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RELIABILITY ASSESSMENT OF FORKLIFT USING ARTIFICIAL NEURAL NETWORKS

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Abstract

The reliability of a component or system is the likelihood that the component or system would operate satisfactorily for a defined period under specified operating conditions. The aim of this research is to evaluate the reliability of Forklift machinery using artificial neural networks (ANN). Maintaining machinery properly is essential to achieving optimal industrial efficiency. Novel machine learning models were developed for the assessment of the reliability of haulage machinery maintenance using pattern recognition artificial neural networks in this research. The choice of a classification model stemmed from the nature of available data. Hence, the input data variables for the forklift were gotten from Hyster H6.00XL. The artificial neural network model was developed using MATLAB. Trial and error was initially used to arrive at the neural network architecture that gave the lowest mean square error. The architecture that was finally selected consists of input layer, three hidden layers and an output layer. The first and the last hidden layers had a total of 10 neurons each, while the second hidden layer had a total of 20 neurons. However, the best prediction accuracy went to PRN-LMA with an accuracy of 92%, followed by PRN-CGF with an overall prediction accuracy of 81.7%. Next were PRN-OSS and PRN-BFG with prediction accuracies of 81.0% and 80.3% respectively, while PRN-BR was the least accurate, with an accuracy of 75.1%. Generally, the PRN-LMA models gave the highest prediction accuracy, while the Bayesian regularization models (PRN-BR) gave the least prediction accuracy. The model could also be implemented in other lifting and manufacturing machineries.

Key word: Artificial Neural Network, Forklift, Reliability

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Introduction

The reliability of a component or system is the likelihood that the component or system would operate satisfactorily for a defined period under specified operating conditions. In general, proper reliability and availability analysis can improve the performance of plant equipment. This is because, the plant's efficiency suffers when the operating system is unavailable and unreliable. Poor availability and reliability lead to failures in production units. Furthermore, degradation affects the equipment's life span at distinct periods, lowering the system's reliability (Bansal et al., 2020). With better understanding and research on maintainability, availability, and reliability assessment, the health and life span of machinery can be significantly improved. In most simple and complex machines, different individual components, subunits, and units are interconnect to form the machine system (Payette & Abdul-Nour, 2023). This therefore means that, the overall machine operational standard depends greatly on the states and mechanics of the various units, subunits and parts. In general, a component's failure can cause other components to fail, or a component's current health status can affect the performance of other components and eventually, the overall performance of the machine. As a result of the inter-dependency of the components of a machine, the state of one component in a mechanical system can affect the status and degradation of other components, implying that stochastic dependence (s-dependence) can exist in genuine and complex systems (Dao & Zuo, 2015). The losses that occur to business, and the economy due to the operations of overhead lifts (harbor) devices used in the Nigerian Wharfs and seaports was observed, and could be ascertain that by properly maintaining available machinery, their reliability and availability will improve which should have a positive effect on the Nigerian economy since this sector is a greater contributor to the gross domestic product (GDP) of the country.

Machine failure is often defined in different ways, for instance, a divergence from the standard/desired performance or an unfavourable outcome of a job is defined as failure. It is also known as the difference between the target and current level (Anandh *et al*., 2014). So, failure is simply the difference between the actual and expected outcomes of a system. Machine breakdowns harm any manufacturing company's operational efficiency. In a traditional manufacturing system, identifying important failures and studying their relationships with other process factors is difficult (Ahmad *et al*., 2018).

Machine failure is a common occurrence in the business, posing a problem for both the management in charge of the equipment's availability and the technician who maintains it. While it may appear to be a maintenance issue, it is also an issue that impacts every stakeholder in a firm because the failure of a single piece of equipment can result in entire downtime and production loss until the equipment is repaired or replaced. Therefore, as much as we hope that these failures do not occur, the reality is that these issues occur and need to be continuously managed (Ezendiokwere *et al*., 2021).

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However, we know that the efficacy of management is determined by the right definition of the problem and the correct identification of the root cause. When a component or a group of components fail, the failure rate of other dependent units in the system can be altered. This is an example of dependent reliability and it is of two categories which is either positive or negative. The reliance is considered to be positive if the failure of one component causes an increased tendency for another component to fail. On the other hand, negative reliance occurs when the failure of one component reduces the likelihood of another component failing.

Dependent failures are in a variety of forms, including cascade failures and common cause failures (CCFs). Countless failures that that result in a single or shared root cause are referred to as common failure causes, whereas, cascading failures are a series of failures caused by the breakdown of a system's single part, which set off a series of events. Despite what definition we give to failure, it is correct to always know that failure is a human perception in itself (Payette & Abdul-Nour, 2023).

Literature Review

Reliability engineering includes several research areas such as reliability, availability, maintainability and safety (RAMS), prognostics and health management (PHM) and asset management (AM). Some production lines and manufacturing industries have often been producing below maximum capacity due to failure challenges embedded in the control panel, gearbox, hydraulic motor, pneumatic pump failure, and other failures of different production systems and functions. Improving reliability and availability assessment for machinery maintenance will reduce maintenance costs while improved productivity will boost revenue. With increased revenue and reduced operation costs, there will be better funding for employees and better pricing for the end users (Odeyar *et al*., 2022). Most organizations now strive to reduce the tendency of production to be discontinued, with malfunctioning machinery as one of the challenges. One of the techniques that this breakdown is minimized in frequency is carrying out maintenance activities (Widyaningrum & Winati, 2022). Salimah et al., (2023) developed a methodology that combines the needs of components and subsystems with the vital maintenance aspects.

Several records have shown that the cost of the unavailability of critical equipment or its failure is a major factor in any production, manufacturing, or service organization. There is a need for a change in the maintenance plan, moving away from a component-based approach to a systems-based approach to tackling maintenance issues. Hence, failure analysis using artificial neural networks (ANNs) remains a better method for the maintenance management of critical equipment (Soualhi *et al*., 2020). The high point of this study is, therefore, to investigate ANNs in the development of an equipment maintenance model that will ensure significant improvements in system reliability, and availability, productivity. Robles-Velasco et al. (2021) used an Artificial Neural Network

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(ANN) based on tangible and procedural input attributes, to categorize pipes according to their propensity to fail. ANN are a revolutionary approach that has proven to be highly useful for both manufacturers and consumers in tackling various challenges in the field of production equipment. Condition monitoring, problem diagnosis, troubleshooting, maintenance, sensor validation, and control are all areas where these challenges can be found. In an attempt to investigate gas consumption, three ANN-based forecasting models which are the feed-forward neural network approach, the recurrent neural network framework, and the sigmoid function regression algorithm were developed by (Ravnik et al., 2021). Using gas consumption data, the models were trained, compared, and verified. The Levenberg-Marquardt technique was used to generate the data for the sigmoid algorithm, and the Genetic optimization approach was utilized to train the neural networks. Sanaye and Hosseini (2020) used artificial neural networks thermodynamics, and turbomachinery models, to estimate the blade life cycle for an industrial gas turbine operating in off-design circumstances. Zhao et al. (2020) investigated the use of a fuzzy second-generation curvelet neural network to estimate the risk of refinery unit maintenance.

Artificial neural network (ANN) approaches have shown tremendous promise in forecasting the remaining useful life (RUL) of machines with greater accuracy (Tian et al., 2010). An Artificial Neural Network (ANN) was satisfactorily implemented into a predictive maintenance mechanism to provide a motor status diagnosis. Data was collected from electrical motors to train the ANN. Vibration characteristics were used as the input layer for this monitoring, and the motor condition was used as proffesional training data (Rad et al., 2011). In research conducted by (Németh et al., 2016) in the analysis for the Production Control of Small Batch Production, forecast the accuracy of production planning using ANN. The model revealed that one of the most crucial elements of small-scale production is precision.

Methodology

The process flow for creating a general artificial neural network has a few essential components (Fontes & Pereira, 2016). These include data collection and preparation, network construction and configuration, initialization of weights and biases, network training, network validation (by post-training analysis), and network demonstration. The failure data used in this study's artificial neural network machine learning model construction came from the Port Harcourt wharf/seaport. Each table contained the date, the start and stop times, the daily working hours, and the frequency of machine failures. The raw failure statistics were totaled by operating month. Moreover, the time between failure (TBF) statistics were also constructed using the raw data.

These input variables were initially used to build a training, test, and validation data set in the ratio 60:20:20. The complete set of data was then loaded into a feed forward neural

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network for pattern recognition and classification. Pattern recognition is the process of categorizing incoming data into objects, classes, or categories using computer algorithms and significant characteristics or regularities as a basis (Serey *et al*., 2023). Pattern recognition networks, or PRNs, are feed forward neural networks that may be taught to classify inputs according to target classes. It has applications in computer vision, image segmentation, object detection, radar processing, speech recognition, and text classification, yet it is rarely used for reliability and availability research (Odeyar *et al*., 2022).

Soualhi *et al*. (2020) contended, however, that given its consistent outcomes and ability to work with artificial intelligence tools like machine learning, this approach offers numerous benefits for defect detection and diagnostics. For pattern recognition networks, the target data typically consists of vectors with all zero values except for the class they are supposed to represent, which has a 1 in element i. The type of data that was provided led to the selection of a categorization model. With MATLAB, the artificial neural network model was created.

Initially, the neural network architecture with the lowest mean square error was found through trial and error. Three hidden layers, an output layer, and an input layer make up the final architecture that was chosen. There were a total of 10 neurons in each of the first and last hidden layers, and 20 neurons in the second hidden layer. The machine failure potential was the output variable in the final model, whereas the easy start status (which indicates whether the machine was readily started or not), daily running hours, and time between failures were the input variables as shown in Figure 1. Each of the MATLAB outcomes was then examined separately.

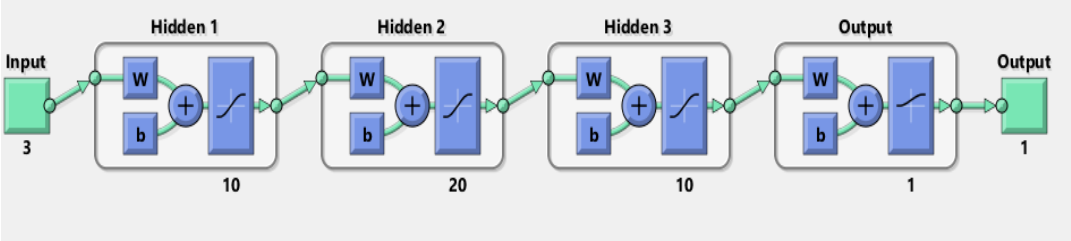

Figure 1 A MATLAB presentation of the utilized pattern recognition neural network architecture.

Artificial Neural Networks

Artificial neural networks (ANNs), are a class of deep learning innovation that is involved in the artificial intelligence (AI) domain. Because artificial neural networks have an essential quality that enables an approximate description of any constant dependence using a neural network with suitable design and weight variables they offer an outstanding analytical approach to address nonlinear challenges (Tenney et al., 2020). ANN is developed using the structure and presumption of a biological neural network,

similar to that of an actual human being. The industrial applications of these advancements are often directed toward solving challenging problems in pattern recognition or signal processing. ANN are applied in the following area; decision making in management, prediction of solid waste, to forecast injection molding machine business (Sharma & Chopa, 2013; Chaudhari & Dhawale, 20216; & Wang et al., 2019). An ANN was also employed in image processing in a variety of industries, including construction, transportation, remote sensing, human-computer interface, and language recognition. An artificial neural network (ANN) is made up of input, hidden, and output layers, each of which contains a neuron a type of data as illustrated by Figure 2.

Information manipulation is performed from the input to hidden layer and from the hidden to the output layer by employing the weight (w) and bias (b) functions. This phase is known as the training and testing process or the learning process. Equation (1) is utilized for determining the net value (n_v), which is the average of all of the weights that define the neuron output value.

The activation function, which in this case employs the transig function (bipolar sigmoid t_h), as found in Equation (2), then transfers the net value. Using error counts and Mean Square Error (MSE), which is obtained from Equation (3), to assess the network's efficiency.

$$n_v = f\sum_{i=0}^{n} w_i\, x_i + b \qquad (1)$$

$$t_h = \frac{1-e^{-x}}{1+e^{-x}} \qquad (2)$$

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(x_i - y_i)^2 \qquad (3)$$

where, x_i and y_i are the input and output data, whereas n is the generated data.

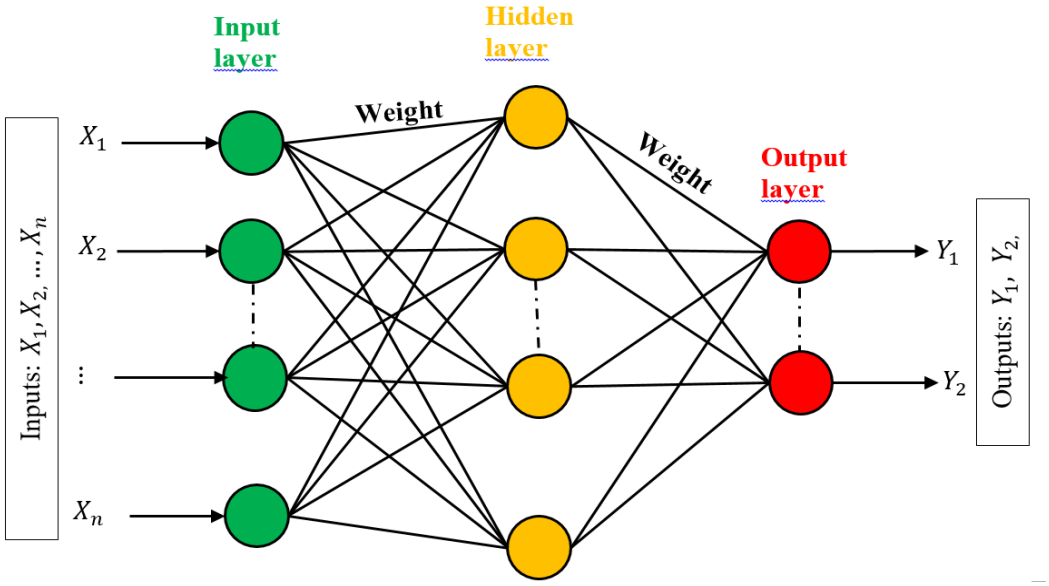

Figure 2: Example of a network structure with a single hidden layer and two outputs.

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Optimization Algorithms

The following were used for the classification of the models; Levenberg–Marquardt Algorithm, Bayesian Regularization (BR) Algorithm, Conjugate Gradient Algorithm, Broyden, Fletcher, Goldfarb, and Shanno (BFGS) Quasi-Newton, and One Step Scant Method.

Levenberg-Marquardt Algorithm (LMA)

In engineering difficulties, the algorithm known as Levenberg-Marquardt (LMA) is employed to identify dynamic least squares solutions (Wu et al., 2020). This curve-fitting technology incorporates two existing approaches, namely Gauss-Newton and gradient descent. Iterative algorithms were used in both approaches, which implies that multiple assumptions are made (based on approximations for x-values) in order to determine the outcome. Tthe gradient matrix and the Hessian matrix estimation used in LMA (Chu et al., 2017), are illustrated in Equation (4).

$$H = J^T J \tag{4}$$

$$g = J^T e \tag{5}$$

where J is the Jacobian matrix, e is the error vector, and T is the matrix transpose operator.

Bayesian Regularization (BR) Algorithm

An artificial neural network training approach called Bayesian regularization adjusts the weight and wavelength variables with the Levenberg-Marquardt strategy (Burden & Winkler, 2008).

The BR algorithm's concept for maximizing the weights and bias of neural networks involves implementing the LMA theory upon generating a problem of minimization containing an objective function with the total of two weighted error terms, squared errors (E_D) and network weights (E_w). This objective function can be expressed by the Equation (6) (Baghirli, 2015).

$$F(\omega) = \alpha E_w + \beta E_D \tag{6}$$

where $E_w \; and \; E_D$ represent the total number of network errors and the squared network weight, $\alpha \; and \; \beta$ are parameters of the goal (regularization) function. Equations (7) and (8) yield the following results for the $E_w \; and \; E_D$ functions:

$$E_w = \frac{1}{n}\sum_{i=1}^{n}(w_i)^2 \tag{7}$$

$$E_D = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2 \tag{8}$$

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where a_i is the i^{th}data output, t_i is the goal value of the tth data, and n is the amount of inputs to the training data, along with the weights or limits for the tth data.
where the parameters of the goal function are revealed by α and β.

Conjugate Gradient Algorithm

All the conjugate gradient algorithms start out by searching in the steepest descent direction (negative of the gradient) on the first iteration as shown in Equation (9).

$$\boldsymbol{p_o = -g_o} \quad (9)$$

Next, a line search is conducted to find the best route to go along the path of the present enquiry using Equation (10).

$$\boldsymbol{X_{i+1} = X_i \alpha_i p_i} \quad (10)$$

Subsequently, a search path is chosen that is conjugate to the one that came earlier it. Generally speaking, the novel steepest descent is put together with the prior search route to identify the novel search range using Equation (11).

$$\boldsymbol{p_i = -g_i + \beta_i p_{i-1}} \quad (11)$$

The method used to calculate the constant β_i distinguishes the various variants of the conjugate gradient technique. The process for the Fletcher-Reeves upgrade is in Equation (12):

$$\beta_i = \frac{\boldsymbol{g_i^T g_i}}{\boldsymbol{g_{i-1}^T g_{i-1}}} \quad (12)$$

Equation (12) represents the ratio between the present gradient's standard squared and the gradient's standard squared from the previous.

Broyden, Fletcher, Goldfarb and Shanno (BFGS) Quasi-Newton

Newton's method can be used instead of conjugate gradient methodologies for rapid optimization. The fundamental action in Newton's technique is as in Equation (13).

$$\boldsymbol{X_{i+1} = X_i - A_i^{-1} g_i} \quad (13)$$

where A_i^{-1} is the performance index's Hessian matrix (second derivatives) for the present weight and bias settings. Conjugate gradient methods usually converge more slowly than Newton's method.
When computing performance derivatives concerning the weight and bias variables X, back-propagation is typically used. Each value is modified according to Equation (14).

$$X_{i+1} = X_i + adX \quad (14)$$

where, dX is the search direction. To reduce throughput within that search path, a value is chosen. To find the lowest point, utilize the line search feature. The inverse of the efficiency slope is the original search vector. Subsequently, the search direction is computed according to Equation (15).

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$$dX = \frac{-H}{gX} \quad (15)$$

where, gX is the slope and H is the extimated Hessian matrix.

One-Step Scant Method (OSS)

Compared to the BFGS algorithm, One Step Scant method uses less computation and storage every epoch. It need a little bit more processing power and storage each epoch than conjugate gradient methods. Equation (16) is used to change every single value.

$$X_{i+1} = X_i + adX \quad (16)$$

where, dX is the search directionTo find the absolute lowest point, utilize the line search feature. The opposite end of the success curve is the initial search orientation. Equation (17) is then used to calculate the search orientation using the current curve, the previous steps, and the levels.

$$dX = -gX + Ac * X_{-step} + Bc * dgX \quad (17)$$

where, gX is the slope, X_{-step} is the variation in the weights on the earlier iteration and dgX is the variation in slope from the final iteration.

Results and Discussion

This section shows Figures from the results obtained from the developed models using data obtained from field survey. The data obtained were computed in the MATLAB and results for the cranes were obtained.

Presentation of Results

The results obtained are presented below.



Figure 3: Training, validation, and testing curves for pattern recognition Levenberg-Marquardt (PRN-LMA) model

Figure 3 shows training, validation, and testing curves for pattern recognition Levenberg-Marquardt (PRN-LMA) model of forklifts. From the graph, it can be seen that all errors including training,

validations, and test errors consistently reduced until after the first epoch. The combined errors continued to generally reduce such that it recorded the lowest combined training, validation and test error values occurred during the thirty third epoch. After this period, both validation and training errors started to increase, while the training error decreased further as the number of epochs increased. The similarity in trend between the training, validations, and test curves depicts a successful training of the pattern recognition Levenberg-Marquardt (PRN-LMA) model and its potential use in assessing the failure potential of forklifts.

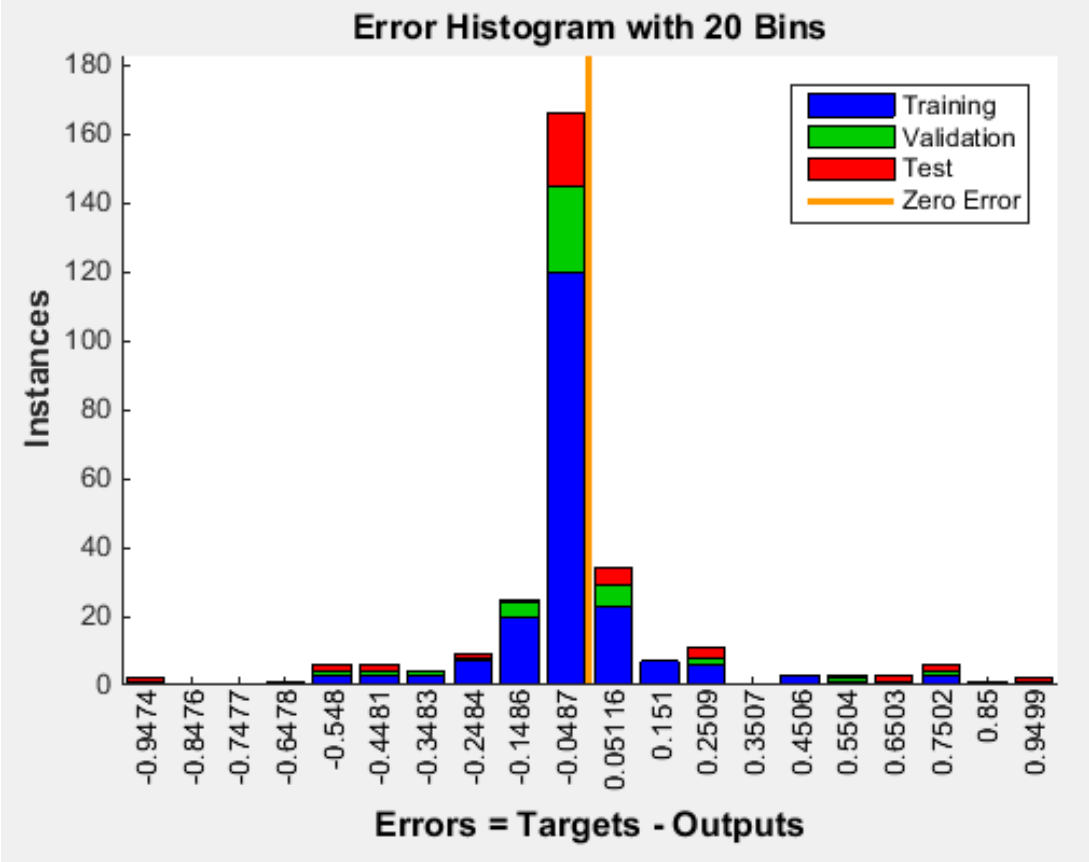

Figure 4: Prediction error histogram for pattern recognition Levenberg-Marquardt (PRN-LMA) model

Figure 4 shows the prediction error histogram for pattern recognition Levenberg-Marquardt (PRN-LMA) model for forklifts. Here, the error is also measured as the difference between the target variable values and the corresponding predicted outcome values. Hence, a good model should have errors congregated around the zero error mark, such that the highest histogram bars would be found around the zero error line. From the histogram, it can be deduced that a majority of the error instances were located around the zero error line, while the error instances recorded further away from the zero error

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line were actually few. This can be confirmed by the smaller number of error instances recorded for errors further from the zero error line. Since the majority of the error instances were congregated around the zero error line, it demonstrates the ability of the pattern recognition Levenberg-Marquardt (PRN-LMA) model to predict failure of forklifts. This result is obviously useful in assessing the failure potential of forklifts.

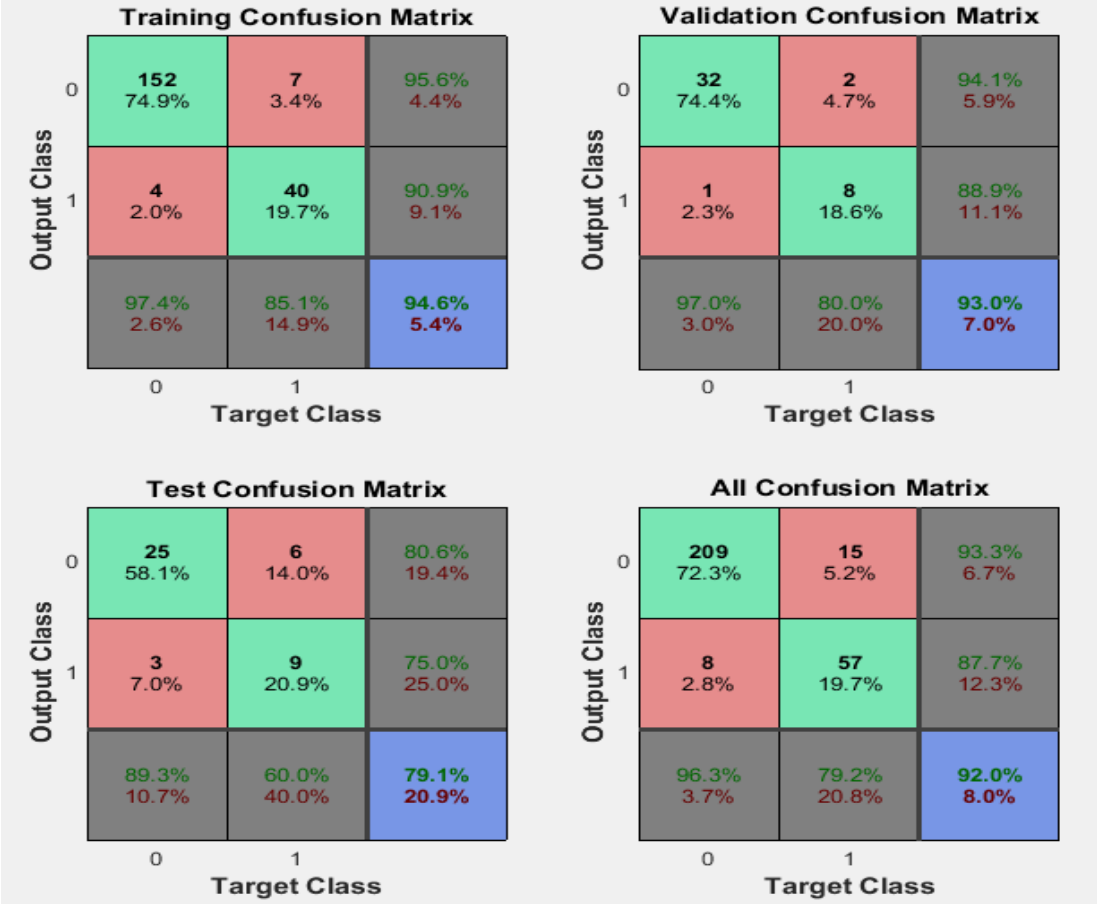

Figure 5: Confusion matrix for pattern recognition Levenberg-Marquardt (PRN-LMA) model.

Figure 5 shows a representation of the confusion matrix for pattern recognition Levenberg-Marquardt (PRN-LMA) model for forklifts. From the figure, it can be noticed that the confusion matrices of the test, validation and test data were all presented. In addition, a combined matrix of all the data was equally presented. The figure shows that after successfully training the Levenberg-Marquardt (PRN-LMA) model, the training result gave 87.6% correct classifications against 12.4% wrong classification. When the trained model was validated using validation data, the validation results gave 86.7% correct predictions, with 13.3% wrong classifications. The trained model was equally tested and

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the test results showed that 84.4% of the test data were correctly classified, while 15.6% were wrongly classified. However, the combined confusion matrix showed that for the whole data set, 87.0% of the data set was accurately classified using the available input variables, but 13.0% of the data set was wrongly classified. The wrong classifications include both false positive and false negative classifications.

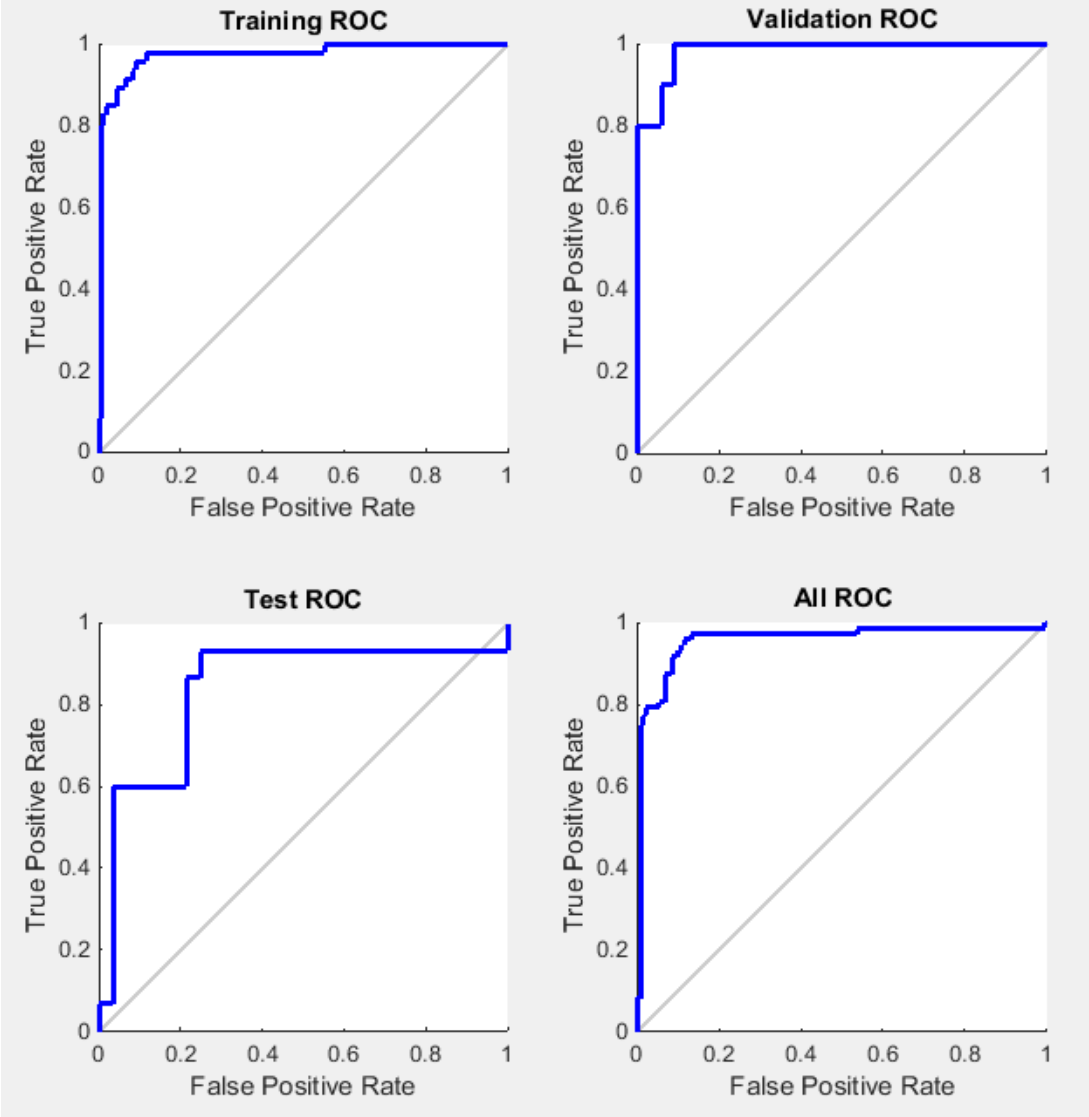

Figure 6: Receiver operating characteristic plot for pattern recognition Levenberg-Marquardt (PRN-LMA) model

Figure 6 shows the receiver operating characteristic plot for pattern recognition Levenberg-Marquardt (PRN-LMA) model for forklifts. The figure depicts a plot of true positive rate against false positive rate. Plots like this are equally helpful in gauging the

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accuracy of machine learning classification models. Ideally, the receiver operating characteristic curve for a good model would normally line the outer edges of the upper triangle formed by counterdiagonal that divides the square of the plot into two. Such that less accurate models have receiver operating characteristic curves that somewhat deviates from the aforementioned ideal curve. The more the receiver operating characteristic curve deviates from the edges, the less accurate the classification model. From the figure, it can be deduced that the receiver operating characteristic curves for training, validation, and test data all had slight deviations from the edges, which confirms the substantial accuracy of the characteristic plot for pattern recognition Levenberg-Marquardt (PRN-LMA) model for accurately classifying the failure potential of forklifts.
Another important metric derivable from the receiver operating characteristic plot is the area under the curve (AUC). The area under the curve of an accurate classification model would amount to unity, given that the square that makes up the receiver operating characteristic plot always has a unit length. But a completely inaccurate model would have a receiver operating characteristic plot that lines the counterdiagonal, which gives an area under the curve value of 0.5. Hence, most classification models will have area under the curve values that lie between 0.5 and 1. Since the receiver operating characteristic plots shown above are considerably far from the counterdiagonal, the Levenberg-Marquardt (PRN-LMA) model can be described as satisfactorily accurate for predicting failure potential in forklifts using available input variables.

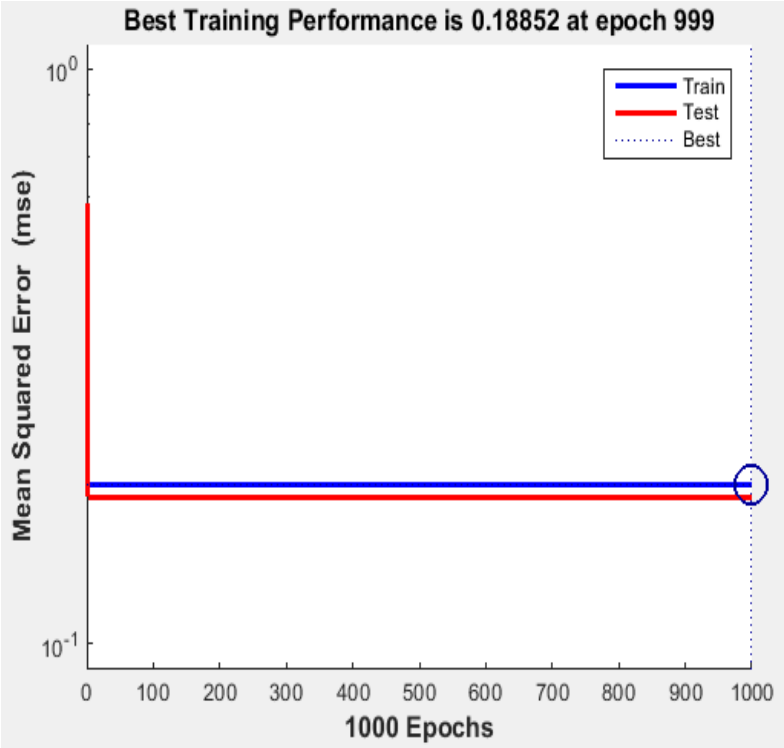

Figure 7: Training, validation, and testing curves for pattern recognition Bayesian regularization (PRN-BR) model.

Figure 7 shows training, validation, and testing curves for pattern recognition Bayesian regularization (PRN-BR) model of forklifts. From the graph, it can be seen that all errors including training, and test errors consistently reduced shortly after

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the training was initiated. The combined errors continued to reduce such that it recorded the lowest combined training, and test error values occurred during the nine hundred and ninety-nine (999th) epoch. The longer time it took the Bayesian regularization (PRN-BR) model to achieve optimality in terms of training and testing errors can be explained by the fact the Bayesian regularization optimization algorithm is a more computationally demanding routine to undertake compared to other optimization algorithms.

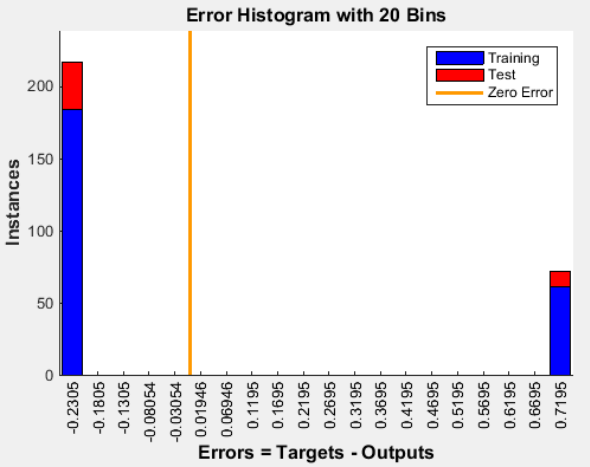

Figure 8: Prediction error histogram for pattern recognition Bayesian regularization (PRN-BR) model.

Figure 8 shows the prediction error histogram for the pattern recognition Bayesian regularization (PRN-BR) model for forklifts. From the histogram, it can be deduced that all the error instances were located far from the zero error line. Since all the error instances were far away from the zero error line, it demonstrates the inability of the pattern recognition Bayesian regularization (PRN-BR) model to predict the failure of forklifts. This result has obviously implications when assessing the failure potential of forklifts. It shows that the Bayesian regularization (PRN-BR) model cannot be used with confidence in assessing the reliability and availability of forklifts.

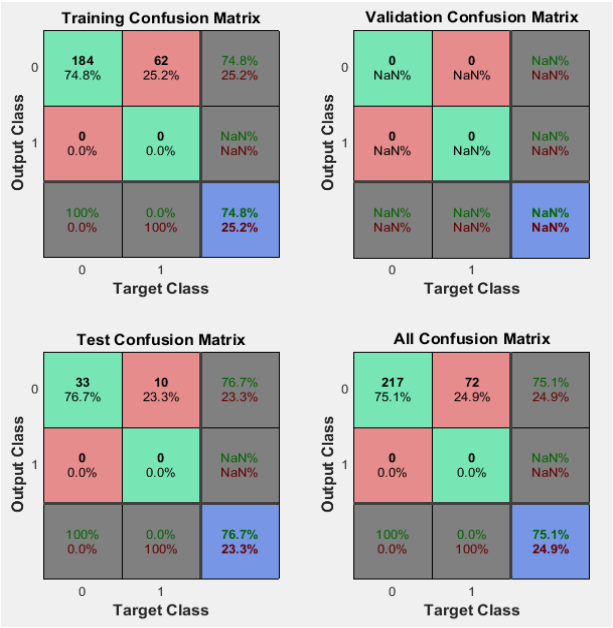

Figure 9: Confusion matrix for pattern recognition Bayesian regularization (PRN-BR) model.

Figure 9 shows a representation of the confusion matrix for pattern recognition Bayesian regularization (PRN-BR) model. From the figure, it can be noticed that the confusion matrices of the test, validation and test data were all presented. In addition, a combined matrix of all the data was equally presented. The figure shows that after successfully training the Bayesian regularization

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(PRN-BR) model model, the training result gave a comparatively low 74.8% correct classifications against an equally high 25.2% wrong classification. The trained model was equally tested and the test results showed that a comparatively low 76.7% of the test data were correctly classified, while an equally high 23.3% were wrongly classified. The model does not have entries for validation confusion matrix because the Bayesian regularization optimization algorithm does not utilize validation data. However, the combined confusion matrix for both training and test data showed that for the whole data set, a meager 75.1% of the data set was accurately classified using the available input variables, and a considerably high 24.9% of the data set was wrongly classified. This result corroborates the error histogram results obtained in Figure 7 above.

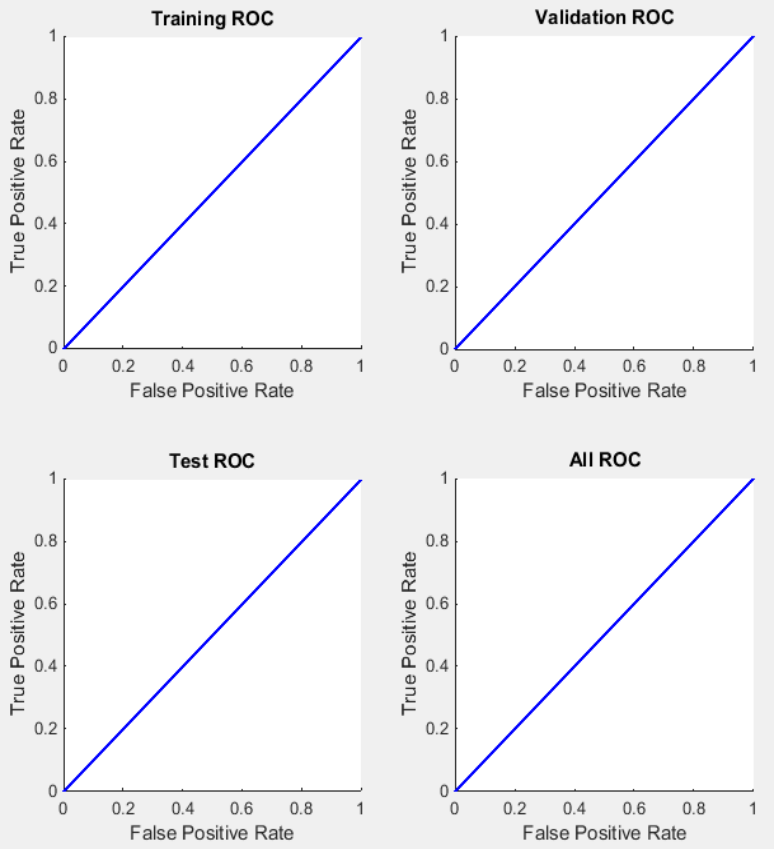

Figure 10: Receiver operating characteristic plot for pattern recognition Bayesian regularization (PRN-BR) model

Figure 10 shows the receiver operating characteristic plot for pattern recognition Bayesian regularization (PRN-BR) model. From the figure, it can be deduced that the receiver operating characteristic curves for training, validation, and test data all lied on the counterdiagonal of the square representing the receiver operating characteristic plot. This confirms the substantial inaccuracy of the characteristic plot for pattern recognition Bayesian regularization (PRN-BR) model for determining the failure potential of forklifts. In addition, since the receiver operating characteristic plots shown above are actually on the counterdiagonal, it gives an area under the curve value of 0.5 for all the plots. This result further confirms that the Bayesian regularization (PRN-BR) model cannot be described as satisfactorily accurate.

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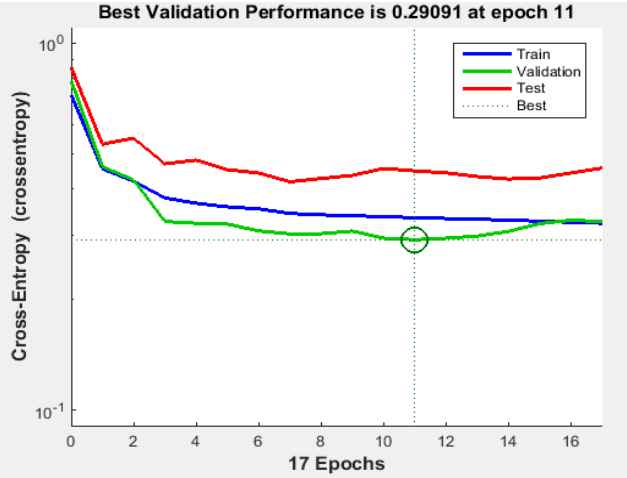

Figure 11: Training, validation, and testing curves for pattern recognition conjugate gradient (PRN-CGF) model.

Figure 11 shows training, validation, and testing curves for pattern recognition conjugate gradient (PRN-CGF) model of forklifts. From the graph, it can be seen that all errors including training, validations, and test errors consistently reduced until after the third epoch. The combined errors continued to reduce (rather slowly) such that it recorded the combined training, validation and test error values at the eleventh epoch. After this period, both validation and training errors started to increase, while the training error decreased further. The similarity in trend between the training, validations, and test curves depicts a successful training of the pattern recognition conjugate gradient (PRN-CGF) model and its potential use in assessing reliability and availability of forklifts.

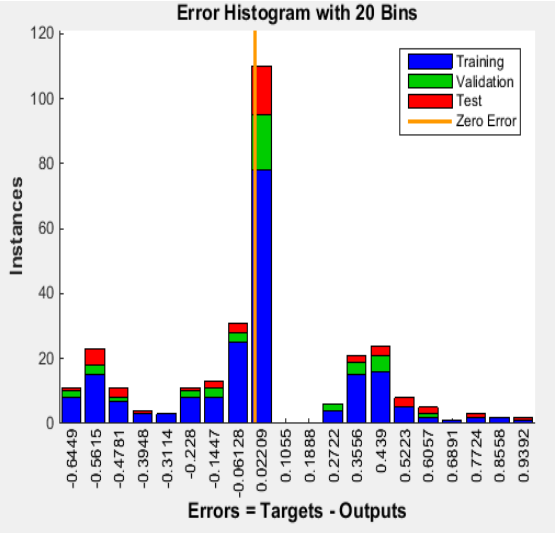

Figure 12: Prediction error histogram for pattern recognition conjugate gradient (PRN-CGF) Model.

Figure 12 shows the prediction error histogram for pattern recognition conjugate gradient (PRN-CGF) model for forklifts. Here, the error is measured as the difference between the target variable values and the corresponding predicted outcome values. A good model should have errors congregated around the zero error mark, such that the highest histogram bars would be found around the zero error line. From the histogram, it can be deduced that a majority of the error instances were located around the zero error line, while the error instances recorded further away from the zero error line were actually few. This can be confirmed by the smaller number of error instances recorded for errors further from the zero error line. Since the majority of the error instances were congregated around the zero error line, it demonstrates the ability of the pattern recognition conjugate gradient (PRN-CGF) model to predict failure of forklifts. This result is obviously useful in assessing the reliability and availability of forklifts.

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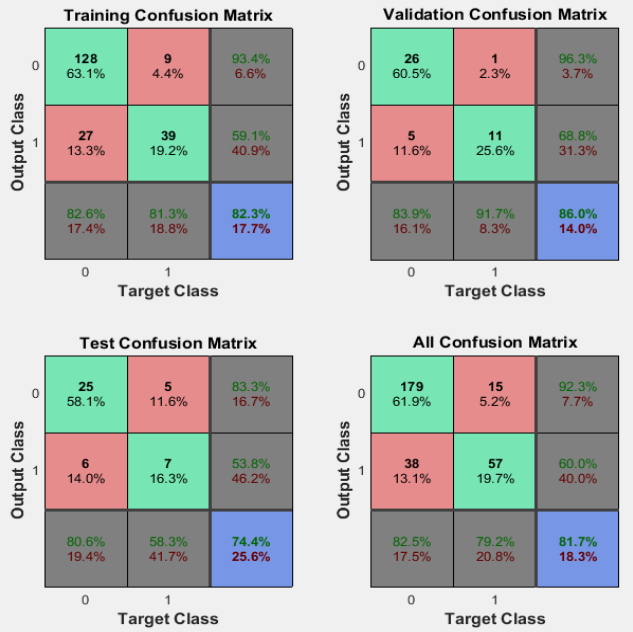

Figure 13: Confusion matrix for pattern recognition conjugate gradient (PRN-CGF) model.

Figure 13 shows a representation of the confusion matrix for pattern recognition conjugate gradient (PRN-CGF) model. From the figure, it can be noticed that the confusion matrices of the test, validation and test data were all presented. In addition, a combined matrix of all the data was equally presented. The figure shows that after successfully training the conjugate gradient (PRN-CGF) model, the training result gave 82.3% correct classifications against 17.7% wrong classification. When the trained model was validated using validation data, the validation results gave 86.0% correct predictions, with 14.0% wrong classifications. The trained model was equally tested and the test results showed that 74.4% of the test data were correctly classified, while 25.6% were wrongly classified. However, the combined confusion matrix showed that for the whole data set, 81.7% of the data set was accurately classified using the available input variables, but 18.3% of the data set was wrongly classified. The wrong classifications include both false positive and false negative classifications.

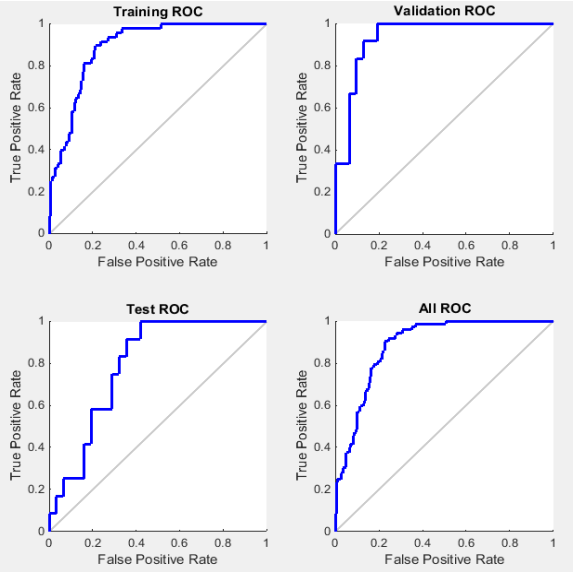

Figure 14: Receiver operating characteristic plot for pattern recognition conjugate gradient (PRN-CGF) model.

Figure 14 shows the receiver operating characteristic plot for pattern recognition conjugate gradient (PRN-CGF) model. From the figure, it can be deduced that the receiver operating characteristic curves for training, validation, and test data all had slight deviations from the edges, which confirms the substantial accuracy of the characteristic plot for pattern

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recognition conjugate gradient (PRN-CGF) model for accurately classifying the failure potential of forklifts. Another important metric derivable from the receiver operating characteristic plot is the area under the curve (AUC). Since the receiver operating characteristic plots shown above are considerably far from the counterdiagonal, the conjugate gradient (PRN-CGF) model can be described as satisfactorily accurate.

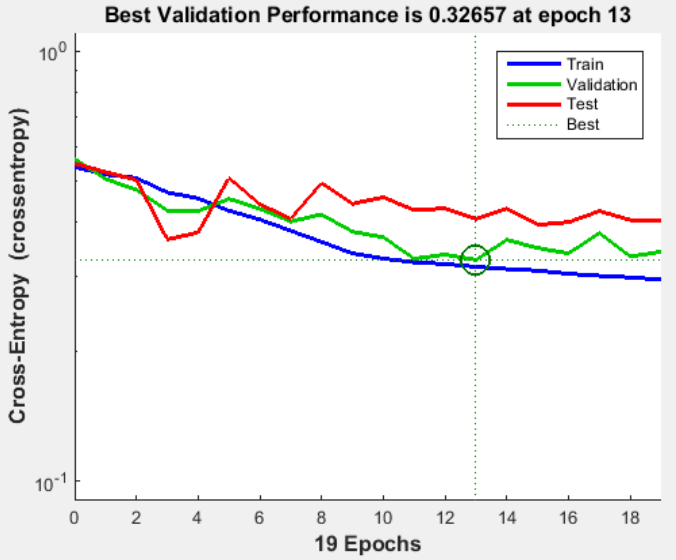

Figure 15: Training, validation, and testing curves for pattern recognition BFGS Quasi-Newton (PRN-BFG) model.

Figure 15 shows training, validation, and testing curves for pattern recognition BFGS Quasi-Newton (PRN-BFG) model of forklifts. From the graph, it can be seen that all errors including training, validations, and test errors generally reduced until after the thirteenth epoch. The third epoch also serves as the epoch with the lowest combined errors, which represents an optimal model. After this period, both validation and training errors started to increase, while the training error decreased further as the number of epochs increased. The similarity in trend between the training, validations, and test curves depicts a successful training of the pattern recognition BFGS Quasi-Newton (PRN-BFG) model and its potential use in assessing the failure potential of forklifts.

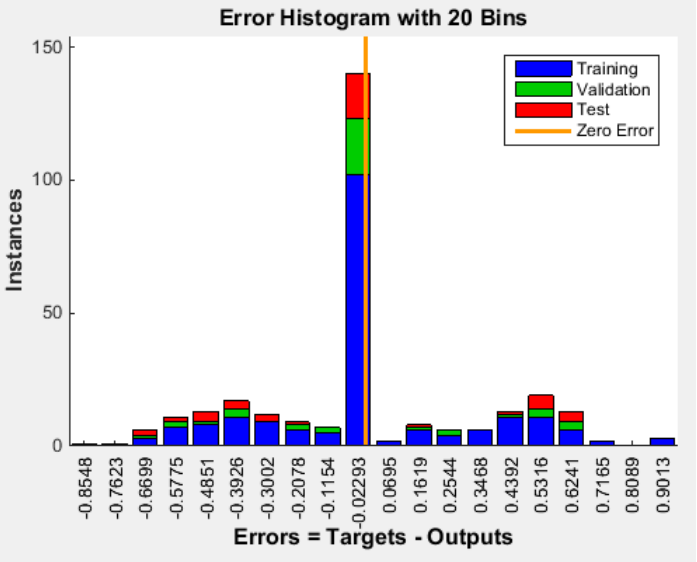

Figure 16: Prediction error histogram for pattern recognition BFGS Quasi-Newton (PRN-BFGS) model

Figure 16 shows the prediction error histogram for pattern recognition BFGS Quasi-Newton (PRN-BFGS) model for forklifts. From the histogram, it can be deduced that a majority of the error instances were located

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around the zero error line, while the error instances recorded further away from the zero error line were actually few. This can be confirmed by the smaller number of error instances recorded for errors further from the zero error line. Since the majority of the error instances were congregated around the zero error line, it demonstrates the ability of the pattern recognition BFGS Quasi-Newton (PRN-BFGS) model to predict failure of forklifts. This result is obviously useful in assessing the failure potential of forklifts.

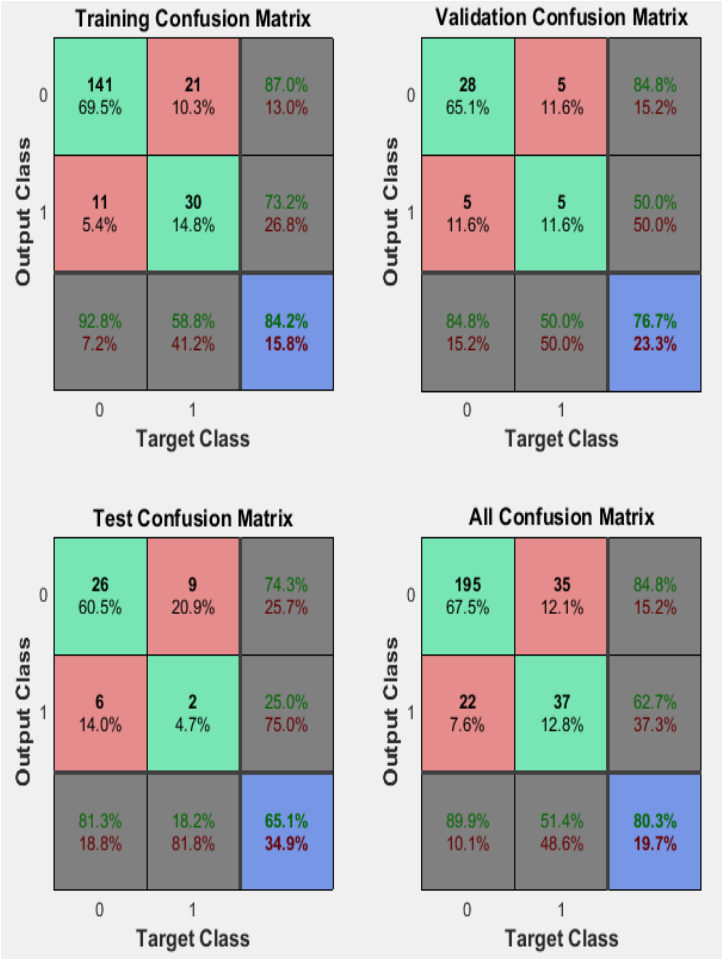

Figure 17: Confusion matrix for pattern recognition BFGS Quasi-Newton (PRN-BFGS) model

Figure 17 shows a representation of the confusion matrix for pattern recognition BFGS Quasi-Newton (PRN-BFGS) model. From the figure, it can be noticed that the confusion matrices of the test, validation and test data were all presented. In addition, a combined matrix of all the data was equally presented. The figure shows that after successfully training the BFGS Quasi-Newton (PRN-BFGS) model, the training result gave 84.2% correct classifications against 15.8% wrong classification. When the trained model was validated using validation data, the validation results gave only 76.7% correct predictions, with considerably high 23.3% wrong classifications. The trained model was equally tested and the test results showed that only 65.1% of the test data were correctly classified, while a substantially high 34.9% were wrongly classified. However, the combined confusion matrix showed that for the whole data set, 80.3% of the data set was accurately classified using the available input variables, but 19.7% of the data set was wrongly classified. The wrong classifications include both false positive and false negative classifications.

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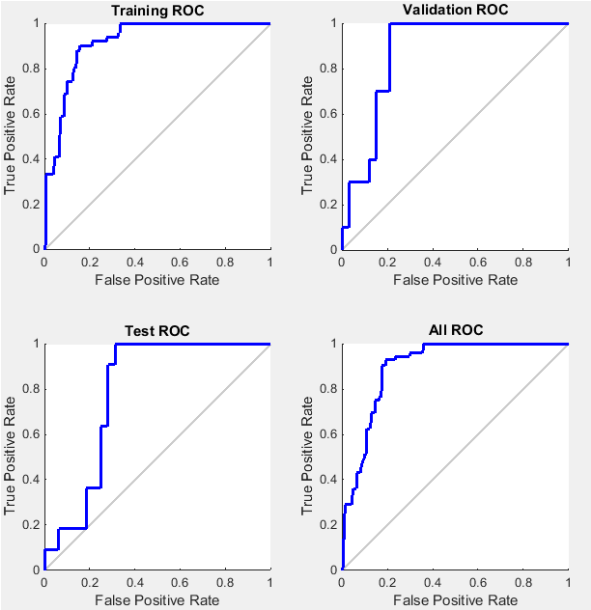

Figure 18: Receiver operating characteristic plot for pattern recognition BFGS Quasi-Newton (PRN-BFGS) model

Figure 18 shows the receiver operating characteristic plot for pattern recognition BFGS Quasi-Newton (PRN-BFGS) model. From the figure, it can be deduced that the receiver operating characteristic curves for training, validation, and test data all had slight deviations from the edges, which confirms the substantial accuracy of the characteristic plot for pattern recognition BFGS Quasi-Newton (PRN-BFGS) model for accurately classifying the failure potential of forklifts. Another important metric derivable from the receiver operating characteristic plot is the area under the curve (AUC). Since the receiver operating characteristic plots shown above are considerably far from the counterdiagonal, the BFGS Quasi-Newton (PRN-BFGS) model can be described as satisfactorily accurate.

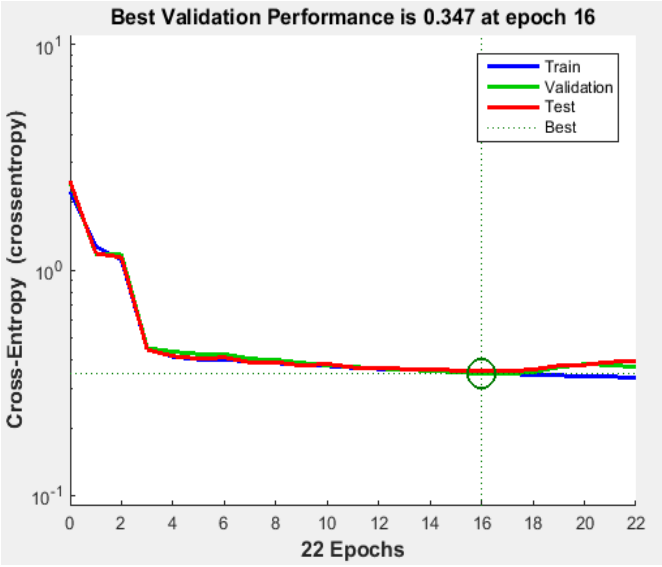

Figure 19: Training, validation, and testing curves for pattern recognition one secant step (PRN-OSS) model

Figure 19 shows training, validation, and testing curves for pattern recognition one step secant (PRN-OSS) model of forklifts. From the graph, it can be seen that all errors including training, validations, and test errors consistently reduced until after the third epoch. The combined errors continued to reduce (rather slowly) such that it recorded the combined training, validation and test error values at the sixteenth epoch. After this period, both validation and training errors started to increase, while the training error decreased further. The similarity in trend between the training, validations, and test curves depicts

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a successful training of the pattern recognition one step secant (PRN-OSS) model and its potential use in assessing reliability and availability of forklifts.

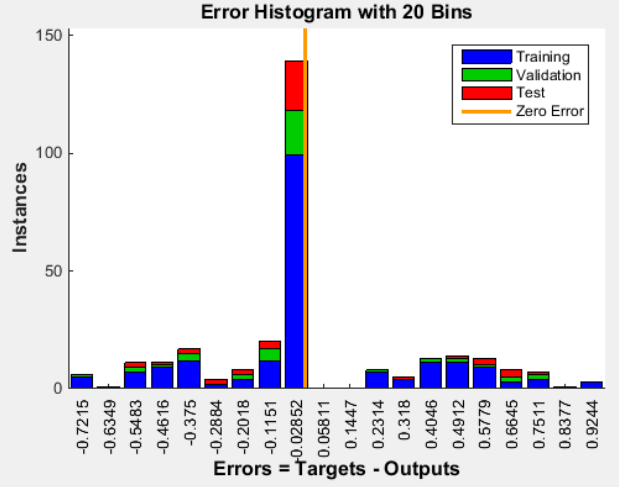

Figure 20: Prediction error histogram for pattern recognition one secant step(PRN-OSS) model

Figure 20 shows the prediction error histogram for pattern recognition one step secant (PRN-OSS) model for forklifts. From the histogram, it can be deduced that a majority of the error instances were located around the zero error line, while the error instances recorded further away from the zero error line were actually few. This can be confirmed by the smaller number of error instances recorded for errors further from the zero error line. Since the majority of the error instances were congregated around the zero error line, it demonstrates the ability of the pattern recognition one step secant (PRN-OSS) model to predict failure of forklifts. This result is obviously useful in assessing the reliability and availability of forklifts.

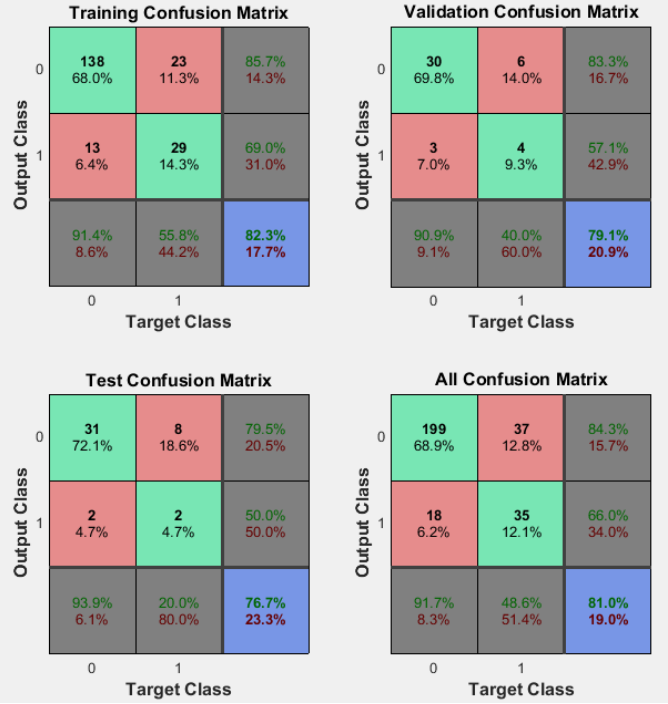

Figure 21: Confusion matrix for pattern recognition one secant step (PRN-OSS) model

Figure 21 shows a representation of the confusion matrix for pattern recognition one step secant (PRN-OSS) model. From the figure, it can be noticed that the confusion matrices of the test, validation and test data were all presented. In addition, a combined matrix of all the data was equally presented. The figure shows that after successfully training the one step secant (PRN-OSS) model,

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the training result gave 82.3% correct classifications against 17.7% wrong classifications. When the trained model was validated using validation data, the validation results gave 79.1% correct predictions, with 20.9% wrong classifications. The trained model was equally tested and the test results showed that a rather small 76.7% of the test data were correctly classified, while a considerably high 23.3% were wrongly classified. However, the combined confusion matrix showed that for the whole data set, 81.0% of the data set was accurately classified using the available input variables, but 19.0% of the data set was wrongly classified. The wrong classifications include both false positive and false negative classifications.

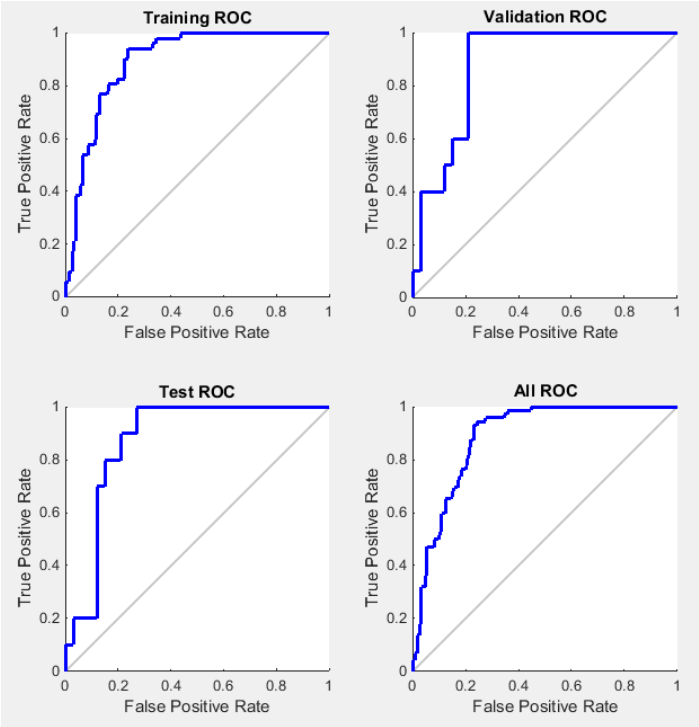

Figure 22: Receiver operating characteristic plot for pattern recognition one secant step (PRN-OSS) model

Figure 22 shows the receiver operating characteristic plot for pattern recognition one step secant (PRN-OSS) model. From the figure, it can be deduced that the receiver operating characteristic curves for training, validation, and test data all had slight deviations from the edges, which confirms the substantial accuracy of the characteristic plot for pattern recognition one step secant (PRN-OSS) model for accurately classifying the failure potential of forklifts. Another important metric derivable from the receiver operating characteristic plot is the area under the curve (AUC). Since the receiver operating characteristic plots shown above are considerably far from the counterdiagonal, depicting an area under the curve (AUC) value significantly greater than 0.5, the one-step secant (PRN-OSS) model can be described as satisfactorily accurate.

Conclusion

From the study, the following conclusions can be drawn

a. New artificial neural network models were developed for assessing the reliability of a forklift.

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b. From the results, the PRN-LMA models gave the highest prediction accuracy.
c. The Bayesian regularization models (PRN-BR) gave the least prediction accuracy.
d. Particularly, both PRN-CGF and PRN-LMA models gave the highest prediction accuracy for failure days.
e. The limitations encountered in this research, were insufficient funds, insufficient data due to unwillingness of the companies visited to release enough data.
f. The research cover time of only two years due to the allowable period limit for the programme.

Recommendations

From the observations and results obtained, the following recommendations were stated:

i. Given the availability of requisite data, this study can equally be carried out on other machineries other than cranes and forklifts.
ii. The safety of employees in the workplace should be considered in future research.
iii. The forklift vibration should be analysed.

References

Ahmad, S., Badwelan, A., Ghaleb, A. M., Qamhan, A., Sharaf, M., Alatefi, M., & Moohialdin, A. (2018). Analyzing critical failures in a production process:Is industrial iot the solution? *Wireless Communications and Mobile Computing*, *2018*.

Amar, M. N., Ghahfarokhi, A.J., & Ng, C.S.W. (2022). Predicting wax deposition using robust machine learning techniques. *Petroleum, 8*(1), 167-173.

Anandh, S., Bogeshwaran, K., Manikandan, G. N., Jamuna, P., & Sandhya, S. (2014). Failure analysis - watanabe model. *International Journal of ChemTech Research*, 6(9), 4333–4336.

Baghirli, O. (2015). "Comparison of Lavenberg Marquardt, Scaled Conjugate Gradient and Bayesian Regularization Backpropagation Algorithm for Multistep Ahead Wind Speed Forecasting Using Multilayer Perceptron Feedforward Neural Network, Dissertation" Uppsala University.

Bansal, S. A., Mehta, M., & Singh, H. (2020). Reliability Analysis in Process Industries-An Overview Reliability Analysis in Process Industries – An Overview. May.

Burden, F., & D. Winkler, D. (2008). Bayesian Regularization of Neural Networks, (23–42).

Chaudhari, S.R., & Dhawale, C. (2017). Solid Waste Prediction using ANN in the Nagpur City IJARCCE 6(1), 39-43.

Chu, Z-Q., Sasanipour, J., Saeedi, M., Baghban A., & Mansoori, H. (2017). Modeling of wax deposition produced in the pipelines using PSO-ANFIS approach. *Petroleum Science and Technology, 35*(20), 1974-1981.

Dao, C. D., & Zuo, M. J. (2015). Reliability analysis of multi-state systems with s-dependent components. *Proceedings - Annual Reliability and Maintainability Symposium*, 1–6.

Ezendiokwere N.E., Joel O.F., Aimikhe V.J., & Dosunmu A. (2021). Modelling fracture mechanics failure in shales with chemical sensitivity. Petroleum & Coal, 63(2), 525-540.

Fontes, C.H., & Pereira, O. (2016). Pattern recognition in multivariate time series: A case study applied to fault detection in a gas turbine. *Engineering Application of Artificial Intelligence,49*, 10-18.

Németh, P., Ladinig, T.B., & B. Ferenczi, B. (2016). Use of Artificial Neural Networks in the Production Control of Small Batch Production. Department of Logistics and Forwarding, Széchenyi István University, Győr, Hungary Rába Axle Ltd, Győr, Hungary.

Odeyar, P., Apel, O.B., Hall, R., Zon, B., Skrzypkowski, K. (2022). A review of reliability and fault analysis methods for heavy equipment and their components used in mining. *Energies, 15,* 6263.

Payette, M., & Abdul-Nour, G. (2023). Machine learning applications for reliability engineering: A review. *Sustainability, 15*(7), 6270.

Rad, M. K., Torabizadeh, M., & Noshadi, A. (2011). Artificial neural network-based fault diagnostics of an electric motor using vibration monitoring. *Proceedings 2011 International Conference on Transportation, Mechanical, and Electrical Engineering, TMEE 2011*, *December*, 1512–1516.

Ravnik, J., Jovanovac, J., Trupej, A., Vištica, N., & Hriberšek, M. (2021). A sigmoid regression and artificial neural network models for day-ahead natural gas usage forecasting. *Cleaner and Responsible Consumption*, *3*(August).

EDITOR-IN-CHIEF
Prof. Saeid Eslamian [IRAN]

Robles-Velasco, A., Ramos-Salgado, C., Muñuzuri, J., & Cortés, P. (2021). Artificial Neural Networks to Forecast Failures in Water Supply Pipes, 13(15), 8226.

Serey, J., Alfaro, M., Fuertes, G., Vargas, M., Duran, C., Ternero, R., Rivera, R., & Sabattin, J. (2023). Pattern recognition and deep learning technologies, enablers of industry 4.0, and their role in engineering research. *Symmetry, 15*(2), 535.

Salimah, S.F., Mu'alima, Purwokoa, S., & Zumrotun, E.N.S F. (2023). Determination the Critical Component Machine using AHP Method for Reliability Centered Maintenance. International Journal of Science, Engineering, and Information Technology, 7(2).

Sanaye, S., & Hosseini, S. (2020). Prediction of blade life cycle for an industrial gas turbine at off-design conditions by applying thermodynamics, turbo-machinery and artificial neural network models Energy Systems Improvement Laboratory, Mechanical Engineering Department., Iran University of Science and Technology, Iran. Published by Elsevier Ltd. Energy Reports, 6, 1268–1285.

Sharma, A., & Chopra, A. (2013). Artificial Neural Networks: Applications In Management. IOSR Journal of Business and Management 12(5), 32-40.

Soualhi, M., Nguyen, K.T.P., & Medjaher, K. (2020). Pattern recognition method of fault diagnostics based on a new health indicator for smart manufacturing. *Mechanical Systems and Signal Processing, 142*, 106680.

Tenney, A., Glauser, M., Ruscher, C., & Berger, Z. (2020). Application of Artificial Neural Networks to Stochastic Estimation and Jet Noise Modeling," AIAAJ Journal, 58(2).

Tian, Z., Wong, L., & Safaei, N. (2010). A neural network approach for remaining useful life prediction utilizing both failure and suspension histories. In *Mechanical Systems and Signal Processing* 24(5).

Wang, P. H., Lin, G. H., & Wang, Y. C. (2019). Application of neural networks to explore manufacturing sales prediction. Applied Sciences (Switzerland), 9(23).

Widyaningrum, M.R, & Winati, F.D. (2022). "Penjadwalan Perawatan Mesin di CV Wijaya Workshop dengan Pendekatan Reliability Centered Maintenance (RCM)," J. TRINISTIK J. Tek. Ind. Bisnis Digit. dan Tek. Logistik, 1(1), 37–43.

Wu, M., Zhong, L., Xu, B., & Xiong, (2020). A consensus-based diffusion levenberg-marquardt method for collaborative localization with extension to distributed optimization, IEEE, 8.

Zhao, B., Chen, H., Gao, D., & Xu, L. (2020). Risk assessment of refinery unit maintenance based on fuzzy second generation curvelet neural network. *Alexandria Engineering Journal*, 59(3), 1823–1831.

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