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Digital Infrastructure Optimization: Aligning System Architecture With Scalable Performance

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Abstract
The digital infrastructure becomes crucial for smart manufacturing, which uses massive amounts of data generated by industrial IoT (Internet of Things). However, the current manufacturing infrastructures face challenges in processing large volumes of heterogeneous data and are unable to provide intelligent high-performance analytics by incorporating the DE-Trans WLSTM. Data is collected using industrial sensors that have been installed inside the machines and monitor different parameters like the temperature, vibration, pressure, and state of the machine. Standardisation using z-score normalization is used as the Preprocessing method in order to regulate the heterogeneous input data and avoid sensitivity to noise. Feature Extraction is done using the discrete wavelet transform which has the ability to decompose the time-series signal into various resolution levels to identify the transient variations as well as steady-state conditions of machine performance. The proposed DE-Trans WLSTM uses differential evolution to tune the parameters, Transformers for context-based learning, and the weighted LSTM for modelling temporal dependencies. Therefore, with this model, predictions on machine failures and workload are performed accurately. Microservices, containerisation, and intelligent resource management have been incorporated into the system to enable scalability, fault tolerance, and low-latency performance. Simulated results of the proposed method significantly overcomes the traditional models, achieving 98.55% prediction accuracy in the Python. The integration of advanced deep learning with optimised infrastructure provides a robust solution for Industry 4.0 environments, facilitating reliable, scalable, and data-driven manufacturing operations.

Keywords: Digital infrastructure, Manufacturing, Industrial Internet of Things (IIoT), Deep Learning (DL).

1. Introduction

The factors like global competition, increasing market demands, and operational efficiency are among those responsible for the speedy growth of the industrial sector. For ensuring efficient operations and high-quality products, it is essential for today's companies to make sure that there is optimal coordination between the processes, resources, and information flow in production. Businesses find it difficult to manage huge volumes of operational information and ensure effective communication between different systems due to increased complexity in industrial processes. But with changing industrial requirements, it becomes essential for organizations to create a reliable digital structure [1]. In order to successfully deal with the aforementioned challenges, it is essential that manufacturing system improve their digital infrastructure.

Efficient management of resources, operational resilience, and visibility of processes can be facilitated through improved infrastructure. Smart manufacturing technologies require state-of-the-art digital technology for ensuring successful, reliable, and highly-efficient manufacturing activities. Through the integration of IoT, Artificial Intelligence (AI), Machine Learning (ML), Cloud Computing (CC), Cyber-Physical Systems (CPS) monitoring, predictions, and intelligent decision-making in manufacturing organizations have become feasible. While cloud-based systems allow scalability in terms of computation and data storage, sensors within the IoT infrastructure continuously collect data from machinery and production lines [2]. High volumes of data can be processed using machine learning and artificial intelligence approaches for predicting equipment failures, scheduling production, and optimizing resource performance. With their ability to support proactive maintenance strategies, digital twins and predictive maintenance systems contribute to greater reliability. Besides, smart supply chains allow seamless information exchange and collaboration between stakeholders. These processes assist in minimizing energy consumption, increasing flexibility, boosting efficiency, and decreasing downtime [3]. The high cost of implementation, security issues, and integration difficulties are the key problems related to implementing IoT, AI, ML, CC, and CPS technologies into smart manufacturing processes. It is quite difficult for many companies, particularly for SMEs, to implement advanced digital technology and replace old-fashioned methods. The enormous volume of data collected through networking requires appropriate means of data management and processing [4]. Performance of machine learning and artificial intelligence models can also be impacted negatively due to poor quality of data, which would make such systems give incorrect predictions and inefficient operation. Industries face great threats from cyber security issues like ransomware attacks, unauthorised access and data breaches. Lack of qualified professionals to manage these advanced technologies is another challenge for adoption. Through digital transformation, it tries to enhance the efficiency of smart manufacturing systems [5].

Research aim: This research aims to develop the DE-Trans WLSTM method to evaluate a digital infrastructure improved for smart manufacturing systems that enhances scalability, operational efficiency, reliability, and resource utilisation.

Research organisation: In Section 1, it provides context and motivation for digital infrastructure optimization in smart manufacturing environments, IIoT, edge computing, cloud platforms, and AI in enabling scalable and high-performance industrial operations. Section 2 discusses relevant works on smart industrial infrastructures, predictive analytics, transformer-based learning models, and drive on deep learning methods. Section 3 discusses the proposed DE-Trans WLSTM and memory prediction, which includes Z-score normalisation and DWT-based feature extraction. Section 4: The comparison of the results obtained from the proposed method and existing methods. Finally, Section 5 outlines future research paths for scalable digital infrastructure management in Industry 4.0 and the conclusion of the Digital Infrastructure Optimization for Smart Manufacturing Systems.

2. Related works

Table 1 shows a comprehensive review of recent studies related to smart manufacturing such as technologies, predictive maintenance, highlighting their methodologies and intelligent industrial systems.

Table 1: Overview of the previous research on Smart manufacturing system.

Ref	Research Focus	Techniques/Methods	Dataset Used	Major Findings	Limitations
[6]	Intelligent condition monitoring and fault diagnostics	ML-based predictive analytics, regression analysis, and reliability testing	Data collected from 241 industry professionals through surveys and operational assessments	Improved operational performance and predictive maintenance effectiveness	Limited sampling and reduced generalizability
[7]	Energy-efficient Industry 4.0 smart factories	IoT, AI, ML, Big Data Analytics (BDA), and Energy Management Systems (EMS)	Industrial energy consumption and smart factory operational datasets	Enhanced efficiency, resource performance, and energy savings	High implementation cost,cybersecurity risks, and complexity
[8]	Digital Twin-based equipment monitoring	Digital Twin (DT), Blockchain, IoT, and Dual-Directional	Simulated industrial equipment monitoring dataset	Achieved 92.25% accuracy with low	Simulation-based validation and

		Convolutional Neural Network (DD-CNN)	generated through DT environment	latency and high monitoring reliability	computational complexity
[9]	Smart tool condition monitoring for CNC machining	Multi-sensor data acquisition, Raspberry Pi controller, Thing Speak cloud platform, and Fuzzy Logic (FL)	Real-time sensor data (vibration, temperature, current, and tool wear measurements) collected from CNC machines	Effective tool wear and machine degradation detection	Dependence on sensor quality and cloud connectivity
[10]	Industry 4.0 wireless communication architecture	Private Hybrid Wireless Access Network (PHWAN), MATLAB simulation, and cost-benefit analysis	MATLAB-generated network simulation dataset	Improved security, bandwidth, and reduced latency	Lack of practical deployment
[11]	Embodied intelligence-driven manufacturing ecosystem	Embodied Smart Manufacturing Empowerment (ESME) framework and Embodied Intelligence (EI) analysis	Conceptual framework and industrial case-based data	Improved flexibility, collaboration, and adaptive decision-making	Limited industrial validation
[12]	Advanced smart manufacturing technologies	Advanced computing technologies, high-performance materials, and scalable manufacturing techniques	Literature-based industrial manufacturing datasets and case studies	Enhanced personalization, production flexibility, and adaptability	High investment cost and interoperability challenges
[13]	Productivity enhancement using Industry technologies	Integration of AI, IoT, and Big Data Analytics (BDA)	Industrial operational and production performance datasets	Improved productivity, product quality, and operational efficiency	Infrastructure and workforce training requirements
[14]	Smart and Sustainable Manufacturing System (SSMS)	Digital Poka-Yoke, Single-Minute Exchange of Die (SMED), Value Stream Mapping (VSM), and Define–Measure–Analyse–Improve–Control (DMAIC)	Manufacturing process data from a real industrial case study	Increased production yield, worker utilisation, and workplace safety	Validation limited to a single case study
[15]	Intelligent industrial maintenance through TPM 4.0	TPM 4.0 integrated with DMAIC and digital maintenance technologies	Equipment maintenance records and machine performance datasets	Enhanced equipment effectiveness, resilience, and predictive maintenance capability	Lack of large-scale industrial validation
[16]	AI-driven smart production and industrial security	ML-based Smart Production Platform (ML-SP2) and ML-based Intrusion Detection System (ML-IDS) using Random Forest (RF), Decision Tree(DT),SupportVector Machine(SVM),andConvolution al Neural Network (CNN)	Industrial network traffic and production system datasets for intrusion detection and performance monitoring	Improved production efficiency, cybersecurity, and operational reliability	Limited evaluation across diverse industrial environments and scalability scenarios

Research gap: Current digital infrastructure optimization techniques for smart manufacturing frequently face challenges. The ability to extract time-frequency characteristics and capture long-term relationships among infrastructure components is limited by traditional ML and DL models. Additionally, they show less flexibility in responding to shifts in resource usage and task patterns. To overcome these issues, the method of integrating DE-Trans WLSTM solves these constraints by integrating optimal feature learning, global contextual analysis, and temporal prediction into a single framework, resulting in increased accuracy, scalability, and decreased computing time.

3. Methodology flow of the system

An open-source smart manufacturing system dataset including machine and infrastructure-related parameters is the starting point for the suggested architecture. To regulate heterogeneous data, Z-score normalisation and time-frequency characteristics are extracted from the standardised signals using DWT. The prediction model's hyperparameters are then improved via DE to improve forecast accuracy and learning efficiency. While the WLSTM learns temporal patterns and workload fluctuations from historical data, the Transformer processes the optimised features to capture global relationships across smart infrastructure metrics and their flow is presented in Figure 1.

Figure 1: The overall assessment of the methodology flow

3.1 Dataset collections: This dataset contains 12,000 smart manufacturing operation records collected from industrial machines and digital infrastructure environments (https://www.kaggle.com/datasets/colabsss/smart-manufacturing-iiot-operations-data). It includes machine sensor readings, production-line details, environmental conditions, workload indicators, infrastructure performance values, resource usage metrics, and operational status labels. The dataset is suitable for examining scalable manufacturing infrastructure, equipment condition, workload performance, resource efficiency, and smart factory operation, the data were splitted with 70% of the data allocated for training and 30% allocated for testing the proposed model.

3.2 Data Preprocessing using z-score normalisation: It is a data Preprocessing technique used to regulate numerical attributes by transforming their values standardized to common scale with mean of 0 and deviation of 1. For the purpose of smart manufacturing systems, data from operations are collected from several sources including IoT sensors, manufacturing machines, networking infrastructure, clouds, and enterprise software. Due to the diverse nature of these features whereby the units and scales differ, a standardisation approach known as Z-Score Normalisation is used for eliminating scaling differences in Equation (1).

$$N_i = \frac{D_I - \bar{D}}{\sigma_D} \qquad (1)$$

Where: N_i = standardised value (Z-score), D_I = original value of the attribute, $\bar{D}$ = mean value of the attribute, σ_D = standard deviation of the attribute.

3.3 Feature extraction using discrete wavelet transform (DWT)

DWT is employed to extract meaningful characteristics in time-frequency analysis of industrial sensor data. DWT decomposes the signal into approximation and detail coefficients at various resolution levels. The approximation coefficients help in extracting information about trend and stable states, while the detail coefficients extract any sudden changes or anomalies that occur in the signal. In this way, DWT provides an improved feature extraction mechanism that is less sensitive to noise. For this reason, DWT improves the performance of the DE-Trans WLSTM model for the prediction of operating levels of the infrastructure as in equation (2).

$$F(a,b) = \sum_t I(t)\, \varphi_{a,b}(t) \qquad (2)$$

Where: $F(a,b)$= wavelet coefficient at scale a and position b, $\varphi_{a,b}(t)$= wavelet basis function, $\boldsymbol{a}$ = decomposition level (scale), b = translation parameter, $I(t)$= infrastructure signal at time, $\sum_t I(t)$ =Summation operator used to compute wavelet coefficients across the signal.

3.4 Predictive maintenance system using DE-Trans WLSTM

A DE-Trans WLSTM architecture is developed to overcome the issues of scalability, resource operation, and infrastructure performance prediction in smart manufacturing environments. DE is an evolutionary optimization algorithm used to identify optimal model parameters and enhance prediction performance. A transformer model that captures complex feature relationships and long-range dependencies within manufacturing data. WLSTM network that assigns adaptive weights to important features for accurate temporal pattern learning and forecasting.

3.4.1 Transformer for contextual learning strength

The Transformer module is used to identify global relationships between digital infrastructure variables in smart manufacturing systems. The Transformer uses its self-attention mechanism to identify complicated correlations between important infrastructure metrics, including network latency, resource allocation score, scalability index, throughput, and system workload. Unlike standard sequential models, it examines interactions between many characteristics at the same time, regardless of where they appear in the input sequence. It is through this method that the model gains an understanding of infrastructure performance and underlying relationship patterns. Additionally, the Transformer enhances feature extraction by emphasizing the most relevant details in prediction.

Self-attention technique: To detect correlations between indicators such as network latency, resource allocation score, scalability index, and throughput, the Transformer helps the model gain an insight into the complex relationships in smart infrastructure equation (3).

$$I_{att} = softmax(\frac{RS^T}{\sqrt{d_S}})\mathrm{U} \quad (3)$$

Where: I_{att}=Representation output from Attention mechanism, R = Query, **S** = Key, U = Value, d_S = dimension of key vectors, $softmax$=Activation function to convert attention outputs into probabilities.

Feed-Forward Network (FFN): Once the self-attention process is done, the FFN obtains high-level infrastructure representation through learning complex operational patterns of equation (4).

$$F_{infra} = c_2 + T_2 \emptyset(c_1 + T_1 \mathrm{Z}) \quad (4)$$

Where: F_{infra} = FFN output, T_1, T_2= weight matrices, $c_1 c_2$ = bias vector, $\emptyset$ = GELU activation function, Z= attention feature vector.

Residual Connection and Layer Normalisation: Residual connections are used to preserve important infrastructure information and improve gradient propagation. The Layer Normalisation is used to fixed the training in equation (5).

$$D_{out} = LayerNorm(D_{in} \oplus F_{infra}) \quad (5)$$

Where: F_{infra} = FFN output, $\oplus$ = residual addition, D_{out}= standardised infrastructure representation, D_{in}= input infrastructure feature.

3.4.2 Weighted long short-term memory for temporal dependency modelling

WLSTM is used to capture temporal dependencies and workload fluctuations in smart manufacturing systems. Unlike typical LSTM models, WLSTM uses a weighted memory mechanism to selectively preserve significant past information while incorporating current operational data. This allows model to successfully learn both short-term fluctuations and long-term interactive patterns from industrial infrastructure data. The adaptive memory update mechanism enhances the depiction of dynamic workload changes and infrastructure circumstances. Consequently, WLSTM improves prediction accuracy, stability, and simplification performance on equation (6).

$$g_t = \sigma(A_g[I_t H_{t-1}, M_{t-1}] + B_g) \quad (6)$$

Where: I_t = current infrastructure state, H_{t-1} = previous hidden representation, M_{t-1} = previous memory state, g_t=Memory gate value at time (t), σ=Sigmoid activation function, A_g=Weight matrix of the memory gate, B_g=Bias term of the memory gate.

Memory update: Its equation uses the gating mechanism to integrate the existing memory state with the newly produced candidate memory state. This allows the WLSTM to preserve vital historical knowledge while also absorbing new operating trends derived from smart manufacturing data on equation (7).

$$M_t = M_{t-1} * g_t + \bar{M}_t * (1 - g_t) \quad (7)$$

Where: M_t=Updated memory state at time (t), M_{t-1}=Previous memory state, g_t=Memory gate controlling information retention, $\bar{M}_t$=Candidate memory state, $*$ =multiplying the 2 values.

Candidate memory state: It generates new information from the input data and the previously hidden representation. Tanh activation function transforms the gathered information within the limited range, thus improving the stability of learning in equation (8).

$$\bar{M}_t = tan\,h\,(A_m[I_t H_{t-1}] + B_m \quad (8)$$

Where: $\bar{M}_t$=Candidate memory state, $tan\,h$= Activation function of hyperbolic tangent, A_m=Weight matrix to generate memory state, B_m=Bias term, I_t =Current input feature vector, H_{t-1} = Previous hidden representation.

Hidden representation: It consists of both the updated memory state and the transformed current input signals. It improves temporal learning and makes accurate predictions about the infrastructure performance possible according to equation (9).

$$H_t = R_t * tan\,H\,(M_t) + (1 - R_t) * L_t \quad (9)$$

Where: H_t= Hidden state at time (t), R_t=output gate, M_t=updated memory state, L_t=current input state, $tan\ H$=Hyperbolic tangent activation function.

Prediction error: It is the absolute difference between the expected operational level of the infrastructure and its actual value. Smaller prediction errors indicate better prediction capabilities of the model in equation (10).

$$E_t = \left|\hat{O}_t - O_t\right| \quad (10)$$

Where: $\hat{O}_t$ = predicted operating level of infrastructure, O_t = Actual operating level of infrastructure, E_t = Error prediction.

3.4.3. Differential evolution (DE) for parameter tuning

DE is used to automatically tune the hyperparameters of Transformer and WLSTM, eliminating the need for manual hyperparameter adjustment. In the process, DE produces candidates and evolves them by means of mutation, crossover, and selection operations. Eventually, DE finds out the best set of hyperparameters that maximises the performance of the algorithms. Tuning the hyperparameters helps in increasing the learning capacity of the Transformer and WLSTM, thus improving their convergence and stability. Hence, the DE-based hyperparameter tuning greatly boosts up the prediction accuracy while reducing the prediction error, as presented in Equation (11).

$$M_{i,t} = P_{a,t} + Y(P_{b,t} - P_{c,t}) \quad (11)$$

Where: $M_{i,t}$ = mutant vector, $P_{a,t},\ P_{b,t},\ P_{c,t}$ = randomly selected solutions, Y = mutation factor.

Algorithm 1: DE-Trans WLSTM

$Input: D, NP, MaxIter$
$Output: O$
$Begin$
$Load\ D$
$Normalize\ data: Ni = (Di - \bar{D})/\sigma D$
$Extract\ DWT\ features: F(a,b) = \Sigma I(t)\varphi(a,b)(t)$
$Initialize\ DE\ population\ (NP)$
$Optimise\ Transformer\ and\ WLSTM\ hyperparameters\ using:$
$M(i,t) = P(a,t) + Y(P(b,t) - P(c,t))$
$Apply\ Transformer\ attention:$
$Iatt = softmax(RS^{T}/\sqrt{d}S)U$
$Apply\ WLSTM\ memory\ update:$
$Mt = Mt - 1 \times gt + Mt \times (1 - gt)$
$Predict\ infrastructure\ operation\ level\ \hat{O}t$
$Compute\ error: Et = |\hat{O}t - Ot|$
$Optimise\ resource\ allocation, workload\ balancing,$
$and\ scalability\ using\ predicted\ outputs$
$Return\ O$
End

Algorithm 1 introduces the DE-Trans WLSTM for digital infrastructure optimization in smart manufacturing systems. The industrial data is first normalised using Z-scores and then converted into useful time-frequency characteristics using DWT. DE is then used to optimise the hyperparameters of the Transformer and WLSTM models. The Transformer identifies global infrastructure dependencies, whereas WLSTM learns temporal operational patterns. Finally, the improved model forecasts the infrastructure operating level, enabling effective and scalable digital infrastructure management.

4. Result and discussion

In this section, the experimental analysis of the proposed predictive maintenance is discussed, integrating the DE-Trans WLSTM model with baseline DL. Performance is assessed using Accuracy, Precision, Recall, and F1-score to predict fault detection and classification reliability, which were stimulated using Python. The results indicate that the proposed approach outperforms others in prediction accuracy and system robustness for diagnosing faults in IIOT smart manufacturing system.

4.1 Data feature exploration analysis

Figure 2 depicts the operational state of the smart manufacturing infrastructure based on important digital infrastructure characteristics such as network latency, temperature and scalability index. Figure 2(a) presents the variation of machine temperature; Figure 2(b) presents the relationship between network latency and operation state. Figure2(c) presents 3D scatter plot showing the relationship between machine temperature, vibration, service response time, and the scalability index. The visualization highlights how variations in these operational parameters influence the scalability and overall performance of the smart manufacturing system.

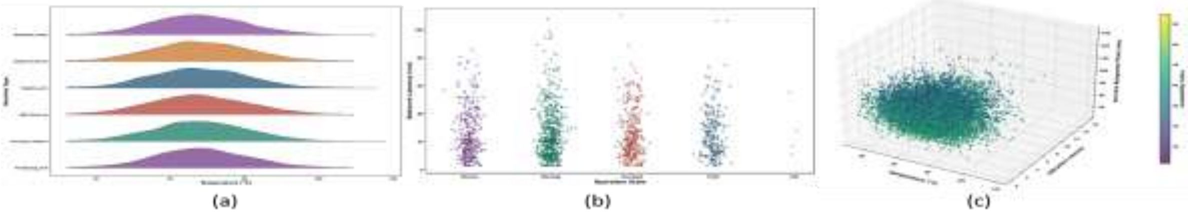

Figure 2: Analysis of (a) the variation of machine temperature, (b) the network latency and operation state analysis. (c)The analysis of temperature, vibration and service response with the scalability index.

Figure 3 shows the proposed DE-Trans WLSTM model predicts infrastructure operation levels. Figure 3(a) depicts the numerous infrastructure performance patterns observed during system operation, allowing for the identification of normal and pathological operating states. Figure 3(b) depicts the link between feature standardisation and machine features, illustrating how the preprocessing stage standardises heterogeneous data and increases feature consistency to enable successful model learning. Figure 3(c) depicts a stacked area depiction of standardised infrastructure characteristics, emphasising the contribution and fluctuation of several operational parameters across time.

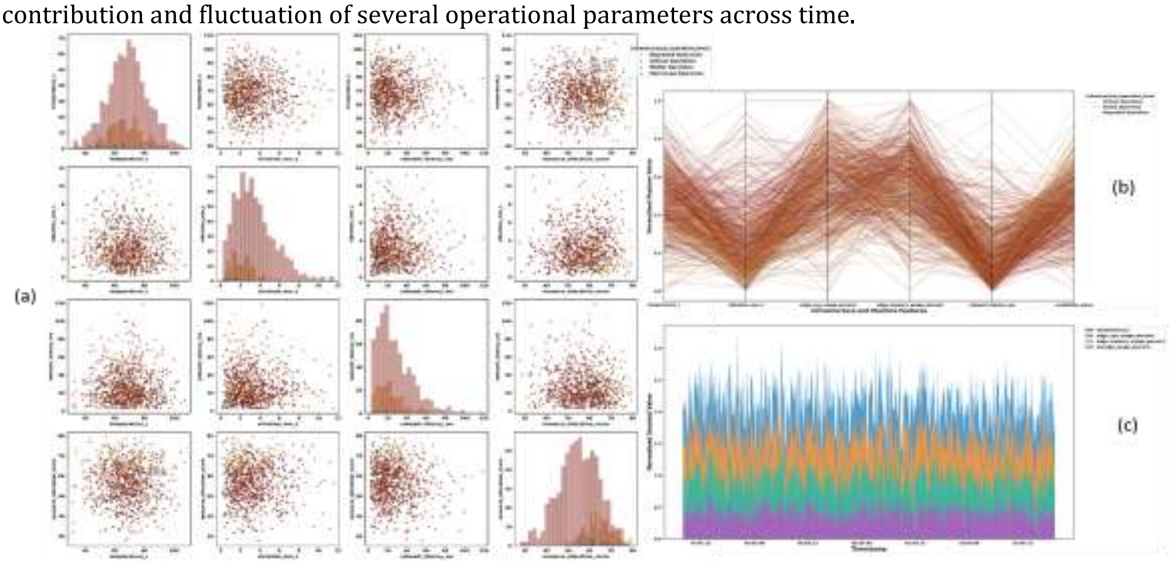

Figure 3: Analysis of (a) Various infrastructure actions to analysis, (b) The analysis of feature standardisation and the machine feature, (c) The stacked areas of infrastructure standardisation.

4.2 Metrics evolution

Accuracy: This metric evaluates the overall accuracy of the model by taking into consideration the percentage of correct classification against the number of total samples. Accuracy gives an idea of the model performance but could be unreliable when the dataset has class imbalance problems. **Precision:** This metric describes the percentage of correct predictions made by the model among those that have been classified as positive. The metric assesses the capability of the model in detecting the true positive cases without making a wrong decision. **Recall:** It describes how many positives can be detected among all existing positives. The metric is significant in predictive maintenance since it evaluates the capability of the model in identifying all possible faults. **F1 score:** It is calculating the harmonic mean of precision and recall metrics. **Computation time:** Time consumed by the model in executing the learning and prediction processes.

Performance evaluation using existing dataset: The DE-Trans WLSTM approach was trained on the Smart Production Processes (SP2) dataset [16], where smart manufacturing facilities and process data have been recorded. In comparison to the existing ML-SP2-IDS [16] system that takes 9.87 s for computation, the new approach managed to attain an optimized computation time of 8.32 s.

Performance evaluation using smart-manufacturing IIoT operations-dataset: Both the suggested DE-Trans WLSTM and the existing ML-SP2-IDS [16] approaches have been trained and tested using the same smart manufacturing IIoT operations-dataset. As shown in Table 2, it is evident that the performance of the new approach exceeds that of the other two approaches in all test criteria. The combination of Differential Evolution, Transformers, and WLSTM in the proposed model makes it possible to learn about the global infrastructural dependence and operation patterns, hence improving prediction and classification accuracy, as seen in Figure 4. The performance results of this method include an accuracy of 98.55%, precision of 97.65%, recall of 97.12%, F1-score of 98.20%, and computation time of 7.34.

Table 2: Comparison of existing and proposed data trained on the SP2 dataset.

Methods	Precision(%)	F1-score(%)	Accuracy (%)	Recall(%)	Computation time (s)
ML-SP2-IDS	97.2	97.14	96.5	96.67	8.54
DE-Trans WLSTM [Proposed]	97.65	98.2	98.55	97.12	7.34

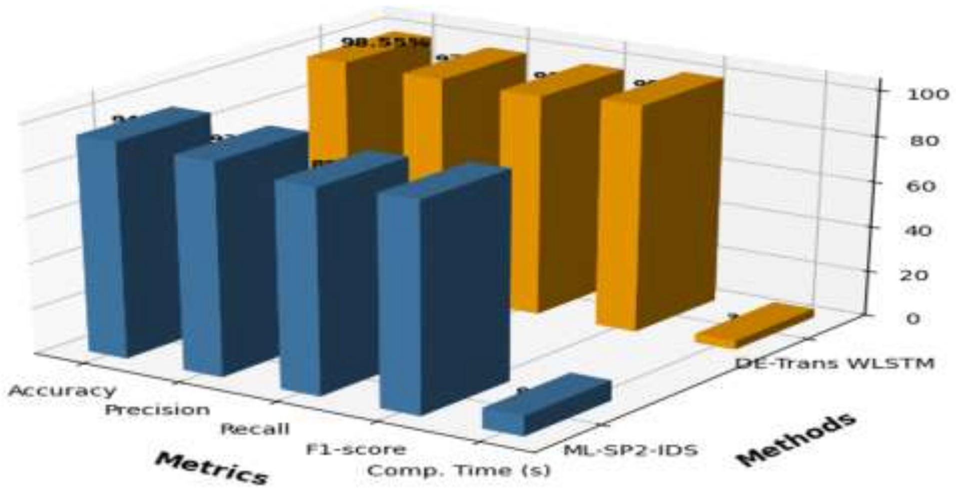

Figure 4: Comparison of existing and proposed data trained on the Smart Manufacturing IIoT Operations dataset.

Discussion: As such, the current ML-SP2-IDS [16] model is unable to identify complex interrelationships among the variables of the industrial machines and the smart manufacturing systems, which affects the prediction accuracy when the operations change. Additionally, tuning the parameters manually is a time-consuming process that adds to the computation cost and decreases flexibility. In addressing these limitations, DE-Trans WLSTM makes use of multiple stages to provide a solution. Through DE, there is automatic tuning of model parameters, thus reducing human intervention in the optimization process. Meanwhile, the transformer will apply self-attention algorithms to handle complex interrelations among the infrastructural variables.

5. Conclusion

The developed DE-Trans WLSTM for optimisation of the digital infrastructure in smart manufacturing system comprises z-score standardisation, DWT feature extraction, DE, Transformer, and WLSTM. It is demonstrated that the suggested approach effectively captured both dependencies of the infrastructure and operational processes and thus improved the performance of prediction. Compared to previous models, the experiments showed an increase in accuracy and computing speed by 7.34. However, the developed DE-Trans WLSTM overcomes the identified limitations through the combination of optimal feature learning, contextual analysis, and prediction in one framework, which increases both accuracy and decreases computing costs. Adding several deep learning units increases the complexity of training and processing. Further studies will focus on lightweight design, edge computing, and the application of new IIoT sources.

References

1. Singh, J., Singh, A., Singh, H. and Doyon-Poulin, P., 2025. Implementation and evaluation of a smart machine monitoring system under the Industry 4.0 concept. Journal of Industrial Information Integration, 43, p.100746.https://doi.org/10.1016/j.jii.2024.100746

2. Zhang, Y., Feng, Q., Fan, D., Ren, Y., Song, Y., Liu, M. and Wang, Z., 2025. Predictive control for operation and maintenance in smart manufacturing systems with multiple operating modes. Computers & Industrial Engineering, 207, p.111196. https://doi.org/10.1016/j.cie.2025.111196
3. Lee, K.L., Wong, S.Y., Alzoubi, H.M., Al Kurdi, B., Alshurideh, M.T. and El Khatib, M., 2023. Adopting smart supply chain and smart technologies to improve operational performance in the manufacturing industry. International Journal of Engineering Business Management, 15, p.18479790231200614. https://doi.org/10.1177/18479790231200614
4. Abaza, B.F. and Gheorghita, V., 2025. Artificial neural network framework for hybrid control and monitoring in turning operations. Applied Sciences, 15(7), p.3499. https://doi.org/10.3390/app15073499
5. Mazhar, T., Shahzad, T., Rehman, A.U. and Hamam, H., 2025. Integration of smart grid with Industry 5.0: applications, challenges and solutions. Measurement: Energy, 5, p.100031. https://doi.org/10.1016/j.meaene.2024.100031
6. Arifeen, S., 2025. AI-Driven Condition Monitoring and Fault Detection in Electrical Power and Industrial Control Systems. ASRC Procedia: Global Perspectives in Science and Scholarship, 1(01), pp.1778-1809. https://doi.org/10.63125/csjs7238
7. Rakic, S., Marjanovic, U. and Medic, N., 2025. Advancements in Smart Manufacturing and Industry 4.0. Applied Sciences, 15(22), p.11903. https://doi.org/10.3390/app152211903
8. Ahanger, T.A., Bhatia, M., Alabduljabbar, A. and Albanyan, A., 2026. Applied artificial intelligence-based equipment condition monitoring in the manufacturing industry. Engineering Applications of Artificial Intelligence, 163, p.113138. https://doi.org/10.1016/j.engappai.2025.113138
9. Jones, T. and Cao, Y., 2025. Tool wear prediction based on multisensor data fusion and machine learning. The International Journal of Advanced Manufacturing Technology, 137(9), pp.5213-5225. https://doi.org/10.1007/s00170-025-15472-4.
10. Othman, N.I., Syed, H.J., Ramly, A.M., binti Suhaimi, N.H.S., Ali, A., Abdulnabi, M. and Ismail, A.F., 2026. Beyond 5G: PHWAN–A secure, low-latency, and cost-effective framework for Industry 4.0 smart manufacturing. Egyptian Informatics Journal, 33, p.100859. https://doi.org/10.1016/j.eij.2025.100859
11. Zhou, X., Hou, H., Liang, W., Wang, K.I.-K., & Jin, Q. (2023). Intelligent containment control with double constraints for cloud-based collaborative manufacturing. IEEE Transactions on Industrial Informatics, 19(6), 7541–7551. https://doi.org/10.1109/TII.2022.3211878.
12. Antony Jose, S., Tonner, A., Feliciano, M., Roy, T., Shackleford, A. and Menezes, P.L., 2025. Smart manufacturing for high-performance materials: advances, challenges, and future directions. Materials, 18(10), p.2255. https://doi.org/10.3390/ma18102255
13. Olsen, T.L. and Tomlin, B., 2020. Industry 4.0: Opportunities and challenges for operations management. Manufacturing & Service Operations Management, 22(1), pp.113-122. https://doi.org/10.1287/msom.2019.0796
14. Rahardjo, B., Wang, F.K., Yeh, R.H. and Chen, Y.P., 2023. Lean manufacturing in Industry 4.0: a smart and sustainable manufacturing system. Machines, 11(1), p.72. https://doi.org/10.3390/machines11010072
15. Gomaa, A.H., 2025. Advancing total productive maintenance in smart manufacturing: from methodology to implementation. Intelligent and Sustainable Manufacturing, 2(2), p.10019. https://doi.org/10.70322/ism.2025.10019
16. Shkarupylo, V., Alsayaydeh, J.A.J., Yusof, M.F.B., Oliinyk, A., Artemchuk, V. and Herawan, S.G., 2024. Exploring the potential network vulnerabilities in the smart manufacturing process of Industry 5.0 via the use of machine learning methods. IEEE Access, 12, pp.152262-152276.https://doi.org/10.1109/ACCESS.2024.3474861.