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ORIGINAL ARTICLE

Evaluation Research on the Crane Failure Prediction based on Machine Learning

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ABSTRACT – It is challenging to spot port machinery and equipment failures, and maintaining such systems is even more complex. Maintenance of such modifications in a reasonable time is a tough challenge since each change might have an endless number of test cases run. It's critical to have a risk assessment of the impact of such maintenance fixes. In the software engineering community, there has been a considerable amount of study on failure prediction. Regrettably, there is little evidence of their application in day-to-day software development in port machinery and equipment. This paper proposes an unsupervised machine learning (k-means clustering) method for categorising cranes for maintenance and uses a machine learning pipeline to solve the classification of crane failure data. The crane's maintenance decision data demonstrate the method's effectiveness. It was shown that the Linear Support Vector Machine could give a superior classification accuracy of crane maintenance prediction with a 100% accuracy in the train set and 94.5% accuracy in the test set.

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INTRODUCTION

The global economy is becoming more and more interconnected every year, resulting in a surge in demand for commodities transportation between geographies and value chains [1]. Container shipping has provided a standardised mode of freight transportation since its creation in the mid-twentieth century, as shown in Figure 1, making it safe and efficient to carry products internationally. Therefore, the port infrastructure plays an essential role since port machinery, and equipment usage is rising in parallel with the expansion of port operations. The failure of port machinery and equipment will directly impact the port's entire functioning [2]. As a result, it is critical to guarantee that port machinery and equipment operate reliably.

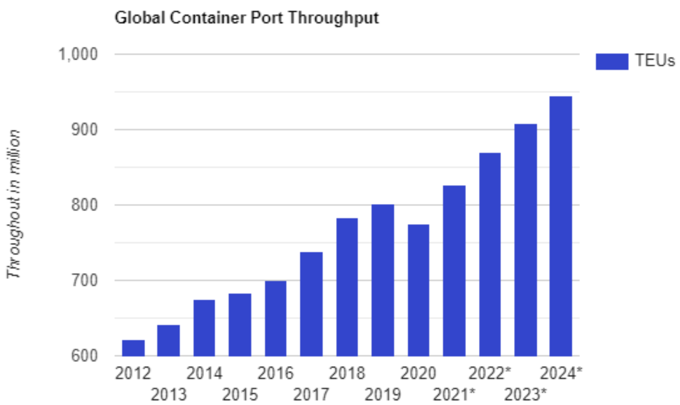

Figure 1. Global Container Port Throughput 2012-2024.

Fatigue failures of deck cranes CHCD 6-25 EH are observed frequently in operation. Wires, Slew Bearings, Sheaves, Mishandling, and Maintenance Misconceptions were the most common causes of fatigue failures[3]. Such cranes are used in the shipping, port, and logistics sectors at container ports to load, unload, and move cargo and stores having a load-lifting capacity of 10 tons at 20 meters radius [4]. The objective was to predict their fatigue behaviour and make crane maintenance decisions to extend their lifespans.

A number of studies have revealed that implementing *k*-means clustering based on database definitions as variables to evaluate and filter the variables for grouping the categories inhomogeneous clusters based on the similarities of the categories [5]–[7]. These results further support the hypothesis that the technicians who rely on their experience to execute fault detection and maintenance will face issues such as slow response times to faults and ineffective repair procedures, both of which will impact the equipment's regular performance during maintenance. It was shown in [7] that *k*-means were used to investigate near-miss accidents at the plant's electric overhead travelling (EOT) crane operations, finding

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that numerous safety improvements influenced the accidents. A similar observation could be seen in the risk potential analysis of the crane [5], attributing the two incidences to the cluster number determined from the *k*-means analysis. Moreover, the required power value for a portal crane can be determined by utilising *k*-means with real-time motor voltage, current, and power factor data [6].

Support Vector Machine (SVM) has been demonstrated to provide the bearing life prediction, and it is useful for the slew bearing life prediction in practice [8]. The model accurately reflects slew bearing degradation, and the test bearing's average life prediction error is lower than the standard algorithm of bearing lifespan error. In separate research, the usefulness of SVM in predicting failure in three-phase line-operated induction devices was demonstrated using statistical and spectral analysis of electric current data [9]. The SVM-based classification algorithms utilise many indications to identify problematic operating modes more precisely when they arise. Its usefulness in evaluating the dependability of hydraulic support has been described in [10], and it may effectively serve as a reference for product development and improvement.

In the literature on Nugroho et al. (2021), the lack of attention paid to the provision of in-house container crane maintenance has resulted in higher maintenance costs [11]. Based on the latest maintenance date, hour meter, breakdown, shutdown, and spare parts, *k*-nearest neighbour (*k*-NN) and random forest can successfully learn the container crane maintenance data (numerical and categorical). These findings enhance our understanding of *k*-NN, which is also described in a correlation of prediction approaches for colliding vehicle accidents [12]. As a result, there is a risk of incidents on the road, and a method is presented to determine the best strategy to forecast unknown cars.

This research work aims to identify the features related to maintenance decision-making that are imperative for classifying deck cranes between repair scales. For the features relevant to maintenance decision-making collected from the deck crane, *k*-means clustering is used to group it throughout the silhouette score. Furthermore, the effectiveness of several machine learning models, such as support vector machine (SVM), random forest (RF), and k-nearest neighbour (*k*-NN), is explored in terms of their capacity to categorise the associated features gathered from deck crane.

MATERIAL AND METHODS

This experimental setup's data comes from offline and online data collected from Malaysian deck cranes. The online data of deck cranes is collected by setting up a web server and using HTTP for human-computer interaction. On the other hand, offline data refers to information gathered by the operator before, during, and after the crane's operation. The data including daily equipment inspection statistics such as reverse gear sensor and warning indicator light, lubrication of all lubrication points, inspection and bucket lubrication, cargo lifting, drive belt tension, and other fault data.

Model overview

The overall methodology is depicted in Figure 2, which starts with the collection of relevant data from the cranes and progresses through feature clustering followed by the classification using machine learning algorithms and the evaluation performance.

Figure 2. The four important steps of the data analysis process.

In the experimental data collection, we were unable to separate the fault data from the overall data. This is done by discovering the groupings that have not been explicitly identified in the data using the *k*-means clustering method. The amount of k for each technique will be determined based on the greatest score using the silhouette analysis of *k*-means clustering. After the data had been labelled, 70% of the total data was utilised for classifier training with 5-fold cross-validation, with the remaining 30% set aside for prospective or executed validation investigations [13]. Consequently, we used the same data splitting ratio in the training and test sets for this investigation because the classification accuracy was satisfactory [14].

K-means clustering

The *k*-means algorithm is a deterministic global search technique that dynamically adds from a suitable initial position at a time using a deterministic global search process comprised of *k*-means run by N (N is the size of the data set) [6], an algorithm that calculates the centroid. The following is the flow of the algorithm which is shown in Figure 3.

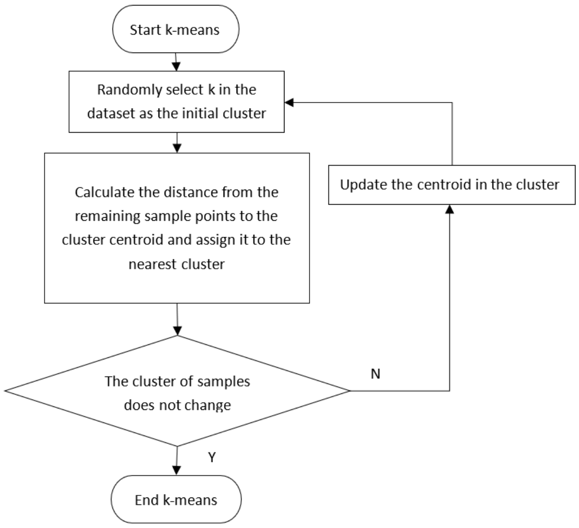

Figure 3. Flowchart of the *k*-means clustering algorithm.

The Silhouette score is used to determine the degree of cluster separation. b_i indicates the shortest mean distance between a point and all points in any other cluster of which i is not a member, whereas a_i represents the mean distance between i and all data points from the same cluster in the formula below [15].

$$Silhouette-score = \frac{b_i - a_i}{max(b_i, a_i)} \tag{1}$$

If b_i is more than a_i, the point is logically well isolated from its adjacent cluster while being closer to all points in the cluster to which it belongs.

Support Vector Machine

A two-class classifier is an SVM, and its objective is to locate a hyperplane [16]. The further the two categories of data are from the hyperplane, the better to properly identify fresh data. There are two forms of data classification: Linear SVM and Non-Linear SVM. The kernel function in SVM should be utilised to make non-separable data into separable data. The four most commonly used kernel functions are the linear SVM, polynomial kernel, radial basis kernel (RBF), and sigmoid kernel [17].

The simplest kernel function is the linear kernel. The expression for its function is

$$k(x, y) = x^{\mathrm{T}} y + c \tag{2}$$

The inner product gives it *(x, y)* plus an optional constant *c*. non-kernel algorithms are often comparable to kernel algorithms employing linear kernels. It is utilised when there's linear separability, which means the feature space and input space have the same dimensions. The classification effect in linearly separable data is ideal due to its few factors and quick speed.

A non-stationary kernel is the Polynomial Kernel (Poly). The polynomial kernel is well suited to the problem of normalisation of all training data. It is possible to transfer the low-dimensional input space to the high-dimensional feature space. The function's definition is as follows:

$$k(x, y) = \left(\alpha x^{\mathrm{T}} y + c\right)^d \tag{3}$$

The slope alpha α, the optional constant *c*, and the polynomial degree *d* are the variables that can be changed.

An RBF kernel is an example of a Gaussian kernel. The function's definition is as follows:

$$k(x, y) = \exp\left(-\|x - y\|^2 / 2\delta^2\right) \tag{4}$$

It's a kernel function that can map a sample to a higher-dimensional space. The adjustable parameter sigma δ is critical to the kernel's performance and must be tuned appropriately for the task at hand. If it is overstated, the index will run linearly, and high-dimensional projections will lose their non-linearity. If it is underestimated, on the other hand, the function will be unregularised, and the decision boundary will be extremely susceptible to noise in the training data.

Sigmoid kernel and Multilayer Perceptron (MLP) kernel are the same as the hyperbolic tangent kernel. The bipolar Sigmoid function is frequently employed as the activation function of artificial neurons in neural networks. Therefore the sigmoid kernel originates from there. A two-layer perceptron neural network is equal to the SVM model applying the sigmoid kernel function. The expression for the function is:

$$k(x, y) = \tanh\left(\alpha x^{\mathrm{T}} y + c\right) \tag{5}$$

The slope alpha α and the optional constant c are two configurable parameters in the sigmoid kernel. 1/N is a typical number for Alpha, where N is the data dimension.

K-Nearest Neighbor

k-NN is a straightforward and effective classification approach [18]. The process described in this study creates a k-NN model for the data that replaces the data as the classification foundation. The value of k is computed automatically, changes depending on the data, and is the most accurate classification accuracy. This model was tested using three distinct distance measurements: Euclidean, Manhattan, and Chebyshev [19]. The L_p distance definition formula in Eqn. 6 where $x_i \in R^n$, $x_j \in R^{n,}$ and p are variable parameters.

$$L_p\left(x_i, x_j\right) = \left(\sum_{l=1}^{n} \left|x_i - x_j\right|^p\right)^{\frac{1}{p}} \tag{6}$$

When p = 1 indicates the distance between two locations in space at a right angle and is the outcome of the sum of distances in many dimensions where L_1 is the norm equivalent to the Manhattan distance. The formula for the Manhattan distance expression is:

$$L\left(x_1, x_2\right) = L_1 = \sum_{k=1}^{n} \left|x_{1k} - x_{2k}\right| \tag{7}$$

When p = 2, the equivalent L_2 norm of Euclidean distance is the true distance between two locations in space. The formula for calculating Euclidean distance is:

$$L\left(x_1, x_2\right) = L_2 = \sqrt{\sum_{k=1}^{n} (x_1 - x_2)^2} \tag{8}$$

The Chebyshev distance is defined as the largest difference in coordinate values between two points in space with p equal to infinity. The Chebyshev distance formula is as follows:

$$L\left(x_1, x_2\right) = \max\left(\left|x_{11} - x_{21}\right|, \left|x_{12} - x_{22}\right|, \cdots, \left|x_{1n} - x_{2n}\right|\right) \tag{9}$$

Random Forest

The Random Forest (RF) algorithm is made up of a number of different decision trees[20]. After entering a new sample in a classification task, each decision tree in the forest will be assessed and categorised individually. Each decision tree will provide its classification result, and RF will select the highest classification of the decision tree's classification results as the final result.

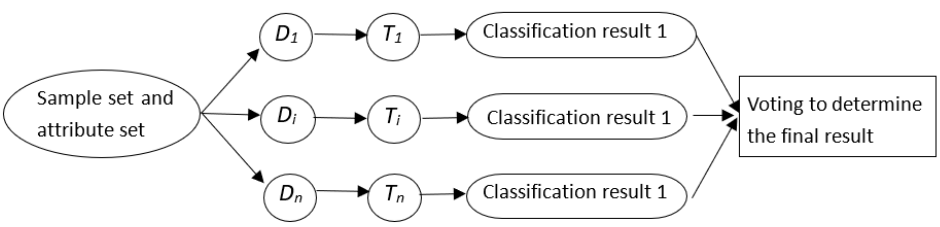

Figure 4. The flow diagram of the RF classifier.

Figure. 4 depicts the RF model training process, with D_i denoting the training set sample and T_i denoting the candidate attribute sample. The RF model can be generally divided into three categories. First, a set of training samples should be chosen at random. The training data used in each round must be randomly picked from the original sample set with replacement to guarantee that all samples get a chance to be drawn once. Second, a collection of candidate features is chosen at random. There are M features in the original data. Choose m features at random from the M features as potential features for the training tree.

Regarding selecting the training samples and features, a decision tree is built on each training sample to obtain the prediction result, with n samples yielding n prediction models. Then, using the RF combination classification model, predict the test samples such that n samples can receive n prediction outcomes, and a simple majority vote chooses the final result. The RF combination classification model is expressed as follows [21]:

$$H(S) = \arg Max \sum_{i}^{n} I\left(h_i(S_i) = Y\right) \tag{10}$$

Where $h_i(S_i)$ represents a single decision tree model; Y represents the prediction result; I represents a linear function. Third, evaluate the RF performance metrics. The number of trees in RF affects its performance significantly. As a result, the technique of evaluation is classification accuracy. The number of trees to be planted and the RF performance index assessment technique is examined and summarised using the offline data. The experiment examined the relationship between the number of trees.

Hyperparameter Tuning of the Machine Learning Algorithms

The relevance of the features selected will be investigated using three different types of machine learning classification models with hyperparameter tuning, namely Support Vector Machine, K-Nearest Neighbor, and Random Forest [22]. For the Linear, Poly, RBF, and Sigmoid in SVM models, the optional constant c hyperparameter is specified between 0.1 and 100 [23]. In Poly, RBF, and Sigmoid, the number of gamma is set between 0.001 and 10 [24], while the number of degrees in Poly is set between 3 and 8[25]. The range of k values in Euclidean distance, Manhattan distance, and Chebyshev distance for the *k*-NN model are 3 to 10 [26]. The RF's number of trees hyperparameter is set to a range of 2 to 100, with a maximum depth of 10 to 100 [27]. The minimum sample split is set to 2, and the minimum sample leaf is set to 1, while the remaining hyperparameters are left at their default settings. For random forest classifiers, the Gini index is employed as the criterion for determining information gain[28].

Evaluation Performance of the Machine Learning Algorithms

The machine learning algorithms predicted results would differ from the actual results [13]. As a result, classification performance in a confusion matrix will be assessed using metrics such as Classification Accuracy (CA). The following are the evaluation metrics:

$$ClassificationAccuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{11}$$

True Positive (TP) refers to an outcome in which the model properly predicts the positive class; False Positive (FP) refers to an outcome in which the model incorrectly predicts the positive class; False Negative (FN) refers to an outcome in which the model incorrectly predicts the negative class; True Negative (TN) refers to an outcome in which the model properly predicts the negative class [29]. The classification accuracy rate is generally utilised as a baseline for analysing the prediction outcomes.

Python is used to implement the *k*-means algorithm as well as the three machine learning methods. These algorithms are implemented using the libraries scipy, math, numpy, sklearn, and Matplotlib. The experiment was performed using a personal computer with an Intel Core i7-4710HQ CPU, with a 3.5GHz processor, 8 GB of RAM, and the Windows 10 Professional 64-bit operating system.

EXPERIMENTAL RESULTS

The fault data from the deck crane yields a total of 10,000 instances. It is hard to rely on manual expertise to hypothesis and categorise due to the varied data and different data kinds. As a result, we used k-means clustering to divide the data, with the population size, number of iterations, and number of test algorithm runs set to 50, 300, and 10. Table 1 illustrates the silhouette scores obtained for each cluster ranging from 2 to 8. It could be noticed that there are differences between the clusters, implying that cluster 2 has a higher score than the rest.

Table 1. Sihouette Analysis in *k*-means clustering.

Number of Cluster	2 Cluster	3 Cluster	4 Cluster	5 Cluster	6 Cluster	7 Cluster	8 Cluster
Silhouette Scores	0.649	0.332	0.345	0.335	0.325	0.363	0.315

Classification Performance

Figure 5 depicts the classification results in the normalised using three different machine learning classifiers. The misclassification components in their respective confusion matrices impact classification accuracy, which is illustrated by the darker shades. As a consequence, Linear SVM and Polynomial SVM outperform all other classifiers.

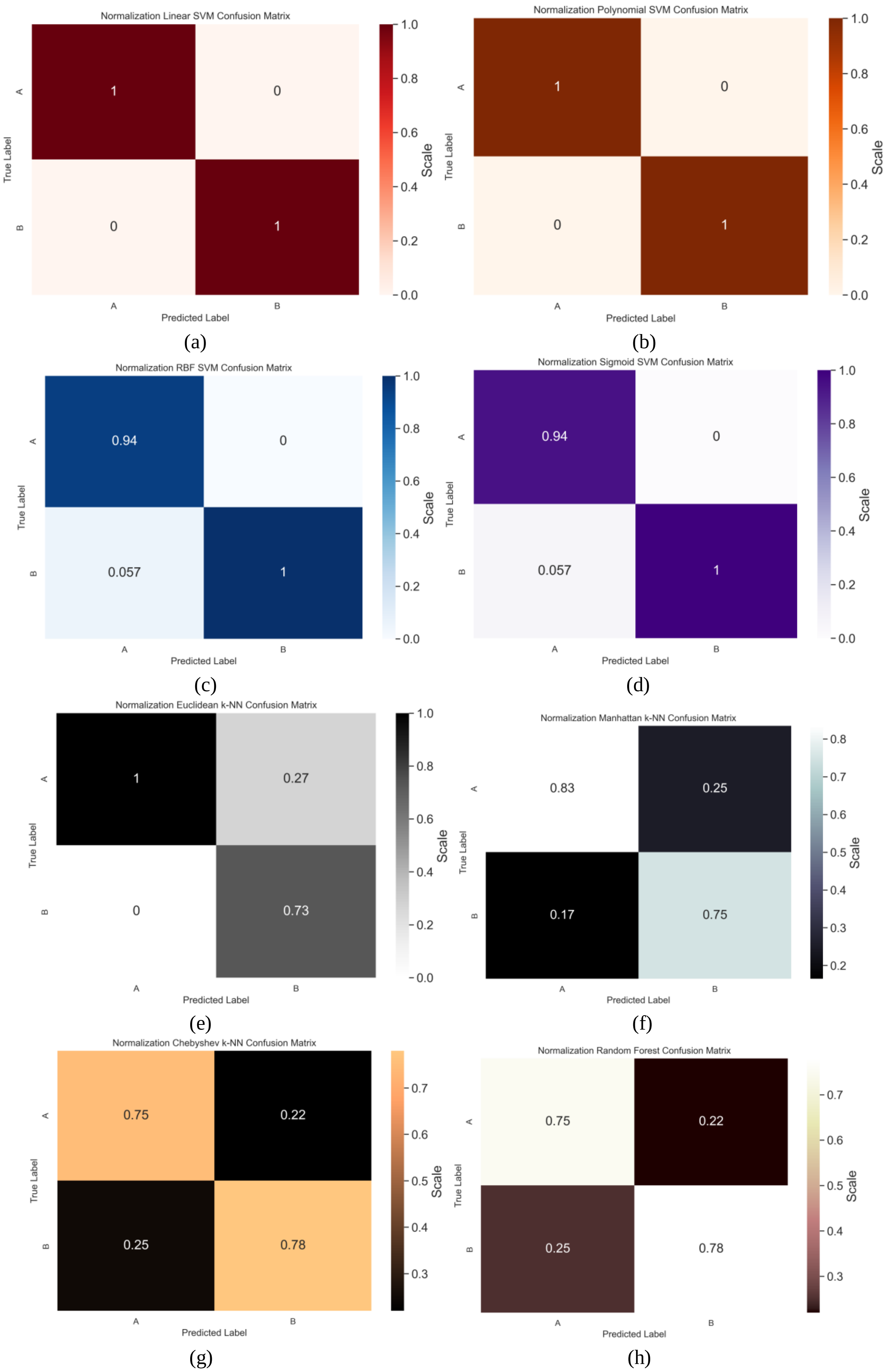

Figure 5. Confusion matrix in train set with different classifiers. (a) Linear SVM. (b) Poly SVM. (c) RBF SVM. (d) Sigmoid SVM. (e) Euclidean *k*-NN. (f) Manhattan *k*-NN (g) Chebyshev *k*-NN (h) Random Forest.

Furthermore, we test the remaining 30% of the data using the classifiers stated in section above, and the tested set results produced by each classifier are presented in the figure below. Figure 5 and Figure 6 depicts the trained set and tested set findings derived from the preliminary formula Equation. 11.

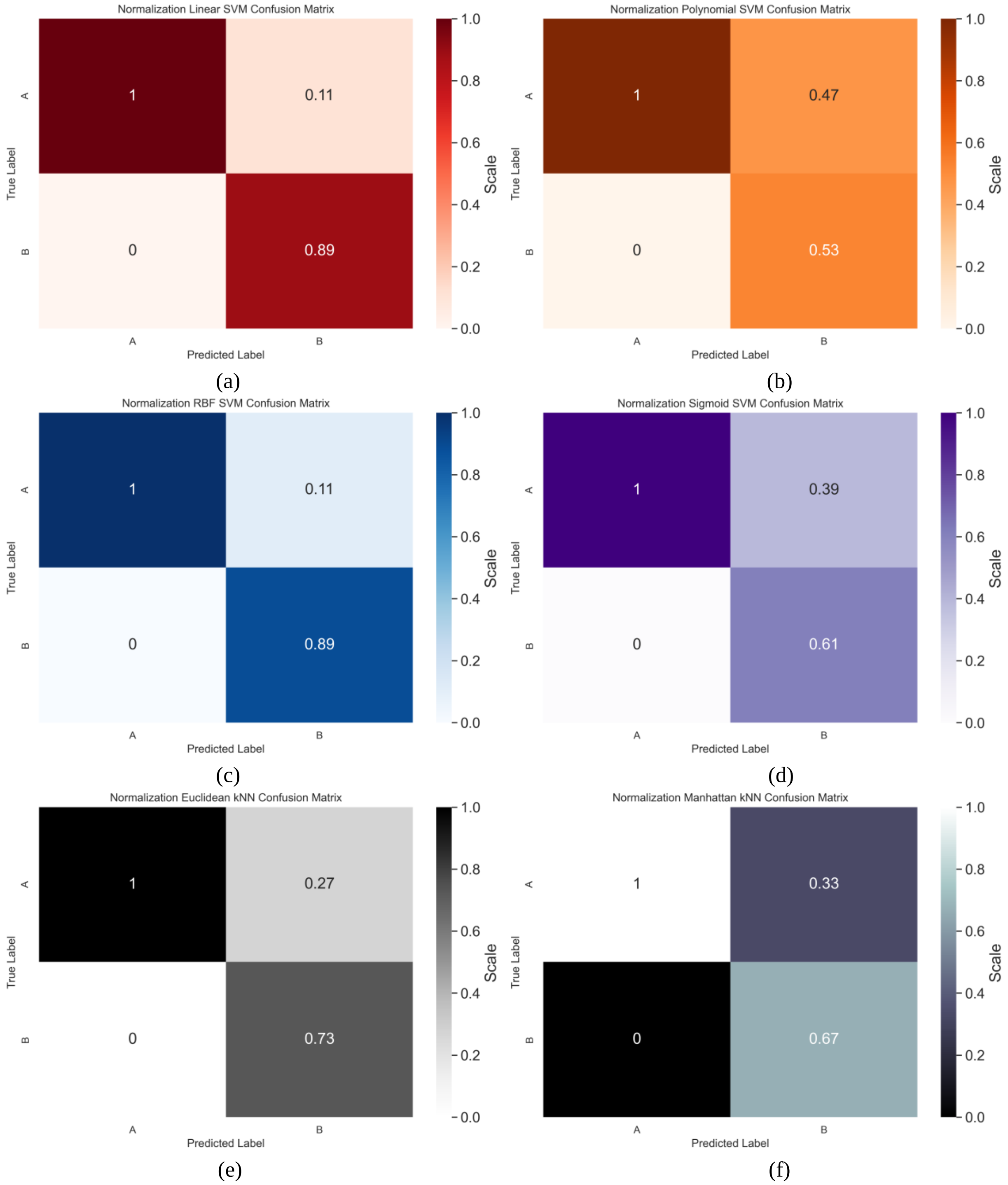

Figure 6. Confusion matrix in test set with different classifiers. (a) Linear SVM. (b) Poly SVM. (c) RBF SVM. (d) Sigmoid SVM. (e) Euclidean k-NN. (f)

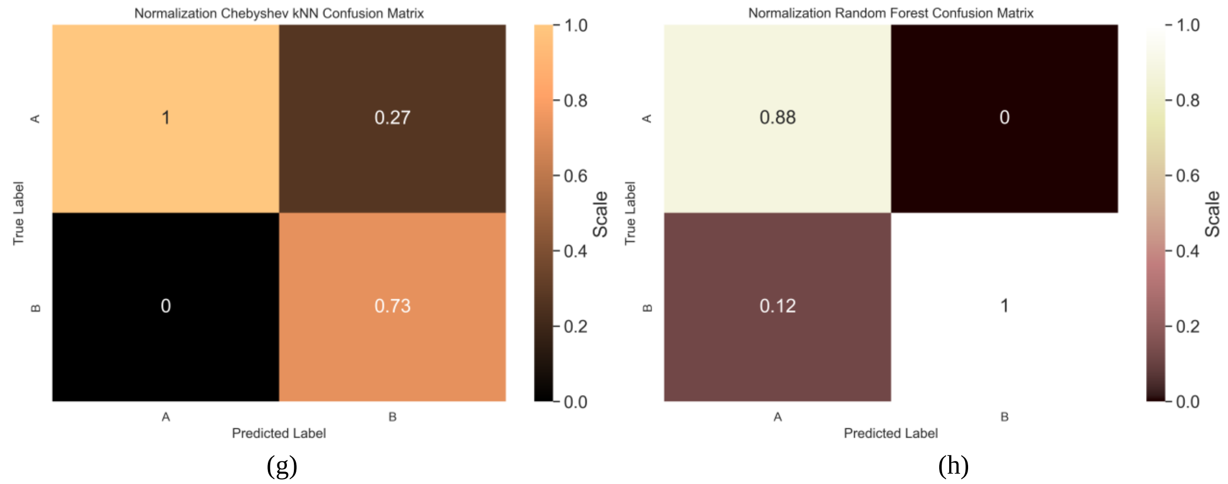

Figure 6. Confusion matrix in the test set with different classifiers. (g) Chebyshev k-NN (h) Random Forest.

Figure 7 illustrates the classification performance of the assessed models. The mean (5-fold cross-validation) of each classifier's CA indicates the reliability of the model suggested. The best CA is achieved by the linear SVM (100%) and the Poly. SVM (100%) models were followed by the RBF SVM (97.15%) and Sigmoid SVM (97.15%) for the trained set.

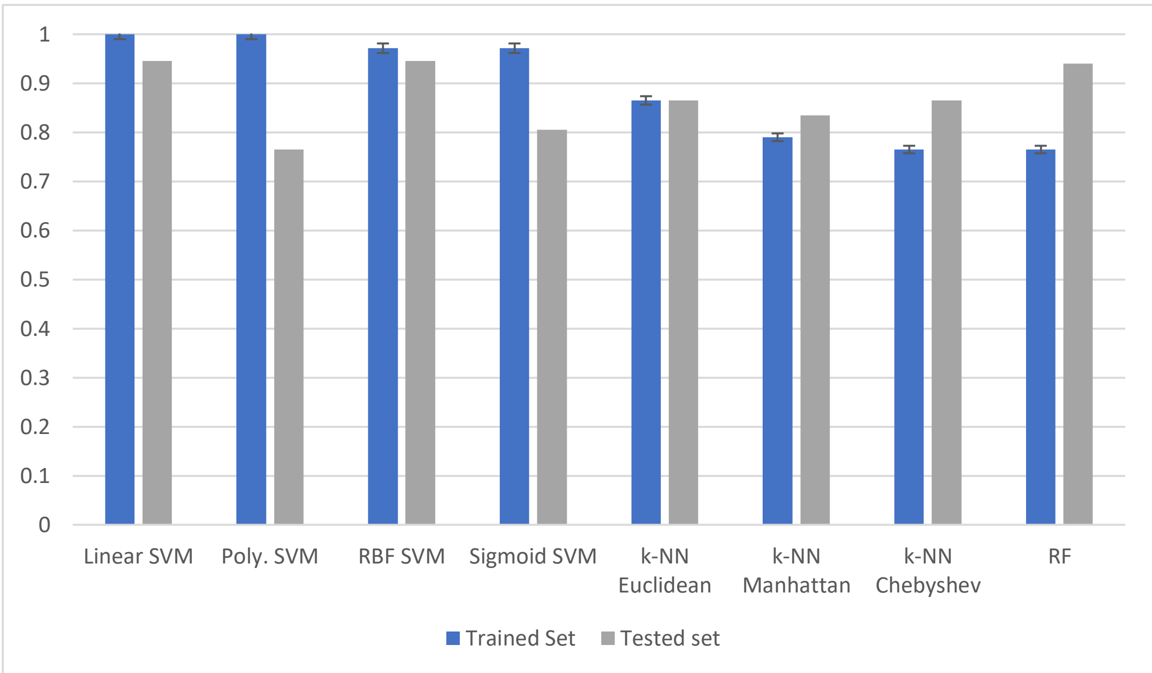

Figure 7. Comparison of accuracy classification distributions obtained from several kinds of machine learning.

CONCLUSION

This study presents a crane maintenance classification technique based on machine learning to decrease time-consuming manual troubleshooting of deck cranes and extend the lifespan of deck cranes. The efficacy of this technique is demonstrated by analysing fault data from the deck crane. In this study, the silhouette score of various data types was first examined through k-means clustering, and the silhouette score was then utilised to categorise various data groups. The data set was then imported into SVM, RF, and *k*-NN models for training, testing, and hyperparameter tuning. Linear SVM was chosen as the best model, with a high score of 100% in the training set and 94.5% in the testing set. In hyperparameter optimisation, the model employs grid search, and the optional constant *c* parameter is 0.1.

Many factors influence the development of crane maintenance, and once a decision is taken, it has a more significant impact on future logistical operations. As a result, understanding how to choose appropriate crane maintenance decision data is critical. In practice, the uncertainty produced by several contributing elements cannot be expressed in words or figures, and it cannot be calculated simply using maintenance decision indicators. As a result, we may use feature selection and extraction algorithms to quantify maintenance decision indications. This feature selection and extraction approach may be used to study the creation of more comprehensive crane maintenance decision-making. In the future study, we will go into further detail about this approach.

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