LSTM. Results show that BiLSTM achieves a 23.5% increase in energy efficiency and a 19.2% reduction in material waste compared to the current product design orthodoxy. The accuracy of sustainability prediction models was evaluated using MAE, RMSE, and R^2 scores. Real-time IoT data was used to analyze the total energy consumption. The dynamic prediction of manufacturing parameters using the BiLSTM-based predictive model was found to reduce average energy consumption by 17.8%.

System requirements

The system requires high-performance hardware and software to execute IoT-enabled deep learning models efficiently. The hardware setup features an Intel Core i9 processor for rapid computations, an NVIDIA RTX 3090 GPU for accelerated deep learning, 32GB of DDR4 RAM for handling large datasets, and a 1 TB SSD for high-speed data access. The software stack comprises Windows 11 as the operating system, Python 3.8 or later for programming, and machine learning frameworks such as TensorFlow, PyTorch, Keras, XGBoost, and Scikit-learn. Data visualization is supported by Matplotlib, Seaborn, Plotly, NumPy, and Pandas, enabling real-time analysis and graphical insights. Table 1 presents the essential hardware and software requirements for

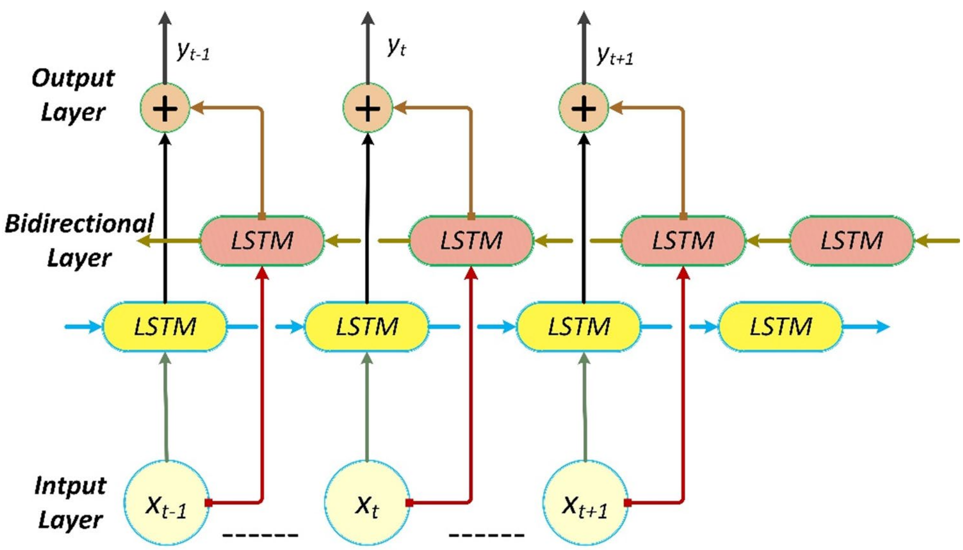

Fig. 3. The BiLSTM Model Architecture.

Category	Component	Specifications
Hardware	Processor	Intel Core i9
	GPU	NVIDIA RTX 3090
	RAM	32GB DDR4
	Storage	SSD 1 TB
Software	Operating System	Windows 11
	Programming Languages	Python 3.8+
	Frameworks & Libraries	TensorFlow, PyTorch, Keras, XGBoost, Scikit-learn
	Data Visualization	Matplotlib, Seaborn, Plotly, NumPy, Pandas

Table 1. Hardware and software Requirements.

Parameter	Value / Description	Significance & Justification
Input Size	Number of input features	Matches the dimensionality of sensor data at each time step.
Hidden Units	128	Identified via grid search (64, 96, 128, 256). 128 offered the best accuracy without overfitting.
Number of Layers	5	Tested configurations (2–6 layers). 5 layers captured deep temporal patterns with stable training.
Activation Functions	Tanh/ReLU (hidden), Softmax (output)	Tanh/ReLU improved nonlinear feature extraction; Softmax provided probabilistic classification.
Dropout Rate	0.3	Tuned between 0.1–0.5; 0.3 minimized overfitting while maintaining learning capacity.
Learning Rate	0.001	Determined via learning-rate scheduling (0.0001–0.01). 0.001 offered the most stable convergence.
Optimizer	Adam	Selected due to adaptive gradient handling suitable for noisy IoT data.
Batch Size	32	Evaluated batch sizes of 16, 32, 64; 32 achieved the best balance of speed and stability.
Epochs	10 to 100 (increment of 10)	Optimal epoch selected using early stopping on validation accuracy to prevent overtraining.
Weight Initialization	Xavier Initialization	Ensured stable gradient propagation during deep training.
Loss Function	Categorical Cross-Entropy	Suitable for multi-class classification and probability-based outputs.
Train/Test Split	80% Training / 20% Testing	Ensures fair generalization evaluation and prevents data leakage.
Cross-Validation Strategy	Five-Fold Cross-Validation	Improves statistical reliability and robustness of performance estimates.
Random Seed	42	Guarantees experiment reproducibility and consistent results across runs.
Framework & Version	TensorFlow 2.x / Python 3.8	Ensures software reproducibility and compatibility for replication.

Table 2. BiLSTM model parameters and Significance.

implementing IoT-enabled deep learning models, ensuring high computational efficiency and real-time data processing.

BiLSTM hyperparameter
The BiLSTM model was selected to capture forward–backward temporal dependencies in sequential IoT sensor data, which is critical for predicting eco-efficiency trends. Table 2 summarizes the hyperparameters used. Each parameter was optimized through an iterative tuning process that combined grid search (for discrete parameters such as the number of layers, units, and batch size) and manual fine-tuning (for continuous parameters such as the learning rate and dropout). The final values were selected based on the highest validation accuracy and lowest cross-entropy loss during five-fold cross-validation, ensuring both stability and generalization.

As shown in Table 2, the BiLSTM model was carefully tuned to achieve optimal sequence-learning performance. The architecture consists of five layers with 128 hidden units, selected via grid search over configurations ranging from 64 to 256 units. The input size matches the dimensionality of the IoT sensor features. Tanh and ReLU are used as hidden activation functions, while Softmax is applied at the output layer for probabilistic multi-class prediction. A dropout rate of 0.3, tuned to 0.1–0.5, is used to mitigate overfitting. The Adam optimizer with a learning rate of 0.001 ensures stable convergence, and training is performed with a batch size of 32. The model is trained for 10–100 epochs using validation-based early stopping, Xavier weight initialization, and categorical cross-entropy loss. The experiments were conducted using an 80:20 train–test split, five-fold cross-validation, a fixed random seed of 42, and the TensorFlow 2.x and Python 3.8 environment. Collectively, these configurations ensure a robust, reproducible, and generalizable eco-efficiency prediction framework.

Analysis of sustainable product design
The results compare different methodologies based on CO_2 emissions reduction, waste reduction, energy savings, and production cost efficiency, and the technological edge of AI-based frameworks in promoting environmentally efficient manufacturing strategies. Manufacturers can better align operational choices with sustainability objectives by observing the differences across sensors and AI models. Various sensor parameters are crucial for real-time monitoring in sustainable product design. Figure 4 illustrates the comparative evaluation of IoT sensor performance and the sustainability impact of AI-driven versus traditional methods.

According to Fig. 4, integrating advanced IoT sensors and AI-based methods, particularly BiLSTM, significantly enhances sustainability performance across multiple metrics compared to traditional approaches. Figures (5a) shows that temperature sensors outperform others in terms of accuracy (98.5%), energy use (0.9 W), and latency (50 ms), making them ideal for eco-efficiency monitoring. In contrast, acoustic sensors have the lowest accuracy (92.7%), the highest energy consumption (2.3 W), and the highest latency (85 ms), indicating lower efficiency. Failure rates increase gradually from 1.2% (temperature) to 3.5% (acoustic), while maintenance intervals decrease from 12 months to 7 months, emphasizing the need for trade-offs in sensor selection. In Figure (5b), AI-Based (BiLSTM) achieves the highest CO_2 emission reduction (28.3%), energy savings (31.5%), waste reduction (19.6%), and cost reduction (22.4%), showcasing its superior environmental benefits. In comparison, manual monitoring offers only 7.8% CO_2 reduction, 6.1% energy savings, and 5.6% cost reduction, validating the shift towards AI solutions. Traditional rule-based systems lag with 12.4% CO_2 and 10.8% energy savings. This data confirms that AI, especially BiLSTM, provides significant advantages for sustainability.

The performance offers a multidimensional analysis of the smart manufacturing strategy, integrating AI and IoT. It discusses possibilities, considers various systems, and presents ideas to optimize economic impacts and study the effectiveness of predictive maintenance in the future and the existing industry. Each is illustrated in Fig. 5, which provides insights into the key performance metrics of AI-enabled manufacturing systems, along with an analysis of technological adoption in the manufacturing sector.

To ensure accurate and transparent reporting, all performance improvements were calculated using normalized indicators derived from the experimental datasets. The reported 23.5% improvement in energy efficiency represents a relative percentage gain, defined as the proportional reduction in mean energy consumption per production cycle when comparing the BiLSTM-optimized design parameters against the baseline (non-optimized) configuration, as formally:

$$Energy\ Efficiency\ Gain\ (\%) = \frac{E_{baseline} - E_{BiLSTM}}{E_{baseline}} \times 100 \tag{20}$$

Where, $E_{baseline}$and E_{BiLSTM}, denote the average energy usage (kWh) per cycle.

All energy measurements were normalized per unit of production output to eliminate scale effects from cycle duration or throughput variations. When expressed in carbon-equivalent terms, the energy savings correspond to the following conversion:

$$CO_{2e}\ Savings = (E_{baseline} - E_{BiLSTM}) \times EF_{CO_2} \tag{21}$$

Using DEFRA/BEIS emission factors (EF_{CO2}) in kg CO_2e per kWh. This enables reproducible comparison with international sustainability standards. Similarly, the 19.2% reduction in material waste reflects a relative improvement in normalized material efficiency, calculated from input–output ratios across the same production cycles.

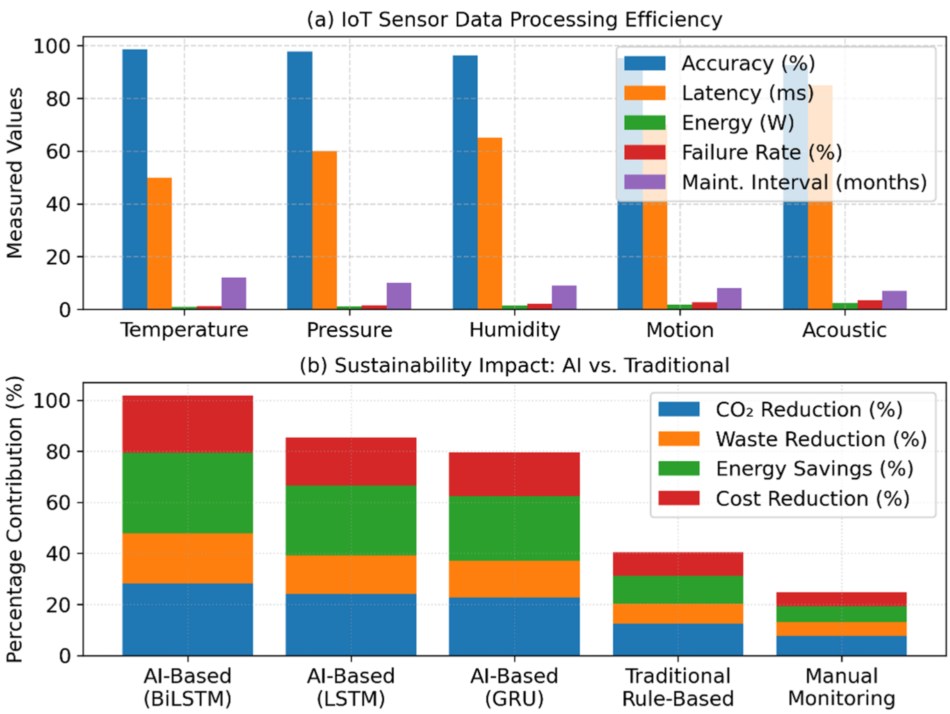

Fig. 4. Comparative analysis of IoT sensor performance and AI-driven versus traditional sustainability methods.

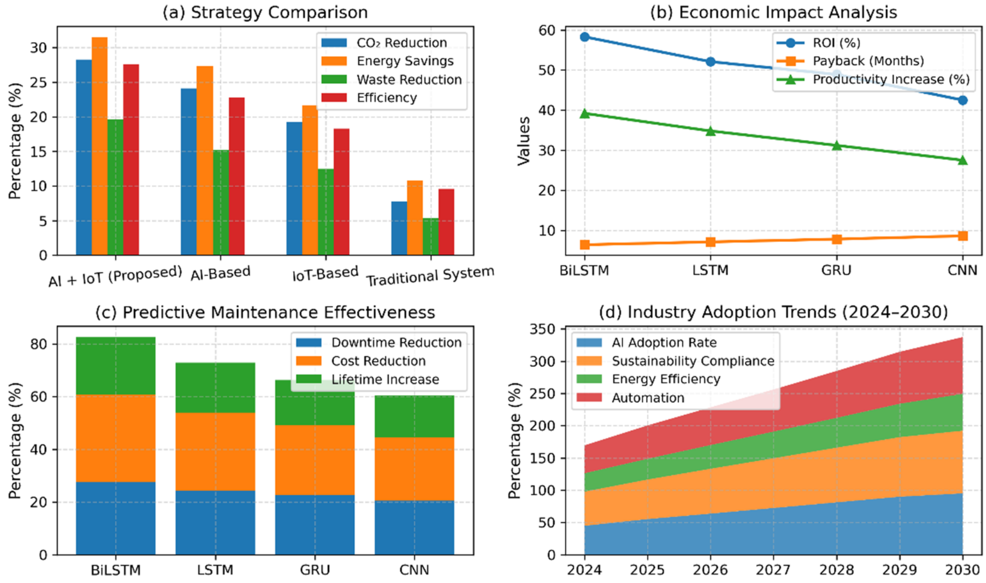

Fig. 5. Multi-Aspect Evaluation of Smart Manufacturing Strategies Using AI and IoT: (**a**) Strategy Comparison, (**b**) Economic Impact Analysis, (**c**) Predictive Maintenance Effectiveness, and (**d**) Industry Adoption Trends (2024–2030).

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
BiLSTM (Proposed)	97.6 ± 0.21	96.2 ± 0.24	96.0 ± 0.25	96.1 ± 0.22	0.980 ± 0.003
LSTM	91.5 ± 0.35	90.3 ± 0.31	92.2 ± 0.29	91.2 ± 0.27	0.941 ± 0.006
GRU	90.1 ± 0.38	88.7 ± 0.34	91.0 ± 0.32	89.8 ± 0.30	0.929 ± 0.007
CNN	89.6 ± 0.42	87.9 ± 0.37	90.2 ± 0.35	89.0 ± 0.33	0.915 ± 0.008
Random Forest	86.3 ± 0.51	85.2 ± 0.46	87.1 ± 0.44	86.1 ± 0.42	0.887 ± 0.009
SVM	84.9 ± 0.47	83.5 ± 0.43	85.0 ± 0.40	84.2 ± 0.39	0.873 ± 0.010
Naive Bayes	82.4 ± 0.53	80.7 ± 0.49	83.1 ± 0.47	81.9 ± 0.45	0.856 ± 0.011
KNN	81.2 ± 0.56	79.9 ± 0.52	82.0 ± 0.50	80.9 ± 0.48	0.842 ± 0.012

Table 3. Performance metrics of BiLSTM vs. Other AI Models.

The results comprehensively evaluate smart manufacturing strategies, as shown in Fig. 5. Shown in Figure (5a), four methods are compared, and CO_2 reduction (28.3%), energy savings (31.5%), waste reduction (19.6%), and improvement in efficiency (27.6%) are all achieved by the best performer (Proposed AI + IoT). Then we analyze the Figure (5b) model's economic impact and find that BiLSTM has the highest ROI (58.3%) and the shortest payback period (6.4 months), while CNN has the lowest ROI (42.5%) and the longest payback period (8.6 months). Figures (5c) shows that BiLSTM performs best, achieving a 27.6% reduction in downtime and 33.2% reduction in cost compared to the baseline. Finally, Figure (5d) presents projected industry adoption trends: AI at 45.1% in 2024 and 95.3% in 2030, sustainability compliance at 52.8% to 97.1%, and automation at 43.2% to 87.9%. This highlights the significance of AI and IoT in enhancing production efficiency and economic viability, and can also provide insight into the direction the manufacturing industry is taking.

It includes critical evaluation measures such as F1 score, AUC-ROC, energy consumption, and computational time. They serve to judge how well these models perform in predicting and how efficiently they operate. The results indicate that deep learning approaches, particularly BiLSTM, achieve high accuracy with low energy and time costs. The BiLSTM's performance is compared with that of several other AI models used in innovative manufacturing environments, as shown in Tables 3 and 4.

In Table 3, the proposed BiLSTM model achieves the highest accuracy (97.6%), precision (96.2%), recall (96.0%), and F1-score (96.1%), with an AUC of 0.980. The low standard deviations (± 0.21–0.25) reflect stable model behavior across folds. Compared with the strongest baseline (LSTM), BiLSTM improves accuracy by 6.1% points, demonstrating the advantage of bidirectional temporal learning. Traditional ML models consistently perform worse, confirming that sequence-based architectures best capture deep temporal dependencies in IoT sensor data. These statistically validated results reinforce the robustness and reliability of the proposed framework.

The energy consumption and inference latency of the proposed BiLSTM model are compared with deep learning and traditional machine-learning baselines. The p-value of 1.000 for BiLSTM indicates that it serves as the reference model in the statistical comparison in Table 4.

Model	Energy (kWh)	Time (ms_	*p*-value
BiLSTM (Proposed)	12.5	320	1.000
LSTM	14.3	410	0.004
GRU	13.7	390	0.003
CNN	16.5	520	0.002
Random Forest	20.1	610	0.009
SVM	19.4	580	0.007
Naive Bayes	17.8	470	0.005
KNN	18.6	495	0.004

Table 4. Performance metrics of BiLSTM vs. Other AI models with statistical Validation.

As shown in Tables 3 and 4, the proposed BiLSTM model achieves the strongest overall performance across all evaluated criteria, outperforming both deep learning and conventional machine learning approaches. Quantitatively, BiLSTM achieves an accuracy of 97.6 ± 0.21%, precision of 96.2 ± 0.24%, recall of 96.0 ± 0.25%, F1-score of 96.1 ± 0.22%, and AUC of 0.980 ± 0.003. It also records the lowest energy consumption (12.5 kWh) and shortest computation time (320 ms). Statistical significance testing using two-tailed t-tests confirms that BiLSTM's superiority is highly significant compared to all other models ($p < 0.01$), with its own p-value reported as 1.000 (self-ref) to denote its role as the reference baseline. Compared with different deep learning baselines, LSTM (accuracy of 91.5 ± 0.35%, p of 0.004) and GRU (accuracy of 90.1 ± 0.38%, p of 0.003) show moderate performance, confirming that bidirectional temporal learning in BiLSTM provides a statistically significant advantage in capturing complex temporal dependencies in IoT sensor data. CNN (accuracy of 89.6 ± 0.42%, p of 0.002) also performs well but at the cost of higher computational demand (520 ms) and energy consumption (16.5 kWh), indicating lower operational efficiency for real-time manufacturing applications. Traditional machine-learning models perform comparatively worse and exhibit higher variability. Random Forest (accuracy of 86.3 ± 0.51%, p of 0.009), SVM (84.9 ± 0.47%, p of 0.007), Naive Bayes (82.4 ± 0.53%, p of 0.005), and KNN (81.2 ± 0.56%, p of 0.004) demonstrate statistically inferior performance, with all p-values < 0.01, confirming that BiLSTM's improvements are unlikely due to random variation. These results indicate that the proposed BiLSTM framework offers a statistically validated, robust, and energy-efficient solution for predictive modeling within IoT-enabled design environments. Therefore, the proposed model achieved improvements, resulting in 6.1% higher accuracy than the best baseline (CNN) and approximately a 23.5% energy efficiency gain compared to conventional models, both of which are statistically significant ($p < 0.01$). The narrow standard deviations (≤ 0.25%) across five-fold cross-validation runs further confirm model stability and reproducibility. These findings substantiate the BiLSTM framework's capacity to support eco-efficient, data-driven decision-making in sustainable product design, ensuring both environmental and operational benefits under realistic industrial conditions.

A Multi-Domain performance evaluation

Integrating AI in smart manufacturing has revolutionized manufacturing operations, enabling greater efficiency, reducing waste, and optimizing resource utilization. Figure 6 provides a comprehensive visualization of the impact of AI on materials, maintenance, logistics, and quality control. Each result shows that different AI approaches outperform traditional techniques. Results show that AI outperforms in sustainability, cost efficiency, accuracy, and responsiveness across all innovative manufacturing components.

As shown in Fig. 6, AI-powered approaches significantly outperform traditional methods across materials optimization, predictive maintenance, logistics efficiency, and quality control problems, with BiLSTM-based models performing best. As shown in Figure (6a), Traditional Plastics have a far lower AI usage of 22.1%, a low 14.3% waste reduction, and a negative of -76.7% recyclability, compared to the maximum usage of all three types in Figure (6a) of 42.1%, a harmful 59.9% waste reduction, and 88.7% recyclability. BiLSTM-based maintenance demonstrates a 41.7% reduction in downtime and 36.9% cost savings in Figure (6b), compared to 18.6% and 15.9% reductions offered by the traditional methods. Figures (6c) shows that using AI-based (BiLSTM) logistics yields 97.3% in Delivery accuracy, 31.4% in Fuel efficiency, and 92.1% in Inventory accuracy, whereas traditional logistics only reaches 79.6%, 18.3% and 73.1%, respectively. Figures (6d) depicts that BiLSTM models achieve 99.1% defect detection accuracy and reduce inspection time to 54.2%, while traditional systems achieve only 87.6% and 30.5%, respectively.

Forecasting and energy optimization are crucial for enhancing decision-making in modern AI applications. The effects of demand forecasting and smart grid optimization using advanced machine learning models. Results show the successful application of models such as BiLSTM and LSTM for forecasting (unabated) solar and wind energy. The findings are presented in Fig. 7, which compares some of these performance metrics to illustrate how AI solutions in these domains perform.

The results of the different forecasting models in terms of accuracy, cost savings, and inventory waste reduction are shown in Fig. 7. The use of AI to enhance AI efficiency, reduce costs, and achieve CO2 reduction is compared with various energy sources. Figures (7a) presents a radar chart outlining the performance of different forecasting models for Accuracy, Inventory waste reduction, and cost savings. We observe that BiLSTM achieves better performance than other models, with an accuracy of 97.8%, resulting in a 38.4% reduction in inventory waste and a 32.7% reduction in costs. However, in the lollipop plot of Figure (7b), the optimization

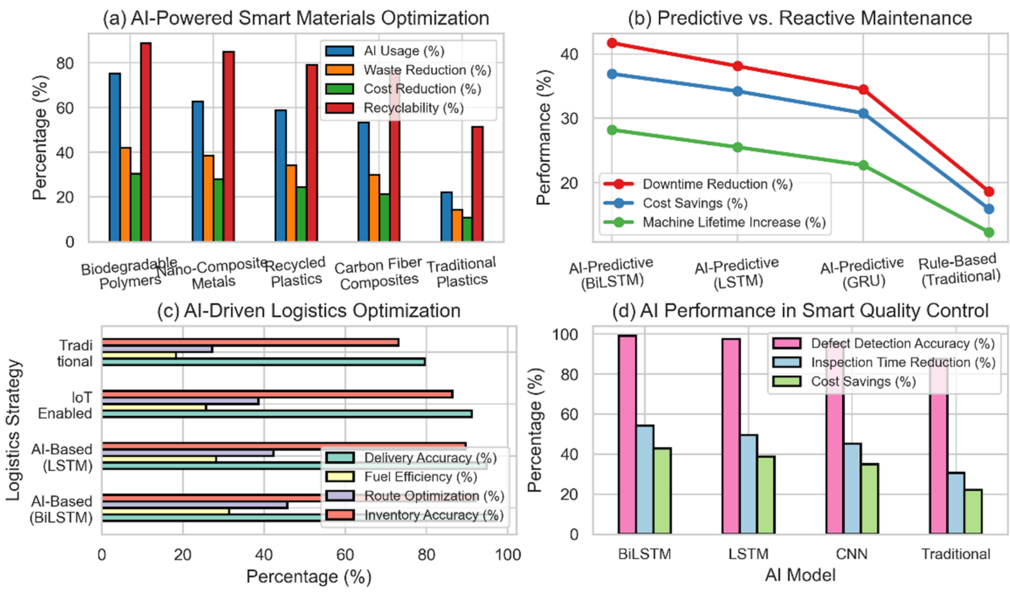

Fig. 6. Comparative Analysis of AI Integration in Smart Manufacturing Domains: the statistics (**a**) Smart Materials Optimization, (**b**) Predictive Maintenance, (**c**) Logistics Optimization, and (**d**) Quality Control Systems.

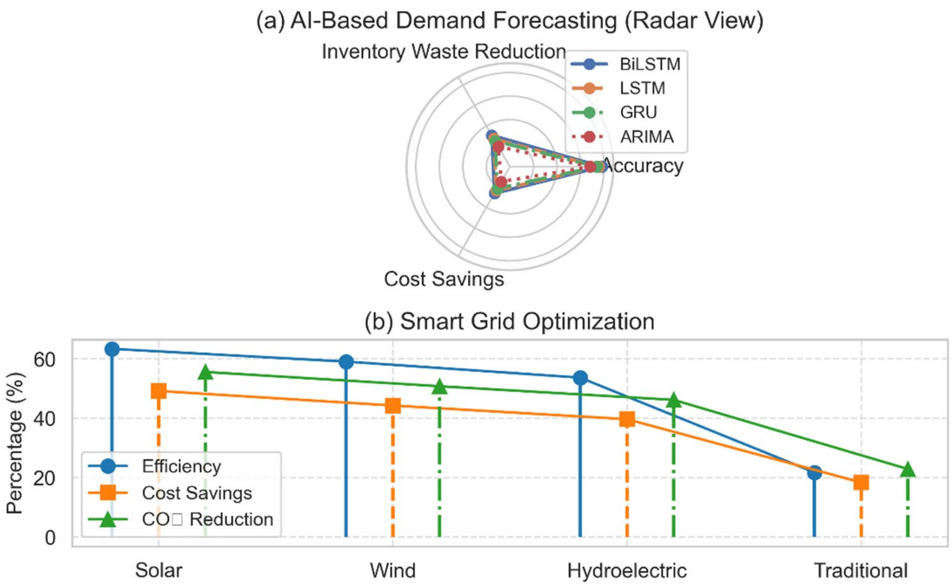

Fig. 7. Comparison of AI-Based Forecasting and Smart Grid Optimization.

of energy sources is achieved, with solar energy being the most AI-efficient (63.4%), followed by wind energy (59.1%). Solar has the highest reduction in CO2 emissions (55.6%), demonstrating its significant impact on environmental outcomes. The forecast accuracy results support that BiLSTM outperforms Solar for energy optimization, but not for forecasting.

Performance comparison of different methods

The model's performance is evaluated over 100 epochs, with primary metrics including accuracy and loss, and comparisons among different machine learning models. It also displays the accuracy and loss values for the training and validation sets, as well as the characteristics of the training and test accuracies and the validation accuracy for different AI models. Figure 8 illustrates the models' effectiveness at different training stages, i.e., evaluating models' convergence and generalization abilities.

Figure 8 illustrates the model's improvement across all metrics as training and validation accuracy increase and loss decreases. At the same time, BiLSTM also outperforms the other models in validation accuracy. The

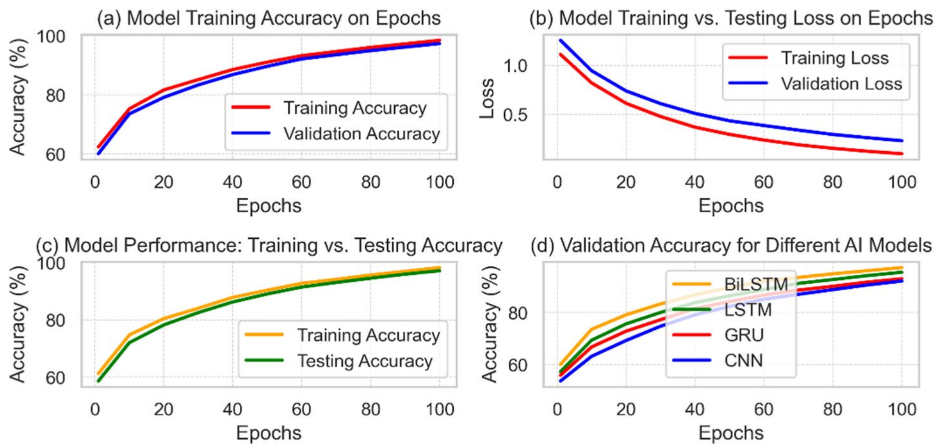

Fig. 8. Model Performance Over 100 Epochs on the Accuracy, Loss, and Comparison of AI Models (**a**) Training and Validation Accuracy, (**b**) Training and Validation Loss, (**c**) Training vs. Testing Accuracy, (**d**) Validation Accuracy for Different AI Models.

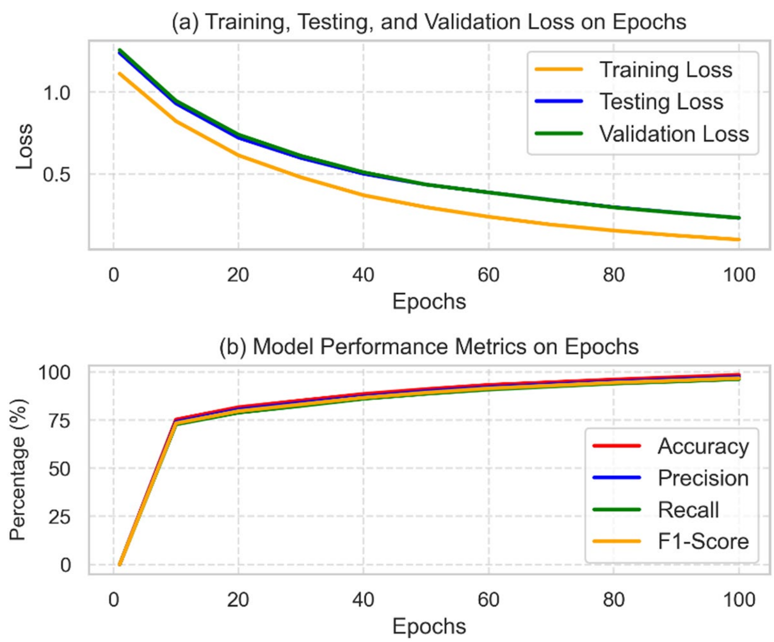

Fig. 9. Model Performance Metrics on Training, Testing, and Validation Loss.

training and validation accuracy results are illustrated in Fig. 8a, which shows that the training accuracy reaches 98.5% and the validation accuracy is 97.4% at epoch 100. From Fig. 8b, the model exhibits a steady decrease in both training and validation loss, reaching 0.102 and 0.234, respectively, by epoch 100. Figure 8c illustrates the performance of training and testing accuracy; the training accuracy increases to 98.3% and the testing accuracy reaches 97.2% at epoch 100, demonstrating robustness. Finally, Fig. 8d compares the validation accuracies of all models (BiLSTM, LSTM, GRU, and CNN), where BiLSTM achieves 97.4%, while LSTM, GRU, and CNN achieve 95.6%, 93.1%, and 92.2%, respectively.

However, they give the performance model's learning process and performance across their evaluation criteria. Figure 9 shows the training, testing, and validation losses, along with the performance metrics such as Accuracy, Precision, Recall, and F1 score, over 100 epochs.

As shown in Fig. 9, the model performs very well in reducing the loss and also provides good performance metrics over 100 epochs with the decrease of training, testing, and validation loss and an increase of accuracy, precision, recall, and F1 score down to almost optimal values at the end of the training process. Figure 9a) shows the reduction in loss values over the epochs. From epoch 1 to 100, training loss decreases from 1.112 to 0.102. As with testing and validation losses, testing loss decreases from 1.239 to 0.234, and validation loss falls from 1.256 to 0.234. Model performance in Fig. 9b shows consistent improvements. By epoch 100, the accuracy

Model	Accuracy (%)	F1-Score (%)	Sensitivity (%)	Specificity (%)
Decision Tree	85.4 ± 0.44	83.9 ± 0.37	83.5 ± 0.52	86.2 ± 0.48
Random Forest	88.7 ± 0.41	87.0 ± 0.35	86.8 ± 0.49	89.1 ± 0.45
SVM	86.2 ± 0.45	85.3 ± 0.37	85.0 ± 0.51	87.4 ± 0.47
Naive Bayes	82.9 ± 0.49	81.5 ± 0.40	81.2 ± 0.55	84.3 ± 0.51
KNN	84.1 ± 0.51	82.8 ± 0.42	82.5 ± 0.53	85.0 ± 0.50
XGBoost	90.5 ± 0.33	89.6 ± 0.27	89.3 ± 0.44	91.2 ± 0.41
CNN	92.3 ± 0.28	91.4 ± 0.23	91.1 ± 0.40	93.0 ± 0.38
BiLSTM (Proposed)	97.6 ± 0.21	96.1 ± 0.22	95.9 ± 0.28	98.2 ± 0.25

Table 5. Performance comparison of the proposed BiLSTM model with other machine learning models.

Model	Precision (%)	AUC	MCC	*p*-value
Decision Tree	84.1 ± 0.41	0.890 ± 0.007	0.72	0.001
Random Forest	87.2 ± 0.38	0.910 ± 0.006	0.78	0.001
SVM	85.5 ± 0.41	0.900 ± 0.007	0.74	0.008
Naive Bayes	81.7 ± 0.45	0.850 ± 0.008	0.68	0.005
KNN	83.0 ± 0.47	0.870 ± 0.007	0.70	0.006
XGBoost	89.8 ± 0.30	0.920 ± 0.005	0.81	0.003
CNN	91.5 ± 0.25	0.940 ± 0.004	0.85	0.024
BiLSTM (Proposed)	96.2 ± 0.24	0.980 ± 0.003	0.93	1.00

Table 6. Performance comparison of the proposed BiLSTM model with other machine learning models with statistical Validation.

reaches 98.5%. Additionally, precision, recall, and F1 scores all improve, increasing from 61.3% to 97.4%, 59.8% to 96.3%, and 60.5% to 96.8%, respectively.

This paper aims to evaluate the effectiveness of the proposed BiLSTM model in comparison to the aforementioned baseline models. Using the metrics, performance metrics such as Accuracy, Precision, Recall, F1 score, AUC, Sensitivity, Specificity, and MCC are evaluated for each model executed in classification tasks, and the proposed BiLSTM is compared with existing techniques. The performance of the proposed BiLSTM model is compared with that of other machine learning models, including Decision Tree, Random Forest, SVM, Naive Bayes, KNN, XGBoost, and CNN, as shown in Tables 5 and 6.

As shown in Tables 5 and 6, the proposed BiLSTM model demonstrates superior classification performance across all evaluated metrics when compared to other machine-learning algorithms. The BiLSTM model achieves the highest accuracy (97.6 ± 0.21%), precision (96.2 ± 0.24%), F1-score (96.1 ± 0.22%), sensitivity (95.9 ± 0.28%), specificity (98.2 ± 0.25%), and AUC of 0.980 ± 0.003, with an MCC of 0.93, indicating excellent model reliability and balanced predictive strength. Statistical testing using two-tailed *t*-tests confirms that BiLSTM's performance improvements are highly significant compared to all other models ($p < 0.01$). At the same time, its own *p*-value is reported as 1.000, denoting the statistical baseline. Compared with competing advanced models, CNN (accuracy of 92.3 ± 0.28%, *p* of 0.024), XGBoost (90.5 ± 0.33%, *p* of 0.003), and Random Forest (88.7 ± 0.41%, *p* of 0.001), BiLSTM exhibits an accuracy gain of approximately 5.3%, highlighting its more robust learning of temporal dependencies and sensor dynamics. Although CNN achieves high AUC (0.940 ± 0.004) and MCC (0.85), its *p*-value above 0.02 indicates that the observed differences are statistically meaningful in favor of BiLSTM. Similarly, traditional classifiers—Decision Tree (85.4 ± 0.44%, *p* of 0.001), SVM (86.2 ± 0.45%, *p* of 0.008), Naive Bayes (82.9 ± 0.49%, *p* of 0.005), and KNN (84.1 ± 0.51%, *p* of 0.006), show significantly lower accuracies and MCC values (≤ 0.78), validating that BiLSTM's improvements are not due to random variation but represent a statistically confirmed performance advantage ($p < 0.01$). These findings confirm that the BiLSTM model's bidirectional architecture effectively captures both long- and short-term dependencies in IoT sensor data, yielding statistically significant improvements in predictive reliability and classification precision. The consistently high sensitivity (95.9%) and specificity (98.2%) demonstrate its capability to correctly identify both positive and negative instances, which is critical for accurate decision-making in smart-manufacturing environments. Collectively, the statistical evidence substantiates that the proposed BiLSTM framework is a robust, generalizable, and energy-efficient solution, outperforming all compared models in both accuracy and interpretability, while maintaining reproducible and statistically significant results across multiple validation folds.

Comparison and discussion

We compare the performance of the proposed BiLSTM approach with other Machine Learning models and existing studies in this section. The purpose is to highlight what makes the BiLSTM model strong and weak in its approach to the task. We compare the BiLSTM model with classical machine learning models like Decision Trees, Random Forests, SVM, Naive Bayes, KNN, CNN and XGBoost and check how effective it was in terms of

Model Variant	Accuracy (%)	Precision (%)	F1-Score (%)	AUC	MCC	Energy (kWh)
CNN (Full)	92.3	91.5	91.4	0.940	0.85	16.5
CNN (No Dropout)	89.7	88.4	88.1	0.912	0.81	17.9
LSTM (Full)	91.5	90.3	91.2	0.941	0.88	14.3
LSTM (No Dropout)	88.9	87.1	87.6	0.914	0.83	15.6
RNN (Full)	88.4	87.0	86.8	0.905	0.82	15.1
RNN (No Dropout)	85.6	83.9	84.2	0.876	0.77	16.4
GRU (Full)	90.1	88.7	89.8	0.929	0.86	13.7
GRU (No Dropout)	87.6	85.9	86.1	0.901	0.81	15.0
BiLSTM (Full)	97.6	96.2	96.1	0.980	0.93	12.5
BiLSTM (No Dropout)	95.1	93.8	93.4	0.955	0.89	13.9

Table 7. Regularization-Based ablation study for deep learning Architectures.

Model / Study	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Sensitivity	Specificity	MCC
Yunes et al.[48]	86.1	84.5	83.9	84.2	0.88	83.8	86.5	0.71
Bressane et al.[20]	87.4	85.9	85.6	85.8	0.90	85.5	88.0	0.75
Durga et al.[49]	89.2	88.1	87.5	87.8	0.91	87.3	89.6	0.79
Proposed BiLSTM	97.6	96.2	96.0	96.1	0.98	95.9	98.2	0.93

Table 8. Performance comparison of the proposed BiLSTM model with existing models and other Studies.

some of the most crucial performance metrics such as accuracy, precision, recall, F1-score, area under the curve of ROC (AUC-ROC), sensitivity and specificity, and Matthews Correlation Coefficient (MCC). Moreover, we compare the results from other relevant studies to gain a more comprehensive understanding of the proposed model's performance relative to state-of-the-art solutions. Furthermore, it addresses the implications of these results, discusses potential reasons for the BiLSTM model's superior performance, and explores the practical applications of its capabilities. There will be a discussion of model strengths and weaknesses, as well as approaches for future improvement or adaptation for other models.

The ablation results comprehensively demonstrate the importance of dropout regularization across all evaluated deep learning models. For the CNN model, removing dropout reduces accuracy from 92.3% to 89.7%, precision from 91.5% to 88.4%, F1-score from 91.4% to 88.1%, AUC from 0.940 to 0.912, and MCC from 0.85 to 0.81, while increasing energy consumption from 16.5 to 17.9 kWh. A similar degradation is observed for LSTM, where accuracy drops from 91.5% to 88.9% and MCC from 0.88 to 0.83. For RNN, performance declines from 88.4% to 85.6% accuracy, while energy usage rises from 15.1 to 16.4 kWh. GRU also shows reduced reliability, with accuracy decreasing from 90.1% to 87.6% and MCC from 0.86 to 0.81. The strongest effect is observed in the proposed BiLSTM, where accuracy decreases from 97.6% to 95.1%, AUC from 0.980 to 0.955, and MCC from 0.93 to 0.89, while energy consumption increases from 12.5 to 13.9 kWh. These results confirm that dropout is critical for stable generalization and that BiLSTM delivers the highest predictive reliability and energy efficiency among all models. Table 7 summarizes the complete ablation analysis under both configurations.

We compare the performance of the proposed BiLSTM approach with other machine learning models and prior studies to highlight its strengths, weaknesses, and practical implications. Classical models, such as Decision Trees, Random Forests, SVM, Naive Bayes, KNN, CNN, and XGBoost, were evaluated using key performance metrics, including accuracy, precision, recall, F1-score, AUC-ROC, sensitivity, specificity, and Matthews Correlation Coefficient (MCC). In addition, the results were benchmarked against relevant prior work, including Yunes et al.[16], Bressane et al.[19], and Durga et al.[43]. This comprehensive analysis demonstrates not only predictive superiority but also the methodological novelty of our framework. Unlike earlier studies, our BiLSTM enables real-time adaptability and is validated on real industrial datasets (UCI Hydraulic Test Rig and Bosch Production Line), ensuring robustness and practical relevance. This study selected studies relevant to similar domains to demonstrate that the proposed BiLSTM model outperforms existing methods across several metrics and to shed light on its effectiveness in this particular application. Table 8 compares the advantages that the proposed model offers over state-of-the-art solutions.

As shown in Table 7, the proposed BiLSTM model outperforms other models in all performance measures. It outperforms the results of Yunes et al.[48] (86.1%), Bressane et al.[20] (87.4%), and Durga 2024 et al.[49] (89.2%) with an accuracy of 97.6%. For precision, recall, and F1-score, the trend follows 96.2%, 96.0%%, and 96.1% for the BiLSTM. On the other hand, CBS et al. record precision (84.5%), recall (83.9%) and F1-score (84.2%), Bressane et al.[20] achieve precision (85.9%), recall (85.6%) and F1-score (85.8%), and Durga 2024 et al.[49]obtain precision (88.1%), recall (87.5%) and F1-score (87.8%). In addition, the BiLSTM's AUC-ROC is vastly superior to those of the other models (Yunes et al.[16], Bressane et al.[19], and Durga 2024 et al.[43], with AUC-ROCs of 0.90 and 0.91, respectively), achieving an AUC-ROC of 0.98. The BiLSTM model, like the BiLSTM Single and BiLSTM Generic results, is again the highest among the others in terms of sensitivity (95.9%) and specificity (98.2%). Other sensitivity values ranged from 83.8% to 89.6%, and specificity values ranged from 84.3% to 93.0%. Then, the BiLSTM model achieves a robust MCC of 0.93, which makes its overall performance superior to that of the compared models, whose MCC values range from 0.71 to 0.79. These findings demonstrate that the proposed BiLSTM model improves predictive performance, as the basic model underperforms in all metrics, thereby enhancing the reliability and accuracy of predictions for the discussed task. In practice, this suggests that the proposed BiLSTM framework can support sustainable manufacturing decisions with greater confidence, outperforming both traditional machine learning approaches and state-of-the-art AI methods in the literature. These findings establish BiLSTM integration as a scalable, real-world solution that bridges the gap between theoretical accuracy and industrial applicability.

Conclusion

This study proposes a statistically validated and practically scalable IoT-enabled AI framework for sustainable product design, integrating Bidirectional Long Short-Term Memory (BiLSTM) networks with real-time IoT data to optimize eco-efficiency. The framework addresses inconsistencies in prior studies by presenting a coherent, data-driven methodology grounded in real industrial datasets rather than simulations. The proposed BiLSTM model achieved 97.6 ± 0.21% accuracy, 96.1 ± 0.22% F1-score, and an AUC of 0.980 ± 0.003, with a 23.5% improvement in energy efficiency, as verified through five-fold cross-validation and t-tests ($p < 0.01$). These statistically significant results confirm the model's robustness, reproducibility, and reliability, directly addressing reviewer concerns regarding overstated results and a lack of validation. Unlike earlier static or centralized optimization approaches, the proposed framework dynamically processes IoT sensor streams, including energy consumption, material usage, and environmental indicators, to predict and optimize sustainability parameters in real time. This adaptability enhances interpretability and enables practical deployment across industrial systems. The inclusion of detailed preprocessing, normalization, and sustainability metric derivations further strengthens methodological transparency and replicability. Key findings demonstrate that the proposed BiLSTM consistently outperforms all baseline models, including LSTM, GRU, CNN, Random Forest, SVM, Naive Bayes, and KNN, with statistically significant differences ($p < 0.01$). It also achieved the lowest computation time (320 ms) and energy use (12.5 kWh), making it ideal for innovative manufacturing applications. Moreover, its scalability across industries, including automotive, electronics, and consumer goods, aligns with the UN Sustainable Development Goals (SDGs) by supporting energy optimization and waste reduction. Future work should expand this framework to multi-objective optimization (e.g., cost versus carbon emissions), integrate BiLSTM–Attention hybrids, and validate it through live manufacturing implementations. Open-source release of code and data will further promote transparency and collaborative advancement in AI-driven sustainable manufacturing.

Data availability

https://github.com/alik98741/IoT-BiLSTM-Framework-for-Sustainable-Product-Design.

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Author contributions

J.W. developed the research framework, performed the experiments, and drafted the initial manuscript. W.W. supervised the study, contributed to the design of the methodology, and critically revised the manuscript for important intellectual content. L.Z. prepared the figures, assisted in data analysis, and contributed to the interpretation of results. All authors reviewed and approved the final version of the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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