Enhancing manufacturing efficiency: leveraging CRM data with Lean-based DL approach for early failure detection

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ABSTRACT

In the pursuit of enhancing manufacturing competitiveness in India, companies are exploring innovative strategies to streamline operations and ensure product quality. Embracing Lean principles has become a focal point for many, aiming to optimize profitability while minimizing waste. As part of this endeavour, researchers have introduced various methodologies grounded in Lean principles to track and mitigate operational inefficiencies. This paper introduces a novel approach leveraging deep learning (DL) techniques to detect early failures in manufacturing systems. Initially, real-time data is collected and subjected to a normalization process, employing the weighted adaptive min-max normalization (WAdapt-MMN) technique to enhance data relevance and facilitate the training process. Subsequently, the paper proposes the utilization of a triple streamed attentive recalling recurrent neural network (TSAtt-RRNN) model to effectively identify Lean-based manufacturing failures. Through empirical evaluation, the proposed approach achieves promising results, with an accuracy of 99.23%, precision of 98.79%, recall of 98.92%, and F-measure of 99.2% in detecting early failures. This research underscores the potential of integrating DL methodologies with customer relationship management (CRM) data to bolster early failure detection capabilities in manufacturing, thereby fostering operational efficiency and competitive advantage.

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1. INTRODUCTION

The "Lean" states to the well-organized use of available resources by reducing non- parameter-auxiliary operations or waste. Lean engineering creates a high-quality, streamlined system that satisfies customer demand by utilizing complementary technologies. Lean manufacturing is a production methodology that prioritizes the identification of customer value integrating processing and their organic integration across the entire organization [1]. Lean production is a complementary approach to automation techniques, and it has gained widespread adoption in several industrial sectors in the past few decades. Researchers have discovered considerable benefits of the Lean method in a variety of service industries, including clinics, sustenance, edification, the public zone, carriers, and trade banking. Originally known as the Toyota fabrication system, it described the enterprise's industrialized solutions. Clinics have produced excellent healthcare outcomes, including a momentous decline in one-month death rates, with respect to [2].

Lean approaches should be implemented in complicated production systems to improve firm operations and procedures. Waste is defined by Lean manufacturing as any activity that doesn't add value for the customers. It describes merchandises, facility, commotion, system, or speculation that demands for proficiency, cash, time, or other resources [3]. This be able to include unexploited measurements, surplus inventories, idle time, less utilized resources, and unproductive processes. Seven non value adding process or wastes in manufacturing are identified by the Lean principles: gesticulation, transference, overproduction, portfolio, delay, malfunctioning items, and unnecessary processing [4]. Subsequent reports state that goods or services that fall short of customers' expectations may be considered surplus. When goods or services are produced without a set order, overproduction waste happens. Increased waste from finished goods, extra labor, and storage facilities might result from overproduction. Work-in-progress, finished goods, and excess raw materials are examples of production-related inventory waste.

Excess inventory may indicate issues in the manufacturing system, such as malfunctioning equipment, unnecessary structural times, and recurrent interruptions. Gesture waste refers to the needless drive of constituents, workforces, or apparatuses. Waste in gesture can cause fabrication delays, dangerous workplace conditions, and a variety of other issues [5], [6]. Delayed waste refers to tasks, goods, or finished products that remain in storage facilities for extended periods of time before delivery. Over-processing refers to superfluous work that does not provide importance to the industry. Finally, there is defective waste that requires rework or results in junk material. Substandard effort sometimes leads to increased fabrication expenses, which could have been avoided with the Lean principles. Transferring from one product to another might lead to waste and make it difficult or impossible to maintain the same setup time [7], [8].

Motivation: downtime is a significant issue in manufacturing companies, leading to lost production time, decreased efficiency, and increased costs. Several studies have shown that implementing Lean principles can effectively reduce downtime and improve overall performance in manufacturing operations. Implementing by identifying and eliminating waste in the production process, companies can streamline operations, reduce lead times, and ultimately minimize the risk of downtime events. By focusing on improving processes, standardizing procedures, and empowering employees to identify and solve problems, companies can proactively prevent downtime and maintain high levels of operational efficiency. These kinds of major motivations motivate us to develop an innovative deep learning (DL) model to detect early failure detection in manufacturing systems. The key contributions of the developed framework are depicted in detail:

- To propose an innovative DL triple streamed attentive recalling recurrent neural network (TSAtt-RRNN) model for detecting downtime reduction in service manufacturing systems.
- To encompass a weighted adaptive min-max normalization (WAdapt-MMN) for removing unwanted null values from the maintenance data.
- To detect the existence and non-existence of machine failures in manufacturing systems using the TSAtt-RRNN model.
- The proposed framework is assessed with the conventional technique by evaluating various assessment measures like accuracy, precision, recall, and F-measure.

The upcoming sections are organized as follows: section 2 outlays the section about related work, section 3 deliberates over the suggested method, section 4 presents the results and discussion, and section 5 represents the conclusion of the proposed framework.

2. RELATED WORKS

Vijayakumar and Suresh [9] defined the DL framework that has been optimized to minimize cycle time reduction in manufacturing organizations through Lean principles. Value stream mapping (VSM) was initially used for the present state mapping of an organizational structure. Next, to identify excessive time usage, a modified deep belief neural network (DBNN) was employed. Using the black widow optimization (BWO) technique, the weight parameter was optimized in order to make the adjustment. To increase the profit, the delay time was prevented using detection process. The utilized black widow deep belief network (BWDBN) approach's simulation study was completed, and the projected and actual values were compared. Nevertheless, this method was highly complex and required a significant amount of data and resources to train and optimize.

Shahin *et al.* [10] introduced Lean-based downtime minimization detection using machine learning (ML) and DL techniques. This study used deep hybrid learning (DHL), ML, and DL to investigate over twenty defect identification approaches. Predicting system failures based on particular features or system settings (input variables) was considered to reduce downtime and avert future breakdowns. However, the implementation and maintenance of such a sophisticated model can be challenging for manufacturing companies, especially if they do not have the necessary expertise or resources in-house.

Elboq *et al.* [11] established the Lean and six sigma integration using the DL technique for a clothing manufacturing company. The DL model was trained to predict the success level rate and customize the Lean and six sigma execution timeline using the weights and development of a set of common key success factors (CSFs), which were chosen as input data. However, this method was complex and difficult to interpret, making it challenging for employees to understand how decisions were being made and potentially hindering buy-in from stakeholders.

Solke *et al.* [12] introduced ML-based prognostic demonstrating and Lean regulator engineering in automotive industrialized corporations. At the first stage, forty-six auto parts manufacturing companies in the Pune region were recognized as having Lean manufacturing methods based on contrivance, effort, capacity, steering, merchandise tractability, and substantial behavior. Twenty-three Lean manufacturing models were developed using system identification (control theory) structures, including autoregressive with external (ARX), autoregressive moving average with external (ARMAX), output error (OE), and Box Jenkins (BJ) approaches. Various performance measures like mean squared error (MSE), and prediction error were scrutinized and compared with other studies. Nevertheless, implementing his model requires a significant investment in technology, resources, and training.

Rahman *et al.* [13] put forth the enhancement of internet of things (IoT)-based data analytics for improving the Lean trade process. The theoretical framework presented here combines life model (LM), statistic analytics, and the IoT to improve verdict sustenance systems in process improvement. Data analytics in the simulation were combined with the IoT to improve bottleneck problems while keeping to the LM principle. The major information flow channel within the LM verdict sustenance system was illustrated in detail to demonstrate how the decision-making process was carried out. The verdict sustenance mechanism has been enhanced, and the proposed framework has shown that the assimilated components can collaborate to better the conclusion. Nevertheless, developing and maintaining the necessary skills and expertise to effectively use IoT-enabled data analytics for decision support can be challenging, particularly for organizations with limited experience in this area.

Quality control and quality assurance are vital for ensuring product/service quality, meeting customer requirements, and achieving organizational objectives. Quality control monitors and maintains quality, while quality assurance ensures products/services meet specified requirements. They prevent defects, detect issues early, support continuous improvement, and comply with standards. Concepts like total quality management, continuous improvement, process control, and compliance enhance these practices. Quality management systems (e.g., ISO 9001), six sigma, and Lean manufacturing/management are interconnected and complement quality control and assurance efforts [14]–[18].

Quality control is crucial in ensuring products/services meet quality standards and customer requirements. It involves systematic monitoring, evaluation, and rectification of deviations. Elements like inspection, testing, process monitoring, and corrective actions contribute to its effectiveness. Quality control ensures consistent quality, customer satisfaction, and loyalty. It reduces defects, non-conformities, and costs, while ensuring compliance with standards and regulations. By emphasizing quality control, organizations enhance their reputation and establish trust with customers and stakeholders [19]–[23]. The following potential research gaps as given in Table 1 are identified from the detailed literature review.

Table 1. Potential research gaps

Area	Gap	Opportunity
Integration of CRM data with manufacturing data	Current research lacks comprehensive methodologies to effectively integrate CRM data with manufacturing data. This integration is crucial for improving predictive accuracy, but challenges such as data compatibility, data volume, and noise in CRM data need further exploration.	Developing robust data integration frameworks that can harmonize CRM data with real-time manufacturing data for more accurate early failure detection.
Lean-based DL models	There is limited exploration of Lean principles being directly incorporated into DL models for manufacturing. While Lean focuses on reducing waste and improving efficiency, the translation of these principles into the architecture and training of DL models remains underdeveloped.	Creating DL models that are not only efficient in processing data but also align with Lean manufacturing principles, focusing on minimizing computational waste, and optimizing resource allocation.
Real-time failure detection	Existing DL models for early failure detection often struggle with real-time applications due to computational latency and the need for large datasets. The gap exists in developing lightweight models that can perform real-time analysis using CRM and manufacturing data.	Research into more agile, real-time capable DL models that can leverage Lean manufacturing data principles, potentially using transfer learning or edge computing techniques.
Cross-domain knowledge transfer	There is a lack of studies on how knowledge from one manufacturing domain can be transferred to another using CRM data and Lean-based DL approaches. Cross-domain knowledge transfer could significantly enhance the robustness of early failure detection models.	Exploring methods for transferring knowledge between different manufacturing domains, using CRM data as a bridge to improve the generalizability of Lean-based DL models.

2.1. Problem statement

Despite the benefits of Lean principles in improving operational efficiency and reducing waste, many manufacturing companies struggle with implementing early failure detection mechanisms based on Lean methodologies. The lack of a structured approach to identifying potential failure points, analyzing root causes, and implementing preventive measures hinders their ability to effectively prevent breakdowns and disruptions in production processes. This results in increased maintenance costs, extended downtime and decreased overall productivity. In the manufacturing sector, optimizing operational efficiency and ensuring product quality are paramount for sustaining competitiveness. However, the detection of early failures in manufacturing processes remains a significant challenge. Despite the adoption of Lean principles and the utilization of customer relationship management (CRM) data, existing methodologies often lack the precision and effectiveness needed for timely failure detection. This gap highlights the need for innovative approaches that leverage both CRM data and advanced DL techniques to enhance early failure detection in manufacturing systems. Therefore, the problem at hand is to develop a comprehensive solution that integrates CRM data with a Lean-based DL approach to effectively identify and mitigate operational inefficiencies in manufacturing processes. Furthermore, the reliance on manual inspection methods and subjective assessments can lead to inconsistencies in the identification of failure symptoms, reducing the accuracy and reliability of the detection process. Additionally, the lack of real-time monitoring systems and data-driven analytics tools limits the ability of manufacturing companies to proactively detect failures before they impact production performance. To address this challenge, an innovative DL model to detect early failure detection in manufacturing systems.

3. DEVELOPED METHOD

In this article, an innovative DL model is introduced to detect early failure detection in manufacturing systems. Initially, the real-time data is collected and pre-processed by performing a normalization process. For the normalization process, the WAdapt-MMN technique is introduced to remove irrelevant data and make the training process easier. Then, the TSAtt-RRNN model is introduced to detect the presence of Lean-based manufacturing failures effectively. Figure 1 depicts the workflow of the developed method.

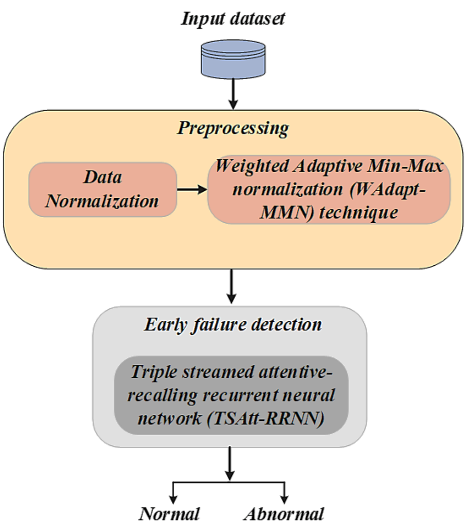


Figure 1. Workflow of the developed method

3.1. Pre-processing stage

Initially, the real-time data is collected and pre-processed by performing a normalization process. Recently, the min-max normalization technique [24] has provided better normalization performance but it may not be suitable when processing with non-linear service level agreements (SLAs). Hence, this framework proposes a WAdapt-MMN technique that correlates the maintenance features using the Pearson coefficient and MM normalization. The updated range of feature vectors is indicated as, U_{min} and U_{max} having the values 0 and 1 respectively. The mathematical formulation of updated weighted values is encompassed in (1)-(3):

$$K = \frac{\sum_{x=1}^{n}(y_x-\bar{y})(v_x-\bar{v})}{\sqrt{\sum_{x=1}^{n}(y_x-\bar{y})^2(v_x-\bar{v})^2}} \tag{1}$$

$$MMNz'_{x,m} = \frac{z_{x,m}-min(z_x)}{max(z_x)-min(z_x)}(Umin_{max} + U_{min}) \tag{2}$$

$$W_{value}p' = \left(\frac{P_{x,y}-nx_y}{nk_y-nx_y}(Umin_{max} + U_{min}())\middle| \left(\frac{P_{x,y}-nx_y}{nk_y-nx_y}\left(Umin_{max} + C\left(P_y, P_{final}\right)\right)\right)\right) \tag{3}$$

here, $W_{value}p'$ indicates the adaptive weighted value, $P_{x,y}$ indicates the actual value, C manipulates the parameter to stabilize the updated range, and $\beta\left(P_y, P_{final}\right)$ indicates the correlation coefficient between column $y$and labeled columns using PC. Moreover, nx_y indicates the minimum value of y^{th} column, nk_y represents the maximum value of y^{th} column, U_{max} and U_{min} represents the updated minimum and maximum value.

3.2. Early failure detection using (triple streamed attentive recalling recurrent neural network)

After data normalization, the system failure detection is performed using the recalling-based recurrent neural network (RRNN) technique. Traditional RNN techniques [25] cause long-term dependency problems while training with a real-time inconsistent database. The proposed RRNN recalls the past information at each time step, and can better capture the underlying structure and dependencies in sequential data. A brief analysis of the recalling enhanced recurrent neural network (RERNN) technique is depicted below.

Consider the input data as $\{x_i, y_i\}_{I=1}^{i}$, which is given to the RRNN classifier. Where, x_i denotes the input data and y_i denotes the output data. Also, the proposed RERNN model involves 7 numbers of layers that can provide detection processes accurately.

Initially, the inputs are given to the RRNN, which includes objects that are denoted as $n + l$ linear objects. It can map the delayed vector with an output of the hidden layer that is denoted as, $x_{i-1} = \left(x_{(i-1)_1}, x_{(i-1)_2}, \ldots.. x_{(i-1)_l}\right) = (x_{i1}, x_{i2}, \ldots.. x_{in})$ and it is represented as the matrix form $m_I^{\bullet} = (m_{I1}, x_{I-1})^T$. After that, the output obtained from the input layer is fed to the next layer, which returns the formal standards as 0/1, which is stored in the RRNN memory layer. This is demonstrated as (4):

$$S(.) = \begin{cases} 0, if\, x_{(I-1)v} unimportant \\ 1, if\, x_{(I-1)v} unimportant \end{cases} \tag{4}$$

here, the state layer is denoted as, $S(.)$ with the convolutional activation layer, which involves the training phase as well as the testing phases, and the gradient functions are denoted as $x_{(I-1)v}$ with the memory layer. Subsequently, use gradient-based methods and $log\, s\, ig$ functions to achieve the state-level plot output with a difference. The weight vectors with input layer and x^{th} state layer node parameters are calculated as (5):

$$K_{Ix} = k(w_x^* y_I^*) = \frac{1}{1+e^{-w_x^* y_I^*}} = \frac{1}{1+e^{-\left(w_x^* y_I^T + w_x^{*x} x_{I-1}^T\right)}} \tag{5}$$

here, $I = 1,2, \ldots, i$, and the weight matrix is denoted as $W^* = \begin{bmatrix} w_1^* \\ \cdots \\ w_k^* \end{bmatrix}_{k\times(l+k)}$, which is attached to two layers that is input layer and the state layer $K_I = (k_{I1}, \ldots. k_{Ix})$. Figure 2 deliberates the architecture of the TSAtt-RRNN model.

Also, the state layer output is passed through the memory layer, which can store the object weights used for testing and training, which are collected from the previous sum layer and the current state layer. Here, the memory layer output is calculated using (6):

$$v_{(I-1)}^* = v_{(I-1)} d_{Ix} \tag{6}$$

here, $v_I = (v_{I1}, v_{I2}, \ldots.. v_{Ik})$, it initializes the memory values as $i_0 = (i_{01}, i_{02}, \ldots.. i_{0k}) = 0$, which is the magnitude value of the previous output, which is given to the following layer using gate value, $d_{Ix} \in (0,1)$. A RERNN structure consists of many neurons and n data in the hidden layer that is calculated as (7):

$$X_{Ix}^{hidden} = tan\,k\,(V_{Ix}) = tan\left(\hat{\hat{V}}_{Ix} + V_{(I-1)}K_{Ix}\right) \tag{7}$$

here, $K_{Ix} = 0$ and tan functions can execute better than the operation of $log\,s\,ig$ functions. The delay value is the current hidden layer output vector concept that is mentioned $d_I = (d_{I1}, d_{I2}, \ldots.. d_{Ik})$.

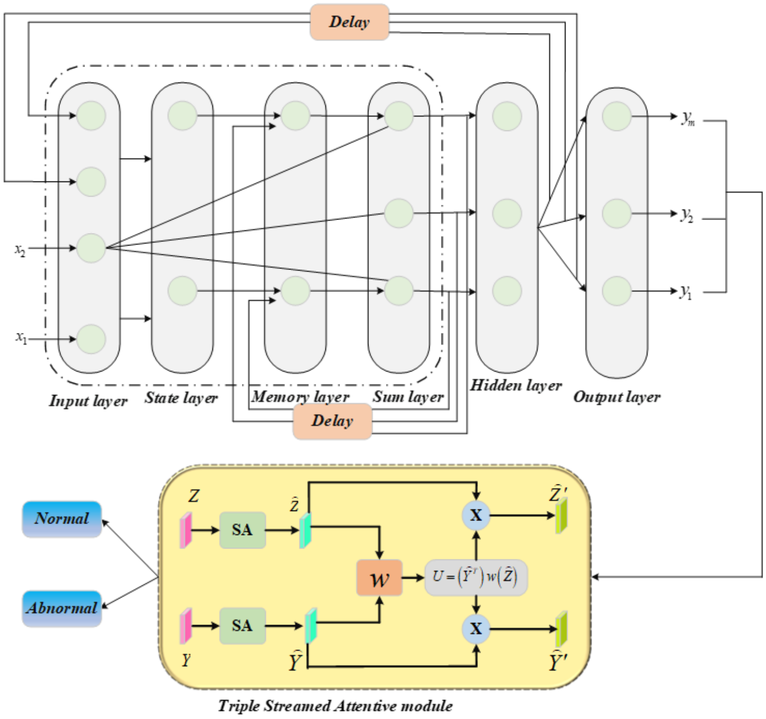


Figure 2. Architecture of the TSAtt-RRNN model

It functions to create the next layer that denotes the innovative input layer as, $K_I^*(K_I, x_{I-1})^T$, then determines the resultant outcome as, $v_I = (v_{I1}, v_{I2}, \ldots.. v_{Ik})$ in the output layer. Thus, the attained input objects and output objects are used for attaining the weight factor by the memory layer.

The attained weight vector of the outcome layer is represented as $v_w = (v_{1w}, v_{2w}, \ldots.. v_{kw})^T \in \aleph^k$ that is associated with the unseen layer by the w^{th} output node. Thus, the output layer of the classifier is defined using (8) with w^{th} output description where $(w = 1,2, \ldots z)$:

$$x_{Iw} = d(f_I c_w) = f_I c_w \tag{8}$$

here, $d(.)$ is the activation function while training the input image the error function I with I^{th} sample is presented in (9):

$$e_I(f_I c) = \frac{1}{2}\|u_I - i_I\|^2 \tag{9}$$

here, $u_I = (u_{I1}, u_{I2}, \ldots, u_{Iz})$ and $i_I = f_I C = (j_{I1}, j_{I2}, \ldots, j_{Iz})$. Also, the error function is calculated using (10):

$$e(y) = \sum_{I=1}^{i} e_I\,(f_I C) \tag{10}$$

here, $I = 1,2, \ldots, i$, error function is $e_I(f_I C)$ through I^{th} sample, the error with the $(I+1)^{th}$ samples are denoted as $e(I+1)$ and i is denotes total number of samples.

The regions from different images contain the inheritance and inconsistent distribution of manufacturing system data. Such inconsistencies are often extracted in three consecutive features X_{k-1}, X_k, and X_{k+1} are fed as input into the three-stream attention module enabling the network to deliberate into the adaptive learning model. In this module, a single convolution (Conv) layer and quadruple residual blocks

(RBs) are present under each stream, and features are extracted in an increasing order separately under each stream.

The features extracted from the Conv layers are fused and fed into the RBs to extract the depth-level features from the diseased images. Using the parallel streams, the interaction between the adjacent features can be determined effectively. The in-between features of the nearby streams $Z \in \Re^{w\times h\times c}$ and $Y \in \Re^{w\times h\times c}$ are modified to improve the primary attentive features $\hat{Z}$ and $\hat{Y}$ using the soft attentive mechanism. The triple streamed attentive (TSAtt) module helps to determine a correlation matrix $P \in \Re^{wh\times wh}$ for generating joint improvements and fusion between two feature subsets. The mathematical expression from the TSAtt module is encompassed in (11)-(13):

$$U = \lambda\left(\hat{Y}^T\right)w\lambda\left(\hat{Z}\right) \tag{11}$$

$$\hat{Z}' = \hat{Z}M_{row}(U) \tag{12}$$

$$\hat{Y}' = \hat{Y}M_{col}(U) \tag{13}$$

here, λ indicates the linear transformation that subsets to lower-dimensional features, w indicates the learnable weight matrices, M_{row} and M_{col} indicates the normalized row and column-wise feature vectors obtained by the soft attentive mechanism.

4. RESULTS AND DISCUSSION

The developed method is simulated and processed via the Python platform and real-time collected manufacturing data is utilized for the training process. The dataset was released by the University of Applied Sciences in Berlin, Germany's School of Engineering, and it has 10,000 records with 14 features like product id, types, air temperature, process temperature, unique identifier, rotation speed, torque, tool wear (TW), outcome features, TW failures, heat degeneracy failure, power failure, overload failure, arbitrary failures, and forecast machine failures.

4.1. Assessment measures

Performance indicators like accuracy, precision, recall, and F-measure are computed to better understand the proposed approach.

4.1.1. Accuracy

It determines the model's overall accuracy, accounting for both true positive (TP) and true negative (TN). It is calculated using (14).

$$Accuracy = \frac{w+x}{w+x+y+z} \tag{14}$$

4.1.2. Precision

It is the measure of finding the reliability of the proposed model in correctly identifying failures that are similar to ground truth samples and it is formulated in (15).

$$Precision(\%) = \frac{x}{x+z} \times 100 \tag{15}$$

4.1.3. Recall

Recall measures the positive outcomes that are accurately predicted model has successfully identified. The calculation is performed using (16).

$$Re\,c\,all = \frac{x}{x+y} \tag{16}$$

4.1.4. F-measure

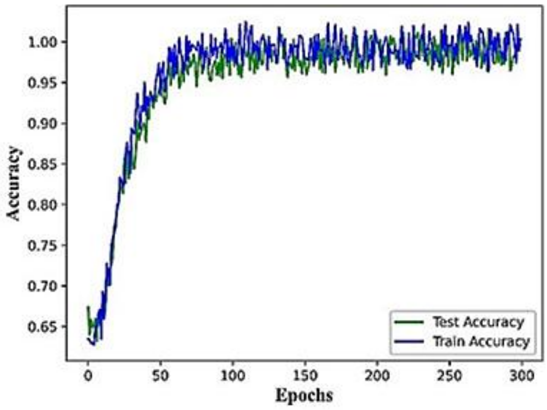
The F-measure displays the harmonic mean of recall and precision. It is computed using (17):

$$F1 - score = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) \tag{17}$$

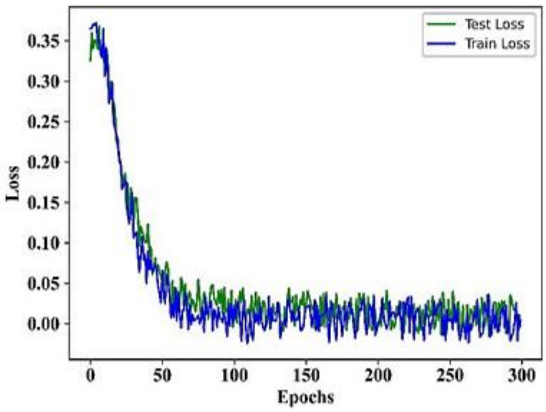
here, w, x, y, z indicates the TN, TP, false negative (FN), and false positive (FP) respectively.

4.2. Comparative analysis of developed method over existing studies

In this section, the performance achieved by the proposed method over the existing schemes is deliberated via graphical illustration. Several existing methods are compared with the proposed framework to prove its efficacy. Figure 3 depicts the accuracy and loss curve. Figure 3(a) shows the accuracy curve and loss curve is shown in Figure 3(b). In the graphical manifestation, it is clear that the training and testing accuracy obtained almost similar performances and proved that the proposed method is highly effective for detecting failures in manufacturing systems. The proposed model minimizes the training error using the adaptive feature learning mechanism. Table 2 indicates the comparative analysis of the developed method over existing schemes. From the tabulation, it is clear that the developed TSAtt-RRNN technique showed outstanding performance compared to conventional studies.



(a)



(b)

Figure 3. Curve developed method of: (a) accuracy and (b) loss

Table 2. Comparative analysis of developed method over existing schemes

Methods	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
Convolutional neural network-long short-term memory (CNN-LSTM)	60	72	60	60
Dual CNN	68	66	68	64
Attention-based long short term memory fully convolutional neural network (ALSTM)-(FCN) with eXtreme gradient boosting (XGBoost)	81	83	81	81
ALSTM-FCN with AdaBoost	75	76	75	76
CNN with XG-Boost	78	80	78	78
Proposed (TSAtt-RRNN)	99.23	98.79	98.92	99.2

5. CONCLUSION

This study introduced the TSAtt-RRNN model, particularly relevant for CRM implementation in manufacturing contexts. This model exhibited remarkable efficacy in pinpointing Lean-based manufacturing failures. Through an adaptive feature learning mechanism, the TSAtt-RRNN minimizes errors, complemented by the WAdapt-MMN technique, which enhances data relevance and combats overfitting. Empirical validation yielded impressive results, including an accuracy of 99.23%, precision of 98.79%, recall of 98.92%, and F-measure of 99.2% in early failure detection within manufacturing systems. Looking ahead, extending the application of WAdapt-MMN holds promise for CRM integration, enabling the development of predictive maintenance strategies. This proactive approach empowers CRM systems to schedule maintenance tasks pre-emptively, preventing costly downtime, and fortifying operational efficiency within manufacturing settings. Future research in enhancing manufacturing efficiency through CRM data and Lean-based DL approaches offers a broad range of opportunities. These include developing advanced hybrid models, real-time adaptive systems, personalization of manufacturing processes, scalability studies, data privacy solutions, and cross-industry applications. Emerging technologies and human-machine collaboration also present exciting avenues for further exploration, all aimed at maximizing efficiency, reducing waste, and improving the overall competitiveness of manufacturing operations.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [VSK], upon reasonable request.

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