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# OPTIMIZING WASTE REDUCTION IN MANUFACTURING PROCESSES UTILIZING IOT DATA WITH MACHINE LEARNING APPROACH FOR SUSTAINABLE PRODUCTION

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**Abstract.** Sustainable manufacturing with the Internet of Things (IoT) reduces environmental impacts, conserves natural resources, saves energy, and improves worker, community, and consumer safety while maintaining economic viability. IoT's network of sensors and intelligent devices collects and analyzes data throughout the production lifecycle, enabling organizations to fulfil sustainability objectives and adopt more efficient, less wasteful operations. Waste management and reduction measures are the focus of sustainable manufacturing research. Improvements are needed to simplify waste management and reduce production waste. Thus, in this study, we introduce an innovative machine learning technology called "EcoEfficientNet", developed to tackle this problem. Our study addresses the issue of waste in manufacturing processes. EcoEfficientNet employs sophisticated deep learning algorithms to analyze complex production data, allowing it to identify significant patterns and determine specific areas where waste can be significantly minimized. EcoEfficientNet's approach to waste reduction in manufacturing processes revolves around three main strategies: data-driven analysis, optimization recommendations, and adaptable learning for continual enhancement. EcoEfficientNet's success lies in its capacity for perpetual learning, enabling it to adapt to novel data and evolve alongside production settings. An extensive case study of a particular manufacturing process is carried out to assess the efficiency of EcoEfficientNet and provide helpful perspectives into the model's effectiveness. By incorporating this method into the manufacturing process, organizations have seen a decrease in waste generation of up to 30%, demonstrating the applicability and efficacy of machine learning in improving sustainable manufacturing processes. The key to EcoEfficientNet's success is its ability to engage in continuous learning, allowing it to adjust to new data and develop in tandem with operational environments.

**Key words:** Waste reduction, IoT Sensed data, deep learning, decision processing, operational efficiency, manufacturing, sustainability.

**1. Introduction.** Sustainable manufacturing [1] is a crucial concept in the manufacturing sector that focuses on reducing environmental consequences, conserving energy and natural resources, ensuring worker safety, and maintaining financial viability. Although there have been notable progressions, the industry still faces challenges in managing and minimizing waste, which presents a promising opportunity for innovation. In response to this identified deficiency, the present study proposes "EcoEfficientNet," an advanced machine learning (ML) network specifically developed to address the shortcomings in waste management in industrial processes.

Integrating real-time data from various sensors and devices across the factory floor, including IoT data in "EcoEfficientNet" for evaluation purpose, significantly enhances its capacity to revolutionize sustainable manufacturing. This convergence allows for accurate monitoring of resource use, operational variables, and waste generation, providing the machine learning network with highly accurate data essential for detecting inefficiencies and forecasting opportunities for waste reduction. EcoEfficientNet utilizes the constant stream of IoT data to acquire knowledge and enhance operations actively, leading to improvements in waste management and the development of a more environmentally friendly production system.

Moreover, the need for technological intervention arises from growing ecological issues and strict rules designed to promote sustainable activities. Conventional waste management systems must be more robust because they cannot adjust to intricate production settings and optimize operations in real-time [2]. Hence, implementing intelligent systems with the capacity to analyze data and optimize processes in real time is beneficial and essential for advancing manufacturing towards increased sustainability.

Thus, in this study, we introduce "EcoEfficientNet", which is at the forefront of this transformation. By using sophisticated deep learning algorithms, this system examines the complexities of production data, revealing

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trends and identifying crucial areas for minimizing waste [3]. The study is essential as it can completely alter waste management by converting extensive data into practical and valuable information. This will contribute to the area's existing knowledge and provide a model that can be replicated to promote sustainable practices.

The initial objective is to showcase the effectiveness of "EcoEfficientNet" in substantially reducing waste via its analytical capabilities. This objective is accomplished by thoroughly examining both past and current production data, allowing for a complete comprehension of trends in waste formation. The second goal is to verify the flexibility and ongoing learning capacities of "EcoEfficientNet." The research intends to demonstrate the model's capacity to smoothly integrate into current production processes and adapt to changes, assuring long-term sustainability and efficacy. This will be achieved via empirical experiments conducted throughout the study.

This study addresses a significant need for sustainable manufacturing and advances the industry by demonstrating the tangible advantages of ML techniques. The expected result is a substantial drop in waste, with first deployments demonstrating a reduction of up to 30%, highlighting the revolutionary potential of "EcoEfficientNet." This study is positioned to establish a standard in sustainable manufacturing, providing a solid basis for future progress and strengthening the importance of technological advances in attaining sustainable and effective manufacturing procedures.

**2. Related Work.** Artificial neural network (ANN) approaches have become commonplace across several academic disciplines owing to their inherent capacity to acquire knowledge from provided instances. ANNs are extensively used and considered the predominant machine learning algorithms [4]. Additionally, they have been proposed for several manufacturing applications, particularly in the context of predictive automation. [5] examines explicitly the use of Artificial Neural Networks (ANNs) to classify the condition of tools in CNC (Computer Numerical Control) milling machines. The distinctiveness of this technique is in its retrofitting strategy, which allows older equipment to conform to the norms of Industry 4.0. The research showcases the successful implementation of tool wear monitoring using integrated detectors on a customizable prototyping platform. The ANN model effectively enables the modernization of outdated equipment and surpasses the performance of Support Vector Machine (SVM) and k-nearest Neighbors (KNN) approaches. [6] introduced a technique in which vibration information from a hypothetical motor unit is used to train an ANN to forecast equipment malfunctions. The method is distinguished by its use of frequency and amplitude data to predict the exact moment at which the vibrating system would break. The Multilayer Perceptron (MLP) approach was selected because of its simplicity in implementation and ability to generalize. The research demonstrates that the ANN outperforms Random Forest (RF), Regression Tree (RT), and SVM in making predictions over medium and long time periods. However, its performance is comparable to these methods in the short term. [7] use ANNs and SVMs to forecast the deterioration of gauges in train tracks.

The study concentrates explicitly on both straight and curved sections. The ANN model has a substantial coefficient of determination, which signifies its robust prediction capability. Although both SVM and ANN models provide excellent outcomes, the ANN model is marginally superior at forecasting gauge variation for linear segments. [8] constructed a test apparatus to replicate the functioning of a wind turbine, with a specific emphasis on observing its state employing vibration evaluation. The created ANN model, designed to identify the health status of essential components, has a remarkable accuracy score of 92.6%. This study highlights the possibility of ANNs in predicting and preventing maintenance issues in the field of green energy. [9] conduct a comparative analysis of physics-based models as well as models built on neural networks (NN) to assess the deterioration of instances in Auxiliary Power Units (APUs). This approach emphasizes a universal modeling strategy to tackle the difficulty of varying component features. The results indicate that the physics-based method is more dependable for deteriorated starts, but the NN model performs very well with starters in optimal circumstances. [10] presented a system that utilizes data to diagnose and predict the performance of machinery and maintenance expenses. Furthermore, a precise data labeling mechanism is devised for supervised learning by contrasting the serial numbers of target components on consecutive dates. The research used actual data from vending machines to verify the concept architecture using three distinct classifiers: SVM, RF, and Gradient Boosting Machines (GBM). The outcomes of the cross-validated simulated events demonstrate that the diagnostic approach can reach an accuracy of over 80%. Therefore, the proposed GBM model can effectively diagnose and monitor complicated machine types. The prognosis approach surpasses one-stage traditional fore-

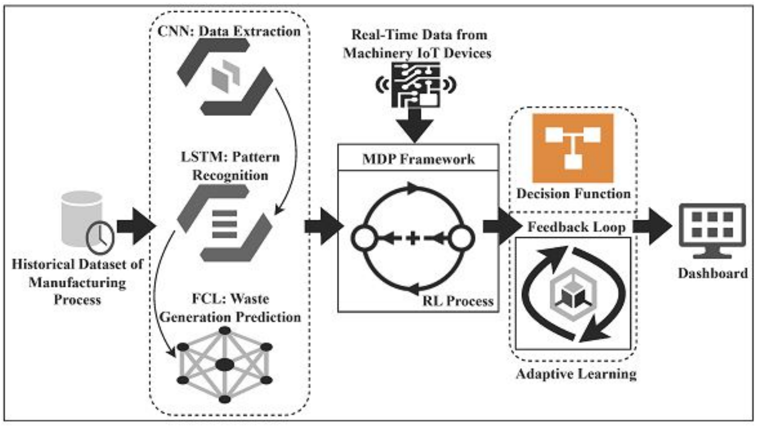


Fig. 3.1: Framework of EcoEfficientNet

casting techniques. Symbolic Regression (SR) has been used to estimate the state of well-functioning industrial equipment [11]. The work introduced a mechanism for handling idea drifts in persistent information streams. In addition, a practical case study was shown with industrial radial fans. The findings from the computerized information indicate that concept drift diagnosis and prognosis were highly effective. [12] addresses the crucial problem of inadequate productivity in an industrial setting, specifically emphasizing a tire manufacturing firm in Peru. The study's primary aim is to combine and design various tools to improve effectiveness, thereby decreasing the expensive upkeep of manufacturing machinery and the significant expenditures of adopting new systems. The primary focus of this work is on the creation of a waste-management strategy. This model is specifically designed to minimize the time required to set up and implement a viable operational control system, with the ultimate objective of enhancing the Overall Equipment Effectiveness (OEE) score. The model's assessment in an actual production setting yielded remarkable results, including a 13% enhancement in the OEE score and a substantial 22.5% decrease in the setup period.

Previous research has shown that ANNs can effectively monitor tool conditions and expected equipment malfunctions and perform scheduled upkeep. However, there has been less emphasis on using such strategies to improve waste management and decrease wastage in industrial environments. It is crucial to address this shortcoming to promote the progress of sustainable manufacturing methods. Suppliers can optimize resource utilization, mitigate environmental consequences, and improve their general productivity by incorporating ML techniques specifically designed for waste reduction.

**3. Methodology.** The EcoEfficientNet framework in Fig. 3.1 depicts a novel strategy in manufacturing that focuses on reducing waste by using sophisticated Deep Learning (DL) and Reinforcement Learning (RL) models. The two-stage procedure starts by using an advanced DL model that integrates Convolutional Neural Networks (CNN), Fully Connected Layers (FCL), and Long Short-Term Memory (LSTM) to detect and examine patterns in the manufacturing process. The second step utilizes these insights using a Reinforcement Learning (RL) model based on a Markov Decision Process (MDP) to implement strategic adjustments based on the real-time data from IoT devices during the manufacturing process. EcoEfficientNet optimizes efficiency and minimizes waste by constantly adjusting activities, aligning manufacturing operations with sustainable principles.

**3.1. First Phase.** Initially, a sophisticated DL model is used to identify patterns in the backdrop of minimizing waste in a manufacturing procedure. A fusion of CNN, LSTM, and FCL is implemented to achieve this. The first phase of the EcoEffiecientNet Model has three primary components. CNN stands for Convolutional Neural Network, LSTM stands for Long Short-Term Memory, and FCL stands for Fully Connected Layer. Input data that contains visuals or spatial trends (like sensor heatmaps) can be extracted using the CNN layers, which deal with spatial features. IoT devices served as the primary sources for continuous, real-time data feeding into the EcoEfficientNet system. LSTM layers excel in processing time-series data by obtaining temporal relationships and sequences of events, such as consumption of resource patterns over time. On the other hand, FCL layers act as the final decision-making layers, interpreting the features extracted by the CNN and LSTM. They are responsible for predicting waste generation in structured data, such as equipment logs and production data.

*Computation at CNN Layers.* The CNN layer utilizes several filters, k, to generate feature maps from the input visual (if applicable) I, which has dimensions H×W×D (height, width, depth) [13]. Such process can be analytically defined as Equation (3.1),

$$f_{ij}^{k} = \mathrm{ReLU}\left[\sum_{r=0}^{R-1}\sum_{c=0}^{C-1}\sum_{d=0}^{D-1} F_{(m\cdot n\cdot d)}^{k}\cdot I_{(i+r),(j+c),d} + e^{k}\right] \tag{3.1}$$

In Equation (3.1), $f_{ij}^{k}$ represents the essential feature at (i, j) at the kth feature map, $F_{(m\cdot n\cdot d)}^{k}$ denotes the $k^{th}$ filter employed at $i^{th}$ input, and $e^{k}$ indicates the bias at $k^{th}$ filter.

*Computation at LSTM.* The acquired attributes are smoothed and then potentially processed via additional substantial layers before inputting into LSTM cells [14]. An LSTM cell sequentially analyzes time-series information, updating and preserving both a cell state ($Z_t$) and hidden state ($h_t$) at each time step. At each successive step t, the LSTM modifies its states in the following manner [15], Equation (3.2) to (3.7) :

$$Forgetgate : F_t = \sigma\left(w_F \cdot \left[h_{(t-1)}, I_t\right] + e_f\right) \tag{3.2}$$

$$Inputgate : I_t = \sigma\left(w_i \cdot \left[h_{(t-1)}, I_t\right] + e_l\right) \tag{3.3}$$

$$Cellcandidate : \tilde{Z}_t = \tanh\left(w_Z \cdot \left[h_{(t-1)}, I_t\right] + e_Z\right) \tag{3.4}$$

$$NewerCellstate : \mathrm{Z}_t = \mathrm{F}_t * \mathrm{Z}_{(t-1)} + I_t * \tilde{\mathrm{Z}}_t \tag{3.5}$$

$$Outputgate : o_t = \sigma\left(w_o \cdot \left[h_{(t-1)}, I_t\right] + e_o\right) \tag{3.6}$$

$$NewerHiddenstate : h_t = o_t * \tan h\left[Z_t\right] \tag{3.7}$$

where $*$ indicates the element-wise multiplication, $\sigma$ denotes sigmoidal function, It indicates the input, e and w denotes the bias and weight for each gate, respectively.

*Computation of FCL.* The LSTM's output, denoted as $h_t$, is then fed into a FCL for the intent of classifying the states of operation into categories like normal, under-efficient, over-efficient (classifying the level of waste production). The FCL does the following operation [16]:

$$\delta = \sigma\left(w_{FCL} \cdot h_t + e_{FCL}\right) \tag{3.8}$$

In Equation (3.8), $e_{FCL}$ and $w_{FCL}$ are the biases and weights of the FCL.

Backpropagation [17] is used to optimize the parameters associated with the model throughout training. The loss function is used to quantify the discrepancy between the actual waste level and the projected waste level for each batch of data.

$$f(L) = \frac{1}{B}\sum_{1}^{B}\left[\delta_i - \widetilde{\delta}_i\right]^2 \tag{3.9}$$

where B denotes the batch size, $\delta_I$ represents the true value, and $\delta_I$ is the predicted value by the model in Equation (3.9).

The derivatives of the loss function concerning the model's parameters are then calculated and used to adjust the parameters employing the Adam optimizer. In the first phase, EcoEfficientNet combines CNN, LSTM, and FCL. This enables the model to comprehend the manufacturing data's temporal and spatial patterns.

Consequently, EcoEfficientNet can make precise predictions about waste emergence, which in turn can be utilized to improve the manufacturing process and minimize such waste.

**3.2. Second Phase.** The second stage involves incorporating a reinforcement learning (RL) model that will execute actions to enhance the manufacturing process by leveraging the predictions generated by the DL model. This phase has two primary components: the Markov Decision Process (MDP) [18] and the learning process. In this context, the issue of waste reduction is conceptualized as a MDP, whereby the state corresponds to the existing condition of the manufacturing process, actions denote potential modifications, and rewards are allocated for actions that minimize waste.

*Decision-Making Process.* The MDP is a conceptual framework used to represent decision-making scenarios in which outcomes are influenced by both random factors and the management-maker's regulation. MDPs are valuable tools for analyzing optimization issues addressed using adaptive programming and RL techniques [18].

The RL model operates within the framework of an MDP and is characterized by the tuple (A, S, T, R, $\phi$). Here, the state signifies the existing condition of the production process, actions denote potential modifications, and incentives are granted for actions that minimize waste. Thus, MDP is characterized by the tuple (A, S, T, R, $\phi$), where:

A is a collection of activities that symbolize potential modifications to the process.

S is a collection of states that represents the present state of the manufacturing process.

The state transition potential matrix, denoted as T, represents the likelihood of moving from state st to state st+1 after performing action at.

The reward function, denoted as $R[a_t, s_t]$, determines the reward obtained when at is taken in st.

The discount factor $\phi$ is used to strike a balance between present and potential rewards in the future.

An MDP aims to identify a strategy $\pi$ that prescribes the optimal action 'a' to be taken in each S to maximize the overall expected reward. Q-learning facilitates [19] sophisticated learning processes, enabling the operation of intricate state spaces and acquiring optimum strategies via time. At first, the model randomly investigates several strategies inside safe operational boundaries to comprehend their influence on waste production. The gradual transition towards optimal strategies as the system gains knowledge from the results of its activities.

*Learning Process.* The DL model's predictions are integrated with the RL model's action-value estimates to facilitate informed decision-making. Furthermore, the DL model enhances the RL model by conveying information about the probable outcomes of various actions, enriching the state representation. This research used a widely used RL approach known as the Q-learning mechanism. The Q-learning update step at each t employs the Bellman formulation in the following manner [20]:

$$q^{new}\left[\alpha_t, s_t\right] = q\left[\alpha_t, s_t\right] + \alpha\left\{\varphi \max a\left[\alpha_t, s_{t+1}\right] + R\left[\alpha_t, s_t\right] - \alpha\left[\alpha_t, s_t\right]\right\} \tag{3.10}$$

In Equation (3.10), $\alpha$ denotes the learning rate, $R[a_t, s_t]$ represents the immediate reward received after taking at in st, $\max a\left[\alpha_t, s_{t+1}\right]$ signifies the estimate of optimal future value.

To balance exploitation and exploration, a method known as $\epsilon$-greedy is applied [21]. This approach involves the model randomly selecting $a_t$ (exploration) with a probability of $\epsilon$ and selecting $a_t$ with the greatest Q-value (exploitation) with a probability of $1 - \epsilon$. Table 3.1 represents the working mechanism of action-value function optimization [22].

Further, for real time data integration, let's assume Dt be the data received at time t. The data stream is fed into the system continuously, which is expressed as in Equation (3.11):

$$a(D_t) = \left\{I_{(\mathbf{1}t)}, I_{(\mathbf{z}t)}, I_{(3t)}, \cdots, I_{(nt)}\right\} \tag{3.11}$$

where $I_{(it)}$ denotes varying features of deployed machines in the production unit.

*Implementation of Strategic Decisions and Continuous Learning:.* At this stage, the EcoEfficientNet framework is evaluated via received continuous, real-time data from IoT devices as its primary sources. This part of EcoEfficientNet involves decision function and feedback looping processes [23]. In the case of decision function, $a(D_t)$ considers the current state data as $I_((it))$ and suggests adjustments.

From Equation (3.12), q denotes the learned action-value function via RL process and A represents the possible set of actions.

$$\alpha\left(D_t\right) = \arg\max x_{a \in A} q\left[\alpha, D_t\right] \tag{3.12}$$

Table 3.1: Working Mechanism of Action-Value Function Optimization

| |
|---|
| **Input:**<br>$s$ (state), $a$ (action), $\alpha$ (learning rate), $\varphi$ (discount factor), $\epsilon$ (exploration rate),<br>$\epsilon_{\min}$ (minimum exploration rate), decayrote (rate at which exploration rate decays),<br>E (number of episodes to tun the algorithm), R (reward function), q (action-value function),<br>and initialized arbitrarily is zeros.<br>**Output:** Optimized action-value function q. |
| For each $E$ from $l$ to $N$ :<br>Initialize $s$ to the starting state.<br>While terminal state is not reached:<br>Choose $a$ from $s$ using policy derived from $q$ :<br>Execute $a$, observe $r$, and $s'$<br>Update $q$-value for $s$ and $a$ :<br>$q[a, s]=q[a, s]+\alpha\left\{\max_{a'} q\left[a', s'\right]+R-q[a, s]\right\}$<br>$s \leftarrow s'$ (move to the new state)<br>Decay $\epsilon$ where $\left(\epsilon \geq \epsilon_{\min}\right)$<br>$\epsilon \leftarrow \max\left(\epsilon, \epsilon_{\min} \cdot \text{ decay }_{\text{rate}}\right)$ |

Simultaneously, on the other hand, the model updates via action outcome recordings which is possible through feedback looping. For action outcome recordings, $R\left[\boldsymbol{\alpha}\left(D_t\right), D_t\right]$ indicate the reward function obtained due to the outcome of $a\left(D_t\right)$ for the given $D_t$ which is expressed as Equation (3.13),

$$R\left[\boldsymbol{a}\left(D_t\right), D_t\right]= \text{ Effieciency }_{\text{gain }}\left(\boldsymbol{\alpha}, D_t\right) \mid \text{ Effieciency }_{\text{loss }}\left(\boldsymbol{\alpha}, D_t\right) \mapsto \boldsymbol{\alpha}\left(D_t\right) \tag{3.13}$$

Thus, the current q is updated based on the new incoming data and the $R\left[\boldsymbol{\alpha}\left(D_t\right), D_t\right]$, which can be expressed as Equation (3.14),

$$q\left[a\left(D_t\right), D_t\right] \leftarrow\left\{q\left[a\left(D_t\right), D_t\right]+\varphi \max a' q\left[a', D_{t+1}\right]+\alpha R\left[a\left(D_t\right), D_t\right]-q\left[a\left(D_t\right), D_t\right]\right\} \tag{3.14}$$

In addition, the dashboard is regularly updated with the essential metrics, m n Equation (3.15).

$$\text{dashboard}_t=\left\{\left(\boldsymbol{m}_t \mid \boldsymbol{m}\right\rangle \in M\right\} \tag{3.15}$$

The system operates cyclically, incorporating actual information, using ML models for making decisions, and continuously refining these models through feedback concerning performance. The system is meant to be adaptable and continually enhance its performance by assimilating fresh data and analyzing the results of its operations. The EcoEfficientNet, developed by integrating hybridized sophisticated ML principles, emerges as a formidable instrument for minimizing waste. It can acquire knowledge and adjust to the unique circumstances and obstacles encountered in a manufacturing process. This leads to an intelligent and data-oriented strategy for sustainable manufacturing.

## 4. Performance Evaluation and Analysis.

**4.1. Dataset.** The dataset must comprehensively cover various aspects of the manufacturing process to effectively train and validate the machine learning model. So we have chosen an appropriate dataset from IEEE Dataport [24] that is meticulously structured to encapsulate a broad spectrum of key metrics and data sources, tailored to address specific needs of the manufacturing process. Few crucial metrics of the dataset are listed and described as follows:

1. Resource consumption in the dataset is the tracking of resources consumed during manufacturing. This encompasses the energy utilized, often quantified in kilowatt-hours (kWh), as well as the raw materials used, typically measured in kilograms or similar units. Accurately monitoring these inputs is pivotal for understanding and optimizing resource utilization.

Table 4.1: Vital Features Considered Process to Optimize Waste Reduction during the Manufacturing Process

| Attribute | Description | Range/Type |
|---|---|---|
| Timestamp | Date and time of data entry | Last quarter of 2023 in the timestamp of $00:00-23:59$. |
| MachineID | Identifier for the machine | [List of Machines] (e.g., Machine_01, Machine_02,..) |
| Resource Consumption | Energy and materials used | [Min Consumption - Max Consumption] (e.g., $50-500$kWh for energy) |
| Production Output | Volume of products made | [Min Output - Max Output] (e.g., 100 - 1000 units) |
| Waste Generated | Waste material produced | [Min Waste - Max Waste] (e.g., $10-100$ kg ) |
| Operational Efficiency | Efficiency of the operation | [Lower Efficiency - Higher Efficiency] (e.g., $0.5-1.5$ ratio) |
| Machine Temperature | Average operational temperature | [Min Temp - Max Temp] (e.g., $20-100°$C) |
| Machine Vibration | Level of machine vibration | [Min Vibration - Max Vibration] (e.g., 0.5 - 2.5 mm/s ) |
| Maintenance Status | Indicates maintenance activity | [$0\,(\mathrm{No}_0)\,,1$(Yes)] |
| Quality Control (QC) Failures | Number of failed QC checks | [Min Failures - Max Failures] (e.g., 0 - 5 failures) |
| Operator Shift | Shift during which data was recorded | [Shift A, Shift B, Shift C] |

2. Production output is another vital metric is the volume of finished products yielded within a given time frame. This output can be measured in various units such as the number of items produced or their total weight or volume, offering a direct insight into the productivity of the manufacturing process.
3. Integral to sustainable manufacturing practices, waste generation metric quantifies the waste produced, which includes material scraps, defective products, and any form of emissions. Tracking this in terms of weight or volume is crucial for environmental impact assessment and for formulating strategies to minimize waste.
4. Operational parameters includes a range of data reflecting the operational health and efficiency of manufacturing equipment, such as machine operating temperatures, vibration levels, operational speed, and instances of downtime. These parameters are key indicators of machine performance and maintenance needs.

The granularity of data collection is meticulously chosen based on the specific nature of the manufacturing process. In high-pace environments like assembly lines, data is often collected at an hourly rate to capture the dynamic nature of operations. Conversely, in slower-paced manufacturing processes such as in chemical production, a daily data collection regime might suffice to provide meaningful insights. In addition, two major data source identifiers are incorporated, Internal and external manufacturing data, which includes machine logs, production records, quality control reports, environmental data, and other industry benchmarks. The complete list of attributes of the dataset is represented in Table 4.1 (Karthick Raghunath, 2024). Table 2 serves as a guide for setting up data collection protocols and designing machine learning models for sustainable manufacturing.

**4.2. Empirical Setup.** Table 4.2 presents the essential requirements for empirically evaluating the EcoEfficientNet model's effectiveness in reducing waste in manufacturing. To assess the efficacy of the EcoEfficientNet, we conduct a comparison study with other established ML techniques such as GBM, SR, MLP, and RF.

The evaluation of the EcoEfficientNet model's accomplishment in waste reduction optimization across manufacturing processes, as well as its comparison with other ML models such as GBM, SR, MLP, and RF, includes incorporating the following four performance criteria. The following metrics are used to measure the efficacy, efficiency, and precision of the models in the particular context: Overall Equipment Effectiveness (OEE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Waste Reduction Percentage (WRP).

Table 4.2: Requirement Components for the Empirical Analysis

| Component | Hyperparameter | Optimal Value |
|---|---|---|
| CNN Layer | Number of Layers | 3 |
| | Number of Filters | 64 |
| | Filter Size | $3 \times 3$ |
| | Stride | 1 |
| | Activation Function | ReLU |
| | Pooling Type | Max |
| LSTM Layer | Number of Layers | 2 |
| | Units per Layer | 100 |
| | Dropout Rate | 0.3 |
| | Recurrent Dropout Rate | 0.3 |
| FCL | Number of Layers | 2 |
| | Units per Layer | 128 |
| | Activation Function | ReLU |
| RL Model | Learning Rate | 0.01 |
| | Discount Factor ($\varphi$) | 0.95 |
| | Exploration Rate ($\epsilon$) | 0.2 |
| | Replay Memory Size | 10000 |
| | Batch Size | 64 |
| | Target Network Update Frequency | Every 5000 steps |
| Software Requirement | Packages &Versions | |
| Programming Language | Python V3.8 | |
| Deep Learning Libraries | PyTorch V1.1 | |
| Machine Learning Libraries | Scikit-learn V0.24 | |
| High-Level Neural Network API | Keras V2.4 | |
| Numerical Computation | NumPy V 1.20 | |

OEE is employed in factory settings to quantify the efficiency of a manufacturing procedure. It consolidates several aspects of business operations into a unified and all-encompassing measure. OEE is computed as [25],

$$OEE = (AvailabilityPerformanceQuality) \tag{4.1}$$

where, Availability is the proportion of run time parted over the intended production time. Performance is calculated as the proportion of Ideal Cycle Time parted by the proportion of run time divided by total components in Equation (4.1). Quality is determined by the proportion of good components parted by total components.

Fig. 4.1 presents a concise graphical representation of the OEE (Overall Equipment Efficiency) for several techniques, such as EcoEfficientNet, GBM, SR, MLP, and RF. The investigation reveals that EcoEfficientNet achieves an outstanding OEE score of 0.85, indicating its exceptional effectiveness in the manufacturing procedure. The improved efficacy can be ascribed to the model's sophisticated use of CNN, LSTM, and FCL, which excel in recognizing patterns and enhancing processes, particularly in waste reduction.

GBM, while it has an OEE of 0.75, performs well compared to other models but is not as capable as EcoEfficientNet. GBM has high prediction accuracy, although it may need to be more proficient in managing the temporal and spatial data patterns crucial in industrial environments. SR with an accuracy of 0.65, and MLP, with an accuracy of 0.70, while valuable in certain situations, demonstrate lower proficiency in effectively managing the intricacies of industrial data compared to EcoEfficientNet. With a score of 0.68, the RF model has modest efficacy but is often surpassed by models that provide more advanced skills for integrating and analyzing data, such as EcoEfficientNet.

The dominance of EcoEfficientNet in this scenario may be attributed to its customized structure, specifically designed to enhance industrial processes by monitoring several data points and operational efficiency. By using

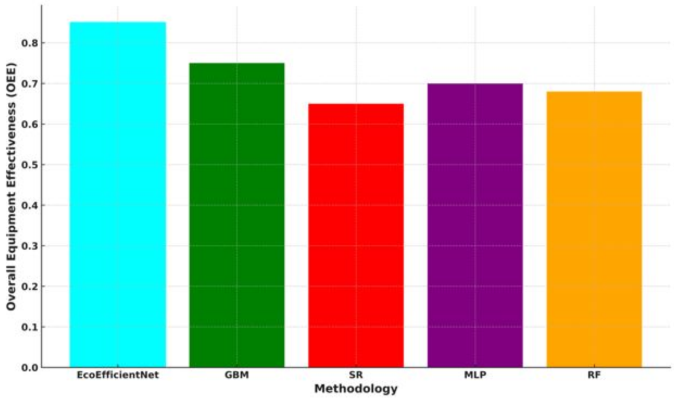


Fig. 4.1: Analysis of OEE in the Manufacturing Process

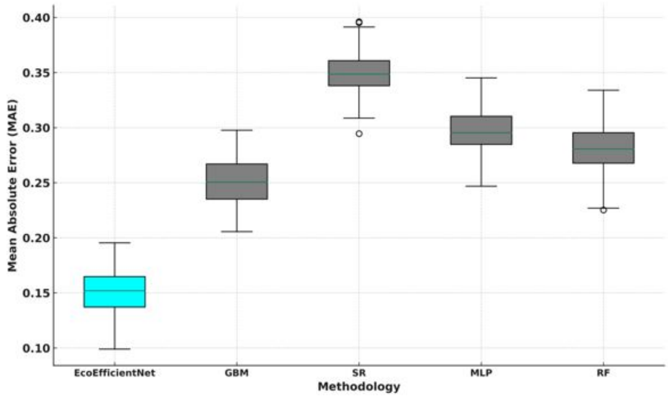


Fig. 4.2: Evaluation of MAE

this holistic approach, it is possible to develop a more refined and efficient optimization plan, resulting in increased OEE values.

MAE quantifies the level of accuracy in predicting continuous information [26].

$$MAE = \left(\frac{1}{n}\right) \times \sum |y_i - \widehat{y_i}| \tag{4.2}$$

In Equation (4.2), $y_i$ is the true value, $\widehat{y_i}$ is the predicted value, and n is the number of observations.

Fig. 4.2 compares the MAE across several techniques, such as EcoEfficientNet, GBM, SR, MLP, and RF. The most notable aspect of this plot is the exceptional performance of EcoEfficientNet, which is highlighted by its distinctive coloration. EcoEfficientNet has superior accuracy and consistency in predictions compared to the other techniques, as seen by its lower median MAE and narrower interquartile range. The exceptional performance of EcoEfficientNet is in line with its innovative deep learning architecture, which seamlessly combines CNN, LSTM, and FCL to identify complex patterns accurately and optimize industrial processes.

On the other hand, GBM, SR, MLP, and RF exhibit more variability in MAE, as seen by their broader box ranges and higher median values. This implies that while these strategies are successful in some instances, they may not be as proficient as EcoEfficientNet in dealing with intricate, uninterrupted data that is unique to reducing waste in manufacturing. Higher MAE levels indicate less precision in forecasts, resulting in less efficient results in real-world scenarios. The lower and more constant MAE of EcoEfficientNet highlights its

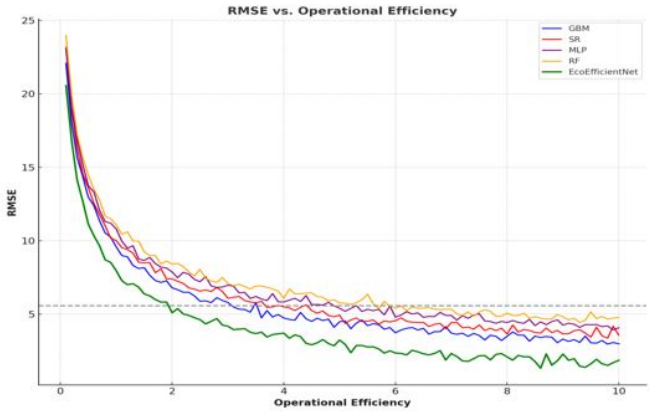


Fig. 4.3: Evaluation of RMSE

appropriateness for complex and ever-changing settings such as sustainable manufacturing. Accuracy and dependability are essential for making informed decisions and optimizing processes in these situations.

RMSE in Equation (4.3) quantifies the magnitude of errors by calculating the square root of the mean of the squared discrepancies between expected and actual outcomes [27].

$$RMSE = \sqrt{\left(\frac{1}{n}\right) \times \sum \left(|y_i - \widehat{y}_i|\right)^2} \tag{4.3}$$

Based on the observed RMSE values in Fig. 4.3 , it can be concluded that EcoEfficientNet demonstrates superior performance compared to the other models (GBM, SR, MLP, and RF) in terms of operational efficiency over the whole range. The EcoEfficientNet regularly exhibits a lower error rate than the other approaches, indicating superior prediction accuracy. This is consistent with the previously mentioned idea that EcoEfficientNet, a model created for environmentally friendly production, utilizes sophisticated DL algorithms such as CNNs, FCLs, and LSTMs to reduce waste by detecting trends and inefficiencies in manufacturing procedures.

The resultant demonstrates the effectiveness of EcoEfficientNet, which can be credited to its advanced design and ability to learn, adapt, and evolve continuously with updated information. This attribute is essential for sustainable manufacturing since adjusting to ever-changing production settings and minimizing waste is necessary. The higher technical performance of EcoEfficientNet, as seen by the reduced RMSE values, validates its usefulness in promoting sustainable manufacturing. It does this by offering data-driven insights that facilitate operational enhancements.

A relevant indicator called Waste Reduction Percentage [28] is used to confirm the extent of waste reduction achieved via the use of EcoEfficientNet in the course of production. The ML model's impact on waste reduction can be quantitatively measured by computing the decrease in waste production Equation (4.4).

$$WRP = \frac{\text{waste }_{\text{before}} {}^{-}\text{wast }_{\text{after}}}{\text{waste }_{\text{before}}} \times 100 \tag{4.4}$$

Fig. 4.4 illustrates the extent of waste reduction in a manufacturing environment before and after adopting several ML techniques. The 'Before' bars represent the original quantity of trash produced, while the 'After' bars display the decreased amount after implementation, with the disparity between them indicating the effectiveness of each machine learning approach in waste reduction.

Upon examining the outcome, it is apparent that all ML approaches have a role in reducing waste. However, EcoEfficientNet has the most effect, decreasing waste from about 91 units to 57.5 units. This is consistent with the prior conversations where EcoEfficientNet, with advanced deep learning techniques, was mainly created to address waste in industrial processes. The model's sophisticated algorithms, such as CNNs, FCLs, and LSTMs, allow it to recognize and respond to patterns that result in waste, thus reducing it.

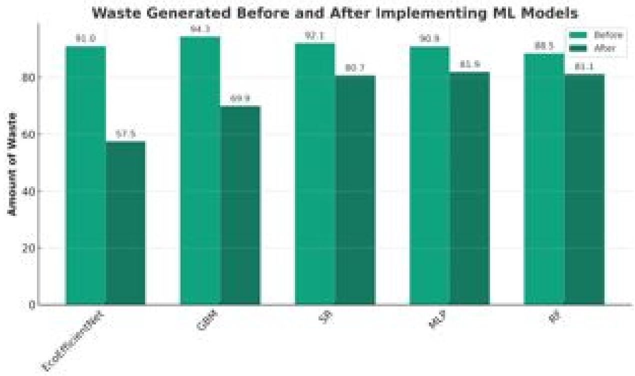


Fig. 4.4: Analysis of Waste Reduction for Various Models

Table 4.3: Sample Segment of the Outcome Showcasing the Optimal Performance for Sustainable Manufacturing over a 24-Hour Period

| | Timestamp | Machine | Resource Consumption (kWh) | Production Output (units) | Waste Generated (kg) | Operational Efficiency (ratio) | Machine Temperature (C) | Machine Vibration (mm/s) | Maintenance Status | Quality Control Failures | Operator Shift |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sensed Data from IoT Devices | 2023-10-01 00:00:00 | Machine_01 | 50.00 | 100.00 | 10.00 | 0.50 | 20.00 | 0.50 | 0 | 0.00 | Shift A |
| | 2023-10-01 00:00:00 | Machine_01 | 69.57 | 139.13 | 13.91 | 0.54 | 23.48 | 0.59 | 0 | 0.22 | Shift A |
| | 2023-10-01 00:00:00 | Machine_02 | 89.13 | 178.26 | 17.83 | 0.59 | 26.96 | 0.67 | 0 | 0.43 | Shift A |
| | 2023-10-01 00:00:00 | Machine_03 | 108.70 | 217.39 | 21.74 | 0.63 | 30.43 | 0.76 | 0 | 0.65 | Shift A |
| | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| | 2023-10-01 00:00:00 | Machine_05 | 500.00 | 1000.00 | 100.00 | 1.50 | 100.00 | 2.50 | 1 | 5.00 | Shift A |

The consequences of reducing such waste are significant for the production ecosystem in an industrial setting. EcoEfficientNet's substantial reduction in waste output decreases the manufacturing process's environmental impact and leads to cost savings and improved resource use. This is especially crucial in sectors where materials disposal leads to environmental deterioration and operational inefficiency.

By integrating EcoEfficientNet into the production process, as shown in Fig. 4.4, it is possible to reduce waste output by about 37%. This demonstrates the practicality and effectiveness of machine learning in enhancing sustainable manufacturing practices. Such waste reduction may lead to a series of beneficial outcomes, such as decreased consumption of raw materials, reduced energy use, and less environmental contamination. These outcomes are essential elements of sustainable industrial operations. The result represents progress towards environmentally friendly production, highlighting the importance of modern technology such as EcoEfficientNet in promoting sustainability in the sector.

Table 4.3 displays the measured data at different time points throughout the production process during 24 hours (sample). These optimal values demonstrate the equilibrium between elevated productivity (increased manufacturing output), effectiveness (enhanced operational efficiency and reduced resource consumption), and sustainability (limited waste generation and minimum machine strain shown by vibration and temperature levels). The observed result directly reflects the critical performance indicators in a manufacturing setting. For example, the Resource Consumption metric represents the equilibrium between using energy and materials and generating manufacturing output. An improved process is shown by a decrease in consumption coupled with an increase in production. The waste-generated feature directly impacts the sustainability element since a smaller amount of trash is associated with improved environmental and economic results.

**5. Conclusion and Future Work.** The thorough examination of sophisticated ML models in manufacturing, namely the implementation of EcoEfficientNet, has uncovered a significant improvement in sustainable manufacturing processes. The DL framework of EcoEfficientNet, which combines CNN, LSTM, and FCL, has shown remarkable effectiveness in waste reduction. Its exceptional OEE score and minimum RMSE values support this, showcasing its superior prediction accuracy and operational efficiency. Compared to other models such as GBM, SR, MLP, and RF, EcoEfficientNet surpasses them due to its specialized skills in handling intricate industrial datasets. The tabulated data from IoT devices for 24 hours provides more evidence of how EcoEfficientNet enhances essential performance parameters. It achieves a harmonious combination of high productivity and sustainability by minimizing resource use and waste production, all while ensuring the machine's well-being. The empirical findings, which demonstrate a substantial decrease in waste before and after adopting EcoEfficientNet, provide evidence of the model's strength in promoting an environmentally friendly, efficient, and economically sustainable IoT-based industrial setting. ML in this paradigm shift is crucial for enterprises that want optimal efficiency while maintaining environmental integrity. This advancement sets the stage for an eventuality wherein sustainable manufacturing becomes the standard.

Subsequent investigations in this field aim to combine diverse IoT datasets [29] with EcoEfficientNet to enhance the agility and reactivity of industrial processes. Investigating the integration of blockchain technology for reliable and transparent monitoring of supply chains, together with AI-powered predictive maintenance, has the potential to improve productivity and sustainability.

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