Failure Log Analytics for Reducing Electrical Machine Downtime using Deep Learning

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Abstract: - Electrical machine downtime reduces productivity across various operation times that are addressed using stored data logs in the controller. Analyzing such logs is useful in preventing/ reducing machine downtime through precise controller options. This article proposes a Downtime Reduction-focused Log Analytical Model (DR-LAM) for improving the machine operation time by reducing operation failures. In this model, deep learning is employed for differentiating the production-less electrical cycles in correlation with the previous output. This differentiation is conditional using run-time failures and failed operation cycles. Therefore the logs are analyzed based on the above differentiations for precise problem identification. The training for the deep learning network is provided using previous differentiated cycle logs improving the detection ratio.

Key-Words: - Deep Learning, Downtime, Electrical Machines, Log Analysis, operation time, orun-time failure, peration cycle.

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1 Introduction

Electrical machine downtime detection is a process that detects the process that is stopped due to unplanned events in a machine. The machine downtime detection detects the exact downtime cause and reasons by identifying the cell of the machine, [1], [2]. The predictive maintenance (PdM) tool-based detection method is used for machine downtime detection. PdM is used as an early machine downtime fault detection which reduces the latency in performing tasks. The PdM method uses features that contain faults in electrical machines, [3], [4].

An electrical machine failure log analysis is a process that provides visible information for further processes. The log analysis uses pattern recognition and classification methods to identify the important logs in electrical machines, [5]. The exact failures that occur in electrical machines are detected based on the information that is collected from machine storage. The accurate failure log search ratio is identified which reduces the complexity level in electrical machines, [6], [7].

Log data analytics is a process that reviews the logs and identifies the threats which are presented in the log, [8]. A Log data analytics-based method is used to reduce the overall electrical machine downtime. Log data analytics ensures compliance and reviews the issues to solve the problems, [9]. The log data analytics-based method protects the downtime level of machines which improves the accuracy level in performing tasks, [10].

2 Related Works

The study, [11], proposed a machine learning (ML) evaluation method for maintenance records in photovoltaic (PV) inverters. The ML method analyzes the datasets and produces leverages to the evaluation process. The failure frequencies and circuits are also analyzed to reduce the computational cost ratio of inverters. The actual inverter-related records are identified which minimizes the energy consumption in the computation process. The proposed method reduces the failure ratio in maintenance which enhances the performance range of PV inverters.

The study, [12], introduced a smart condition-monitoring strategy using wireless accelerometer sensor modules. The main aim of the strategy is to maintain the records and operations that are presented in smart devices. Data-driven capabilities and the Internet of Things (IoT) are used in condition monitoring systems. The data-driven capabilities improve the cost-effective range of heavy machinery. The introduced strategy increases the feasibility level of the devices.

The study, [13], designed a principal component analysis (PCA) approach for fault detection. The PCA approach uses an analysis method that analyzes the exact health conditions and scenarios of the patients. The analyzed data produce optimal information for issues and faults detection in the condition monitoring system. Both vibrational and electrical signatures are used here to predict the issues in the systems. The designed PCA approach improves the accuracy of the fault detection process.

The study, [14], proposed a new analysis methodology for failure prediction in automotive industries. Electrical terminals are used to detect the root and cause of the problems in industries. The actual failure mechanisms, characteristics, and features are detected based on the analyzed data. The proposed methodology improves the energy efficiency range of the systems. The proposed method provides quantifiable services and functions to automotive industries.

The study, [15], introduced a support vector machine (SVM) based failure diagnosis method for PV generators. The actual goal of the method is to detect the failures which are occurred in the generators. The introduced method identifies the issues based on operational and functional data. The normal and abnormal failures are classified based on the severity of the issues. The introduced method increases the accuracy of failure diagnosis which enhances the performance level of PV generators.

The study, [16], developed a multi-class SVM classifier, particle swarm optimization (PSO) algorithm-based fault diagnosis method for electrical machines. The developed method also uses a gravity search algorithm (GSA) to diagnose the faults in machines. The SVM classifier is mainly used here to classify the types of faults based on the condition of the machines. The developed method reduces the faults which improves the performance range of electrical machines.

The study, [17], proposed a new combined failure severity analysis method for rotating machines. The proposed method is used as a machine failure prediction that predicts the exact issues in rotating machines. A supervisory system is implemented to monitor the machine and identify inappropriate issues in the machines. The supervisory system sends an alert message to alert the devices via smart signals. The proposed method enhances the feasibility and significance range of the machines.

3 Proposed Analytical Model

The proposed DR-LA model is designed to improve the electrical machine operation time for precise problem identification. The stored data logs analysis in the controller in different operation times is addressed for reducing electrical machine downtime. The objective of this model is to analyze such logs to prevent downtime using precise controller options in different time intervals. Addressed electrical machine downtime reduces productivity in different time intervals using stored data logs for reducing the adverse impact occurrence in electrical machines.

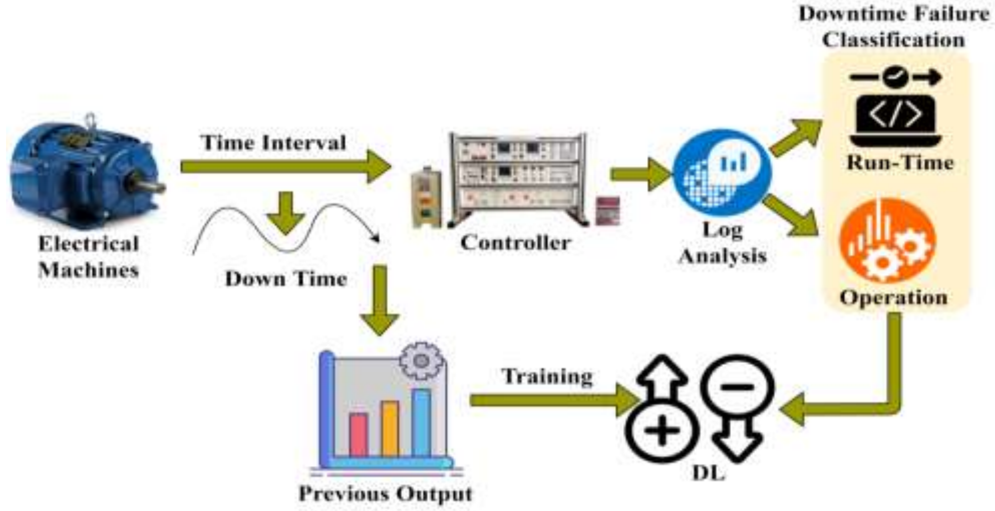

Fig. 1: Proposed Model Illustration

In this model, deep learning is used for differentiating run-time failure and operation failure detected at the time of processing the electrical machine. This learning is employed for differentiating the production-less electrical cycles in correlation with the previous output for downtime failure classification. The electrical machine operations are observed across various networks and time intervals for analyzing such logs through the proposed model and deep learning paradigm for preventing machine downtime. The proposed model is illustrated in Figure 1.

The failure differentiation is pursued to improve the machine operation time for processing the stored data logs in the controller. Based on the above differentiation, precise problem detection is achieved. These run-time and operation failures are differentiated to ensure support for the electrical machine users. In this proposed model, the training is provided for the deep learning network using previous differentiated cycle logs for better operation and improving detection ratio. The operation time is computed to identify and differentiate the run time and operation failure from the controller at different time intervals. In this article, the stored data logs are analyzed for training the deep learning network using DR-LLAM to reduce operation time and failures in the controller.

4 Stored Data Log Analysis

The data log analysis DL_a is pursued by differentiating run-time failures and operation failures through a deep-learning network for reducing operation time. The input data logs can be stored and retrieved for further processing. In this scenario, the operation cycles can adapt their nature based on the services. Therefore, the first data log analysis is represented as

$$DL_a(T_i) = \sum EM_{dwn_T}(Run_T \times Opr_T) \quad (1)$$

where,

$$EM_{dwn_T} = \sum(DL_a \; of \; P_l + [\sum EM_{dwn_T} \; for \; all \; electrical \; machines \; based \; on \; Run_T \; and \; Opr_T]) \quad (2)$$

The above equation (1) and (2) validates the overall electrical machine operations based on data logs analysis using the proposed model irrespective of the machine downtime EM_{dwn_T} in the controller is identified for rectifying the problems. Where, P_l used to denote the number of production-less electrical cycles in the network. These production-less electrical cycles are addressed in the controller leading to run-time failures and operation failures. The variables Run_T and Opr_T indicates run-time and operation time are computed at the time of log analysis for improving the machine operation time by reducing operation failures. In this analysis, the machine run-time and operation time differ. Therefore, the downtime failure classification should be optimized to perform log analysis. The proposed model verifies the available resources and their services rely on the above differentiation. The downtime failure classification DWN_{fc} based on log analysis output is computed as follows:

$$DWN_{fc} = \frac{DL_a(N(Opr_{Cyp}) - P_l)}{Run_T + Opr_T} \quad (3)$$

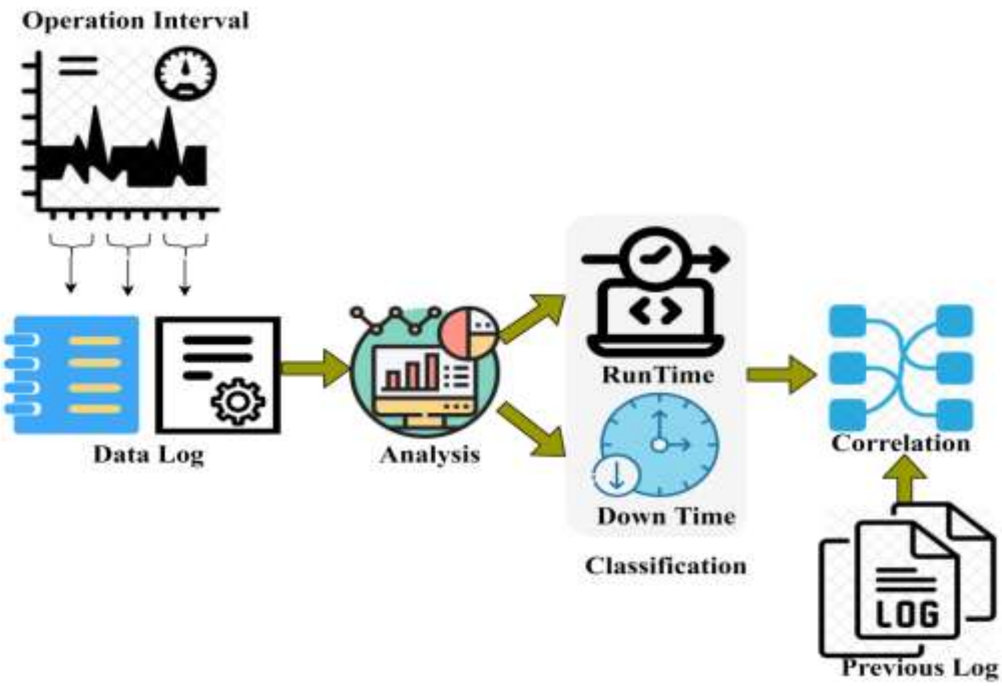

Fig. 2: Log Analysis Process

In equation (3), the different operations performed by the electrical machines reduce human work and ease to completion of the work. If the variable $N(Opr_{Cyp})$ represents the number of active operation cycles in electrical machines. Based on the log analysis, the controllers are regulated by the machines for processing multiple operations in that network. The downtime failure classification is pursued using deep learning and correlates with previous output for reducing operation failures. Hence, this proposed model differentiates the run-time failures and operation failures for accurate problem detection. Using this deep learning, the time interval addressed from the machine downtime is balanced for reducing failure occurrence in the deep learning network. The log analysis process is illustrated in Figure 2.

The operation interval generates logs based on machine operations. The run time and downtime analysis are performed to validate failures. The classification using DL is valid under the above data logs for correlation. In this correlation, the previous logs are used for verifying the failure. Using this deep learning, the proposed model is used for processing multiple operations in less processing time (Figure 2). Based on deep learning, the production-less electrical cycles are identified. After identifying this problem, the learning helps to differentiate run-time failure and operation failure in any operation instance. The operation time is computed based on the service requirements of users to reduce failures; reliable operations are made by the electrical machine. Later, the stored data logs are analyzed priority-wise to reduce production-less cycles in that network. Therefore, maximum productivity is achieved with less run time and less operation time is the successful output. The correlation of current differentiated cycles with previous differentiated cycles $\Delta_{\exists}$ for the problem, identification is expressed as:

$$\Delta_{\exists} = \frac{1}{\sqrt{2\pi}} \left[\frac{\left(\frac{min(Run_T + Opr_T)}{max(Run_T + Opr_T)} - EM_{dwn_T} \right)}{P_l} \right] \quad (4)$$

In equation (4), precise problem identification is achieved from the previous operation output and downtime failure classification based on minimum and maximum machine downtime. This condition differentiates the minimum and maximum failures at different time intervals. The identified operation failures from the controller used for differentiating production-less electrical cycles in correlation with the previous output. The failure data log analysis for reducing electrical machine downtime using deep learning in different time intervals. In this condition, the run-time and operation failure are identified and differentiated for precise problem identification.

Hence, the logs are analyzed based on the above differentiations at any downtime time interval. Therefore, the final log analysis for the available controller $\in_{LA}$ (T_i) is computed as:

$$\in_{LA}(T_i) = \frac{(Run_T + Opr_T)^2}{PL\left(\frac{min(P_l)}{max(P_l)} - \Delta_\exists\right)^{T_i}} \quad (5)$$

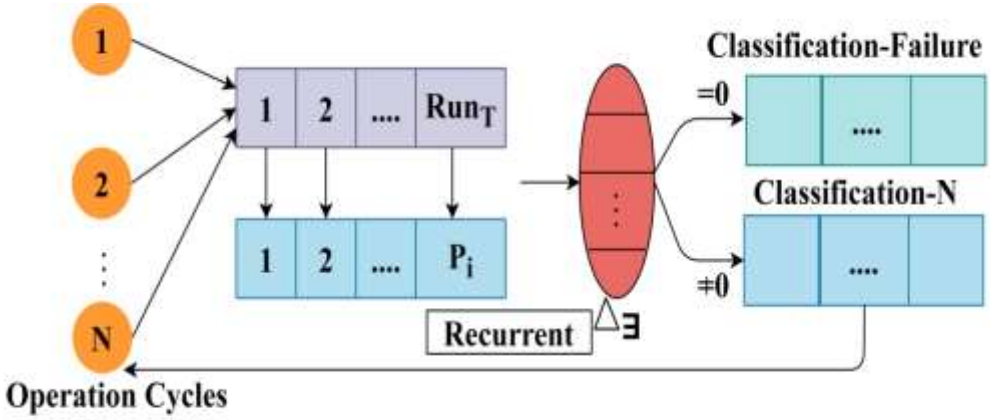

Fig. 3: Learning Process Illustration

In equation (5), the final log analytics is performed to reduce operation time and failures in different time intervals. The electrical machine downtime is identified for improving machine operation time based on the differentiation for time intervals. This proposed model is used to ensure the seamless support of the electrical machine is improved. Therefore, precise problem identification and production-less cycle differentiation are performed sequentially to improve operation time by reducing failure occurrence. The learning process is illustrated in Figure 3.

The Run_T is analyzed for all N in detecting ρ_i. The output is classified using deep learning as $\Delta_\exists = 0$ or $\Delta_\exists \neq 0$. The $\Delta_\exists = 0$ represents a classification failure and $\Delta_\exists \neq 0$ denotes the N classification. This second classification is validated recurrently for new N (refer to Figure 3). The minimum and maximum possibility of run-time failure and operation failure are differentiated for accurate problem identification. Based on the occurrence of the failure and downtime, the training provided for the learning process is provided using previous differentiated cycle logs for reducing operation time. Now, the previous differentiated cycle logs are represented as:

$$C_{dcl} = 2^{\frac{\in_{LA}(T_i)}{2}} * DL_a[(Run_T + Opr_T) - P_l] \quad (6)$$

$$C_{dcl} = \frac{1}{T_i}\left[\int_0^\infty Run_T\left[\left(\in_{LA}(T_i) \times DWN_{fc}\right) - \Delta_\exists\right] dT - \int_{-\infty}^0 Opr_T\left[\left(\in_{LA}(T_i) \times DWN_{fc}\right) - \Delta_\exists\right] dT\right] \quad (7)$$

As per equations (6) and (7), the downtime failure classification is pursued for reducing operation failures in different time intervals. The logs are sequentially analyzed based on differentiation output. This proposed model and deep learning are used to improve the operation of electrical machines. Based on the data provided in [18], the log analysis is performed for N and C_{dcl} as in Figure 4. The variation in $\Delta_\exists$ is used for the analysis.

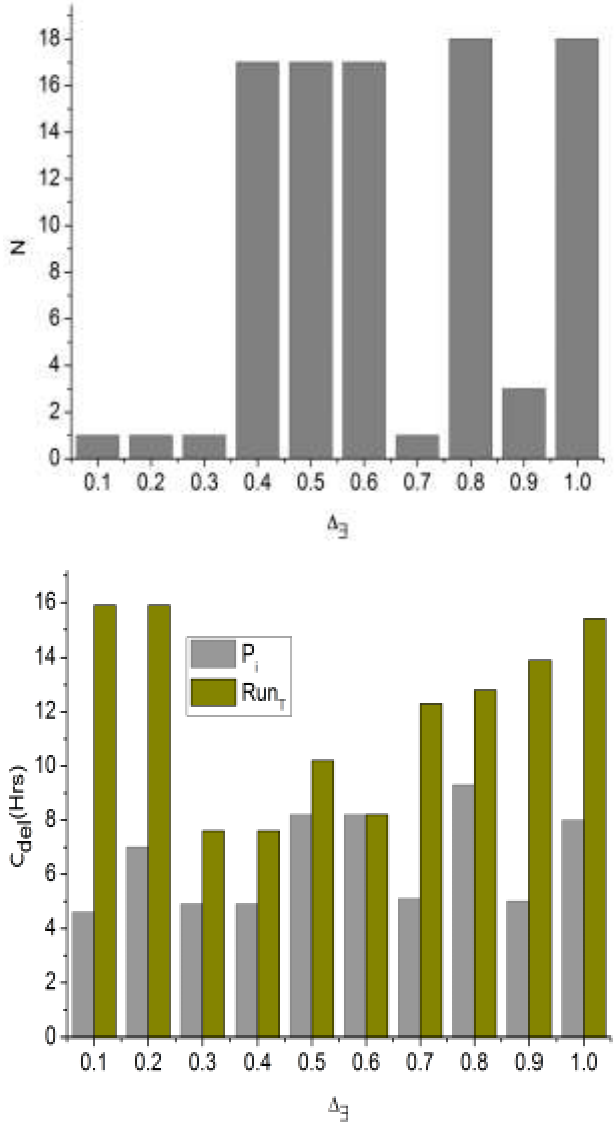

Fig. 4: N and C_{dcl} Analysis

The $\Delta_\exists$ varies accordingly for multiple operation hours of the electrical machine. The lag analysis for N and C_{dcl} are validated for the event's accuracy. The event of downtime/ failure is identified throughout the operation hours for improving the Run_T without P_i. Therefore consecutive N variations are handled using successful $\Delta_\exists$ preventing maximum downtime.

5 Performance Assessment

The performance assessment is validated using the metrics detection ratio, analysis rate, operation failure, and analysis time. The operation time is considered from 1 to 18 hours, with the existing methods H-GSAPSO, [16], and DF-PCA, [13].

6 Detection Ratio

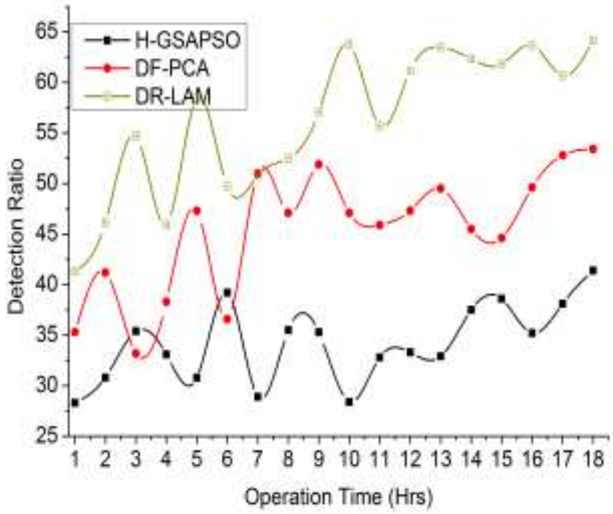

Fig. 5: Detection Ratio

The high electrical machine downtime is reduced through deep learning and the proposed model based on log analytics. Using the proposed model, deep learning is employed for differentiating the production-less electrical cycles for problem detection. The proposed model is used for differentiating the run-time failures and failed operation cycles in different time intervals to achieve high downtime detection as presented in Figure 5.

7 Analysis Rate

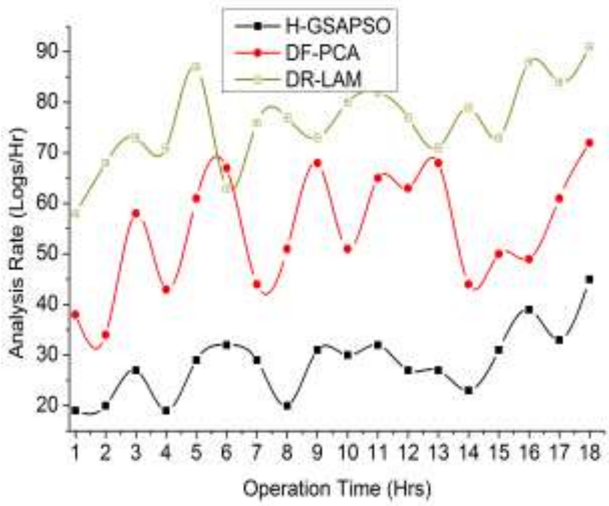

Fig. 6: Analysis Rate

This proposed DR-LAM achieves a high analysis rate for computing the stored data based on previous operation output and downtime failure classification for reducing the operation failure occurrence (Refer to Figure 6). The production-less electrical cycles in an electrical machine are reduced using deep learning. Therefore, regardless of consistent operation is achieving a high analysis rate.

8 Operation Failure

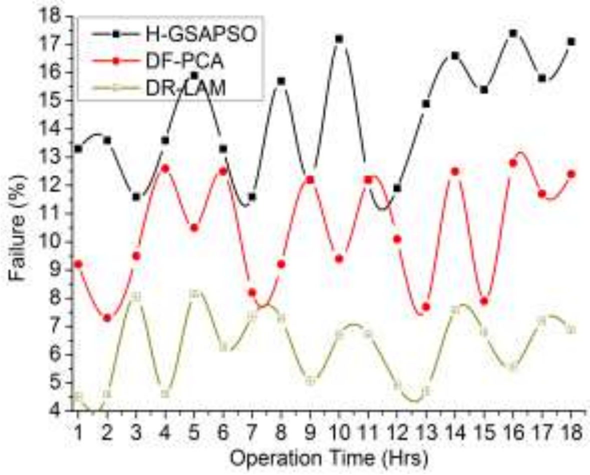

Fig. 7: Operation Failure

This proposed model achieves high operation failure compared to the other factors as represented in Figure 7. The operation failures are identified to ensure the support of electrical machine processing. Therefore, the proposed model improving the detection ratio using previous differentiated cycle logs for training the deep learning is provided to achieve less operation failure.

9 Analysis Time

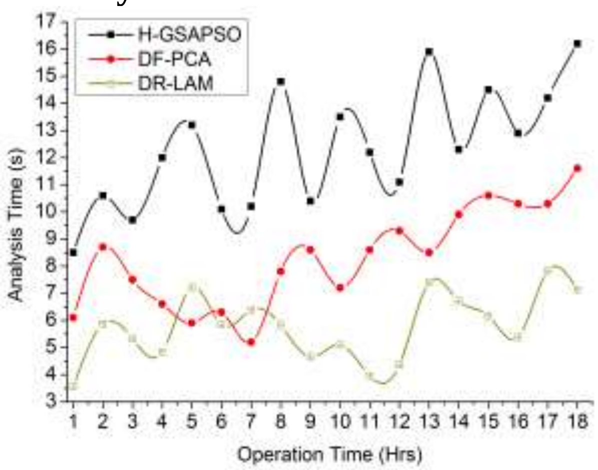

Fig. 8: Analysis Time

This proposed model used to achieve high data log analysis time based on the above differentiation is pursued by precise problem identification. The downtime failure classification is verified with previous operation output for differentiating the production-less operation cycle outputs in less failures and analysis time is represented in Figure 8. If the operation failure is high in this analysis, the downtime is reduced. Deep learning is used to reduce operation failures and reduces analysis time. From the discussion above the comparative analysis summary is presented in Table 1. The analysis of the proposed system is compared with the help of performance metrics to find the detection ratio, analysis rate, failure, and analysis time. The proposed DR-LAM detects the highest detection ratio of 64.15% when compared to other approaches H-GSAPSO and DF-PCA. The analysis rate of DR-LAM achieves a higher rate of 91%; the proposed model DR-LAM reduces the failure rate and also reduces the analysis time when compared to other approaches.

Table 1. Comparative Analysis Summary

Metrics	**H-GSAPSO**	**DF-PCA**	**DR-LAM**
Detection Ratio	41.4	53.4	64.15
Analysis Rate (Logs/Hr)	45	72	91
Failure (%)	17.1	12.4	6.88
Analysis Time (s)	16.2	11.6	7.13

The proposed model is found to improve the detection ratio and analysis rate by 8.38% and 11.9% respectively. This model reduces the failure and analysis time by 7.87% and 8.12% respectively.

10 Conclusion

This article introduced a downtime reduction-focused log analytical model for recommending better machine operation times. The machine operation times are validated for the different failure logs analyzed over the different operation intervals. The failures between successive operation intervals are reduced by validating less or no-output intervals. Based on the active operation cycles the log is correlated for providing multiple recommendations for mitigating the maximum downtime. The log analysis is repeated until optimal recommendations are provided for different cycles under run and operation times. From the comparative analysis, it is seen that the proposed model reduces failure by 7.87% whereas it increases the detection ratio by 8.38% for different operation cycles. The proposed work is planned to integrate self-analytical operation modules for prediction-based operation control. This is required to prevent machine detentions in timer-less work allocations.

The algorithm described in this research is a method towards a reliable and versatile method for electrical machine failure prediction, which may be applied to a variety of faults. This research suggests an innovative Deep-learning method for electrical machine preventive maintenance. As a novel idea, this one may require further development and investigation. This method reduces electrical downtime by using the current characteristic variances that result from failure log analysis in electric devices. Future studies will also involve applying this technique to more complex defects and larger data samples.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.