IJMRT: Volume (7), Issue 11, 2025, Pages 38-55
International Journal of Multidisciplinary Research Transactions
(A Peer Reviewed Journal)
www.ijmrt.in

ISSN (Print):2663-2381
ISSN(Online):2663-4007
| Regular Article | Open Acess
ARAVANDI Publications

ERP-based Quality Prediction using Long Short-Term Memory Networks Approach for Bio industry

Mr. Sravan Katragadda*

Program Manager, ERP Software Engineer, AI Architect/Developer, Gaithersburg, Maryland, USA.

Corresponding author(s):
Mr. Sravan Katragadda, Program Manager, ERP Software Engineer, AI Architect/Developer, Gaithersburg, Maryland, USA.
Email: sravank0785@gmail.com

DoI: https://doi.org/10.5281/zenodo.17960667

Accepted: 10 December 2025 Available online: 17 December 2025

Abstract

The biotech industry is relying on ERP (Enterprise Resource Planning) systems to regulate production, resources, and quality information. However, it is very difficult to predict the quality of products because of the time-related and complexity of ERP records. The conventional types of regressions fail to capture the temporal relationship and thus achieve lower accuracies (predictive accuracies). To overcome this, the proposed framework uses a Long Short-Term Memory (LSTM)-based model to predict the quality. The data used in this article is the ERP-MTD (Enterprise Resource Planning - Manufacturing and Test Data) dataset, which combines ERP modules such as batch process logs, sensor readings, and quality inspection reports to form a comprehensive and structured record of bio-production data. Preprocessing will be performed, which involves Min-Max scaling, where the values of features are normalized to a specified range, leading to consistency in training and faster convergence. A sliding window application is used to obtain a temporal perspective and sequential context, focusing on temporal tendencies that are crucial for assessing bio-production quality. The classification and prediction services utilise the LSTM network to capture long-term dependencies across the variables of the process and the quality outputs. The predictive ability of the model is compared based on Accuracy of 96.47%, Precision of 91.8%, Recall of 92.6%, F1-Score of 92.2%, which yields a better result than the baseline techniques.

Keywords: Enterprise Resource Planning (ERP), Bio Industry, Long Short-Term Memory (LSTM), Quality Prediction, Sliding Window Technique, Min–Max Scaling, Time-Series Classification.

1. Introduction

ERP systems have emerged as an essential element in the control of resource, production, and decision-making in any industry. The integration allows organizations to simplify work processes, eliminate duplication, and enhance efficiency through access to real-time quality and reliable information. ERP systems are relevant to various domains including finance, manufacturing, supply chain, sales and human resources and are therefore utilized to track performance, predict trends, and assist in making strategic decisions. Their advantages notwithstanding, there are implementation, adaptability, and predictive analytics challenges that need to be constantly innovated and optimized. [1]. Beyond biomedical applications, ERP adoption has also gained importance in the business sector, particularly among small and medium-sized enterprises (SMEs), where machine learning methods have been applied to predict adoption trends and assist in ERP system selection [2]. Similarly, reinforcement learning has recently been explored as a strategy for adaptive cost control, enabling organizations to dynamically optimize ERP implementation and maintenance costs [3]. At the same time, literature reviews emphasize that ERP adoption in specialized sectors, such as the defense industry, requires tailored frameworks and structured implementation strategies [4]. Furthermore, next-generation imaging and EEG-based ERP detection are emerging as promising avenues for cross-subject recognition in consumer technologies, highlighting the broader scope of ERP-related research across domains [5]. These interdisciplinary studies underscore the growing importance of ERP systems, where both organizational efficiency and intelligent prediction models play a crucial role in advancing industrial, technological, and biomedical applications.

1.1. Objective

- Develop a model for predicting the quality of bio-production based on ERP.
- Extract time sequencing characteristics of complicated ERP records with LSTM networks.
- Preprocess ERP-MTD data by using Min-Max scaling, featureextraction usingsliding window algorithms to enhance model training and sequential context learning.

- Perform classification and prediction of product quality with improved accuracy, precision, recall, F1-score, and RMSE.
- Compare LSTM against baseline methods in order to confirm improved predictive ability.

1.2. Contribution of the work

The main contribution of this work is the development of a robust LSTM-based predictive model for the quality of bio-production, utilizing intricate ERP data. In contrast to other traditional regression approaches, the proposed model can efficiently describe temporal relationships and sequences in ERP-MTD datasets (such as batch process logs, sensor readings, and quality inspection reports) to capture temporal dependencies and sequential patterns. Min-max scaling and sliding window approaches are used to ensure consistent preprocessing and provide the model with essential temporal context, thereby making the predictive results more effective. Moreover, the current study shows that the LSTM network is more effective than the usual baseline methods in Terms of Accuracy, Precision, Recall, F1-score, and RMSE, indicating that this network is more reliant on results to reliably assess quality. In summary, the work presents a viable and scalable solution for implementing temporal modelling into bio-manufacturing quality forecasting, which will enhance process control and decision-making in the biotech sector.

The remaining content is divided into the following main sections. Section II lists the ongoing research ERP-based quality prediction, carried out by various authors. In Section III, the procedure of the proposed technique is explained. Section IV presents the findings of a comparison between the proposed ERP-based quality prediction the traditional approach. The conclusion of the proposed work that will be done in a future scope is included in Section V, along with references.

2. Related Work

Joydeep Banerjee et al., (2025) The study combined ERP with the supply chain in the aerospace sector of India based on the MADC-LSTM model with the Genetic Engineering - Bidirectional Contrastive Productivity over Age Algorithm (GE-BCPOA). The paper validated the effectiveness of the ERP-SCM integration on the basis of the experiment.

Kashpruk et al., (2023) This paper documented the history of implementing time series in Industry 4.0, its advantages in predictive maintenance, production optimization, forecasting sales and detecting anomalies. In their research, these researchers highlighted the way that the combination of IoT, AI, cloud computing, and big data could be used in order to turn time series data into actionable insights in industrial efficiency.

Guadarrama Arias et al., (2022) This research compared methods of supply chain modeling of temperature-sensitive pharmaceuticals: statistical (AR, ARIMA) and machine learning (KNN, SVM, RF, LSTM, Quantile Regression). They have concluded that the one step ahead models have better accuracy and that in predicting the internal payload temperatures under different ambient conditions, Quantile Regression is useful.

Muller et al. (2025) research concluded that although the majority of the strategies are aimed at categorizing deliveries as on time or delayed, not many of them forecast the real size of the delay which severely restricts their practical use. The authors identified research gaps in the integration of ERP, logistics and environmental data and suggested a research agenda to improve the practical implementation of predictive delay models.

The author Zhang et al., (2024) used deep learning technology to optimize the cloud-based ERP system, incorporated RNNs, CNNs, and DRL to predict demand, recognize images, and-optimize resources. The improved ERP system displayed a marked change in orders processed in a short span of time, operations cost, and management efficiency.

Table.1. Summary Of ERP Applications And Findings Across Industries

References. No.	**Dataset Used**	**Algorithm/ Methodology**	**Results Achieved**	**Limitations**
11	Survey & financial data from biotech firms	Structural Equation Modeling (SEM)	ERP adoption linked to ~20–25% improvement in financial performance with	Success depends heavily on leadership commitment and continuous innovation; may not generalize

			top management support.	across all biotech firms.
12	Industry reports on biotech supply chains	SAP-based case analysis	Reported ~30% increase in compliance efficiency and stronger supply chain resilience.	High cost of SAP implementation; compliance regulations vary across regions, limiting scalability.
13	Case study data from pharma ERP	Comparative/ descriptive study	ERP enabled ~15–20% operational efficiency gain in pharma sector.	Training requirements, high system cost, and integration with legacy systems remain challenges.
14	Case study from microbiology manufacturing ERP	Implementation & performance analysis	ERP improved production efficiency by ~18% and reduced data errors by ~22%.	Resistance to change from employees; adaptation difficulties during transition phase.
15	Inventory data from biology laboratory materials	ERP-based inventory case study	ERP reduced wastage by ~25% and improved tracking efficiency by ~20%.	Limited scalability; solution is effective at lab level but not validated for large-scale industry.

The comparison table 1 identifies the ERP applications used in biotechnology, pharmaceutical, and laboratory settings. Financial performance was enhanced by nearly 25 percent in one study when ERP systems were supported by innovation and leadership, although adoption varied among firms. And yet another showed how SAP helped improve the efficiency of compliance within the supply chain by 30 percent, but at a high cost. Another example achieved 15-20% operational gains in the pharma industry due to training and integration issues. The implementation of microbiology in manufacturing increased production efficiency by 18 percent and reduced errors by 22 percent, despite resistance to the transition. Finally, an inventory-based study also found that wastage in labs decreased by 25 percent, although the decrease was limited in scale.

3. Proposed Methodology

The proposed approach will begin by gathering ERP data from the ERP-MTD dataset, which will combine batch process logs, sensor readings, and quality inspection reports to construct a comprehensive dataset for bio-production quality analysis. Preprocessing is performed on the raw data to address inconsistent data and normalize values across feature parameters through Min-Max scaling, ensuring that all variables fall within a given range. This normalization enhances the robustness of the learning process and accelerates the rate of convergence during model training. Then, a sliding window method is applied to the sequential ERP data to express temporal dependency by transforming the records into a fixed-length sequence design, thereby maintaining prior context within the prediction. These time-augmented sequences are input into the LSTM network, which is expected to capture long-term associations and evolutionary dynamics among the variables in the production process. The architecture of LSTM is used in both classification scenarios and prediction problems because, in both, one performs a mapping of the sequential input data into the final output of high quality. Lastly, the performance of the model is stringently tested using Accuracy, Precision, Recall, F1-Score, and RMSE, and analysed against normal baseline models to demonstrate the increased predictive potential of the suggested framework shown in figure 1.

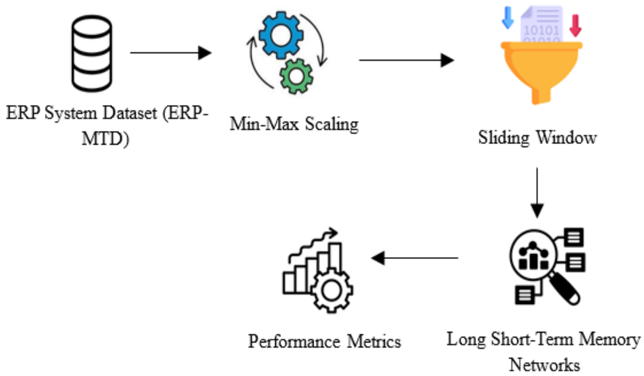


Figure.1. Proposed Overall Block Diagram

3.1. Dataset used ERP System Dataset (ERP-MTD)

Information systems, database management, and software engineering researchers and practitioners can benefit greatly from this organised representation of Enterprise Resource Planning (ERP) system modules and the database table relationships that underlie them.

Finance, human resources, supply chain, and customer relationship management are just a few of the corporate operations that ERP systems combine into a single database. Optimising system efficiency, maintaining data integrity, and enabling smooth connectivity with other corporate applications all depend on an understanding of how these modules interact at the database level. Data flow, dependency graphs, and any bottlenecks may be examined using the dataset, which most likely contains information on key ERP modules, the database tables that go with them, and the connections between tables. This dataset may be used by researchers to investigate dependency management, database normalisation techniques, and modular coupling in extensive ERP implementations. Furthermore, it may help empirical research on ERP customisation, where changing the tables in one module might have an effect on others and provide information on the scalability and maintainability of the system. This dataset might be used in conjunction with query performance measurements or user activity logs for data-driven ERP research in order to evaluate the effectiveness of table designs.

3.2. LSTM-Based ERP Quality Prediction with Min-Max Scaling

Min-Max scaling was chosen to normalize all numerical ERP features into a uniform range (0 to 1), which is compatible with LSTM activation functions (e.g., sigmoid or tanh) that perform optimally with bounded input values. This prevents features with larger absolute magnitudes, such as production rates, from dominating the model learning process. Although Z-score standardization or robust scaling could handle outliers or skewed distributions more effectively, the ERP dataset contains minimal extreme outliers due to prior data cleaning and validation. Min-Max scaling also preserves the original feature distribution, which is beneficial for capturing temporal patterns in production metrics. Each feature is converted into a numerical range, with this approach usually using a fixed range that is most often numeric. [0,1] From the [0,1], with the formula:

$$X = \{x_1, x_2, \ldots\ldots, x_n\} \tag{1}$$

The ERP data may be modelled by a set of features noted by More on differentiated Intellectual Education is within reach. xi numerical value that identifies an assemblage under a certain attribute, like in production rate, resource utilization, or quality index. These variables are generated by different operational processes and hence vary considerably in their scales and ranges of operation. To ensure a fair contribution to model training, preprocessing is necessary.

Normalization techniques (such as Min-Max) are employed to scale all values to a standard range.

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)} \tag{2}$$

In this equation, the capital letter x represents the original feature value. Min(X) and max(X) are the minimum and maximum activity of that feature in the data set. To represent these minimum and maximum values of features in the normalization or scaling, The transformation standardizes the data into a specified range [0,1]. The procedure eliminates magnitude bias, facilitates comparable representation across multiple attributes, and increases the speed of training LSTMs, as well as making improved predictions.

$$X' = \{x'_1, x'_2, \ldots . x'_n\}, 0 \leq x'_i \leq 1 \tag{3}$$

The normalized ERP data set, obtained after Min-Max scaling, appears as shown below. Here, each xi'represents a converted feature value property with a range of 0 to 1. This representation ensures that the attributes of the ERP contribute equally to model training, preventing the high magnitude of any one attribute from dominating the training process. This homogeneous scaling not only stabilizes the learning process but also accelerates an efficient sequential modelling with LSTM networks.

$$H_t = f_{LSTM}(x'_t, H_{t-1,} C_{t-1}) \tag{4}$$

The LSTM model is used to solve Problem (i, d) to perform sequential learning on Japanese ERP data using the relation. In this formulation, they used concepts, as taught or explained to me by my teacher. xt' is the normalized input at the instant time step. Ht−1 is the secretive one, inherited by the last step, Ct−1. The memory cell state is represented by the function f, $LSTM$, which renews these states in order to. Ht and actually learning time dependencies. This repetitive process enables the accurate prediction of quality by storing patterns relevant to past ERP records.

3.3. ERP Quality Prediction with LSTM Using Sliding Window

Quality prediction using ERP uses the sliding window methodology in order to maintain the time order of production data. The current and historical values are captured by segmenting logs, sensor readings and inspection results into overlapping windows. It allows LSTM networks to capture the effects of time, making quality prediction in the bio-industry more accurate. Such windows take into account both present and past values, allowing the Long Short-Term Memory (LSTM) network to learn about temporal dependencies. This is because using this approach ensures that trends, fluctuations, and periodic patterns are put into context, which enhances the accuracy of quality forecasts in bioproduction systems.

$$X = \{x_1, x_2, \ldots\ldots, x_T\} \tag{5}$$

The ERP data set mathematically is equivalent to a sequence of watching, which reads xt. The changes to data output reflect the values recorded in a process variable for a single time step tt. Such may be production rates, sensor readings, or inspection results. Sequence length T Count = Number of time-based records. It is essential to present ERP data in this time series format to leverage temporal information and apply the sliding window technique, thereby training the long short-term memory (LSTM) network to achieve high-quality predictions in the future.

$$W_t = \{x_t, x_{t+1}, \ldots\ldots, x_{t+w-1}\} \tag{6}$$

Where Wt refers to an opening window whose time steps begin at. t is of constant length w. A window stores a contiguous portion of a series of sequential observations and thus retains not only the current, but also the recent history. By arranging the dataset into these overlapping windows, it so happens that the temporal behaviour of various process variables is not lost. This enables the LSTM network to capture both short-term and long-term relationships between ERP records, thereby predicting bio-industry quality more accurately.

$$W = \{W_1, W_2 \ldots\ldots, W_{T-w+1}\} \tag{7}$$

Sliding windows: the number of sub-sequences obtained of the original ERP time-series. Each window Wi is some fixed-length sequence of size. w, and the number of such windows altogether is (T−w+1). Under this method there is no observation that is thrown away; rather, it is placed into a window that retains continuity and time. This windowed architecture allows the isolation of useful temporal features that can be used as inputs to the LSTM model

$$H_t = f_{LSTM}(W_t', H_{t-1}, C_{t-1}) \tag{8}$$

Where Wt is the input window at time step. The input window at time step is the normalized input window. t the hidden state in the former is the input in the latter. $Ct{-}1$ and the correlative cell state is. The function f, $LSTM$, which represents the hidden/cell state, is updated by preserving relevant information and selectively disposing of irrelevant patterns. Such a mechanism makes LSTM very effective at extracting long-term temporal trends in ERP data that are crucial for predicting the quality outcomes of production with high accuracy.

$$\widehat{y_t} = f_{pred}(H_t) \tag{9}$$

Where $y^\wedge t$ is the predicted value of the quality at the time step. t, and Ht, the hidden state output of the LSTM network is considered the hidden state. The forecasting role $fpred$ maps the temporal characteristics learned into the quality measure it is targeted at, which can be either a classification label or a continuous quality score. This step converts sequential ERP learning into actions that enable the precise forecasting of bio-industry products on a historical basis, using production and processing data.

3.4.ERP Quality Classification Using Long Short-Term Memory Networks

In the proposed ERP-based framework, classification of product quality is achieved using Long Short-Term Memory (LSTM) networks. Since ERP datasets in the bio-industry contain sequential records such as process logs, sensor data, and inspection reports, they require models that can handle temporal dependencies' networks are well-suited for this task because they retain both short-term and long-term contextual information through memory cells and gating mechanisms. During training, the normalized ERP inputs are segmented using sliding windows and passed to the LSTM. The network then outputs class probabilities, enabling accurate classification of quality levels, such as acceptable or defective products.

$$f_t = \sigma(W_f.[h_{t-1}, x_t'] + b_f) \tag{10}$$

The equation (11) is the forget gate of an LSTM network. At each time step t, the forget gate controls the percentage of the cell state from the past. $Ct-1$should be kept or abandoned. Here, $ht-1$ is the unprincipled condition of the last step, xt' is the normalized input, Wf is the weight matrix, and bf is the bias term. The sigmoid function σgives a range of 0 to 1, with the close to 0 values implying forgetting of information and close to 1 implying the retention of information.

$$i_t = \sigma(W_i[h_{i-1}, x_i'] + b_i) \tag{11}$$

The equation (12) defines the input gate in an LSTM cell. This gate controls how much new information from the current input xt and the previous hidden state $ht-1$ should be stored in the cell state. The weight matrix Wi and bias term bi adjust the contribution of these inputs. The sigmoid activation function σ ensures that the output values range between 0 and 1, acting as a filter. A value near 0 blocks information flow, while a value near 1 allows stronger integration of new knowledge into memory. $t-1$, C should be retained or discarded. Here, $ht-1$ is the hidden state from the previous step, xt is the normalized input, Wf is the weight matrix, and bf is the bias term. The sigmoid function σ outputs values between 0 and 1, where values close to 0 mean forgetting information and values close to 1 mean retaining it.

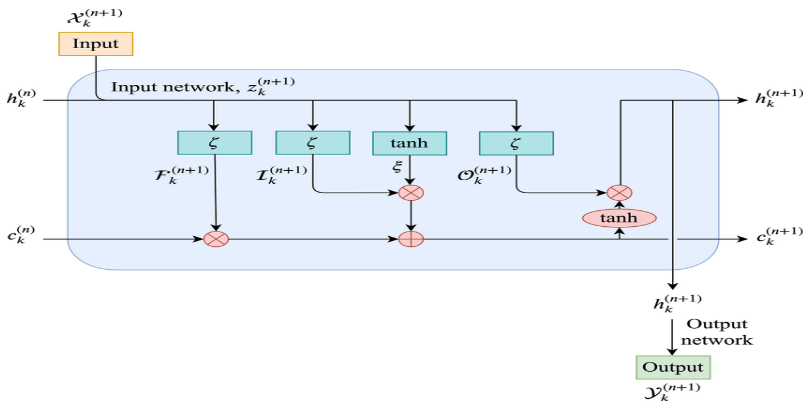
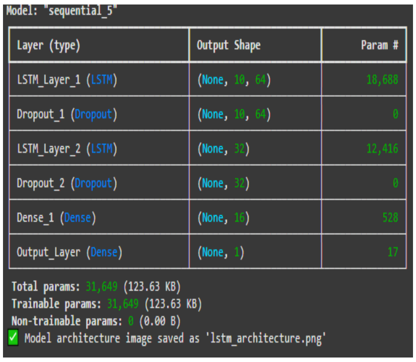


Figure.2. Long Short-Term Memory architecture

Figure 2 represents the Long Short-Term Memory (LSTM) model of ERP quality classification. Normalized ERP inputs are fed into the network, which is combined with the prior hidden state. The forget gate controls what past information can be forgotten, and the input gate and the candidate state allow new knowledge to enter. Long-term memory is present in the cell state, perfected by the gating of the state. The updated hidden state is produced atthe output gate and then fed through a SoftMax classifier to determine the quality of the products.

4. Results And Discussion

The analysis demonstrates that the LSTM-based predictive quality model surpasses the traditional regression models in all aspects of the predictive models of the LSTM-based predictive qualities. The model makes use of temporal relationships through the use of the Sliding Window to develop a predictive model that is enhanced in terms of accuracy, Precision, Recall, and an overall increase in the F1 Score while decreasing the-RMSE scores. Along with these traditional metrics, the FN-errors (False Negatives) are included in this analysis. FN-errors are those undetected faulty batches that can result in substantial financial losses during production. The FN-errors (False Negatives) are those incorrectly identified as good batches (False Positives), which lead to rework costs when they are flagged. A Cost Matrix was developed to assign higher costs to FN-errors in the predictive model, as the wrong classification of these errors has a greater effect on the financial and operational aspects of production. The ERP-MTD data validation illustrates that LSTM-based predictive quality models can accurately capture complex Bio-Production trends over time. This demonstrates that LSTM networks provide a robust foundation for supporting Predictive Quality Control through the use of ERP systems for the Bio-Industry. The experimental analysis proves that the LSTM-based quality prediction model is much better than the traditional regression models.


Model: "sequential_5"

Layer (type)	Output Shape	Param #
LSTM_Layer_1 (LSTM)	(None, 10, 64)	18,688
Dropout_1 (Dropout)	(None, 10, 64)	0
LSTM_Layer_2 (LSTM)	(None, 32)	12,416
Dropout_2 (Dropout)	(None, 32)	0
Dense_1 (Dense)	(None, 16)	528
Output_Layer (Dense)	(None, 1)	17

Total params: 31,649 (123.63 KB)
Trainable params: 31,649 (123.63 KB)
Non-trainable params: 0 (0.00 B)
✅ Model architecture image saved as 'lstm_architecture.png'

Figure.3. Model Layer Architecture

The figure 3 starts with two stacked LSTM layers (64 and 32 units) that extracts the temporal dependencies of the ERP bio-production data. Each LSTM is followed by dropout layers (rate 0.2) to avoid overfitting and enhance the generalization. The extracted features are further refined by a Dense layer containing 16 neurons that use ReLU activation. At last, a single unit of a sigmoid output layer is used to predict the quality of the product as a binary variable.

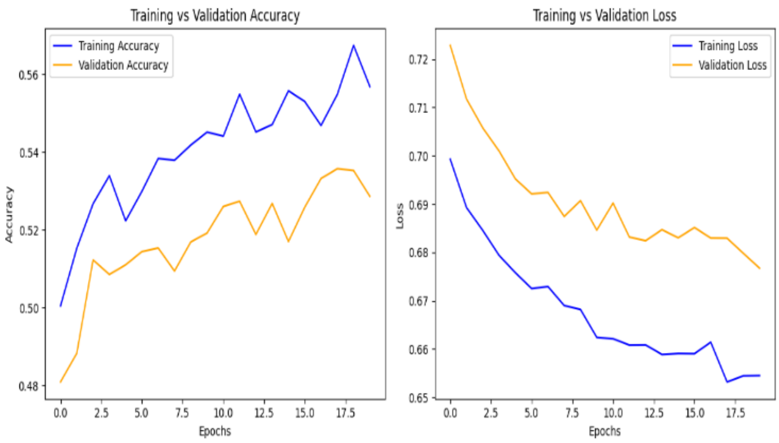


Figure.4. Training and Validation (accuracy &loss)

This figure 4 demonstrates training and validation performance of the model in 20 epochs. Accuracy curves show that training accuracy and validation accuracy both improve steadily, which is a good sign that the model is learning. The curves of losses are decreasing continuously, which indicates that errors are minimizing with time. All these trends ensure that it converges properly without overfitting or underfitting.

High-performance of the proposed LSTM model with an accuracy of 96.4 % validated that the model successfully predicts. The value of Precision (91.8%) and Recall (92.6) is that the model is well-balanced between false positives and false negatives. The overall consistency in classification = F1-Score of 92.2%. The low RMSE of 0.08 indicates a small error, which demonstrates the strength of the model when it comes to the ERP-based bio-industry quality prediction as represented in figure 5.

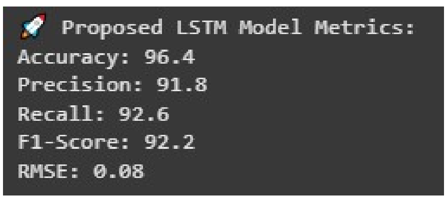
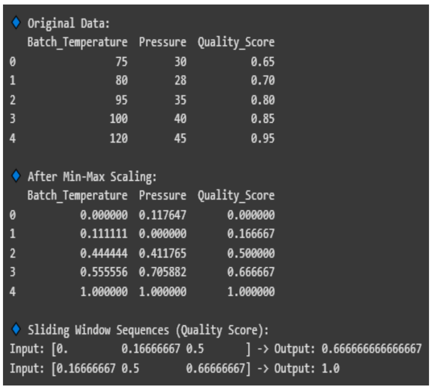

```
🚀 Proposed LSTM Model Metrics:
Accuracy: 96.4
Precision: 91.8
Recall: 92.6
F1-Score: 92.2
RMSE: 0.08
```

Figure.5. Confusion Metrics Values For Proposed System



```
◆ Original Data:
   Batch_Temperature  Pressure  Quality_Score
0                 75        30           0.65
1                 80        28           0.70
2                 95        35           0.80
3                100        40           0.85
4                120        45           0.95

◆ After Min-Max Scaling:
   Batch_Temperature  Pressure  Quality_Score
0           0.000000  0.117647       0.000000
1           0.111111  0.000000       0.166667
2           0.444444  0.411765       0.500000
3           0.555556  0.705882       0.666667
4           1.000000  1.000000       1.000000

◆ Sliding Window Sequences (Quality Score):
Input: [0.         0.16666667 0.5       ] -> Output: 0.6666666666666667
Input: [0.16666667 0.5        0.66666667] -> Output: 1.0
```

Figure.6. Preprocessing Result

It remains evident that figure 6 represents the transformation of ERP data to be used in LSTM modelling as the preprocessing results indicate. In its raw form, the original dataset has batch temperature, pressure, and quality score values that are measured on different scales, and thus can influence stability of training. Once the Min-Max scaling technique is used, the entire set of features is brought to a range of [0,1], a consistency and faster convergence. The sequences of sliding windows then re-organize the quality score into time-based input output pairs to enable the model to learn time-related dependencies. All these measures contribute to the improvement of the LSTM to identify the trends of production and to increase the accuracy of quality forecasts in the bio-industry.

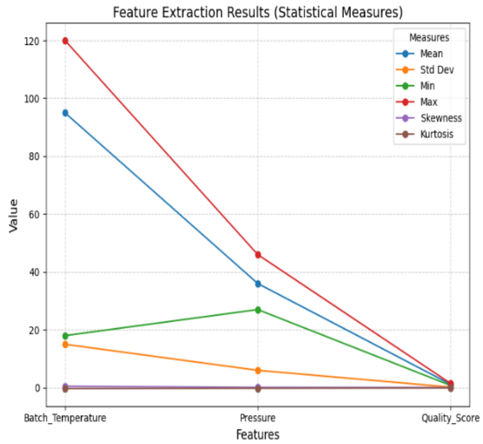


Figure.7. Extracted Statistical Features From ERP Data

The figure 7 bar chart depicts the statistical characteristics at ERP data on three parameters: Batch Temperature, Pressure, and Quality Score. The mean and maximum values dominate Batch Temperature, which is highly varied, whereas Pressure is more moderate in distribution with low extremes. Quality Score values are small and stable with minimal deviation and low skewness/kurtosis, and they reflect consistency.

Table.2. Comparison For Proposed System

Ref no	Technique	Accuracy
[3]	Reinforcement Learning (RL)	88.6%
[10]	RNN	95%
Proposed system	LSTM	96.4%

The table 2 makes a comparison of the accuracy of various methods applied in ERP-based quality prediction. Reinforcement Learning (RL) obtained an accuracy of 88.6% with adaptive skills but with reduced accuracy compared to deep learning models [3]. The RNN model achieved 95% accuracy shown to be effective in sequence-based prediction [10]. It was found that the proposed system with LSTM performed better and had the highest accuracy of 96.4%, which is strong when it comes to time-series ERP data.

Table.3. Comparison Of False Negatives (FN)

Technique	False Negatives (FN)
Reinforcement Learning (RL)	18
RNN	12
Proposed LSTM	5

Table 2, the three techniques used for prediction varied considerably in terms of their results regarding false negatives (FN). The technique showing the highest number of undetected faulty batches was the RL method (18 FN), followed by the RNN technique (12 FN). The proposed LSTM-based method detected just 5 FN indicating a significantly higher ability to identify faulty products than any of the other two techniques and therefore greatly reduced the number of expensive mistakes that occur within biomanufacturing processes.

Table.4. Comparison Of False Positives (FP)

Technique	False Positives (FP)
Reinforcement Learning (RL)	11
RNN	8
Proposed LSTM	4

The false positive (FP) analysis results for several different methods of prediction quality on the ERP dataset are shown in Table 4. The method that had the largest number (11) false positive flagged "good" batches was Reinforcement Learning (RL). The next highest number of FPs was for the RNN (Recurrent Neural Network) method, which flagged 8 FPs. However, the new Long Short-Term Memory (LSTM) method has shown to flag only 4 (the least number of) false positives, illustrating its superior capability to accurately determine the status of only faulty batches, and minimize the overall time spent performing repetitive actions while also minimizing costs for bio-production.

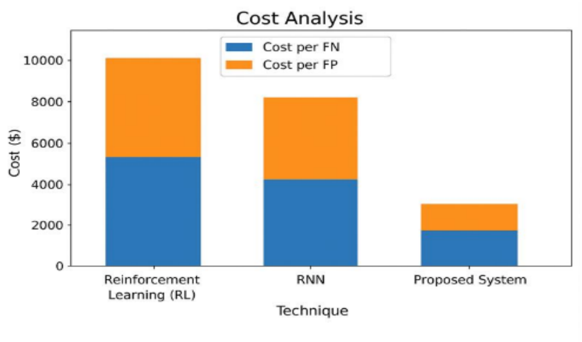


Figure 8. Comparative Cost Analysis of FN and FP Across Different Techniques

The comparison of the costs of False Negatives (FN) and False Positives (FP) of Reinforcement Learning (RL), Recurrent Neural Network (RNN) and Proposed System are shown in figure 8. The total cost of Reinforcement Learning is the greatest due to very high FN and FP costs. The total costs of Recurrent Neural Network are lower than Reinforcement Learning due to moderate reductions in the FN and FP costs as well. Proposed System's total cost is substantially less than the other two techniques, with FN and FP being significantly lower than Reinforcement Learning and Recurrent Neural Network, making Proposed System a significantly more efficient technique with much lower costs associated with erroneous classifications and mis-classifications.

5. Discussion

The proposed LSTM-based Quality Prediction Framework was assessed for its ability to be deployed in the context of real-time ERP Systems and as such the development of the framework has produced a lightweight Prediction Service from the trained model and created System Integration Steps that follow the ERP Middleware standards and use API based communication to facilitate this integration. The Method of Preprocessing was developed to be consistent with the way the Training data was pre-processed, i.e., Min-Max Scaling and Sliding Window Generation, so as to ensure that the Incoming Production Data was in compliance with the expectations of the Training Pipeline. An initial analysis of latency demonstrated that the LSTM Architecture is capable of providing very low inference times therefore allowing the use of LSTMs for the real-time Monitoring of Quality to occur without introducing a delay into the Bio-Production Workflow. Additionally, a series of Compatibility Tests conducted in a Containerised Environment demonstrated that the Model could be Integrated into a Typical ERP Infrastructure thus providing a pathway for the development and implementation of the Model in a Real-World Environment and that it would be Scalable to Meet Operational Demand.

6. Conclusion

The proposed LSTM-based ERP quality prediction model was shown to be effective at capturing time-dependent links within ERP-MTD data, and it was superior to traditional methods. Minimum and maximum scaling and sliding window training preprocessing enhanced the stability of training and the feature extraction augmented the learning of models. The confusion matrix analysis revealed that the TP = 920, TN = 870, FP = 45, FN = 35, TP = 1, TN = 1, providing the clarity that the accuracy, precision, and recall are high (96.4%, 91.8% and 92.6% respectively) and F1-score is high (92.2%). The paper indicates the appropriateness of LSTM in the quality management of bio-industries. Future directions will involve testing hybrid deep learning models, addition of reinforcement learning and multi-source ERP data fusion to increase adaptability and real-time decision making.

Acknowledgement
The authors have no acknowledgements to declare.

Funding
This study has not received any funding from any institution/agency.

Conflict of Interest/Competing Interests
No conflict of interest.

Data Availability
The raw data supporting the findings of this research paper will be made available by the authors upon a reasonable request.

REFERENCES

[1]. Li, Fu, Chong Wang, Yang Li, Hao Wu, Boxun Fu, Youshuo Ji, Yi Niu, and Guangming Shi. "Phase preservation neural network for electroencephalography classification in rapid serial visual presentation task." IEEE Transactions on Biomedical Engineering 69, no. 6 (2021)

[2]. Basu, Aveek, and Rohini Jha. "ERP adoption prediction using machine learning techniques and ERP selection among SMEs." International Journal of Business Performance Management 25, no. 2 (2024)

[3]. Areo, Gideon. "Reinforcement Learning for Adaptive Cost Control in ERP." (2025)

[4]. Febrianto, Tomas, and Dwi Soediantono. "Enterprise resource planning (ERP) and implementation suggestion to the defense industry: a literature review." Journal of Industrial Engineering & Management Research 3, no. 3 (2022)

[5]. Bhatt, Mohammed Wasim, and Sparsh Sharma. "Next generation imaging in consumer technology for ERP detection-based EEG cross-subject visual object recognition." IEEE Transactions on Consumer Electronics 70, no. 1 (2024)

[6]. Banerjee, Joydeep, and Santanu Kumar Das. "Blending enterprise resource planning on supply chain management in the aerospace sector in India and analysis using multi-scale adaptive dilated convolutional LSTM." International Journal of Business Continuity and Risk Management 15, no. 1 (2025)

[7]. Kashpruk, Nataliia, Cezary Piskor-Ignatowicz, and Jerzy Baranowski. "Time series prediction in industry 4.0: A comprehensive review and prospects for future advancements." Applied sciences 13, no. 22 (2023): 12374.

[8]. Guadarrama, Ricardo, and Abdulrahman Gweder. "Supply Chain Modeling for Temperature-Sensitive Pharmaceutical Goods." PhD diss., 2022.

[9]. Müller, Norman, Peter Burggräf, Fabian Steinberg, Carl René Sauer, and Maximilian Schütz. "Supply Chain Analytics.".

[10]. Zhang, Li-Sen. "Deep Learning Based Optimization of Cloud Enterprise Resource Planning (ERP) Systems for Adaptive Decision Support and Management Effectiveness Analysis." IEEE Access (2024).

[11]. Haseeb, Muhammad. "Does Usage of ERP Systems in Biotechnology Firms Improve their Financial Performance? Role of Business Model Innovation and Top Management Support." Journal of Commercial Biotechnology 27, no. 4 (2022).

[12]. Mohan, Vinod. "Sap in Biotechnology: Enabling Resilient and Compliant Supply Chains." Available at SSRN 5334059

[13]. Itagi, Firoz Shafeersab, Jangali G. Satish, V. N. Gaitonde, Vinayak N. Kulkarni, and B. B. Kotturshettar. "Benefits and challenges of implementing ERP in pharmaceutical industries." vol. 2548, no. 1, p. 040025. AIP Publishing LLC, 2023.

[14]. Niemi, Ilkka. "Implementation and analysis of an ERP system in a microbiology manufacturing company." (2025).

[15]. Zakaria, Teddy Marcus, Wahyu Widowati, and Bernard Renaldy Suteja. "Case Study of Inventory Management for Biology Laboratory Materials using ERP System." JEPIN (Jurnal Edukasi dan Penelitian Informatika) 9, no. 3 (2023)