SvedbergOpen
DISSEMINATION OF KNOWLEDGE
International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

Human–Machine Coordination in Adaptive Industrial Automation Systems

Dr. Sandip Sane[1], Sachin Sharma[2], Hadasha Nobel Tune[3], Swati Shivkumar Shriyal[4], Dr. Swati Gopal Gawhale[5], Nisha Pandey[6], Priyadharshini K[7], Dr. S. Ayem Perumal[8]

[1] Professor and Director, Symbiosis Skills and Professional University, Pune, Maharashtra, India. Email: dir_retail@sspu.ac.in ORCID: 0000-0003-3272-6749
[2] Assistant Professor, Department of Computer Application, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India. Email: socse.sachin@dbuu.ac.in ORCID: 0009-0000-7449-5809
[3] Assistant Professor, Department of Commerce, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: nobel@maher.ac.in
[4] Department of Artificial Intelligence, Vishwakarma University, Pune, Maharashtra 411048, India. Email: swati.shriyal@vupune.ac.in
[5] Department of Electronics and Telecommunication Engineering, Bharati Vidyapeeth's College of Engineering, Lavale, Pune, Maharashtra, India. Email: gawhaleswati@gmail.com
[6] Assistant Professor, Department of Computer Science & Engineering, Noida International University, India. Email: nisha.pandey@niu.edu.in
[7] Assistant Professor, Department of Management Studies, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: kpriyamba@maher.ac.in
[8] Assistant Professor, Department of Management Studies, SKR Engineering College, Anna University, Nazarathpettai, India. Email: pdrsphd@gmail.com

Abstract
Coordination of Human-Machine in Adaptive Industrial Automation refers to the integration of intelligent systems with human operatives to improve production efficiency and decision-making within industrial processes. The existing approaches are restricted by limited adaptability, contextual analysis, and inefficiency in human-machine interactions. This research presents an approach that uses Deep Learning (DL) based on Gannet Optimization-driven Adaptive Long Short-Term Memory (GO-ALSTM) to optimize the coordination of human-machines within adaptive industrial automation systems. Industrial operational data are subjected to preprocessing by Min–Max normalization and feature reduction using Principal Component Analysis (PCA), to enhance data quality, reduce redundancy, and improve the representation of underlying patterns for subsequent analysis. The GO-ALSTM approach makes use of ALSTM for identifying long-term dependencies and GO for optimizing parameters. The research makes use of deep learning libraries within the Python programming environment. The experimental evaluation proves that the proposed technique achieved precision, F1-score, recall, and accuracy 96.8 ± 0.4%, 97.0 ± 0.4%, 97.2 ± 0.5%, and 97.0 ± 0.3%, respectively, surpassing both the Deep Learning (DL) and Machine learning (ML) methods. Proposed model is able to significantly enhance the adaptability, reliability, coordination capability, and intelligent decision-making process in industry operations with complex and changing conditions.

Keywords: Human–Machine Coordination, Industrial Process Monitoring, Deep Learning (DL), Principal Component Analysis (PCA), Industrial Automation Systems.

1. Introduction

The development process in the industry is moving at an increasing rate owing to technological developments and innovations. With the advent of digitalization, automation, and smart manufacturing in Industry 4.0, coordination between humans and machines becomes most important in closing the gap between automation and human decision-making capability. One of the most prominent problems in modern industries is assembly line balancing [1]. Machine vision is extensively employed in the manufacturing industry for tasks like identification, measurement, and defect detection using automatic inspection. The system works uninterruptedly and provides enhanced results regarding quality, yield, and cost when compared to manual inspection. Reflections and small components make defect detection intelligent, which is required for machine vision [2]. Industry 3.0 introduced automation through information technology and electronics, resulting in improvements in manufacturing processes. Artificial Intelligence (AI), the Internet of Things (IoT), digital twins, and big data advanced this change in Industry 4.0, enabling intelligent manufacturing systems. Despite these developments, there is still a dichotomy between machines and humans, as they do not possess cognitive ability [3]. As a result of rapid evolution in smart manufacturing, Cyber-Physical Production Systems (CPPS) offer integration of machine-human interactions in terms of sensors. This technology offers highly sophisticated data of the industry that must be analyzed to guarantee safety, efficiency, quality, and preventive maintenance of the manufacturing plant [4]. Fully automated operation and unmanned operation are the prime goals of industrial intelligence; however, the rising level of complexity, unpredictable operations, and ethics make automation impossible. Therefore, human participation becomes crucial to ensure safety and effective decision-making, and hence human-machine interaction gains prominence [5, 6].

1.1 Research Aim: The primary purpose of the research is to design an intelligent human-machine coordination system for adaptive industrial automation using Gannet Optimization-driven Adaptive Long Short-Term Memory (GO-ALSTM). This system can be used to improve the efficiency of the coordination, make adaptive decisions, and enhance model stability along with the response in the dynamic industrial environment.

Research Organization: This research is organized into different sections. In Section 1, the introduction of adaptive industrial automation and Human-Machine coordination is discussed. In Section 2, the relevant previous Section 3 highlights the methodology used. Section 4 presents the experimental results and analysis, and Section 5 is concluded along with recommendations for further improvement.

2. Related work

The research [7] proposed that the fault diagnosis of rotating machinery in industries uses Continuous Wavelet Transform (CWT) to transform motion data toward Red, Green, Blue (RGB), and Convolutional Neural Network (CNN) classification technology combined with IoT/Message Queuing Telemetry Transport (MQTT), with the accuracy of 93.27%, but the fault type is limited, and it is tested under the condition of a controlled environment. Safety-Aware Multi-Agent Reinforcement Learning (SA-MARL) [8] has yielded fault-tolerant control for partially observable industrial systems that are safe (no violations), and robust (good operation) under a variety of constraints, but the results have not been tested outside the Chip-in-Package (CIP) system. Modular, Scalable, User-Centered AI model enhanced the efficiency of human–machine interaction using instant feedback and communication by 10–20%, but this is yet to be validated in the real world of industry [9]. The research involved proposing a Hybrid Context Transformer-based Detection model (HCT-Det) [10], a Window Self-Attention Residual (WSA-R) version; an Intra-Scale Feature Interaction-Cross (ISFI) coupled with Scale Feature Interaction (CSFI); a soft Intersection over Union (IoU) awareness; and a hybrid sampling for the detection of industrial steel surface defects. Its results include achieving Mean Average Precision (mAP) @0.5 scores of 0.795 and 0.733 defective samples aimed at tiny targets of interest. The research [11] proposed the in-situ based Laser Wire Direct Energy Deposition (LW-DED) monitoring adopted You Only Look Once version 8 (YOLOv8) for separation and geometry prediction of the melt pool with mAP 0.925/0.853 and >114 Frames Per Second (FPS), but the results were only applicable to certain deposition conditions and specific industrial materials. The research developed a synthetic Two-Dimensional/Three-Dimensional Computer-Aided Design (2D/3D CAD) image with Transfer Learning (TL) and unsupervised adaptation for the automated assembly quality control in industries, which achieves an accuracy level of 95%, but is limited to the pedal car assembly [12]. The research [13] used Deep Neural Network (DNN) soft sensors with high-resolution Optical scans for industrial quality control in gravure cylinders with 98.4% accuracy, but with a restriction of a limited number of defect types. Hand tool assembly inspection utilized Region of Interest (ROI) based image processing along with Region-based Convolutional Neural Network (R-CNN) method [14] to recognize 28 defect types, but only in three assembly stations with an overall recognition accuracy of 92.64%, a rate of misjudgement of 6.68%, and an accuracy of classification of 88.03%. A Machine Learning (ML) technique-based anomaly detection scheme is developed for Industrial Control System (ICS) communication networks with the application of one-Dimensional (1D) CNN, Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and Isolation Forest (IF), which uses simulation-based Transmission Control Protocol (TCP) along with Internet Protocol (IP) traffic where highest results were obtained for 1D CNN with 0.92 accuracy and 0.91 F1 score, but with the limitations of simulations [15]. The research on predictive maintenance using CNN, LSTM models, and hybrid models for industrial monitoring was evaluated, with CNN-LSTM achieving a detection accuracy of 96.1% together with F1-Score of 95.2%, but not being tested with other datasets [16].

3. Methodology

The proposed human–machine coordination model for adaptive industrial process monitoring, shown in Figure 1, starts with the collection of industrial data from manufacturing systems, including sensor readings, machine state information, environmental conditions, and process parameters. The collected data is pre-processed through Min-Max Normalization aimed at improving quality of data and reliability. Following this step, the next technique employed is called the PCA. This method serves the purpose of reducing dimensions and extracting relevant features. These features can then be used as the inputs for the process prediction through the Adaptive Long Short-Term Memory (ALSTM) model. Moreover, the Gannet Optimization (GO) Algorithm can help optimize the hyperparameters of the ALSTM model.

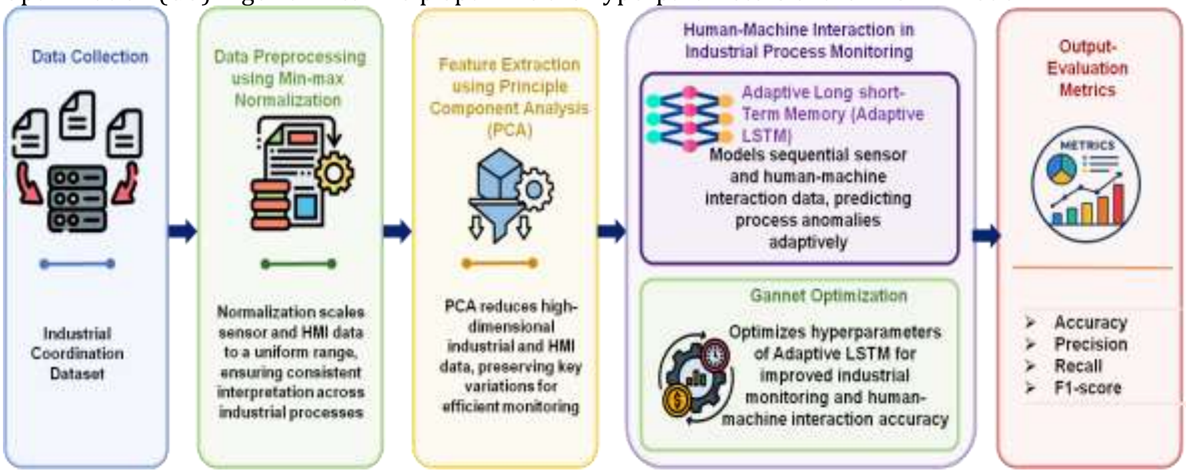

Figure 1: Workflow of the introduced model

3.1 Acquisition of Data

Industrial coordination data used to build a human-machine coordination model in adaptive industrial process monitoring were sourced from Kaggle (https://www.kaggle.com/datasets/programmer3/industrial-coordination-dataset/data), and they consist of 7050 entries in industrial operations. Examples of such data include readings data, states of the machine, environmental variables, and process data generated during production. The data serve as representations of what the industries do and interactions between the machines and humans. This data is obtained from the industrial coordination data. The data set is divided into two data sets; 80% for model building and 20% for testing the model.

3.2 Scaling of Features using Min-Max Normalization in Data processing

The concept of normalization is used for numerical attributes in process control applications such as sensor data, machine status, and environmental data to ensure that all numerical attributes have a similar range. The use of normalization makes sure that no particular attribute dominates other attributes because of its larger range of values while using the data for predictive modeling purposes. Furthermore, normalization improves data consistency, enhances model performance, and contributes to faster and more stable training of DL models by facilitating efficient convergence during the optimization process.

$$V_{normalized} = \frac{V_{feature} - V_{min}}{V_{max} - V_{min}} \quad (1)$$

In Equation (1), $V_{normalized}$ denotes the normalized output after scaling between 0 and 1,$V_{feature}$refers to the value of the input feature extracted from the industry dataset,andV_{max} and V_{min}represent the maximum and minimum regarding attribute of data source.

3.3 Data Feature Compression using Principal Component Analysis (PCA)

To support strong feature learning in capturing the interactions among machines, sensors, and operators in industrial process monitoring, PCA is performed after the data pre-processing. The dataset includes key operational variables such as temperature, pressure, vibration, flow rate, and machine operating status. Since these features are measured in different units and scales, min–max normalization is applied during preprocessing to standardize the data, ensuring that all features contribute equally to the learning process and improving the effectiveness of subsequent analysis and model training.

$$D_{va} = \frac{(E_{va} - \mu_{va})}{\sigma_{va}} \quad (2)$$

In Equation (2), D denotes the feature value of standardization, v refers to the observation of the sample or instance, a denotes the index of the feature, D_{va}refers to the standardized form of attribute a of the instancev,E refers to the feature intensity associated with the initial image, E_{va} represents the estimate derived from attribute before standardization, σ and μ denotes the standard deviation and mean across features, σ_{va} together with μ_{va} refers to the standard deviation and mean values of the attribute respectively.

3.4 Human-Machine Coordination in Industrial Process Monitoring

The Adaptive Long Short-Term Memory (ALSTM) model is designed to monitor and coordinate human–machine interactions in industrial environments using an industrial coordination dataset comprising sensor data, machine status information, and machine operation records. Unlike conventional LSTMs, ALSTM enhances the forget gate mechanism and utilizes historical cell states more effectively, enabling efficient control of information retention and updating. This feature enables the model to identify complex interdependencies among multiple industrial datasets, thus allowing for accurate predictions of machine behavior. To further optimize performance, the Goshawk Optimization (GO) algorithm is employed for parameter tuning, efficiently exploring the search space to identify the optimal ALSTM configuration.

3.4.1 Optimize the coordination of human-machines within adaptive industrial automation systems using Adaptive Long Short-Term Memory (ALSTM): The ALSTM neuron improves upon the traditional LSTM neuron through optimization of the forget gate and effective use of the previous cell state. As shown in Figure 2, such changes allow for simultaneous control of both storage and updating of knowledge in the model, thus improving its capability to learn complex patterns.

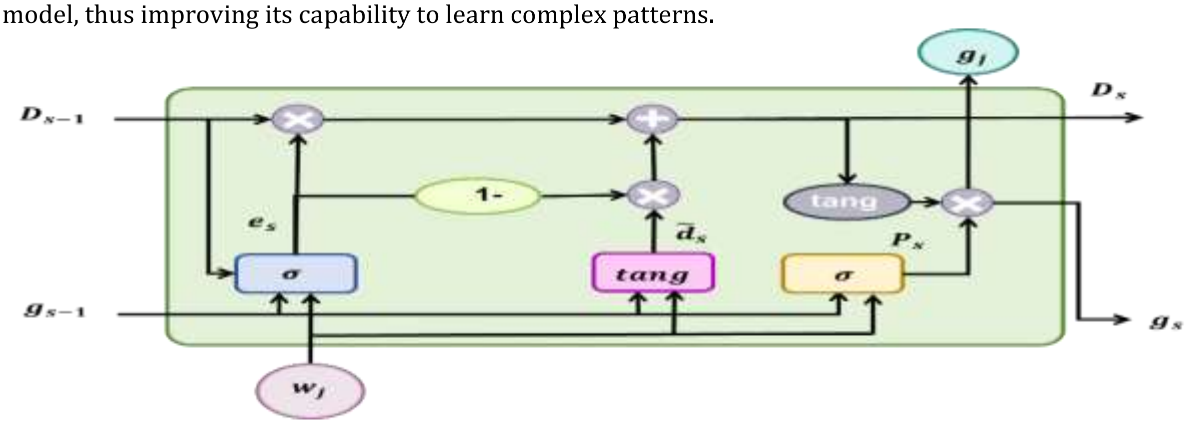

Figure 2: Architecture of ALSTM

$$D_s = e_s D_{s-1} + (1 - e_s)\tilde{D}_s \quad (3)$$

In Equation (3), D refers to the memory of the cell state,$D_s$and D_{s-1}denote the state of the current and the previous cell, s represents the step of the current time, e depicts the value of update gate,e_s denotes the Forget gate for retaining past information from the previous process,$1 - e_s$refers to the weighting factor of complementary, and$\tilde{D}_s$refers to the state of candidate cell.

$$e_s = \sigma\left(X_e \begin{bmatrix} D_{s-1} \\ g_{s-1} \\ w_s \end{bmatrix} + a_e\right) \quad (4)$$

In Equation (4), e depicts the value of update gate,e_s denotes the Forget gate for retaining past information from the previous process,σ refers to the activation function of sigmoid,X denotes the matrix of weight transformation, X_e represents the matrix of learnable weight,D refers to the memory of the cell state, D_{s-1}denotes the state of the current and the previous cell,g depicts the vector of hidden state, g_{s-1} denotes the past hidden feature,w depicts the vector of the input feature, $w_s$denotes the vector of the input,a depicts the vector of bias parameter,a_e denotes the bias term of learnable.

3.4.2 Hyperparameter tuning with Gannet Optimization (GO): GO is a nature-inspired optimization strategy based on the behavior of gannets, which are seabirds that demonstrate accurate diving capabilities when hunting prey. In industrial process control applications, GO is utilized to optimize the hyperparameters of the ALSTM model, enabling accurate machine states prediction and effective coordination between the human and machine activites. This is achieved by implementing the survival of the fittest approach through the evolution of a group of potential solutions until an optimum solution is reached. The process of solving the problem using GO involves three stages:

Stage 1 - Initialization: The initial positions of agents are kept in a memory matrix, which keeps getting updated based on their fitness scores calculated as predictive performance on industrial process data.

$$m_{o,r} = c_1 \times (upA_r - lwA_r) + lwA \quad (5)$$

In Equation (5), m refers to the position value of random search, o denotes the value of random probability, r refers to the index value of the dimension, c_1 represents the random number between 0 and 1, lw and up represents the lower limit and upper limit during the search process, upA_r and lwA_r bound of the lower and upper of hyperparameter,A refers to such space boundary of search, andlwA denote the parameters of lower bound.

Stage 2 - Exploration: Exploration involves moving widely in search of an optimal solution, as done by gannets while scanning water for their prey. This stage helps identify optimal regions of the hyperparameter space.

$$H_i(m+1) = \begin{cases} H_i(m) + b1 + b2, & o \geq 0.5 \\ H_i(m) + b1 + b2, & o < 0.5 \end{cases} \quad (6)$$

In Equation (6), H denotes the vector of the candidate solution,i denotes the index of the solution,m refers to the position value of random search,H_i refers to the population position vector,$H_i(m)$ and $H_i(m+1)$ denote the value current and updates solution, b1 and b2 represent the adjustment term of first and second parameter,o denotes the value of random probability, and, ≥ and < denote the greater than or equal to and the less than operator.

Stage 3 - Exploitation: Exploitation refers to optimization of the optimal solutions that have been found in the searching process, much like the way gannets exploit their prey once it has been found. This phase is meant to improve the precision, ability to converge, and response rate of the ALSTM algorithm.

$$H_i(m+1) = \begin{cases} m * \delta * (H_i(m) - H_{as}(m)) + H_i(m), & D_o \geq s \\ H_{as}(m) - (H_i(m) - H_{as}(m)) * R * m, & D_o < s \end{cases} \quad (7)$$

In equation (7), H denotes the vector of the candidate solution,i denotes the index of the solution,H_i refers to the population position vector,$H_i(m)$ and $H_i(m+1)$ denote the value current and updates solution,m refers to the position value of random search, $*$ represents the operator of multiplication, δ denotes the adjustment parameter of scaling,H_{as} represents the position across best solution,as refers to the process across adaptive search,$H_{as}(m)$ denotes the vector of the best solution, D represents the parameter of the detection probability, s denotes the comparison value of threshold, ≥ and < denote the greater than or equal to and the less than operator, andR denotes the coefficient of the random movement.

3.4.3 Hyperparameter of the introduced method: Hybrid LSTM architecture optimized through a GO search process, with various hyperparameters adjusted for better prediction accuracy. The important training parameters include learning rate (0.0001), batch size (128), 300 epochs, and five layers of stacked LSTMs, with each layer having 32 hidden units. Some of the other techniques used for overcoming the problem of overfitting include drop-out rate of 0.5, recurrent drop-out rate of 0.4, and gradient clipping threshold of 0.5. Adam optimizer along with Mean Squared Error (MSE) along with loss function of cross-entropy is selected for effective training. There are some more parameters that help in achieving optimization such as exploration/exploitation ratio, population size, attention, and dynamic memory.

4. Result

System design and implementation can both be achieved and managed in an optimal high-performance computing setting to enable the effective execution of deep learning and optimization algorithms. The hardware setup is made up of an Intel Core i7 or AMD Ryzen 7 processor that runs at a speed range of 3.4 GHz - 5.0 GHz, as well as 16 GB-64 GB DDR4 RAM and 512 GB-1 TB solid-state drives. Moreover, an NVIDIA RTX 3060/RTX 4060 GPU with 8-12 GB GDDR6 can also be used.

4.1 Explorative data analysis: Industrial coordination performance evaluation with the help of the selected key metrics is shown in Figure 3, where coordination efficiency, system reliability, operational features, and adaptation behavior are considered. Figure 3(a) demonstrates the frequency distribution of coordination efficiency metric values with a nearly normal distribution curve with a maximum of cases within the medium category. Hence, there is stable and balanced performance of industrial coordination processes. Figure 3(b) represents the dependence between the percentage share of system reliability and coordination efficiency. Scattered observations at different values of reliability indicate a uniform distribution of observations, which proves stability and balance of industrial coordination performance in various situations. Figure 3(c) shows the variability in operational feature parameters of operator reaction time, workload indicator, operator's attention level, probability of making a mistake by a person, and machine speed at different surveillance periods. Variability of the parameters is observed due to human-machine interactions' dynamics. Figure 3(d) provides the results of summing up contributions of adaptation response, coordination efficiency, and automation adaptation throughout a series of observation periods.

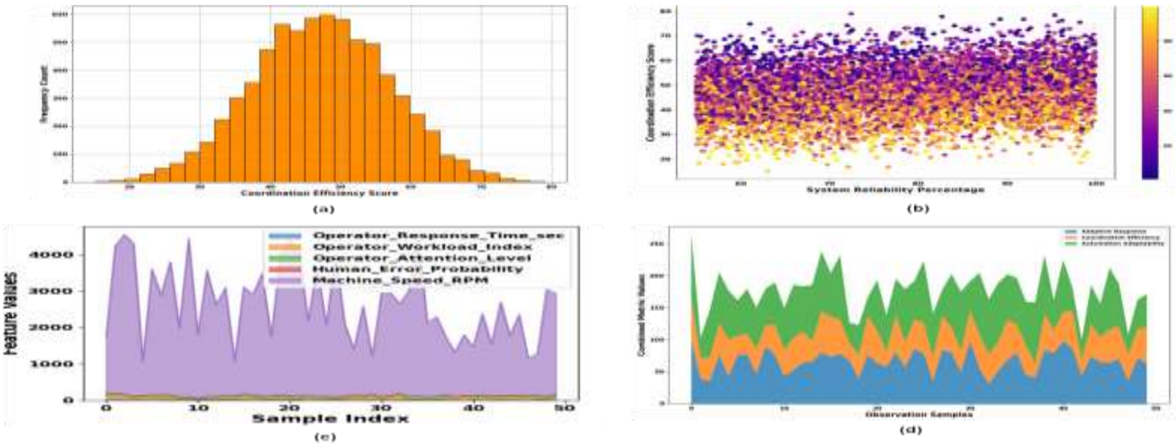

Figure 3: Visualization of (a) Score Distribution for Coordination, (b) Reliability and Efficiency Analysis, (c) Comparison of Industrial Features, (d) Adaptation Measurement Evaluation

4.2 Evaluation Metrics: The **Accuracy** determines the aggregate performance of the predicted values made by the GO-ALSTM algorithm in the industry coordination system. The level of **Precision** indicates the extent of accuracy with which the algorithm recognizes the relevant cases while reducing false negatives in the process of decision-making. **Recall** is used to determine the extent to which the algorithm recognizes all the relevant cases, thus making sure that all the important aspects of the industrial process are recognized reliably. The **F1 score** gives an even-handed evaluation of the model performance by calculating the harmonic mean of both Precision and Recall scores.

4.3 Performance analysis: From the analysis of the comparative performance of both traditional DL and ML algorithms depicted in Table 1 and Figure 4. Commonly used ML methods like SVM [16], Logistic Regression [LR] [16], and Random Forest [RF] [16] have lower accuracy and F1 scores compared to DL methods, implying that the former lack feature learning capabilities. DL models like CNN [16], LSTM [16], and their combinations perform relatively better compared to others due to feature-learning capabilities. The combination of CNN [16] and LSTM [16], CNN-LSTM [16], improves performance by incorporating spatial-temporal learning. The best-performing model is the GO-ALSTM, with an accuracy of 97%.

Table 1: DL and ML methods Comparison with the introduced method

Model	***Accuracy*** (%)	***Precision*** (%)	***Recall*** (%)	***F1 − score*** (%)
SVM [16]	89.3 ± 1.2	88.7 ± 1.4	87.2 ± 1.6	87.9 ± 1.3
RF [16]	91.8 ± 0.9	91.2 ± 1.1	89.8 ± 1.3	90.5 ± 1.0
LR [16]	87.6 ± 1.4	86.9 ± 1.6	85.4 ± 1.8	86.1 ± 1.5
CNN [16]	95.2 ± 0.6	94.8 ± 0.8	93.6 ± 1.0	94.2 ± 0.6
LSTM [16]	94.5 ± 0.8	93.9 ± 1.0	92.7 ± 1.2	93.3 ± 0.8
Attention − basedLSTM [16]	95.6 ± 0.6	95.1 ± 0.8	93.9 ± 1.0	94.5 ± 0.6
BidirectionalLSTM [16]	95.8 ± 0.6	95.3 ± 0.8	94.2 ± 1.0	94.7 ± 0.6
CNN − LSTM [16]	96.1 ± 0.4	95.7 ± 0.6	94.8 ± 0.8	95.2 ± 0.4
GO − ALSTM [*Proposed*]	97.0 ± 0.3	96.8 ± 0.4	97.2 ± 0.5	97.0 ± 0.4

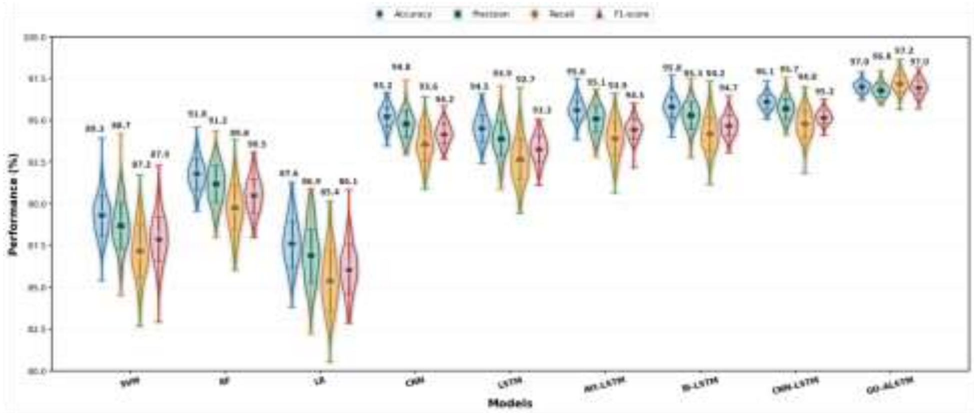

Figure 4: Performance Comparison of existing models with the proposed model

Retraining was conducted on the industrial coordination dataset for all baseline models using an identical experimental setup and the same train–test data split, as presented in Table 2. To make sure that there is a valid comparison, all models have been subjected to consistent data pre-processing techniques such as Min-Max normalization and PCA for feature extraction. The evaluation results of all models has been analyzed by using Accuracy, Precision, Recall and F1 score as evaluation measures. Experimental results show that the proposed GO-ALSTM model has better performance than any other baseline model [16].

Table 2: Results retained from the baseline model using introduced architecture

Model	*Accuracy* (%)	*Precision* (%)	*Recall* (%)	*F1 − score* (%)
SVM [16]	86.2 ± 1.4	85.7 ± 1.5	84.9 ± 1.6	85.2 ± 1.4
RF [16]	88.1 ± 1.1	87.6 ± 1.2	86.8 ± 1.3	87.0 ± 1.1
LR [16]	85.4 ± 1.5	84.9 ± 1.6	83.7 ± 1.8	84.1 ± 1.5
CNN [16]	89.6 ± 0.9	88.9 ± 1.0	88.1 ± 1.1	88.4 ± 0.9
LSTM [16]	88.7 ± 1.0	88.0 ± 1.1	87.2 ± 1.2	87.5 ± 1.0
Attention − based LSTM [16]	89.1 ± 0.9	88.5 ± 1.0	87.6 ± 1.1	88.0 ± 0.9
Bi − directional LSTM [16]	89.4 ± 0.8	88.8 ± 0.9	88.0 ± 1.0	88.3 ± 0.8
CNN − LSTM [16]	90.0 ± 0.7	89.4 ± 0.8	88.7 ± 0.9	89.0 ± 0.7
GO − ALSTM [*Proposed*]	97.0 ± 0.3	96.8 ± 0.4	97.2 ± 0.5	97.0 ± 0.4

4.4 Discussion: These models have multiple limitations pertaining to performance, scalability, and generalization ability. SVM [16], for example, lacks scalability and sensitivity to its parameter value and cannot accommodate nonlinear, noisy, and high-dimensional data. RF [16] has limitations regarding temporal modeling capability, relatively high computational cost, and low interpretability when dealing with complex ensembles. LR [16] is linear and poorly learns nonlinearity; it is sensitive to scaling problems. CNN [16] lacks temporal dependency consideration, requires large datasets, and has high training costs. LSTM [16] has a problem with a slow training process and overfitting on small data sets; it also need for complex tuning processes. Attention-based LSTM [16] is computationally complex, uses much data, and yields noisy attention weights. Bidirectional LSTM [16] is resource-intensive, unsuitable for instant processing, and overfits data. CNN-LSTM [16] is resource-intensive, needs complex designs, and needs careful tuning. To overcome the drawbacks of the previous models, the proposed GO-ALSTM model improves the capabilities for nonlinear feature learning, handles temporal dependencies, avoids overfitting, and increases the accuracy with improved generalization and convergence optimization.

5. Conclusion

The proposed model involves the utilization of the GO-ALSTM-based deep learning algorithm for human-machine coordination in adaptive industrial automation through IoT sensor data, feature reduction via PCA, and optimized temporal learning. The performance obtained using the proposed model was outstanding, with improved accuracy of 97.0 ± 0.3%, superior precision 96.8 ± 0.4%, high recall 97.2 ± 0.5%, along with F1-score of 97.0 ± 0.4%, which was higher than the performance obtained using SVM, RF, and other DL algorithms. The results show that GO-ALSTM demonstrated better performance when compared to CNN-LSTM with 96.1 ± 0.4% accuracy in the prediction task. The proposed model improves adaptability, reliability, and decision-making in industrial environments. However, its effectiveness is limited by high computational complexity and extensive hyperparameter tuning requirements. Future research needs to be concerned with the development of lightweight optimization methods, automation of parameter tuning, real world industrial testing, and inclusion of edge computing.

Reference

1. Zhang, J. and Fujimura, S., 2026. An innovative meta–heuristic for balancing and scheduling human–robot collaborative assembly lines in Industry 5.0. Journal of Industrial and Production Engineering, 43(1), pp.117-137.https://doi.org/10.1080/21681015.2025.2533436
2. Silva, C.A.D.S. and Paladini, E.P., 2025. Smart machine vision system to improve decision-making on the assembly line. Machines, 13(2), p.98.https://doi.org/10.3390/machines13020098
3. Langås, E.F., Zafar, M.H. and Sanfilippo, F., 2026. Exploring the synergy of human-robot teaming, digital twins, and machine learning in Industry 5.0: a step towards sustainable manufacturing. Journal of Intelligent Manufacturing, 37(3), pp.999-1022. https://doi.org/10.1007/s10845-025-02580-x
4. Miao, X., Hou, W. and Li, Z., 2026. Fine-Grained Implicit Intention Pattern Recognition for Key Interactive Tasks in Industrial Human–Machine Collaboration. Symmetry, 18(2), p.317.https://doi.org/10.3390/sym18020317
5. Kaasinen, E., Anttila, A.H., Heikkilä, P., Laarni, J., Koskinen, H. and Väätänen, A., 2022. Smooth and resilient human–machine teamwork as an industry 5.0 design challenge. Sustainability, 14(5), p.2773.https://doi.org/10.3390/su14052773
6. Zhao, S., Zhang, H., Sun, B. and Wang, Y., 2026. Spatio-Temporal Graph Neural Networks for Anomaly Detection in Complex Industrial Processes. Sensors, 26(5), p.1597.https://doi.org/10.3390/s26051597
7. Le, T.M., Tran, H.M., Wang, K., Pham, H.V. and Dao, S.V., 2025. An Internet of Things-Integrated Deep Learning Model for Fault Diagnosis in Industrial Rotating Machines. IEEE Access, 13, 57266-57286. https://doi.org/10.1109/ACCESS.2025.3553155
8. González-Potes, A., Félix-Cuadras, R.A., Mena, L.J., Félix, V.G., Martínez-Peláez, R., Ostos, R., Velarde-Alvarado, P. and Ochoa-Brust, A., 2026. Safety-Aware Multi-Agent Deep Reinforcement Learning for Adaptive Fault-Tolerant Control in Sensor-Lean Industrial Systems: Validation in Beverage CIP. Technologies, 14(1), p.44. https://doi.org/10.3390/technologies14010044
9. Alam, S. and Khan, M.F., 2024. Enhancing AI-human collaborative decision-making in Industry 4.0 management practices. IEEE access, 12, pp.119433-119444.https://doi.org/10.1109/ACCESS.2024.3449415
10. Chen, X., Zhang, X., Shi, Y. and Pang, J., 2025. HCT-det: A high-accuracy end-to-end model for steel defect detection based on hierarchical CNN–transformer features. Sensors, 25(5), p.1333.https://doi.org/10.3390/s25051333
11. Asadi, R., Queguineur, A., Wiikinkoski, O., Mokhtarian, H., Aihkisalo, T., Revuelta, A. and Ituarte, I.F., 2024. Process monitoring by deep neural networks in directed energy deposition: CNN-based detection, segmentation, and statistical analysis of melt pools. Robotics and Computer-Integrated Manufacturing, 87, p.102710.https://doi.org/10.1016/j.rcim.2023.102710
12. Zhu, X., Mårtensson, P., Hanson, L., Björkman, M. and Maki, A., 2025. Automated assembly quality inspection by deep learning with 2D and 3D synthetic CAD data. Journal of Intelligent Manufacturing, 36(4), pp.2567-2582.https://doi.org/10.1007/s10845-024-02375-6
13. Islam, M.R., Zamil, M.Z.H., Rayed, M.E., Kabir, M.M., Mridha, M.F., Nishimura, S. and Shin, J., 2024. Deep learning and computer vision techniques for enhanced quality control in manufacturing processes. IEEE Access, 12, pp.121449-121479.https://doi.org/10.1109/ACCESS.2024.3453664
14. Lin, H.D., Jheng, C.K., Lin, C.H. and Chang, H.T., 2024. Utilizing deep learning for defect inspection in hand tool assembly. Sensors, 24(11), p.3635.https://doi.org/10.3390/s24113635
15. Benka, D., Horváth, D., Špendla, L., Gašpar, G. and Stremy, M., 2025. Machine learning-based detection of anomalies, intrusions, and threats in industrial control systems. IEEE Access, 13, pp.12502-12514.https://doi.org/10.1109/ACCESS.2025.3530902
16. 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