SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Trust-Aware Models For Machine-Mediated Human–AI Interactions

Ganesh Pathak[1], Rajashri CK[2], Malarvizhi S[3], Gaoudam Nadarajane[4], Raman Verma[5], Jennifer D[6]

[1] Associate Professor, Balaji Institute of Modern Management, Sri Balaji University, Pune – 411033, Maharashtra, India. ORCID: 0000-0003-0427-2145
[2] Assistant Professor, Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: rajashrick@maher.ac.in
[3] Assistant Professor, Department of Commerce, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: malarvizhicom@maher.ac.in
[4] Associate Professor, Department of Medical Surgical Nursing, Vinayaka Mission's College of Nursing, Karaikal, Vinayaka Mission's Research Foundation (Deemed to be University), Salem, India. Email: gaoudam@gmail.com, ORCID: 0000-0002-4615-2689
[5] Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab 140401, India. Email: raman.verma.orp@chitkara.edu.in, ORCID: 0009-0006-5137-2260
[6] Assistant Professor, Department of Computer Science and Engineering, Panimalar Engineering College, India. Email: jenniferg.cse@gmail.com, ORCID: 0000-0003-3362-4242

Abstract
The rapid growth in industry resulted in the development of intelligent manufacturing systems that combine automation, Artificial intelligence (AI), and collaboration. Predictive Maintenance (PdM) systems available so far lack trust mechanisms and human-AI interaction capabilities. To solve this problem, this research introduced a trust-aware PdM approach by designing a hybrid Giant Trevally-optimized Intelligent Bidirectional Long Short-Term Memory (GT-IntBiLSTM) model. For this purpose, the Industrial Equipment Monitoring Dataset from Kaggle is used, which consists of multivariate data. Data preprocessing employs the Isolation Forest (IF) algorithm for removing outliers and a robust scaler for normalization. Independent Component Analysis (ICA) is used for feature extraction of latent features in industry data. The IntBiLSTM algorithm captures bidirectional dependencies within machine behavior and predicts faults and health status of machines. The GTO technique optimizes parameters used by learning models to improve learning capabilities. The proposed model provides trust-aware decision-making aids, helping people make informed choices about the maintenance of equipment and machines. The experimental findings prove that the suggested method outperforms the baseline methods regarding Root Mean Square Error (RMSE) of 30.178, Coefficient of Determination (R^2) of 0.978, and Mean Absolute Error (MAE) of 20.034. The proposed model is implemented using Python-based Deep Learning (DL) tools which emphasizes the significance of incorporating trust-aware learning into advanced DL algorithms.

Keywords: Artificial Intelligence (AI), Industry, Trust, Human-AI, Predictive Maintenance (PdM), Fault Detection.

1. Introduction

The concept of Industry 4.0 has brought about revolutionary changes in the world of manufacturing through automation, Artificial Intelligence (AI), and the use of sensors, ensuring efficiency improvements, quality of the manufactured products, and operations management [1]. Machinery health management in industry improves the surveillance, evaluation, and optimization of machinery within manufacturing, packaging, and assembling. Using sensors and intelligent fault diagnostics, industries achieve more reliable operations with reduced downtime and efficient processes [2]. Predictive maintenance (PdM) plays an important role in maintaining industrial equipment. It helps reduce downtime, cut costs, and improve reliability. Using sensor information and analytics enables fault prediction and ensures smooth industrial operations [3]. An economical modular sensor platform provides an efficient solution for PdM operations within the industrial sector through its ability to predict failure occurrences and enhance operational efficiency and adaptability to changing industrial needs [4]. AI can change the dynamics of power production through improved fault management and efficient operation. Smart grid and AI-based surveillance systems can identify and fix faults to ensure an efficient and reliable source of energy in industrial infrastructure [5]. The data-driven Digital Twin (DT) in Industry 4.0 provides simulations for manufacturing processes. The benefits of Machine Learning (ML) include accurate predictions that help identify faults earlier, efficient energy consumption, proper controls, and sustainable quality manufacturing [6]. Industry 5.0 focuses on human-centric manufacturing through the combination of AI and collaboration technologies for promoting well-being, sustainability, and resilience. Through human-machine collaboration and additive manufacturing, Industry 5.0 transforms traditional manufacturing performance to enhance personalized, efficient, and socially responsible [7]. The goal of this research aims at developing a trust-oriented hybrid Giant Trevally optimized-Intelligent Bidirectional Long Short-Term Memory (GT-IntBiLSTM) system for machine-enabled Human-AI Interaction within smart industrial Decision Support Systems (DSS).

Research Organization: Segment 1 shows the introduction of the research, Segment 2 discusses related works conducted on industrial fault detection and PdM techniques, Segment 3 introduces the methodology, Experimental analysis of the developed technique and discussion is shown in Segment 4, and Segment 5 depicts the conclusion of the research.

2. Related Work

Fault Diagnosis-Reproducible, Executable, Streaming Toolkit (FD-REST) approach based on the Deep Neural Network (DNN) model enables continuous diagnosis of faults in industrial machines with an MSE of 0.00253, F1-score 0.8436, and accuracy of 93%, though industrial applications still need improvement [8]. Research [9] presented an Optimization Technique (OT) and ML technique that incorporates AI to design DT applications in industry, focusing on improving fault detection; the highest accuracy rate obtained was 96.8%, although more testing is required within the industrial environment. Light Gradient Boosting Machine (LightGBM) [10] can be optimized by a systematic approach which combines the Simulated Annealing (SA), and Arithmetic Optimization Algorithm (AOA) searching methods for fault prediction in industries. The results showed that the proposed algorithm gave 90% accuracy, which was significantly improved. Nevertheless, its generalization needs further verification. An intelligent approach that combined the multimodal sensor fusion, correlation across sensors, multiscale feature extraction, as well as the Temporal Convolutional Network (TCN) [11] is highly accurate for classification of tool condition and the Remaining Useful Life (RUL). It result with an 86% success rate; nonetheless, more research should be conducted to test different types of machinery. An algorithm for PdM based on Long Short-Term Memory (LSTM), hybrid Convolutional Neural Network- Long Short-Term Memory (CNN-LSTM), and Convolutional Neural Networks (CNNs), models utilizes industrial sensor data for the prediction of equipment failures and estimation of the RUL. The algorithm demonstrated 96.1% accuracy; however, industrial testing is needed [12]. An intelligence-based PdM system [13] through Support Vector Machine(SVM) based selection of networks for optimal classification and Recurrent Neural Network (RNN) based predictions enhances sustainability in the manufacturing process through reduced failure rates and decreased material waste generation, attaining 96.9% Root Mean Square Error (RMSE) improvement. Fault Detection & Diagnosis (FDD) [14] approach uses statistical regression with Kalman Filter (KF)-based I-V curve metrics and adaptive thresholding via classification techniques attains an accuracy of 90.16%, although its effectiveness needs to be validated through other Photo Voltaic (PV) systems. The ML-based system [15] utilizes Artificial Neural Networks (ANNs), Decision Trees (DTs), Random Forest (RF), Extreme Gradient Boost (XGBoost), and Gaussian Naive Bayes (GNB) to identify faults with a significant accuracy rate. Its performance is good, but it needs more research. A sensor fusion algorithm combining force signals, vibration signals, wavelet-based feature extraction, and ML classifiers was proposed for tool fault diagnosis. RF obtained 98% accuracy. However, reliance on hand-crafted features and particular machining conditions restricts its flexibility and generalization ability [16]. CNNs, LSTMs, and hybrid CNN-LSTM [17] were applied to predict multivariate time series for PdM based on industrial sensor data to enhance prediction accuracy. CNN-LSTM produced the highest accuracy with $R^2 = 0.968$, but the drawbacks included complicated data dependency and modeling optimization.

3. Methodology

The suggested model starts with data acquisition, where multiple streams of data from machines, to user interactions were collected from the industrial machinery. In preprocessing, IF and robust scaling algorithms are used to detect outliers and eliminate noise from the collected data. Next, the ICA method is used to find independent attributes via collected records. The extracted attributes are utilized as inputs to an Intelligent Bi-directional Long Short-Term Memory (IntBiLSTM). This model considers forward and backward dependencies among operation sequences. The GTO algorithm is finally used for weight optimization for the model. The methodology pipeline is presented in Figure 1.

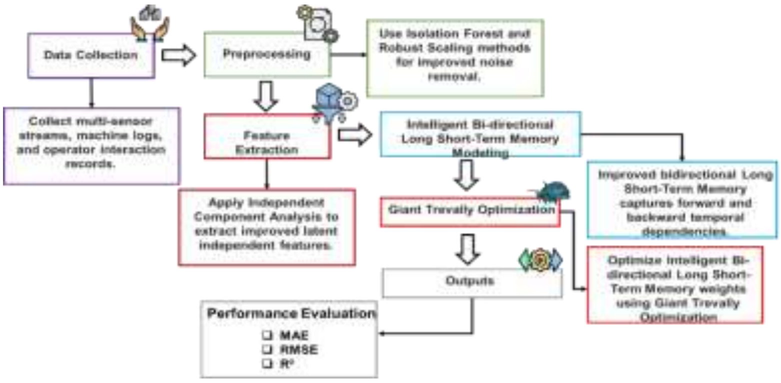

Figure 1: Methodology of Introduced Architecture

3.1 Data Collection

The industrial equipment monitoring dataset is sourced from Kaggle (https://www.kaggle.com/datasets/dnkumars/industrial-equipment-monitoring-dataset), and it comprises approximately 7672 monitoring records of equipment used in industry applications like turbines, pumps, and compressors. This dataset consists of measurement variables like temperature, pressure, vibration, and humidity, together with fault indicators that help predict faults in the machinery. In ML modeling, the dataset is usually split into 80% training dataset and 20% testing dataset.

3.2 Data Preprocessing

Data preprocessing makes the readings better regarding the reliability, and quality, preparing them towards advanced evaluation. IF method helps in detecting and removing anomalies and outliers from the dataset, whereas Robust Scaler technique helps in normalizing data using median and Interquartile Range (IQR) calculations. The preprocessing increases data reliability and helps in obtaining consistent inputs for monitoring machine health and detecting faults.

Isolation Forest (IF): IF is an anomaly detection algorithm that has been developed for detecting anomalous patterns in the data recorded in industrial operations. To detect anomalies, it creates multiple isolation trees that recursively partition readings into disjoint subsets until the instances become isolated or when the tree depth reaches its maximum limit. The anomalies, which can be indicative of early stages of machine failures, can be detected using a shorter path length on average from the root of the tree. Using parameters like the number of trees and maximum features, IF can be utilized for identifying anomalous patterns in vibrations, temperatures, and currents.

$$\mathrm{V(d)} = 2\mathrm{M(d-1)} - \left(\frac{2(\mathrm{d}-1)}{\mathrm{d}}\right) \tag{1}$$

In Equation (1), Vdepicts themeasure of fault path, d and $\mathrm{d}-1$represent the present and previous number of data samples, $\mathrm{V(d)}$indicates themeasure of average fault in machines, Mrepresents the function of harmonic distribution, and $\mathrm{M(d-1)}$depicts themeasure of harmonic distributions with the data sample.

$$\mathrm{L(S,d)} = 2^{-\frac{\mathrm{H(m(d))}}{\mathrm{V(d)}}} \tag{2}$$

In Equation (2), Lindicates the value of faults in machines, Srefers to the sample of input data, d indicates number of data samples, $\mathrm{L(S,d)}$ represents the score value of fault detected in input machine data, H denotes function regarding path length, m refers to the node of the isolation tree, $\mathrm{m(d)}$ indicates the structure of tree in machinery faults,$\mathrm{H(m(d))}$ represents the path length measure in detecting machinery faults, Vdepicts the measure of fault path, and $\mathrm{V(d)}$indicates the measure of average fault in machines.

Robust Scaler: The Robust scaler standardizes the data collected from machines and operators in an industry through the median and interquartile range instead of the minimum and maximum values. This makes the robust scaler robust to outliers and any anomalies in values because such things are common in the industry. Through this, it makes sure that the data collected captures the normal behavior of the machines. The standardized data makes the analysis that follows more reliable for various processes such as PdM and human-AI collaboration in intelligent industrial DSS.

$$\mathrm{W'} = \frac{\mathrm{W} - \mathrm{Median(W)}}{\mathrm{IQR(W)}} \tag{3}$$

In Equation (3),Wrefers to the value of the original feature, $\mathrm{W'}$ denotes the value of the scaled feature, Median represents thecentral tendency, $\mathrm{Median(W)}$ indicates the feature value of the central tendency, IQR refers to the Interquartile Range, and $\mathrm{IQR(W)}$ denotes the spread of the Interquartile Range.

3.3 Independent Component Analysis (ICA) for Feature Extraction

The ICA approach analyzes multivariate data in an effort to find out their underlying hidden factors or components. When applied in industrial AI-assisted decision-making, the ICA approach is highly beneficial for determining various independent attributes that influence machine state. As the result, the recorded data from the industrial systems and the operator-machine interactions, the process of ICA becomes helpful in extracting independent components, making it possible to have an effective collaboration between man and machine.

$$\mathrm{w(s) = Bt(s)} \quad (4)$$

In Equation (4), w denotes the vector of unmixing weights in predicting faults, s refers to the index of the recorded data,w(s) depicts the vector of the separated data,B indicates the matrix of unmixing transformation of faults,trepresents the data observed, andt(s) indicates the recorded data monitoring.

$$\mathrm{z = Xw} (5)$$

In Equation (5), z refers to the output of the independent component, X denotes the matrix of mixed data, andw represents the projection vector of weights.

$$\beta_1 = \frac{\mathrm{F(w-\mu)^4}}{\mathrm{(F(w-\mu)^2}} - 3 = \frac{\mu_4}{\sigma^4} - 3 \quad (6)$$

In Equation (6),β indicates the measure of kurtosis, β_1 refers to the statistical coefficient of kurtosis, Fdenotes the operator of nonlinear expectation, w indicates the projection vector of weight, andμ and σ refer to the mean and standard deviation of fault data.

3.4 Machine Health Monitoring and Maintenance by Human-AI interactions

The fusion of GT-IntBiLSTM allows efficient machine health monitoring and PdM, allowing precise fault diagnosis and effective operational decision-making in an industrial setting. In IntBiLSTM, time sequence analysis is performed by looking at time sequence analysis from past to present as well as from present to past, making it possible to identify anomalies and provide trust-aware suggestions. GTO, which imitates the hunting behavior of giant trevally fish, tunes the parameters of the models using the techniques of search, areas, and attacks.

Machine Health Monitoring using Intelligent Bi-directional Long Short-Term Memory (IntBiLSTM): The IntBiLSTM model is capable of identifying complex temporal relationships in the data collected from machines and operators in industrial settings. This model analyses data sequences in two opposite directions, enabling the analysis of past and future information. Two hidden layers have been used in IntBiLSTM; one layer performs analysis along the feed forward path, and another one analyzes data in reverse path. Through a combination of outputs of both layers, the IntBiLSTM is capable of predicting states of machines, detecting anomalies, and giving recommendations that are based on trust. This helps in AI-based maintenance decision-making and improves seamless human-machine cooperation in industrial monitoring and control systems.

$$\vec{g}_s = LSTM_{Forward}(w_j, \vec{g}_{s-1};\ X^*, V^*)(7)$$

$$\overleftarrow{g}_s = LSTM_{Backward}(w_j, \overleftarrow{g}_{s-1};\ X^*, V^*)(8)$$

In Equation (7 and 8), g denotes the vector of the hidden state which captures temporal data in industry,s indicates the step of time,$\vec{g}_s$and$\vec{g}_{s-1}$refers to the current and prior hidden state vector of fault prediction in forward direction,$\overleftarrow{g}_s$ and$\overleftarrow{g}_{s-1}$ indicates the ongoing and existing hidden state vector in fault prediction backward direction,$LSTM$represents the Long Short-Term Memory, $Forward$ refers to the forward movement,$LSTM_{Forward}$ represents LSTM in subsequent path,$LSTM_{Backward}$ depicts the LSTM in Reverse flow,w indicates the parameter vector of weight,$j$refers to the feature, w_j represents the weight vector of input feature, X refers to the feature set of the industrial input, V denotes the parameter set of initial weight, $*$ represents the optimized value, X^* represents the feature value of optimized input, andV^* indicates the parameters of the optimized weight with human-AI interaction.

$$g_s = [\vec{g}_s; \overleftarrow{g}_s](9)$$

In Equation (9), g refers to the vector of the hidden state which captures temporal data in industry,s indicates the step of time, g_s refers to the hidden state vectorin machinery faults of time step, and$\vec{g}_s$and $\overleftarrow{g}_s$refer to the present hidden state vector of detecting the faults in forward and backward direction.

Hyperparameter Tuning using Giant Trevally Optimization (GTO): GTO is a metaheuristic algorithm that has been modeled after the behavior of the giant trevally fish during their hunting process. Some of its behavioral models include pattern-based hunting and searching, optimization of its hunting areas, and quick attacks on the prey to catch them. These behaviors have been incorporated into the algorithm through the use of three main processes, namely extensive searches, selection of the best hunting grounds, and finally, the targeted attacks. This algorithm has numerous industrial applications, where it is applied in the optimization of parameters used in decision-making and PdM. Through effective exploration of the solution space, it improves the precision in the identification of significant machine states, facilitates early detection of failures, and helps to build trust in human-AI decision-making.

$$W(s+1) = Best_o \times Q + ((Maximum - Minimum) \times Q + Minimum \times Levy(Dim) \quad (10)$$

In Equation (10), Wrefers to the vector of Weight solution for detecting faults, $s+1$ denotes the current and future step index of iteration, $Best$ represents the vector of best solution, o indicates the index of optimal solution,$Best_o$ refers to the optimal candidate solution to enhance maintenance for the faults,Qrefers to the scaling factor of exploration,$Maximum$ and $Minimum$ denotes the upper and lower bound limit, $Levy$ represents the function levy flight for predictive performance, Dim indicates the search space dimensionality,and $Levy(Dim)$ denotes the dimensional space of levy flight for the fault prediction and maintenance.

$$W(s+1) = BestP \times B \times Q + Mean\_Info - Wj(s) \times Q \quad (11)$$

In Equation (11), Wrepresents the vector of Weight solution to detect the faults, s and $s+1$ denotes the current and future step index of iteration, $Best$ represents the vector of best solution,Prefers the population, $BestP$ denotes the best solution of population to predict the faults accurately,B refers to the factor of behavior coefficient in predicting the faults, $\times$ denotes the multiplication operator, Q refers to the scaling factor of exploration, $Mean\_Info$ represents the average information from the faults, j denotes the solution of fault identifier index, $j(s)$ indicates the identifier index of predictive solution j, and$Wj(s)$ represents the vector of current solution.

$$W(s+1) = K + U + G \quad (12)$$

In Equation (12), W represents the vector of Weight solution to predict faults, s and $s+1$ denote the current and future step index of iteration,K refers to theexploitation term of knowledge from faults to provide maintenance, U indicates the updated component of exploration to improve maintenance performance, and G indicates the factor of global guidance for predictive maintenance.

Hyperparameter of the Proposed GTO-IBiLSTM Model: The model that is being developed involves setting a number of optimized hyperparameters to train and perform optimally. Some important parameter values are Population Size (P = 50), Learning Rate (LR) = 0.001, Maximum Iteration (T = 100), Batch Size 32, Search Dimension 5, and Number of Epochs (E = 100). The count of input features varies depending on the dataset, while Sequence Length (SL = 50). For Bi-LSTM, the count of hidden units is 128, and count of layers is 2. Some other hyperparameters include Dropout (DR = 0.30) and Recurrent Dropout (RD = 0.20). Some of the activation functions are Tanh and Sigmoid, Dense Neurons (DN = 64), and Softmax.

4. Result

The experimentation was performed using a high-end machine equipped with an NVIDIA GeForce Ray Tracing Texel eXtreme (RTX) 4090 Graphics Processing Unit (GPU) with 24 GB Graphics Double Data Rate 6X (GDDR6X) memory, Intel Core i9-13900K Central Processing Unit (CPU), 2 TB Non-Volatile Memory Express Solid-State Drive (NVMe SSD) storage, 64 GB Double Data Rate 5 Random Access Memory (DDR5RAM), and a Z790 motherboard. The computing platform used Compute Unified Device Architecture (CUDA) 12.2 and CUDA Deep Neural Network Library (cuDNN) 9.0 running on Windows 11 Pro 64-bit operating system. The software suite used in this research comprised Python 3.11, TensorFlow 2.16.1, Keras 3.0, NumPy, Pandas, Scikit-learn, Matplotlib, Seaborn, SciPy, Jupyter Notebook, and Visual Studio Code.

Explorative Data Analytics: The analysis of correlation and distributions helps understand the behavior of measurement systems impacting fault detection in industries is shown in Figure 2. The correlation of different variables related to temperature, pressure, vibration, humidity, and the state of faults is represented in Figure 2(a). It can be seen that vibration has the highest correlation with faults, indicating its importance in assessing machine health. The distribution as well as the interaction of features in the industrial data is illustrated in Figure 2(b). Differentiating behavior in the case of fault and no fault helps in fault detection and maintenance.

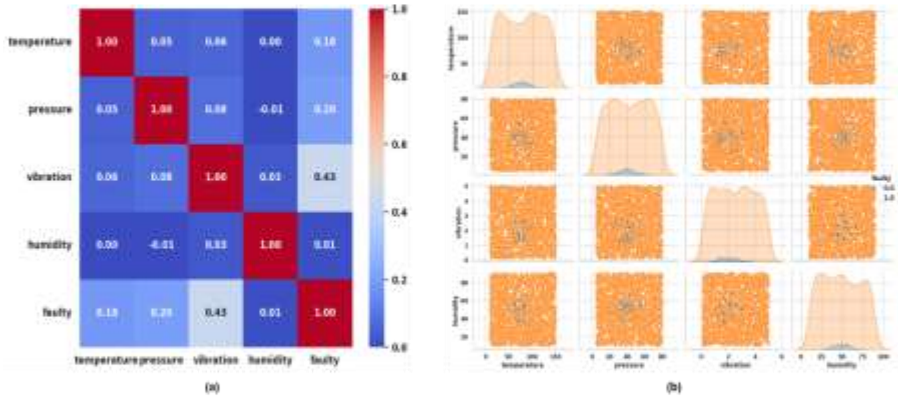

Figure 2: Visualization of (a) Analysis of Feature Correlation, and (b) Relationships and Distribution of Features

Distribution of measurement systems and equipment, which help to make fault predictions for industries is shown in Figure 3. Distribution of temperature and pressure is represented in Figure 3(a) and the vast majority of data points fall within regular operational values, showing common equipment states and measurement systems pattern distributions. Comparison among temperature, pressure, vibration, and humidity of different equipment is indicated in Figure 3(b) and the similar distribution shows consistency in monitoring conditions, while the number of faults represents class imbalance properties.

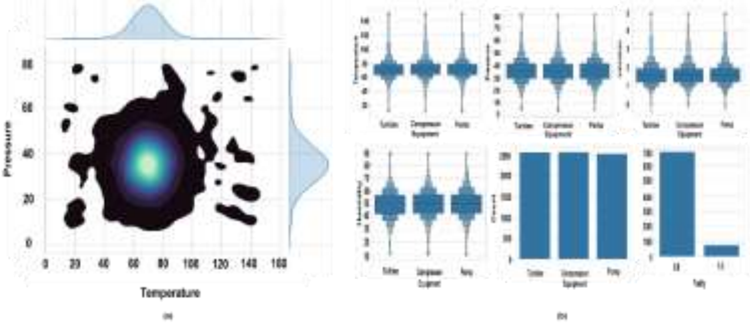

Figure 3: Graphical representation of(a) Density Distribution of Pressure and Temperature, and (b) Distribution Analysis of Equipment Features

Evaluation Metrics: The Predictive Capability of GT-IntBi-LSTM method assessed based on RMSE, Coefficient of determination (R^2), and Mean Absolute Error (MAE). MAE provides average of absolute differences between real and predicted values of machine states, and thus assesses the model accuracy. RMSE is obtained as the square root of the average squares of forecasted errors and thus assigns higher weight to higher errors; hence, RMSE is better suited to measure the quality of fault prediction. R^2 determines the degree to which variance in industrial equipment monitoring can be explained by the model, and thus its performance in terms of predicting the future.

Performance Evaluation: Predictive performance of various models using different measures like MAE, RMSE, and R^2 is provided in Table 1 and Figure 4. The CNN model gave MAE, RMSE, and R^2 as 32.985, 45.012, and 0.932, respectively. The LSTM model performed better, giving MAE, RMSE, and R^2 as 30.125, 42.980, and 0.952, respectively. The hybrid approach of the CNN-LSTM model further minimized the errors, giving MAE, RMSE, and R^2 as 27.021, 38.701, and 0.968, respectively. The suggested GT-IntBi-LSTM model performed well with the least MAE of 20.034, the least RMSE of 30.178, and the highest R^2 of 0.978, showing that the model is more accurate.

Table 1: Performance analysis of Proposed and Baseline Methods

Method	MAE	RMSE	R^2
CNN [17]	32.985	45.012	0.932
LSTM [17]	30.125	42.980	0.952
CNN-LSTM [17]	27.021	38.701	0.968
GT-IntBi-LSTM [Proposed]	20.034	30.178	0.978

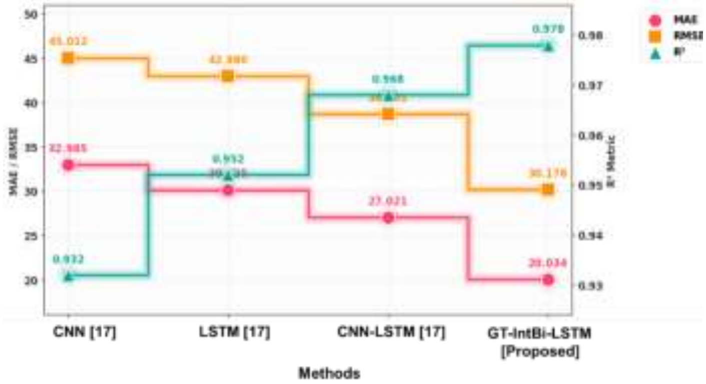

Figure 4: Performance Analysis of the Proposed Model using Baseline Models

Baseline models like LSTM [17], CNN-LSTM [17], and CNN [17], were retrained based on the corresponding experimental conditions using the industrial equipment monitoring dataset. IF was employed as preprocessing technique to identify and eliminate outliers in measurement systems readings, while Robust Scaler helped in normalizing the dataset. Important features were selected by ICA based on measurements of temperature, pressure, vibrations, and humidity. The suggested GT-IntBi-LSTM model performed better than other baselines as depicted in Table 2 by learning bidirectional relationships in time series data and setting optimum values of hyperparameters using GTO.

Table 2: Retained Analysis of Baseline Methods with the Introduced Architecture

Method	MAE	RMSE	R^2
CNN	38.652	52.481	0.901
LSTM	34.718	47.925	0.925
CNN-LSTM	28.946	40.364	0.956
GT-IntBi-LSTM (Proposed)	20.034	30.178	0.978

Discussion: Traditional approaches are constrained by their ability to incorporate complete temporal dependencies, handle intricate industrial measurement systems, and attain predictive accuracy. The CNN [17] architecture is not capable of capturing temporal dependencies over a larger period of time in the case of industrial sequences, thus reducing its predictive capabilities regarding evolving machinery conditions and hindering the development of accurate predictive models. LSTM [17] operates on sequential data in one direction only and fails to exploit future context, which leads to an inability to understand complex behaviors within the working system. Despite integrating both convolutional and recurrent learning principles, the CNN-LSTM [17] architecture exhibits high computational cost, long training times, and vulnerability to parameter tuning. To overcome these disadvantages, the suggested GT-IntBi-LSTM architecture combines bidirectional temporal learning along with giant trevally optimization for effective extraction of context data from previous and upcoming data sequences. It increases the efficiency of predicting faults, minimizes errors in predictions, and ensures trust-aware decision support in intelligent industries.

5. Conclusion

The trust-aware machine-mediated Human-AI interaction is very significant for enhancing decision-making, robustness, and PdM in smart industries. The proposed GT-IntBi-LSTM model integrates preprocessing using IF, feature extraction using ICA, bidirectional learning in time series, and hyper-parameter optimization using GTO. Experimental results using the industrial equipment monitoring dataset have shown better performance in prediction as compared to CNN, LSTM, and CNN-LSTM models. The GT-IntBi-LSTM model achieved the minimum MAE value of 20.034, the minimum RMSE value of 30.178, and the maximum R^2 value of 0.978. These results confirm the efficiency of GT-IntBi-LSTM in providing an accurate machine health diagnosis and intelligent industrial decision-making. In addition, the suggested GT-IntBi-LSTM model was tested using only one monitoring dataset for an industrial system, which may reduce its generalizability across different industrial settings and machines. Future research will examine the proposed approach using large real-world industrial datasets and incorporate explainable AI techniques.

References

1. Ali, A.R. and Kamal, H., 2025. Time-to-fault prediction framework for automated manufacturing in humanoid robotics using deep learning. Technologies, 13(2), p.42.https://doi.org/10.3390/technologies13020042
2. Saeed, A., A. Khan, M., Akram, U., J. Obidallah, W., Jawed, S. and Ahmad, A., 2025. Deep learning based approaches for intelligent industrial machinery health management and fault diagnosis in resource-constrained environments. Scientific Reports, 15(1), p.1114.https://doi.org/10.1038/s41598-024-79151-2
3. Mavrelis, I., Chatzopoulos, A. and Zacharia, P., 2026. Hybrid Deep Learning for Predictive Maintenance in Industrial Machinery Using LSTM and MLP Models. Machines, 14(2), p.191.https://doi.org/10.3390/machines14020191
4. Dera, P., Talaśka, T. and Długosz, R., 2026. A new, cost-efficient modular sensor platform for IoT and predictive maintenance in industrial applications. Journal of Computational and Applied Mathematics, 473, p.116777. https://doi.org/10.1016/j.cam.2025.116777
5. Almasoudi, F.M., 2023. Enhancing power grid resilience through real-time fault detection and remediation using advanced hybrid machine learning models. Sustainability, 15(10), p.8348.https://doi.org/10.3390/su15108348
6. Khan, T., Khan, U., Khan, A., Mollan, C., Morkvenaite-Vilkonciene, I. and Pandey, V., 2025. Data-driven digital twin framework for predictive maintenance of smart manufacturing systems. Machines, 13(6), p.481.https://doi.org/10.3390/machines13060481
7. Rani, S., Jining, D., Shoukat, K., Shoukat, M.U. and Nawaz, S.A., 2024. A human–machine interaction mechanism: additive manufacturing for Industry 5.0—design and management. Sustainability, 16(10), p.4158.https://doi.org/10.3390/su16104158
8. Kocatekin, T., Ovacıklı, A.K. and Yağcıoğlu, M., 2026. FD-REST: A lightweight RESTful platform for real-time fault detection and diagnosis in industrial systems. SoftwareX, 33, p.102513.https://doi.org/10.1016/j.softx.2026.102513
9. Zayed, S.M., Attiya, G., El-Sayed, A., Sayed, A. and Hemdan, E.E.D., 2023. An efficient fault diagnosis framework for digital twins using optimized machine learning models in smart industrial control systems. International Journal of Computational Intelligence Systems, 16(1), p.69.https://doi.org/10.1007/s44196-023-00241-6
10. Li, S., Jin, N., Dogani, A., Yang, Y., Zhang, M. and Gu, X., 2024. Enhancing LightGBM for industrial fault warning: An innovative hybrid algorithm. Processes, 12(1), p.221.https://doi.org/10.3390/pr12010221
11. Khan, A., Junaid, A., Siddique, M.F., Iqbal, A., Samkari, H.S., Allehyani, M.F. and Husnain, G., 2026. Smart Predictive Maintenance: A TCN-Based System for Early Fault Detection in Industrial Machinery. Machines, 14(2), p.164.https://doi.org/10.3390/machines14020164
12. Li, W. and Li, T., 2025. Comparison of deep learning models for predictive maintenance in industrial manufacturing systems using sensor data. Scientific Reports, 15(1), p.23545.| https://doi.org/10.1038/s41598-025-08515-z
13. Abidi, M.H., Mohammed, M.K. and Alkhalefah, H., 2022. Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. Sustainability, 14(6), p.3387.https://doi.org/10.3390/su14063387
14. Alrifai, Y., Aguilera-González, A., Vechiu, I. and Becerra-Becerra, G., 2026. Hybrid fault detection and identification strategy for PV systems combining statistical data-driven and Kalman filter algorithms. Electric Power Systems Research, 252, p.112381.https://doi.org/10.1016/j.epsr.2025.112381
15. Aslam, S., Navarro, A., Aristotelous, A., Garro Crevillen, E., Martınez-Romero, A., Martínez-Ceballos, Á., Cassera, A., Orphanides, K., Herodotou, H. and Michaelides, M.P., 2025. Machine learning-based predictive maintenance at smart ports using IoT sensor data. Sensors, 25(13), p.3923.https://doi.org/10.3390/s25133923
16. Kotha Amarnath, S., Inturi, V., Rajasekharan, S.G. and Priyadarshini, A., 2025. Combining sensor fusion and a machine learning framework for accurate tool wear prediction during machining. Machines, 13(2), p.132.https://doi.org/10.3390/machines13020132
17. Wahid, A., Breslin, J.G. and Intizar, M.A., 2022. Prediction of machine failure in industry 4.0: a hybrid CNN-LSTM framework. Applied Sciences, 12(9), p.4221. https://doi.org/10.3390/app12094221