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COMPARATIVE RELIABILITY ANALYSIS OF CRANES AND FORKLIFTS USING ARTIFICIAL NEURAL NETWORK-BASED MODELS

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ABSTRACT

Artificial neural network-based models were developed for assessing the reliability of two types of machinery: cranes and forklifts. This was done to be able to predict the operating conditions of the machinery. It entails the ability to predict the functional days of the machinery without failures and the exact days on which they would experience failure given a number of input variables.

INTRODUCTION

Reliability and availability analysis for machinery maintenance, currently command high attraction from the academic world, oil and gas sectors, manufacturing industry, etc. These days, companies are established to meet customer satisfaction by the production of quality products aligning the aim and objectives to attract market demands. The majority of both basic and complicated machines are made up of a network of interconnected individual parts, subunits, and units (Odeyar *et al.*, 2023). This implies that the states and mechanics of the numerous components, subunits, and pieces have a significant impact on the overall machine operating

The input variables considered in these models were an easy-start variable, hours run per day and cumulative time between failure, while the output variable was failure potential for a given day. The output variable assesses whether the machinery would fail on a given working day or not. Hence, the input data variables for cranes were obtained from Hyster RS45-27 CH and Konecranes Liftace TFC 45 97-2002, while forklift input data was from Hyster H6.00XL. The data was gotten from machines which were found in a Lagos seaport. The neural network models were later developed, trained, tested and validated using MATLAB. From the results, the PRN-LMA models for both crane and forklifts gave the highest prediction accuracy.

Keywords: Cranes, Forklift, Pattern Recognition, Reliability

standard. Generally speaking, when one part fails, it can lead to the failure of other parts, or the state of one part can influence the functioning of other parts and ultimately the machine as a whole. Because machine components are interdependent, the condition of one part in a mechanical system can influence the condition and deterioration of other parts, suggesting that real and complex systems might exhibit stochastic dependence (Dao & Zuo, 2015). In addition to being far more complicated, it is anticipated that the devices of this century will be more reliable and automated. As systems become automated, software maintenance will become even more crucial, if not as important as machine maintenance (Gala et al., 2016; Achour et al., 2017). Realizing potential benefits and converting them into income requires new ways of thinking and doing things. Overall, businesses using contemporary thinking to develop an equipment management strategy that effectively utilizes new knowledge, technology, and techniques will be the most successful (Herath et al., 2021).

Manufacturing systems can now monitor physical processes and make intelligent decisions by collaborating and communicating in real-time with people, machines, sensors, and other devices thanks to the Internet of Things and machine learning techniques (Tienbui et al., 2019). By employing machine learning technologies that learn from experience, artificial intelligence helps manufacturers eliminate equipment downtime, identify production flaws, enhance the supply chain, and expedite design timelines. More study was necessary due to the abrupt and unplanned breakdown of machinery-in-operation modules and urgent demands. It has not yet been possible to estimate failure times with accuracy and precision. Creating predictive models that can detect possible malfunctions or failures in general algorithm lifting equipment was the main goal of the study on the prediction of crane and forklift failure using artificial neural network models. By facilitating a good maintenance style and decreasing unscheduled downtime, this advancement would increase the effectiveness of lifting machinery operations.

Literature Review

In the world of information technology (IT), an artificial neural network (ANN) is a hardware and/or software system that mimics the operation of neurons in the human brain. Neural networks, or 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. Figure 1 shows a simple structure of an ANN with four nodes in the input layer, four nodes in the hidden layer, and two nodes in the output layer. Neurons are connected to form an artificial neural network. Typically, the neurons are put together in layers (Barad et al., 2012). Numerous basic neuron processing components, known as nodes or neurons, make up each layer.

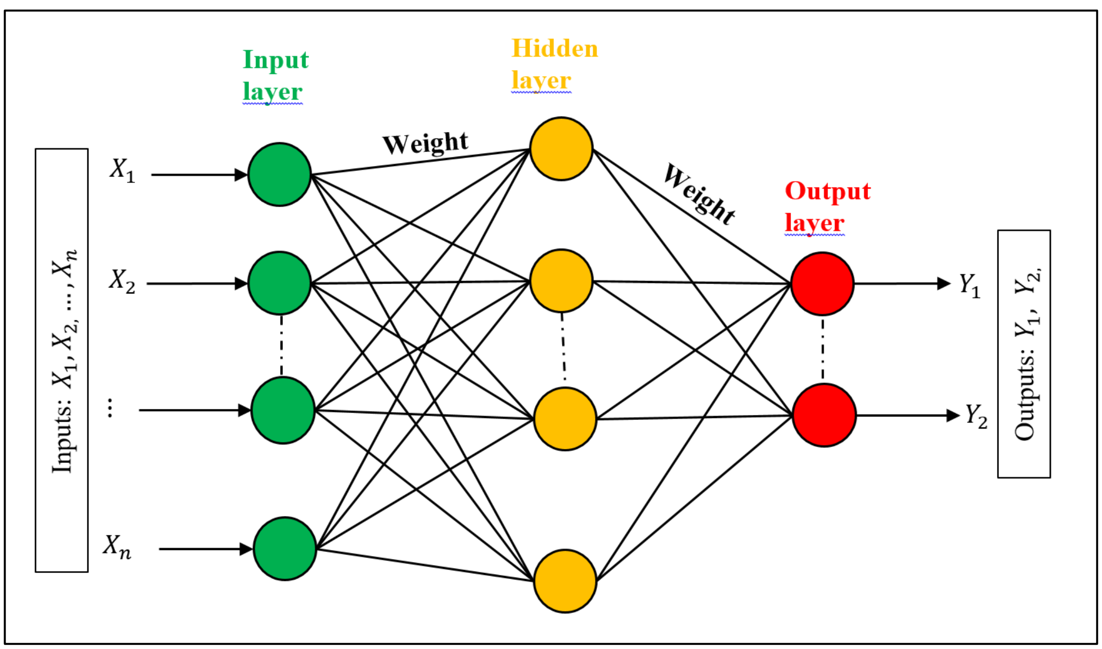

Figure 1: The Artificial Neural Network Architecture (source: Zhang et al., 1998).

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These neurons communicate with one another through numerically weighted connections (Peng et al., 2010). A neural network typically has n layers of neurons, of which two are input and output layers. While the latter is the final layer and the one that outputs the calculations' results, the former is the first and only layer that receives and sends external signals. In relays, the n-2 inner ones known as hidden layers extract pertinent characteristics or patterns from received signals.

Promising techniques for pattern detection of previous data from machine attributes are available in machine learning (a branch of artificial intelligence) (Caggiano et al., 2019). The tools are programmed to support two distinct learning paradigms for nonlinear data analysis: supervised and unsupervised (Wachowiak et al., 2019). A stimulus is presented to the learner, who classifies it, and then receives corrected feedback in supervised classification learning (Love, 2002).

There is a gap in supervised machine learning models, which indicates the need and possibility to use unidentified data in unsupervised methods of learning (Jati & Georgiou, 2019), regardless of all the exciting journals with supervised DP models for breakdown classification in rotating equipment (Li et al., 2020; Souza et al., 2021). Yang et al. (2021) reviewed the applications of artificial neural networks in pavement engineering. It was recommended that CNN-based pavement health inspection and monitoring could be better because of its capabilities to substitute human operation.

Applications of Artificial Neural Networks (ANN)

Robles-Velasco et al. (2021) used an Artificial Neural Network (ANN) based on tangible and procedural input attributes, to categorize pipes according to their propensity to fail. The methods of under- and over-sampling were also examined. Kutyłowska. (2014) submitted that the application of ANN to model the damage frequency in a system required large data in thousands and not in hundreds in order to obtain accurate results. Artificial neural networks were applied to examine the failure history in the essential nine primary engine-related subsystems, which is consistent with condition-based maintenance applications and also aids in highlighting probable breakdowns in the historical failure data (Goksu & Erginer, 2020). According to Chaudhari & Dhawale (2017), artificial neural network (ANNs) models were utilized to predict solid waste. An ANN was also employed in image processing in a variety of industries, including construction, transportation, remote sensing, human-computer interface, and language recognition.

Machine Failure

Machine failure can be defined in a variety of ways. For example, it can be the difference between the target and current level of performance, a deviation from the standard or desired performance, or an unfavorable outcome of a job (Anandh *et al*., 2014). In other words, failure can be defined as the difference between the actual and expected outcomes of a system. The operational efficiency of any manufacturing company is negatively impacted by machine breakdowns. In a traditional manufacturing system, it can be challenging to identify significant failures and investigate their relationships with other process factors (Ahmad *et al*., 2018).

Machinery breakdown could result in output disruption, therefore, leading to a loss of the machine's availability (Kolte & Dabade, 2017). 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). Generally speaking, machinery experiences a protracted degeneration process that could take several years or months to go from operational to downtime.

Machine failure is a frequent occurrence in business, which presents challenges for both the management responsible for the equipment's availability and the technician who maintains it. Although it may seem like a maintenance issue, it affects all stakeholders in a company because the failure of a single piece of equipment can result in complete downtime and production loss until the equipment is repaired or replaced (Ezendiokwere *et al*., 2021). As a result, despite our best efforts to prevent these failures, they do happen and must be continuously managed (Payette & Abdul-Nour, 2023).

Nonetheless, we are aware that accurately defining the issue and locating its core cause decide how effective management is. The failure rate of the system's other dependent units can change when one or more components fail. This is an illustration of dependent reliability, and it falls into one of two categories: positive or negative. If the failure of one component increases the likelihood that another component would fail, then the reliance is seen as positive. Conversely, negative dependency happens when one component fails and lessens the chance that another component will fail (Fontes & Pereira, 2016).

Several study fields are included in reliability engineering, including asset management (AM), prognostics and health management (PHM), and reliability, availability, maintainability, and safety (RAMS). Due to problems with the control panel, gearbox, hydraulic motor, pneumatic pump, and other production system and function failures, several production lines and manufacturing industries have frequently been producing below capacity. While increased productivity would increase revenue, better reliability and availability assessment for machinery maintenance will lower maintenance expenses. Better funding for staff and more affordable prices for end customers will result from higher income and lower operating costs (Soualhi *et al*., 2020).

Numerous studies have demonstrated that a fundamental component in any manufacturing, industrial, or service company is the cost of crucial equipment failure or unavailability. A shift from a component-based to a systems-based approach to addressing maintenance issues is required in the maintenance plan. For this reason, failure analysis with artificial neural networks (ANNs) continues to be a superior technique for critical equipment maintenance management (Serey *et al*., 2023). Investigating ANNs in the creation of an equipment maintenance model that will guarantee notable increases in system availability, productivity, and reliability is, thus, this study's highlight.

Methodology

There are several crucial elements in the workflow for designing a general artificial neural network (Fontes & Pereira, 2016). A collection of cranes and forklift machines from the African Global Logistics, Apapa-Lagos were used to develop the artificial neural network-based models. These consist of gathering and preparing data, building and configuring networks, initializing weights and biases, training networks, validating them (by post-training analysis), and demonstrating them. The African Global Logistics bonded terminal provided the failure data that was utilized in this study's artificial neural network machine learning model development. The raw failure statistics were tallied by operating month, and each table included the date, the start and stop times, the hours of operation each day, and the frequency of machine failures. Furthermore, the raw data was similarly used to construct the time between failure (TBF) statistics. Tables 1-6 in the appendix shows some of the obtained results.

Initially, a training, test, and validation data set in the ratio 60:20:20 was created from these input variables. Later, a feed forward neural network for pattern identification and classification was fed the entire collection of data. Using computer algorithms and important traits or regularities as a basis, pattern recognition is the process of classifying incoming data into objects, classes, or categories (Serey *et al*., 2023). Feed forward neural networks that can be trained to categorize inputs based on target classes are called pattern recognition networks, or PRNs. Although it is infrequently utilized for reliability and availability research, it has applications in fields including computer vision, image segmentation, object detection, radar processing, speech recognition, and text classification (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. The artificial neural network model was created with MATLAB.

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. Each of the MATLAB outcomes was later examined separately. The MATLAB results were first evaluated individually before a comparative statistical analysis of the models was later carried out. Figure 1 shows the MATLAB presentation of the utilized pattern recognition neural network architecture.

To develop a model from training data, machine learning methods employ it without explicit programming to make conclusions or predictions. Reliability and risk assessment using machine learning has garnered significant attention from investigators and managers in recent years. It is possible to find significant parameters that predict failures as well as anticipate failures themselves using a machine learning approach. Figure 2 illustrates a fundamental comprehension of ML implementation for downtime evaluation.

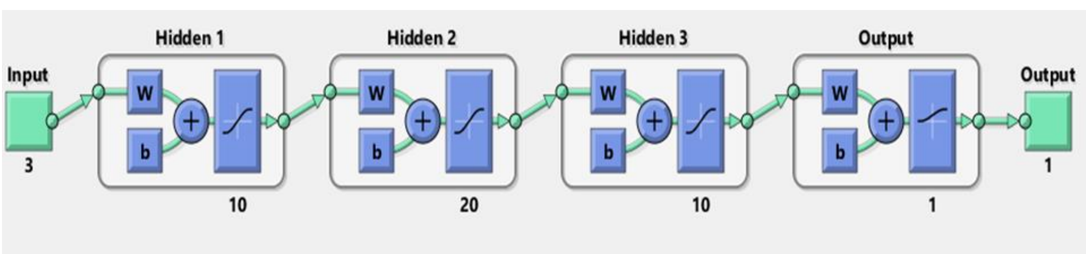

Figure 1: A MATLAB presentation of the utilized pattern recognition neural network architecture.

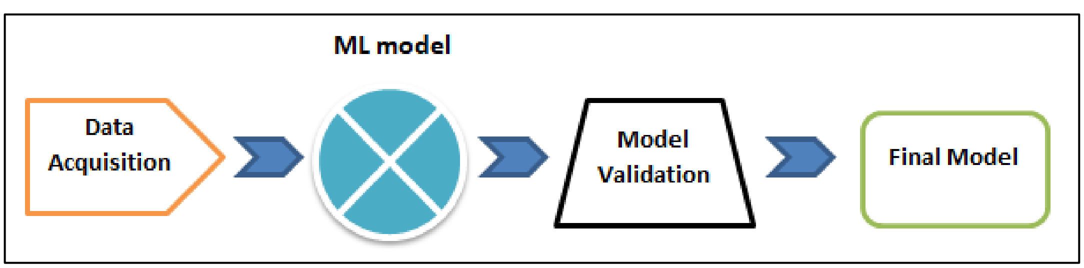

Figure 2: Flow chart of adopted research methodology

Optimization Algorithms

Series of Optimization Algorithms were utilized in training the pattern recognition neural network models. These Algorithms include the following; Levenberg Marquardt Algorithm, Bayesian Regularization (BR) Algorithm, Conjugate Gradient Algorithm, Broyden, Fletcher, Goldfarb, and Shanno (BFGS) Quasi-Newton, and One Step Secant Method.

Levenberg-Marquardt Algorithm (LMA)

Levenberg-Marquardt (LMA) is employed to identify dynamic least squares solutions (Wu et al., 2020). For small and medium-sized data sets, LMA works well. Compared to other algorithms, LMA operates faster and has steady convergence. Equation (1) and (2) can be used to calculate the gradient (g) of the Hesian (H) matrix style, which is used in the process of updating the weights and biases (Chu et al., 2017).

$$H = J^T J \tag{1}$$

$$g = J^T e \tag{2}$$

where J is the Jacobian matrix, e is the error vector, and T is the matrix transpose operator. The weights in the MLP weights optimization situation are represented by the x term in Equation (3).

$$x_{i+1} = x_i - (H - \lambda I)^{-1} \times g \tag{3}$$

where, $x_i = (v_{11,}\, v_{12,}\, v_{13,}\, v_{14,}\, \ldots, v_{jk}\ ;\ v_{01,}\, v_{02,}\, v_{03,} v_{04,}\, \ldots, v_{0j}\ ;\ w_{11,}\, w_{12,}\, w_{13,} w_{14,}\, \ldots,$ $v_{jk};\ w_{01,}\, w_{02,}\, w_{03,} w_{04,}\, \ldots, w_{0k}\ ).$ λ is the learning constant and I is the identity matrix.

Bayesian Regularization (BR) Algorithm

The development phase is enhanced by the Bayesian Regularization (BR) approach, whic h optimizes the network's weights and squared errors. By using the weights and bias sta ndard deviation, BR modifies the error performance. Equation (4) illustrates how the BR approach improves error efficiency by including weight and standard deviation bias (Baghirli, 2015).

$$F(\omega) = \alpha E_w + \beta E_D \tag{4}$$

where E_w *and* E_D represent the total number of network errors and the squared network weight, α *and* β are parameters of the goal (regularization) function. Equations (5) and (6) yield the following results for the E_w *and* E_D functions:

$$E_w = \frac{1}{n} \sum_{i=1}^{n} (w_i)^2 \tag{5}$$

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$$E_D = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2 \qquad (6)$$

where a_i is the i^{th}data output, t_i is the goal value of the t^{th} data, and n is the amount of inputs to the training data, along with the weights or limits for the t^{th} data. The approach of Bayesian Regularization artificial neural network programme is illustrated in Figure 3.

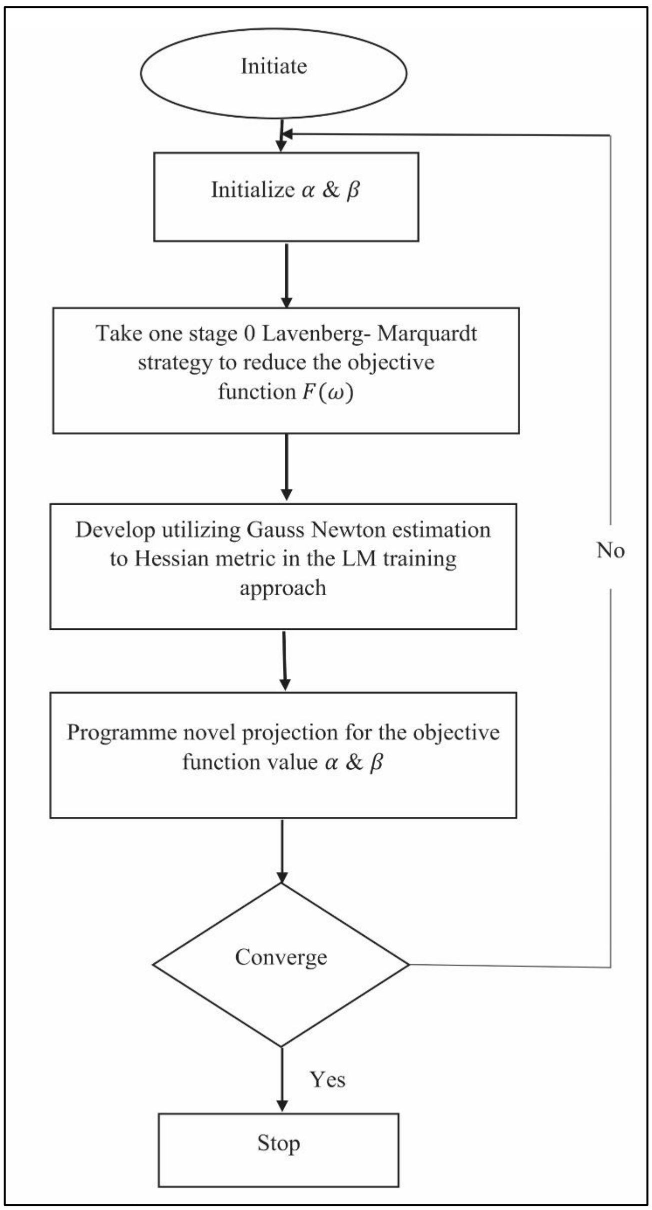

Figure 3: Concept of Bayesian Regularization Approach

Conjugate Gradient Algorithm (CG)

The conjugation direction serves as the foundation for the Conjugate Gradient Algorithm, which does not run line searches on each iteration. It is intended to save time through minimizing tedious line searches. All the conjugate gradient algorithms start by searching in the steepest descent direction (negative of the gradient) on the first iteration.

$$\boldsymbol{p_o} = -\boldsymbol{g_o} \qquad (7)$$

$$\boldsymbol{X_{i+1}} = \boldsymbol{X_i}\alpha_i\boldsymbol{p_i} \qquad (8)$$

Generally speaking, the novel steepest descent is put together with the prior search route to identify the novel search range using Equation (9).

$$\boldsymbol{p_i} = -\boldsymbol{g_i} + \beta_i \boldsymbol{p_{i-1}} \tag{9}$$

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 as follows:

$$\beta_i = \frac{g_i^T g_i}{g_{i-1}^T g_{i-1}} \tag{10}$$

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 (11).

$$\boldsymbol{X_{i+1}} = \boldsymbol{X_i} - \boldsymbol{A_i^{-1}} \boldsymbol{g_i} \tag{11}$$

where A_i^{-1} is the performance index's Hessian matrix (second derivatives) for the present weight and bias settings. When computing performance derivatives concerning the weight and bias variables X, back-propagation is typically used. Each value is modified according to Equation (12)

$$X_{i+1} = X_i + adX \tag{12}$$

where, dX is the search direction. Subsequently, the search direction is computed according to Equation (13).

$$dX = \frac{-H}{gX} \tag{13}$$

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

One-Step Scant Method (OSS)

A novel method to close the gap between the quasi-Newton (secant) technique and the conjugate gradient algorithm is the One-Step-Secant (OSS) method. The OSS technique assumes that the identity matrix was the earlier Hessian at each iteration and does not keep the whole Hessian matrix. Equation (14) is used to change every single value.

$$X_{i+1} = X_i + adX \tag{14}$$

where, dX is the search direction. The opposite end of the success curve is the initial search orientation. Equation (15) is then used to calculate the search orientation using the current curve, the previous steps, and the levels.

$$dX = -gX + Ac * X_{-step} + Bc * dgX \tag{15}$$

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

Results and Discussion

The illustration of findings in the way of tables and figures are presented and discussed below.

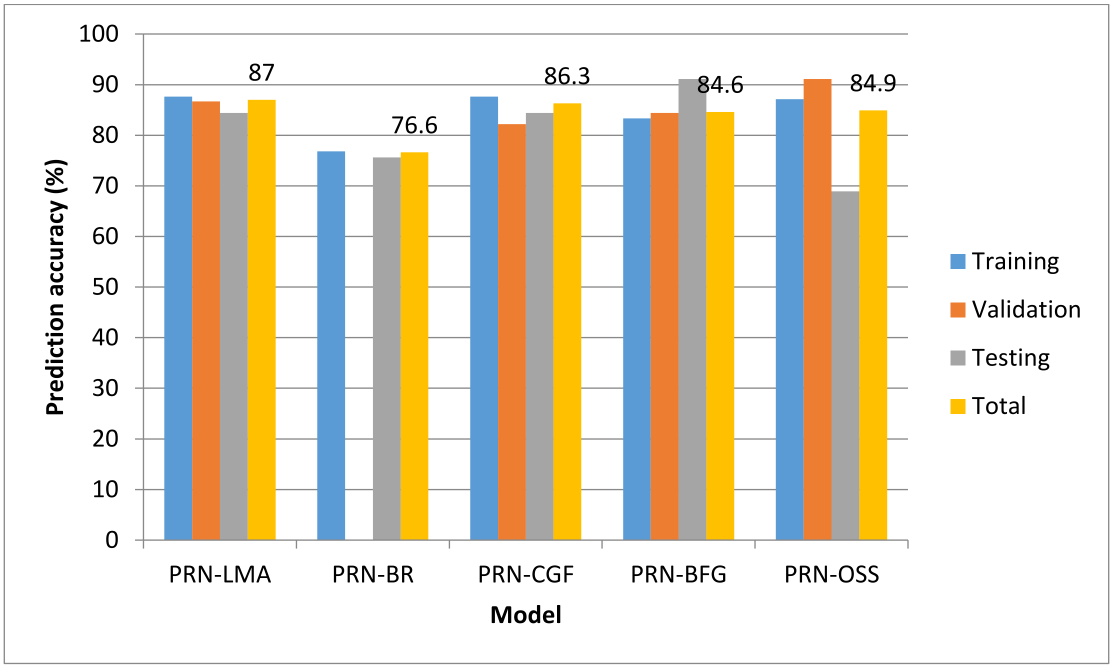

Figure 2: Comparative percentage accuracies of training, validation, testing and combined data for cranes

Figure 2 shows the comparative percentage prediction accuracies of training, validation, testing and combined data for cranes. From the figure, it can be deduced that the models that posted highest training accuracies were PRN-LMA and PRN-CGF with accuracies of 87.6%, followed by PRN-OSS with a training data accuracy of 87.1%. PRN-BFG had a training data accuracy of 83.3% while the least training data accuracy went to PRN-BR, which had a training data accuracy of 76.8%. The highest test data accuracy went to PRN-BFG with an accuracy of 91.1%, followed by PRN-LMA and PRN-CGF with 84.4% accuracies respectively. The least test data accuracies belonged to PRN-BR and PRN-OSS with test data accuracies of 75.6% and 68.9%.

The highest validation data accuracy was for PRN-OSS with an accuracy of 91.1%, followed by PRN-LMA and PRN-BFG with percentage accuracies of 86.7% and 84.4% respectively. But the least validation accuracy went to PRN-CGF with an accuracy of 82.2%. Meanwhile, there was no validation accuracy for PRN-BR model since its optimization algorithm does not work with a validation data. However, for the combined data, the highest prediction accuracy went to PRN-LMA with an accuracy of 87%, followed by PRN-CGF with an overall

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prediction accuracy of 86.3%. Next were PRN-OSS and PRN-BFG with prediction accuracies of 84.9% and 84.6% respectively, while PRN-BR was the least accurate, with an accuracy of 76.6%.

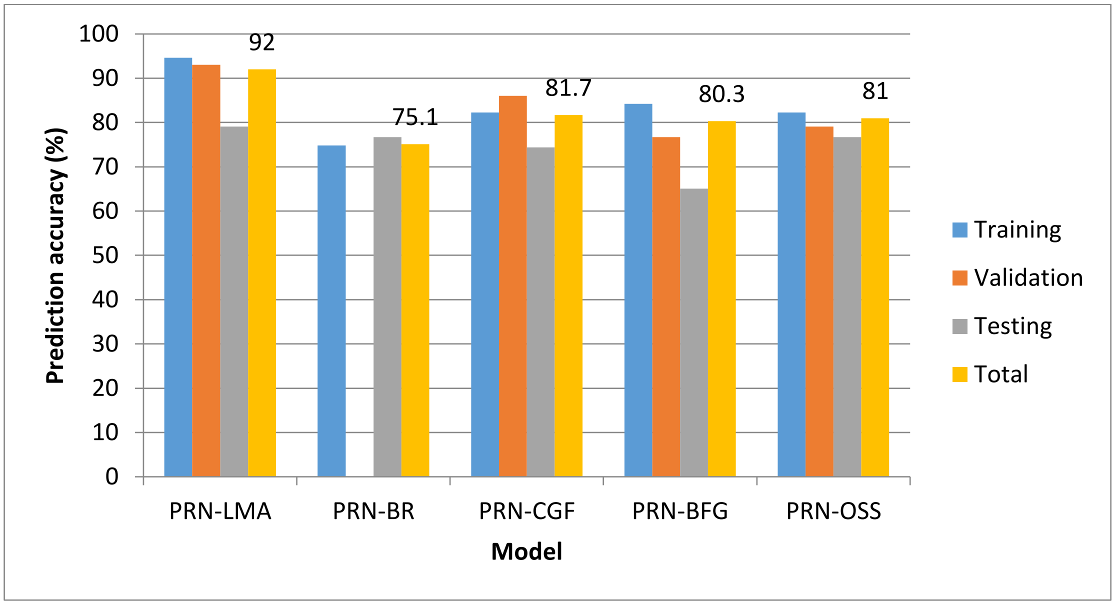

Figure 3: Comparative percentage prediction accuracies of training, validation, testing and combined data for forklifts

Figure 3 shows the comparative percentage prediction accuracies of training, validation, testing and combined data for cranes. From the figure, it can be deduced that the models that posted highest training accuracies were PRN-LMA and PRN-BFG with accuracies of 94.6% and 84.2%, followed by PRN-OSS and PRN-CGF with a training data accuracies of 82.3%. The least training data accuracy went to PRN-BR, which had a training data accuracy of 74.8%. The highest test data accuracy went to PRN-LMA with an accuracy of 79.1%, followed by PRN-OSS and PRN-BR with 76.7% accuracies respectively. The least test data accuracies belonged to PRN-CGF and PRN-BFG with test data accuracies of 74.4% and 65.1%.

The highest validation data accuracy was for PRN-LMA with an accuracy of 93%, followed by PRN-CGF and PRN-OSS with percentage accuracies of 86% and 79.1% respectively. But the least validation accuracy went to PRN-BGF with an accuracy of 76.7%. Meanwhile, there was no validation accuracy for PRN-BR model since its optimization algorithm does not work with a validation data. However, for the combined data, the highest 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%.

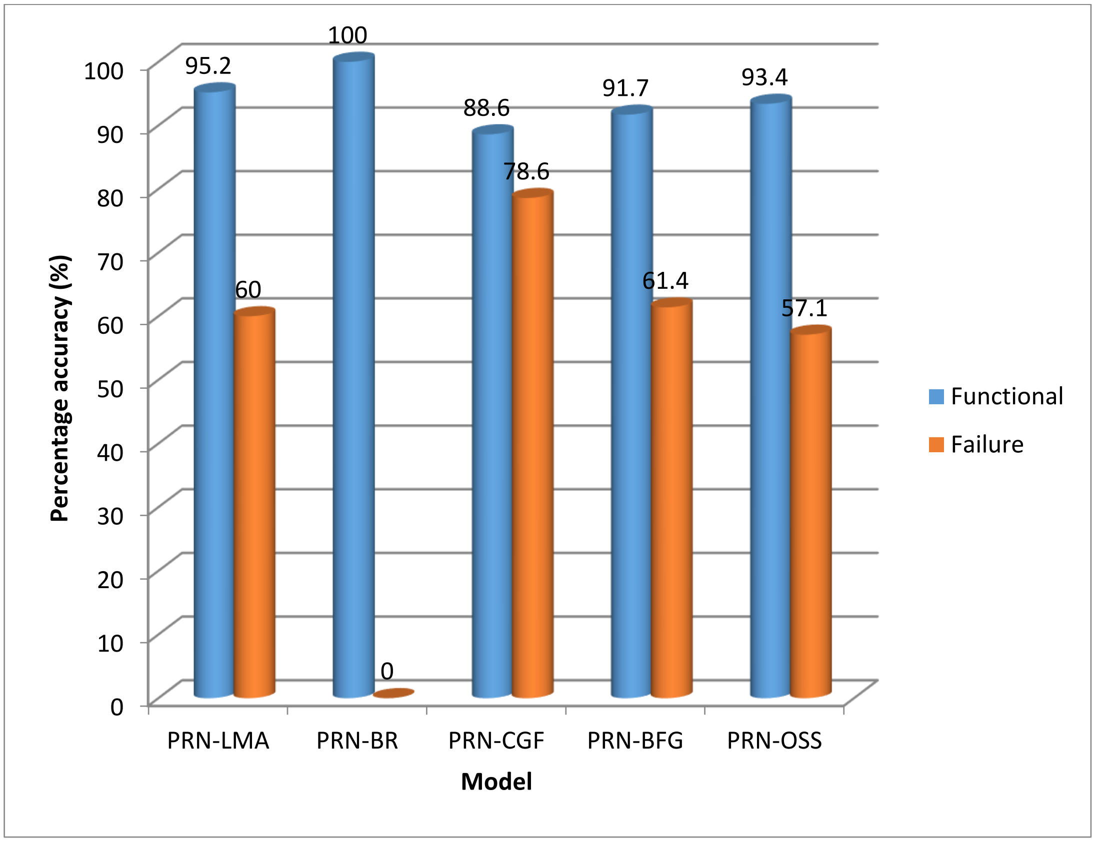

Figure 4: Comparative reliability and availability predictions of various models for cranes

Figure 4 shows the comparative reliability and availability predictions of various models for cranes. From the figure, it can be noticed that the model that predicted the highest percentage of the functional days for cranes was PRN-BR, which correctly predicted all the days the cranes were functional. This was followed by PRN-LMA and PRN-OSS, which correctly predicted 95.2% and 93.4% of all functional days of the cranes considered. The models that predicted the least functional days were PRN-BFG and PRN-CGF with 91.7% and 88.6% respectively.

The model that correctly predicted days of failure for cranes was PRN-CGF, with a prediction accuracy of 78.6%, followed by PRN-BFG and PRN-LMA which correctly predicted 61.4% and 60% of the days of failure for cranes respectively. Next was PRN-OSS, which correctly predicted 57.1% of the days of failure. But PRN-BR could not correctly predict any of the failure days of the crane, hence it had 0%.

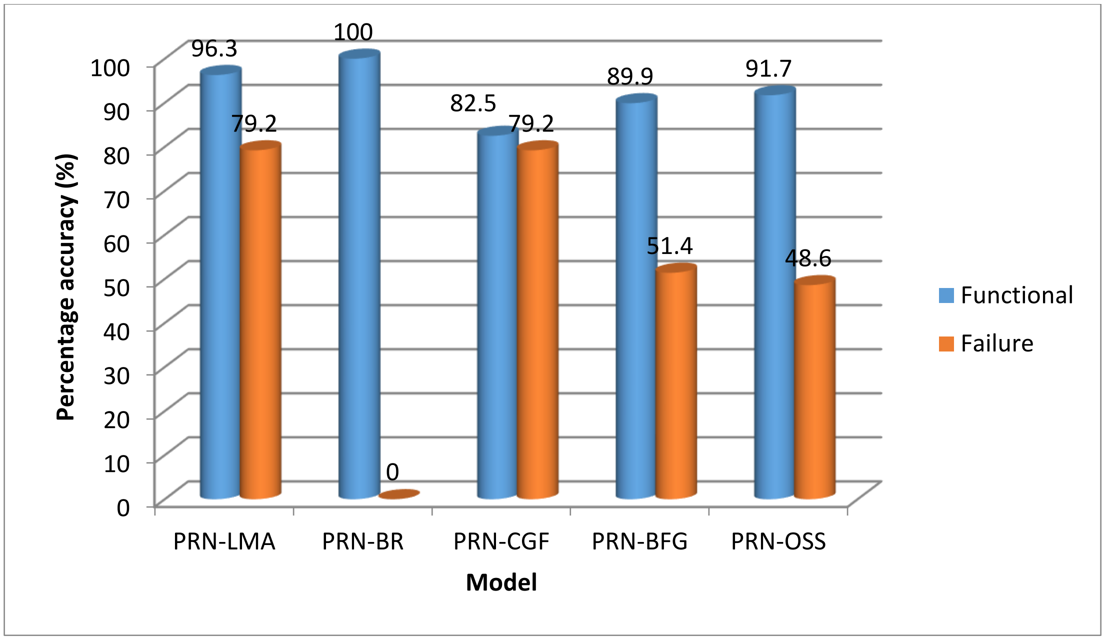

Figure 5; Comparative reliability/availability predictions of models for forklifts

Figure 5 shows the comparative reliability and availability predictions of various models for forklifts. From the figure, it can be noticed that the model that predicted the highest percentage of the functional days for cranes was again PRN-BR, which correctly predicted all the days the cranes were functional. This was followed by PRN-LMA and PRN-OSS, which correctly predicted 96.3% and 91.7% of all functional days of the forklift considered. The models that predicted the least functional days were PRN-BFG and PRN-CGF with 89.9% and 82.5% respectively.

The models that correctly predicted days of failure for forklift were PRN-LMA and PRN-CGF, with prediction accuracies of 79.2% each, followed by PRN-BFG, which correctly predicted 51.4% of the days of failure for forklift. Next was PRN-OSS, which correctly predicted 48.6% of the days of failure. But PRN-BR could not correctly predict any of the failure days of the crane, hence it had 0%.

Conclusion

From the research and findings obtained, the following conclusions could be drawn:

a. Artificial neural network-based models were developed for assessing the reliability of both cranes and forklift.
b. Insights gained from the results showed that the PRN-LMA models for both crane and forklifts were found to give the highest prediction accuracy.

c. On the other hand, the Bayesian regularization models (PRN-BR) gave the least prediction accuracy for both cranes and forklifts.
d. Meanwhile, the PRN-CGF model, followed by the PRN-LMA model were able to predict the highest number of failure days for cranes, while both models also gave the highest prediction accuracy for failure days.
e. Despite the fact that the Bayesian regularization models gave the highest functional days predictions, yet they could not correctly predict any of the failure days. This explains why they ranked low in terms of prediction accuracy.

Recommendations

From the observation and results obtained, it is therefore recommended that:

a. The Federal Government of Nigeria and other larger companies should adopt the developed models to optimize the cost of purchasing sophisticated software.
b. For more accurate results, further study should be conducted combining artificial neural networks and machine learning to assess the reliability of other haulage or lifting machinery.

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Appendix

Table 1 Comparative percentage prediction accuracies of training, validation, testing and combined data for cranes

Model	Data	Percentage Accuracy (%)
PRN-LMA	Training	87.6
	Validation	86.7
	Testing	84.4
	Total	87.0
PRN-BR	Training	76.8
	Validation	-
	Testing	75.6
	Total	76.6
PRN-CGF	Training	87.6
	Validation	82.2
	Total	84.4
	Testing	86.3
PRN-BFG	Training	83.3
	Validation	84.4
	Testing	91.1
	Total	84.6
PRN-OSS	Training	87.1
	Validation	91.1
	Testing	68.9
	Total	84.9

Table 2 Comparative percentage prediction accuracies of training, validation, testing and combined data for forklifts

Model	Data	Percentage Accuracy (%)
PRN-LMA	Training	94.6
	Validation	93.0
	Testing	79.1
	Total	92.0
PRN-BR	Training	74.8
	Validation	-
	Testing	76.7
	Total	75.1
PRN-CGF	Training	82.3
	Validation	86.0

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	Testing	74.4
	Total	81.7
PRN-BFG	Training	84.2
	Validation	76.7
	Testing	65.1
	Total	80.3
PRN-OSS	Training	82.3
	Validation	79.1
	Testing	76.7
	Total	81.0

Table 3 Comparative reliability/availability predictions of models for cranes

Model	Predicted status	Percentage Accuracy (%)
PRN-LMA	Functional	95.2
	Failure	60.0
PRN-BR	Functional	100
	Failure	0
PRN-CGF	Functional	88.6
	Failure	78.6
PRN-BFG	Functional	91.7
	Failure	61.4
PRN-OSS	Functional	93.4
	Failure	57.1

Table 4 Comparative reliability/availability predictions of models for forklifts

Model	Predicted status	Percentage Accuracy (%)
PRN-LMA	Functional	96.3
	Failure	79.2
PRN-BR	Functional	100
	Failure	0
PRN-CGF	Functional	82.5
	Failure	79.2
PRN-BFG	Functional	89.9
	Failure	51.4
PRN-OSS	Functional	91.7
	Failure	48.6

Table 5 Classification bias for various models developed for cranes

Model	Classification	Bias (%)
PRN-LMA	True positive	88.6
	True negative	79.2
PRN-BR	True positive	76.6
	True negative	0
PRN-CGF	True positive	93.1
	True negative	67.9
PRN-BFG	True positive	88.6
	True negative	69.4
PRN-OSS	True positive	87.7
	True negative	72.7

Table 6 Classification bias for various models developed for forklifts

Model	Classification	Bias (%)
PRN-LMA	True positive	93.3
	True negative	87.7
PRN-BR	True positive	75.1
	True negative	0
PRN-CGF	True positive	92.3
	True negative	60.0
PRN-BFG	True positive	84.8
	True negative	62.7
PRN-OSS	True positive	84.3
	True negative	66.0