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EMERGING TECHNIQUES FOR MARITIME FAULT DIAGNOSIS

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Abstract. Emerging technologies are transforming the maritime sector, enabling innovations such as port automation and smart ports. This paper presents a data-driven approach for fault diagnosis in containerized gantry cranes, focusing on fault detection and isolation. Two fault types are considered: one affecting the horizontal motor (Fault 1), causing abnormal trolley movements, and another in the vertical motor due to voltage degradation (Fault 2). The study compares Support Vector Machine (SVM), Random Forest (RF), and Neural Network (NN) classifiers, achieving fault detection accuracies of 86.5% (NN), Fault 1 isolation accuracy of 93.4% (NN), and Fault 2 isolation accuracy of 93.9% (SVM), respectively. The results demonstrate the method's effectiveness in enabling proactive maintenance and ensuring efficient crane operation, minimizing downtime and costly delays in container handling.

Keywords: Fault Detection; Fault Isolation; Fault Diagnosis; Model-Based Fault Diagnosis; Emerging Techniques; Gantry Crane.

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1. INTRODUCTION

The maritime industry is undergoing a significant transformation fueled by emerging technologies that are reshaping port operations, logistics, and ocean-related services. Innovations such as autonomous vessels, intelligent maritime transport systems, decarbonization strategies, and the development of smart ports are driving increased efficiency, safety, and environmental sustainability in maritime operations (Zou et al., 2025). Within this broader evolution, port automation has emerged as a critical pillar, enabling smarter, data-driven, and resilient infrastructures (Zheng et al., 2025).

Container gantry cranes play a fundamental role in maritime terminals by facilitating the loading and unloading of cargo. Their reliable and uninterrupted operation is vital to maintaining port productivity and avoiding costly delays (Safaei et al., 2024). As complex electromechanical systems, cranes are susceptible to faults in the electric motors responsible for moving the load and in the sensors and actuators. Any faults in these container gantry crane systems can affect performance and safety. Consequently, the need for fault diagnosis systems has become increasingly important.

Fault diagnosis typically involves two main stages: fault detection (identifying the presence of a fault) and fault isolation (determining its type and location) (Isermann, 2006). Traditional model-based methods require accurate physical models, which can be difficult to obtain due to system complexity. In contrast, data-driven approaches have gained popularity, using real-time operational data to monitor equipment health and detect anomalies without needing explicit physical models (Melo et al., 2024; Lee et al., 2020).

This paper proposes a data-driven fault diagnosis approach for a container gantry crane. The method utilizes normal operating data to detect deviations from expected behavior and fault data to train models capable of isolating specific fault types. A decision-making component is included to enable timely intervention and ensure operational continuity.

The focus is placed on two representative faults, Fault 1 and Fault 2. Fault 1 represents a failure in the horizontal motor, which is responsible for moving the trolley. This fault occurs due to a progressive or sudden loss of power in Motor 1, for example a drop-in voltage beyond a certain point. As a result, the trolley's horizontal position shows abnormal variations, and the system may slow down or completely stop moving horizontally. The Fault 2 refers to a failure in the vertical motor, which controls the cable. This fault occurs due to a gradual degradation in the supply voltage of Motor 2. This condition leads to unexpected behavior in the cable length variation and may cause instability in the cable angle, indicating difficulties in lifting the load.

These faults are representative of common degradation patterns in port machinery and serve to evaluate the proposed system's responsiveness and accuracy. The fault diagnosis system demonstrates excellent performance, making it suitable for proactive maintenance and smart port integration.

This paper is organized as follows. The next section presents intelligent methods for gantry crane fault diagnosis. Section 3 presents the gantry crane process and motor faults, the proposed gantry crane fault diagnosis, and the machine learning techniques used in gantry crane fault diagnosis. The results obtained when applied the proposed approach of fault diagnosis are presented in section 4 and finally some conclusions and future work are drawn in section 5.

2. INTELLIGENT METHODS FOR GANTRY CRANE FAULT DIAGNOSIS

2.1. Types of Gantry Crane Faults

Gantry cranes are vulnerable to a range of faults, which can be broadly categorized as electrical, operational, or structural. Electrical faults are among the most critical, as they involve components such as motors, sensors, control panels, and wiring systems, potentially compromising operational safety and continuity (Shankar, 2024; Kudelina et al., 2021). For instance, malfunctions in sensors or failures in load limiters may result in lifting operations that exceed safe thresholds, posing significant safety risks (Kumar et al., 2022). Furthermore, defects within control panels, such as degraded relays or malfunctioning contactors, can lead to unanticipated shutdowns and reduced system reliability (Shankar, 2024; Kudelina et al., 2021).

Operational faults typically arise from improper handling practices, including overloading, abrupt stopping, or unbalanced movements. Such practices accelerate mechanical wear and increase the likelihood of component failure, particularly when preventive maintenance procedures are inadequate or inconsistently applied (Verschoof, 2002).

Structural faults, in contrast, are often attributed to material fatigue and corrosion. Prolonged exposure to cyclic loading can initiate microcracks within the crane's structure, while harsh environmental conditions, such as humidity or exposure to corrosive agents, may accelerate material degradation and compromise overall structural integrity (Lu et al., 2012; Abo Nassar, 2022).

2.2. Intelligent Diagnosis Techniques

The growing complexity of industrial systems has propelled the advancement of intelligent diagnostic techniques, particularly those utilizing machine learning, to facilitate early and accurate fault detection. Among the most commonly employed methods are Neural Networks (NN), Random Forests (RF), and Support Vector Machines (SVM), all of which are well-equipped to handle nonlinear patterns and high-dimensional sensor data.

Neural Networks, especially deep learning architectures, have demonstrated outstanding performance in modeling complex relationships in vibration and current signals collected from gantry cranes. These models can identify subtle anomalies associated with bearing defects, rotor faults, or cable fatigue with high precision (Wang et al., 2022). Additionally, they support the implementation of predictive maintenance strategies by learning from both historical failure data and real-time monitoring inputs.

Random Forest is a robust ensemble learning method particularly effective in noisy industrial environments. It builds multiple decision trees and aggregates their predictions, enhancing classification accuracy and reducing the risk of overfitting. This technique has proven effective in detecting faults such as imbalance, misalignment, and loose electrical or mechanical connections (Yang et al., 2008).

Support Vector Machines are especially advantageous when working with high-dimensional but limited datasets. By maximizing the decision margin between fault classes, SVMs improve generalization performance and reduce misclassification rates, making them suitable for real-time fault detection scenarios (Souza et al., 2014).

2.3. Comparison with Previous Work

Recent studies have investigated hybrid models that integrate these techniques to capitalize on the strengths of each method. For example, Neural Networks (NN) can be employed to extract complex features from raw input signals, which are subsequently classified using Random Forest (RF) or Support Vector Machines (SVM) to enhance robustness and accuracy (Stefan et al., 2022). When combined with Internet of Things (IoT)-based condition monitoring systems, these intelligent approaches enable continuous diagnostics, leading to significant reductions in maintenance costs (Doorsamy, 2025).

In comparison to traditional rule-based or thresholding methods, intelligent models have demonstrated superior performance. Previous research has evidenced that deep neural networks outperform conventional signal analysis techniques in the detection of early-stage faults (Wang et al., 2022). Similarly, Random Forest classifiers provide greater reliability than individual decision trees when operating in noisy industrial environments (Yang et al., 2008). Support Vector Machines have also been validated as highly effective tools in industrial condition monitoring, particularly when working with limited datasets (Souza et al., 2014).

Building upon these findings, the present study applies and compares NN, RF, and SVM methodologies for fault classification in gantry crane operations, thereby contributing to the advancement of intelligent maintenance systems within industrial settings.

3. CONTAINER GANTRY CRANE

3.1. Gantry Crane Process and Motor Faults

The gantry crane system is driven by two primary control inputs: the horizontal motor voltage ($V_{horizontal}$) and the vertical motor voltage ($V_{vertical}$). These voltages serve as control signals to the respective motors that move the crane trolley horizontally and vertically. The system's measurable outputs include the horizontal position of the trolley (x), the cable length (l), and the cable angle (θ). These outputs characterize the physical state of the crane and the load, enabling precise monitoring and control. Figure 1

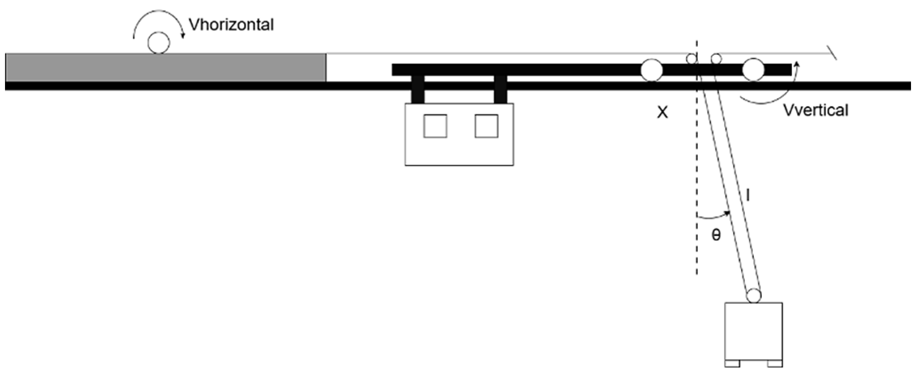

Figure 1. Container gantry crane.

shows the container gantry crane as well as the variables.

Understanding the relationship between inputs and outputs is critical for ensuring safe and efficient crane operation. Deviations from expected behavior can indicate faults or failures within the system, particularly in the electric motors that drive the crane. Electric motors, especially those used in industrial equipment like gantry cranes, are subject to various faults that can degrade performance or cause failures. Key types of faults include:

- **Bearing Faults:** Damaged or worn bearings generate vibrations and noise, leading to increased friction and possible motor seizure. Bearing defects are among the most frequent causes of motor failure (Jardine et al., 2006).
- **Rotor Faults:** Broken rotor bars or rotor eccentricity affect the motor's magnetic field and torque production, causing unbalanced operation and vibrations (Benbouzid, 2000).
- **Stator Faults:** Insulation degradation or winding short circuits in the stator cause increased currents and heat, risking permanent damage (Skowron et al., 2020).
- **Supply Voltage Issues:** Voltage unbalance, dips, or spikes in the motor supply can lead to inefficient operation, overheating, or premature aging.

In the context of gantry cranes, these faults often manifest as abnormal motor responses, which reflect in the input voltages ($V_{horizontal}$ and $V_{vertical}$) and the resulting output measurements (x, l, θ). For example, a bearing fault may cause irregular trolley movement or abnormal oscillations in cable angle.

Monitoring the inputs and outputs of the gantry crane allows for early detection of motor faults, preventing costly downtime or accidents. Feature extraction from input voltages and output measurements combined with machine learning classifiers (e.g., Random Forest or SVM) enables effective fault diagnosis by identifying patterns associated with different fault conditions.

3.2. Proposed Gantry Crane Fault Diagnosis

In industrial automation, gantry crane systems are widely used for load handling, requiring precise control over movement in both horizontal and vertical directions. The system under study utilizes two independent actuators: a horizontal drive motor for trolley displacement and a vertical motor for hoisting control via a suspended cable. Accurate modeling of operational states is critical for developing robust fault detection and isolation (FDI) methodologies. In the following the different operating states of the container gantry crane are presented: normal operation, under horizontal motor fault (Fault 1) and under vertical motor fault (Fault 2).

Normal Operation (Without Fault Condition)

Under normal operating conditions, the system receives voltage inputs $V_{horizontal}$ and $V_{vertical}$, which control the horizontal and vertical motion, respectively. The measured outputs horizontal trolley position (x), cable length (l), and cable angle (θ) exhibit stable and predictable dynamic responses. This nominal behavior reflects proper functionality of both motors and mechanical components, forming the baseline for comparison with faulty states. Signal trajectories follow expected profiles derived from the system's physical dynamics and control strategy, ensuring safe and efficient load transportation.

Fault 1 – Horizontal Motor Fault

Fault 1 is defined by the degradation or failure of the horizontal drive motor, which is responsible for translating the trolley along the gantry axis. This condition is typically simulated as a progressive or sudden drop in the supply voltage $V_{horizontal}$, emulating power loss scenarios due to rotor bar defects, winding insulation faults, or bearing degradation (Benbouzid, 2000; Nandi et al., 2005). As a result, the horizontal position response (x) becomes erratic or ceases altogether, indicating impaired translational movement. Such anomalies can lead to incomplete or failed transport operations and may pose safety risks if not promptly addressed.

Fault 2 – Vertical Motor Fault

Fault 2 corresponds to the malfunction of the vertical motor, which manages the cable's retraction and extension. This fault is modeled as a progressive voltage degradation in $V_{vertical}$, simulating issues such as stator winding faults, voltage imbalance, or motor overload (Jardine et al., 2006). The most immediate effect is observed in the cable length (l), which no longer follows expected changes, compromising the system's ability to lift or lower the load accurately. Moreover, instability in the cable angle (θ) may arise due to unbalanced tension or irregular cable dynamics, further indicating impaired vertical actuation.

The identification and modeling of these three operational states nominal, fault in horizontal motor, and fault in vertical motor provide a structured basis for supervised fault diagnosis using classification models such as Support Vector Machines (SVM) and Random Forests. By extracting meaningful features from the system's input-output data, it becomes possible to detect and classify faults based on deviations from nominal behavior, enabling proactive maintenance and improved system reliability (Widodo, Yang, 2007; Zhang et al., 2019).

Figure 2 shows the approach proposed in this paper for the diagnosis of two faults considered through the detection and isolation stages. Figure 2 shows the gantry crane models under normal operation conditions, with Fault 1 and with Fault 2. The aim of this paper is to evaluate the fault diagnosis performance of three types of model, NN, RF and SVM, so the fault diagnosis approach shown in Figure 2 was tested with these models. Fault detection occurs when, using the existing input data, the gantry model under normal operation has outputs that are not identified with the outputs that would occur with the process under normal operation. In this situation, it is necessary to assess which of the fault models, Fault 1 or Fault 2, performs better. Given the same inputs, if the model with the best performance is the one corresponding to Fault 1, this is the isolated fault. On the other hand, if the best performing model is the one corresponding to Fault 2, this is the isolated fault.

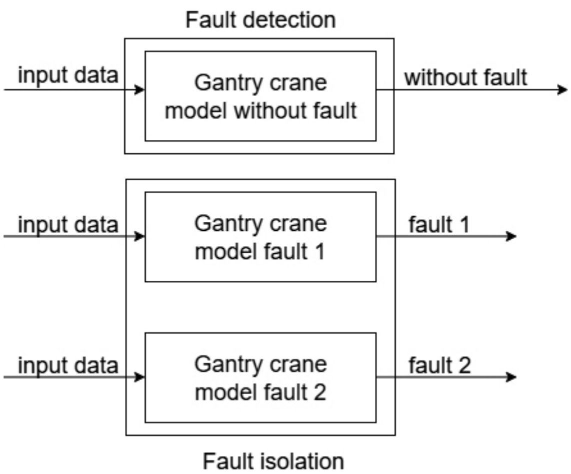

Figure 2. Gantry crane fault diagnosis. Fault detection is shown at the top and fault isolation at the bottom.

To evaluate the performance of the models, is presented the confusion matrix of fault diagnosis, the percentage results of fault diagnosis and the metrics Precision, Recall, and F1-Score, which are standard in machine learning classification tasks, particularly for multiclass and imbalanced datasets. Precision measures the proportion of true positive predictions among all positive predictions for a given class, defined as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

where TP denotes true positives and FP false positives. Recall, also known as sensitivity, quantifies the proportion of actual positive instances correctly identified by the model:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

with FN representing false negatives. The F1-Score, calculated as the harmonic mean of Precision and Recall,

$$\text{F1} = 2 \text{ x} \frac{\text{Precision x Recall}}{\text{Precision+Recall}} \tag{3}$$

provides a balanced measure of the classifier's accuracy, particularly valuable when class distributions are uneven. These metrics comprehensively characterize the trade-off between identifying positive cases and minimizing false alarms. Further details on their definitions and applications can be found in (Powers D.M.W. 2011).

3.3. Machine Learning Techniques

The characteristics of machine learning techniques used in gantry crane fault diagnosis, as shown in Figure 2, are presented below.

The data used in this study were generated through simulations of a dynamic gantry crane model, totaling 90.000 samples equally distributed across three classes: normal operation, Fault 1, and Fault 2 (30.000 samples per class). The considered 12 features from input signals and outputs are: horizontal and vertical velocities, load position, cable position, swing angle, the mean and standard deviation of load and cable positions, the absolute difference between velocities, the ratio of load position to cable position, the products of swing angle with both load and cable positions, and the sine of the swing angle.

Neural Network Fault Diagnosis

A fault diagnosis system for a container gantry crane uses a feedforward Artificial Neural Network (ANN) to classify normal operation and two fault conditions (Fault 1 and Fault 2). The process begins by loading three datasets corresponding to each class. From the input signals (e.g., velocities) and output signals (e.g., position, cable length, angle), twelve features are extracted, including statistical metrics, ratios, differences, and trigonometric transformations that enhance the recognition of fault patterns. These features are labeled accordingly and combined into a single input matrix, with the corresponding labels forming the target vector. Next, the feature values are normalized to the range [0, 1], and the labels are encoded numerically to suit the classification model. The dataset is then partitioned into training and validation subsets, with 70% of the data used for training and 30% reserved for validation. A feedforward neural network with two hidden layers is initialized and trained on the training data for a specified number of epochs. After training, the network predicts labels for the validation set, and the model's performance is evaluated using a confusion matrix and overall accuracy metric. The metrics Precision, Recall, and F1-score were also used to evaluate the model's performance.

Random Forest Fault Diagnosis

A Random Forest classifier is employed to diagnose faults (Fault 1 and Fault 2) in a container gantry crane by analyzing features extracted from datasets representing normal operation and two fault conditions. The feature vectors, composed of twelve dimensions, include velocities, positions, and derived statistical metrics. After applying min-max normalization to scale the features between 0 and 1, the data is divided into training and validation subsets, with 70% used for training and 30% for validation. The Random Forest model is trained on the training data and subsequently used to predict fault classes on the validation set. After training, the network predicts labels for the validation set, and the model's performance is evaluated using a confusion matrix and overall accuracy metric, as well as the metrics Precision, Recall, and F1-score.

Support Vector Machines Fault Diagnosis

A fault diagnosis system for a gantry crane is developed using a multiclass Support Vector Machine (SVM) classifier. The methodology begins by loading datasets corresponding to normal operation and two distinct fault types (Fault 1 and Fault 2). From the input-output data, twelve-dimensional feature vectors are extracted, combining velocities, positions, cable lengths, angles, and derived statistical measures to create informative features for classification. These features are then normalized to the range [0,1]. The dataset is partitioned into training and validation subsets, with 70% of the data used for training and 30% reserved for validation. The multiclass SVM model is trained with automatic hyperparameter optimization to enhance its performance. Finally, the trained model predicts fault classes on the validation set, and its performance is evaluated using a confusion matrix, classification accuracy, as well as Precision, Recall, and F1-score metrics.

4. RESULTS

The results obtained with the three approaches are presented below. The confusion matrix is presented for each of the approaches used, as well as the percentage results of correct and incorrect evaluations. The confusion matrix is presented for each approach used, along with the percentages of correct and incorrect classifications, and the model's performance is further evaluated using the metrics Precision, Recall, and F1-score. Finally, a comparative analysis of the results is made.

The fault diagnosis results obtained using NN are presented in Table 1 using the confusion matrix.

Table 1. Confusion matrix of fault diagnosis using NN.

		Predicted Classes		
		Normal operation	**Fault 1**	**Fault 2**
True Classes	Normal operation	2596	158	246
	Fault 1	58	2802	140
	Fault 2	86	169	2745

Analyzing the results shows that the use of NNs performs well in detecting and isolating the faults considered. It should also be noted that when the system is operated in normal conditions, the model corresponding to the container gantry crane under normal operation also performs well. Table 1 shows the results in bold and there is a direct correspondence between the true classes and the predicted classes.

Table 2 presents the percentage results of correct and incorrect diagnoses in each of the situations, process in normal operation, with Fault 1 or with Fault 2.

Table 2. Percentage results of fault diagnosis using NN.

	Correct diagnosis (%)	Incorrect diagnosis (%)
Normal operation	86.5	13.5
Fault 1	93.4	6.6
Fault 2	91.5	8.5

The results in Table 3 demonstrate that the model performs well across all classes. For normal operation, it shows good recall (91.5%) but slightly lower precision (87.6%).

Table 3. Precision, Recall and F1-Score results of fault diagnosis using NN.

	Precision (%)	Recall (%)
Normal operation	87.6	91,5
Fault 1	94.7	86.5
Fault 2	89.6	93.4

Fault 1 has very high precision (94.7%) but lower recall (86.5%), suggesting some missed detections. Fault 2 shows balanced performance with both high precision (89.6%) and recall (93.4%), resulting in the best F1-score (91.4%). Overall, the model is effective, especially in detecting faults.

The fault diagnosis results obtained using RF are presented in Table 4 using the confusion matrix.

Table 4. Confusion matrix of fault diagnosis using RF.

		Predicted Classes		
		Normal operation	Fault 1	Fault 2
True Classes	Normal operation	**2400**	135	465
	Fault 1	18	**2730**	252
	Fault 2	13	198	**2789**

The use of RF also provides good performance in detecting and isolating the faults considered, as well as when operating in normal conditions. Table 4 shows the results obtained when RF was used, with the best results shown in bold, and there is a direct correspondence between the true classes and the predicted classes.

Table 5 presents the percentage results of correct and incorrect diagnoses in each of the situations, process under normal operation, with fault 1 or with fault 2.

Table 5. Percentage results of fault diagnosis using RF.

	Correct diagnosis (%)	Incorrect diagnosis (%)
Normal operation	80.0	20.0
Fault 1	91.0	9.0
Fault 2	93.0	7.0

The results in Table 6 demonstrate that the model shows strong performance overall, with some trade-offs between precision and recall across classes. For normal operation, the very high precision (99%) indicates almost no false positives, but the lower recall (80%) suggests that some normal cases were misclassified, resulting in an F1-score of 88%. Fault 1 demonstrates a well-balanced performance, with precision (89%) and recall (91%) both high, leading to a strong F1-score of 90%. Fault 2 shows high recall (93%), meaning most fault cases are detected, but with a lower precision (80%), indicating more false positives. The F1-score of 86% reflects this imbalance. Overall, the model is effective, especially in minimizing false alarms for normal operation and in reliably detecting faults.

Table 6. Precision, Recall and F1-Score results of fault diagnosis using RF.

	Precision (%)	Recall (%)	F1-Score (%)
Normal operation	99	80	88
Fault 1	89	91	90
Fault 2	80	93	86

The fault diagnosis results obtained using SVM are presented in Table 7 using the confusion matrix.

Table 7. Confusion matrix of fault diagnosis using SVM.

		Predicted Classes		
		Normal operation	Fault 1	Fault 2
True Classes	Normal operation	**2473**	163	364
	Fault 1	57	**2752**	191
	Fault 2	57	126	**2817**

Table 7 shows the results obtained when the SVM was used, with the best results shown in bold, verifying that there is a direct correspondence between the true classes and the predicted classes. The use of SVM also provides good performance in detecting and isolating the faults considered, as well as when there is no fault.

Table 8 presents the percentage results of correct and incorrect diagnoses in each of the situations, process under normal operation, with fault 1 or with fault 2.

Table 8. Percentage results of fault diagnosis using SVM.

	Correct diagnosis (%)	Incorrect diagnosis (%)
Normal operation	82.4	17.6
Fault 1	91.7	8.3
Fault 2	93.9	6.1

The results in Table 9 demonstrate that the model demonstrates strong overall performance. For normal operation, the high precision (96%) indicates few false positives, while the recall (82%) suggests some true cases were missed. The F1-score of 89% shows solid performance. Fault 1 shows balanced and high values for both precision (90%) and recall (92%), leading to a strong F1-score of 91%, indicating reliable detection of this fault. Fault 2 has high recall (94%), meaning most cases are detected, but with a slightly lower precision (84%), suggesting more false positives. The resulting F1-score (88%) still reflects good performance. Overall, the model is effective, with particularly strong fault detection capabilities and very few false alarms in normal operation.

Table 9. Precision, Recall and F1-Score results of fault diagnosis using SVM.

	Precision (%)	Recall (%)	F1-Score (%)
Normal operation	96	82	89
Fault 1	90	92	91
Fault 2	84	94	88

Analysis of the results shows that the three approaches presented perform well in detecting and isolating the faults considered, Fault 1 in the motor that moves the carriage, Fault 2 in the motor that lifts the cable. It should also be noted that when there is no fault, the model corresponding to the container gantry crane under normal operation performs well. Evaluating the results shown in the tables 2, 5 and 8, for correct diagnosis and incorrect diagnosis, NN performs better at detecting faults and isolating Fault 1 and SVM at isolating Fault 2.

The differences in performance between the classifiers reflect their learning characteristics. The NN showed the best overall performance for normal operation (86.5%) and Fault 1 (93.4%), indicating its strong ability to distinguish both normal and faulty conditions through learning complex, nonlinear patterns in the data. The RF classifier was slightly less accurate in detecting normal operation (80.0%) but performed well in identifying Fault 2 (93.0%), likely due to its strength in handling localized and structured patterns typically associated with decision trees. The SVM achieved the highest accuracy for Fault 2 (93.9%), showing its effectiveness in defining clear decision boundaries in the feature space. However, its performance on normal operation (82.4%) and Fault 1 (91.7%) was slightly lower compared to the NN. These results highlight how each classifier's strengths align differently with the characteristics of the data: the NN excels in generalization, RF captures structured fault patterns well, and SVM is particularly effective in separating distinct fault conditions.

5. CONCLUSIONS

This study presented a comparative evaluation of three machine learning approaches, Artificial Neural Networks (NN), Random Forest (RF), and Support Vector Machines (SVM), for fault diagnosis in a gantry crane system. The classification models were trained using features extracted from system inputs and outputs, capturing relevant dynamic behaviors under three distinct operational conditions: normal operation, horizontal motor fault (Fault 1), and vertical motor fault (Fault 2).

The results demonstrated that all three models achieved high accuracy in identifying both types of faults as well as distinguishing them from the fault-free condition. Each approach effectively captured the underlying patterns in the data, providing reliable fault classification based on variations in trolley position, cable length, and cable angle.

These findings confirm that data-driven methods are well-suited for automated fault diagnosis in electromechanical systems and support their deployment in real-time monitoring frameworks for increased system reliability and operational safety.

Although this work focused on two specific fault types, the proposed methodology is designed to be scalable and adaptable to additional fault scenarios, provided that representative signal data are available. Furthermore, the approach is not limited to the studied crane system. Given its data-driven nature, the method can be retrained and applied to other cranes or similar maritime equipment, enabling fault diagnosis across a broader range of operational contexts.

Future work will explore hybrid models, online learning strategies, and expanded fault scenarios to further enhance diagnostic performance in complex industrial environments.

Conflict of interest: The authors declare that they have no conflict of interest.

REFERENCES

Abo Nassar, N.E., 2022. Corrosion in marine and offshore steel structures: Classification and overview. International Journal of Advanced Engineering, Sciences and Applications, 3(1), 7–11. https://doi.org/10.47346/ijaesa.v3i1.80

Benbouzid, M. E. H., 2000. A review of induction motors signature analysis as a medium for faults detection. IEEE

Transactions on Industrial Electronics. 47(5), 984–993. https://doi.org/10.1109/41.873206

Doorsamy, W., 2025. Condition Monitoring of Electric Machines: Modern Frameworks and Data-Driven Methodologies. Machines, 13, 144. https://doi.org/10.3390/machines13020144

Isermann, Rolf, 2006. Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance. 1st ed. Berlin, Heidelberg: Springer Berlin Heidelberg.

Jardine, A. K. S., Lin, D., & Banjevic, D., 2006. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing. 20(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

Kudelina, K.; Vaimann, T.; Asad, B.; Rassõlkin, A.; Kallaste, A.; Demidova, G., 2021. Trends and Challenges in Intelligent Condition Monitoring of Electrical Machines Using Machine Learning. Appl. Sci., 11, 2761. https://doi.org/10.3390/app11062761

Kumar, R., Singh, P. and Sharma, M., 2022. Hybrid intelligent systems for predictive maintenance of gantry cranes, Journal of Intelligent Manufacturing, 33(4), pp. 1207-1221.

Lee, J., Davari, H., Singh, J. and Pandhare, B., 2020. Industrial AI: Applications with Sustainable Performance. Springer.

Lu, Shi Qing, et al., 2012. Structural Fatigue Analysis of a Container Crane. Applied Mechanics and Materials, vol. 159, Trans Tech Publications, Ltd., Mar., pp. 272–276. https://doi.org/10.4028/www.scientific.net/amm.159.272

Melo, A.; Câmara, M.M.; Pinto, J.C., 2024. Data-Driven Process Monitoring and Fault Diagnosis: A Comprehensive Survey. Processes, 12, 251. https://doi.org/10.3390/pr12020251

Nandi, S., Toliyat, H. A., & Li, X., 2005. Condition monitoring and fault diagnosis of electrical motors—A review. IEEE Transactions on Energy Conversion. 20(4), 719–729. https://doi.org/10.1109/TEC.2005.847955

Powers, D. M. W., 2011. Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness & Correlation. Journal of Machine Learning Technologies, 2(1), 37–63. https://doi.org/10.48550/arXiv.2010.16061

Safaei, M., Hejazian, M., Pedrammehr, S., Pakzad, S., Ettefagh, M. and Fotouhi, M., 2024. Damage Detection of Gantry Crane with a Moving Mass Using Artificial Neural Network. Buildings. https://doi.org/10.3390/buildings14020458

Shankar, B. M., 2024. Intelligent Fault Diagnosis in Electric Motors Using AI Techniques, RJCSE, vol. 5, no. 1, pp. 106–117, Jul.

Skowron, M.; Orlowska-Kowalska, T.; Wolkiewicz, M.; Kowalski, C.T., 2020. Convolutional Neural Network-Based Stator Current Data-Driven Incipient Stator Fault Diagnosis of Inverter-Fed Induction Motor. Energies, 13, 1475. https://doi.org/10.3390/en13061475

Souza, D., Granzotto, M., Almeida, G., Oliveira L. and Cláudio L., 2014. Fault Detection and Diagnosis Using Support Vector Machines a SVC and SVR Comparison. Journal of Safety Engineering. 18-29.

Stefan W., Konstantin K., Karl H., Marco L., Alexandros B., Gregoris M., Klaus-D. T., 2022. Hybrid-augmented intelligence in predictive maintenance with digital intelligent assistants, Annual Reviews in Control, Volume 53, 382-390, ISSN 1367-5788, https://doi.org/10.1016/j.arcontrol.2022.04.001

Verschoof J., 2002. Cranes: Design, Practice, and Maintenance, John Wiley & Sons. ISBN: 978-1-86058-373-5

Wang, Z., W. Bian, T. Li, X. Zhang and D. He., 2022. Research on Motor Fault Diagnosis Methods Based on Machine Learning. 2022. 34th Chinese Control and Decision Conference (CCDC), Hefei, China, pp. 1879-1884, https://doi.org/10.1109/CCDC55256.2022.10033462

Widodo, A. and Yang, B. S., 2007. Support vector machine in machine condition monitoring and fault diagnosis. Mechanical Systems and Signal Processing. 21(6), 2560–2574. https://doi.org/10.1016/j.ymssp.2006.12.007

Yang, B.-S., Di, X., Han, T., 2008. Random forests classifier for machine fault diagnosis. Journal of Mechanical Science and Technology. 22. 1716-1725. https://doi.org/10.1007/s12206-008-0603-6

Zeng, F., Chen, A., Xu, S., Chan, H.K., Li, Y., 2025. Digitalization in the Maritime Logistics Industry: A Systematic Literature Review of Enablers and Barriers. J. Mar. Sci. Eng., 13, 797. https://doi.org/10.3390/jmse13040797

Zhang, W., Yang, D., & Wang, H., 2019. Data-driven methods for predictive maintenance of industrial equipment: A survey. IEEE Systems Journal. 13(3), 2213–2227. https://doi.org/10.1109/JSYST.2019.2905565

Zou, Y., Xiao, G., Li, Q., Biancardo, S.A., 2025. Intelligent Maritime Shipping: A Bibliometric Analysis of Internet Technologies and Automated Port Infrastructure Applications. J. Mar. Sci. Eng., 13, 979. https://doi.org/10.3390/jmse13050979