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PREDICTIVE MAINTENANCE FOR CEMENT FACTORY PLANT EQUIPMENT USING MACHINE LEARNING METHODS

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ABSTRACT

Maintenance is essential in ensuring smooth and reliable operation of equipment in the cement plant. Predictive maintenance stands to be cost effective, ensure quality product and plant safety compared to corrective and preventive maintenance. Induction motor plays a crucial role in operation of kiln in the setup of the cement factory. This studyused machine learning models to predict the maintenance conditions of induction motor main drive based on three historical datasets of some of its components.The dataset consist of motor current signature analysis that is made up of rotor current measurements as its variables. The study tested five machine learning models, namely, decision tree, k-nearest neighbours (kNN), support vector machine (SVM), gradient boost tree (GBT), and random forest (RF) to ensure outstanding outcome.A 25:75 ratio holdout validation was used in the study. It has been found that four of the models could accurately predict condition of the induction motor main drive. However, the kNN model performed the best due to its ability to handle nonlinear relationships.It has accuracy of 89.47%, precision of 87.82 %, recall of 87.82% and f-score of 87.82% for the rotor cable dataset 1, while GBT has the least performance among the prediction models with accuracy of 68.42%, precision of 68.42%, recall of 50% and f-score of 57.78%. The performance for the other datasets shows similar trendto the one obtained in the rotor cable dataset with kNN having the best performance and GBT has the least performance among the prediction models. Therefore, GBT model seems not to be a good predictive maintenance model for the datasets used in this study. The findings shows that withimplementation of predictive maintenance, there could be decrease in downtime and increase in the efficiency of operation of the production line.

Keywords: Predictive Maintenance, Machine learning, Induction motor, Fault detection, Historical dataset

INTRODUCTION

The cement industry has witnessed a lot of changes over the years, though still encounter several challenges, in which some resulted in opportunities to usher advancement in the sector. Dry kiln production line system has taken over from the wet kiln production line system as the more enhanced process. Even with implementation of sophisticated system in the industry, issues regarding safety, product quality, environmental impact and sustainability remain persistent (Mishra & Siddiqui, 2014). In the face of globalization, marketing competition is the order of the day and the industry has to find a way to have qualitative product with minimal cost of production.

As a result of advancement in machineries and information and communication technology, digitalization of industries is on the rise. With a combined implementation of predictive analysis, industries stand to tremendously benefit in maximizing their production and services(Hippmann, Klingner, & Leis, 2019). The cement industry will gain by considering these strategies to effectively address some of its major issues such as maintenance, energy consumption, logistic problem, system complexity and environmental concern.Predictive maintenance would benefit the cement industry in cost reduction, ensuring product quality and providing safe plant. Though, it faces challenges such as the choice of amodel that would give an accurate prediction of the equipment condition when presented with a new set of data. This paper presents a predictive maintenance scheme using machine learning methods for some components of induction motor main drive of cement plant kiln.

Related work

(Colabianchi, Costantino, Cristian, Massimiliano, & Quatrini, 2020) proposes a machine learning approach to predict and assess when a component in a cement plant is likely to fail. A predictive model was developed using data from an industrial fan within the plant, selected due to the critical nature of maintaining rotating components. Parameters to ascertain the fan's condition were taken and tested in the models. To get the critical condition of the fan, classification techniques were used with fan vibrations serving as the threshold for labelling. While to estimate the residual useful life (RUL) of the fan, regression techniques were used. This model offers significant advantages, including a reduction in unplanned downtime, production losses, and operating in critical conditions.

(Mahmud, Ismail, & Baharudin, 2022) utilized machine learning algorithms using data mining to develop a predictive maintenance system for turbofan engines. Four models—decision tree, random forest, gradient boosted tree, and support vector machine—were trained. The engine's condition was categorized into three states: normal, warning, and critical. The results revealed that the support vector machine (SVM), with an accuracy of 88.6%, outperformed the other decision tree-based models in terms of overall prediction accuracy.However, adopting a more robust ML model could improve the prediction accuracy.

(Benchekroun, Zaki, Hezzem, & Laacha, 2023) proposed a scheme to predict the vibrations in the cement's kiln through the use of artificial intelligent techniques to enhance the overall performance of the cement kiln. The result shows that random forest model has effective performance compared to other models tested having 72.38% for R^2 and an RMSE of 1.21. Although these results fall within acceptable range in the prediction error minimisation, the model performance could be improved with a better hyperparameter tuning.

(Mahmud *et al.*, 2024) introduced an analytical hierarchy process (AHP) technique to select the optimal maintenance strategy for a cement plant in Northern Nigeria. Three maintenance strategies— predictive maintenance, preventive maintenance, and corrective maintenance were evaluated for induction motor and pump motor in the case study. Based on the study's findings, a combination of the three strategies was determined to be the most suitable for the plant, with predictive maintenance being the preferred choice at 41.76%, followed by PM at 31.66%, and CM at 26.68%. This result aligns with recommended practices; however, future research should explore additional criteria and performance indicators. (Polat, Kervancı, & Özceylan, 2024) leverages on machine learning algorithms capability to perform predictive analytics on a cement factory production data, located at Southeastern Anatolia, for the products quality and marketability. The study utilized five years of production data from a cement factory. The Support Vector Regression (SVR) model, an application of the Support Vector Machine (SVM) algorithm, was evaluated using four kernels: RBF, linear, sigmoid, and polynomial. Among these, the SVR model with the RBF kernel demonstrated the best performance based on four evaluation metrics: Mean Squared Error (MSE) of 0.002926, Root Mean Squared Error (RMSE) of 0.054094, Mean Absolute Error (MAE) of 0.048611, and Mean Absolute Percentage Error (MAPE) of 0.052697. These results underscore the effectiveness of the SVR-RBF model in delivering reliable production forecasts, thereby supporting strategic decision-making to address fluctuating market demands. Despite its promising outcomes, the study's scope is limited to the SVR model, leaving room to explore other potentially effective algorithms. Furthermore, the dataset is restricted to a single factory and specific variables, excluding external factors like market trends or environmental impacts that may affect cement production. Another limitation is the model's dependency on retraining to adapt to changing conditions, which highlights the need for dynamic updates. Future research could aim to enhance forecasting accuracy by using updated datasets and optimizing parameters for diverse deep learning algorithms. Additionally, incorporating energy efficiency and best maintenance strategy considerations into production planning models offers opportunities to reduce costs and improve sustainability.

MATERIALS AND METHODS

A cement production facility in northeastern Nigeria was selected as a case study for the predictive maintenance scheme. The factory operates two identical dry process systems, with an installed annual capacity of 800,000 metric tonnes. A typical dry process for Portland cement production involves three main stages, as illustrated in Figure 1. In the initial stage, the raw materials (limestone and clay) are mixed and crushed to produce powder. The next stage is going to the pyroprocessing unit which is the clinker production. The last stage is the production of the final product through cooling and grinding of the clinker. Equipment such as the kiln, crusher, booster fans, induction motors and pumps are paramount to the overall operation process of the production line.

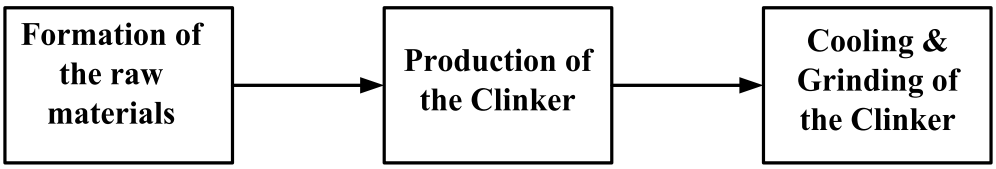

Figure 1: Process Flow for a Dry Portland Cement Plant

The equipment selected to be used in this study is Kiln induction motor main drive from the cement company. The main drive has several components that are used in extracting data for maintenance and operational purpose. Table 1 shows the components, their possible cause of breakdown and the methods used in obtaining the control variables. The datasets obtained from the rotor cable and induction regulator were used in the predictive maintenance scheme.
The rotor cable historical maintenance records were taken in the period of six years (from 08/01/2014 to 10/09/2020). It has 79 entries that were recorded from the rotor current magnitudesfor two datasets of six rotor cables (E, F, D, G, K and H).
The induction regulator historical maintenance records were taken in the period of six years (from 27/01/2014 to 10/09/2020). It has 61 entries that were recorded from the temperature measurement of two variables; cooling water (CW) and internal air (IA) for the motor and the induction regulator.

Table 1: Components of Induction motor main drive

Equipment	Component	Cause of Failure of component	Methods
Main Drive			
Drive	Bearings	Vibration/defects/broken/temperature	Measurement
Drive	Stator Winding	Burnt/lost insulation	Measurement
Drive	Rotor Commutator	Lost insulation/burnt/wear	Measurement
Drive	Coupling	Crack/damaged/worn	4 Senses
Drive	Induction Regulator	Excessive Temperature/Water flow/air	Measurement
Drive	Rotor Cable	Rotor current	Measurement
Drive	Resistor Bank	Excessive Temperature	Measurement
Drive	Induction Regulator	Excessive temperature	Thermography
Drive	Motor	Crack/damaged/broken feet	4 Senses
Drive	Cooling fan	Broken/crack/worn	4 Senses

Three tree-based machine learning, k-NN and support vector machine are the prediction models used in this work. These are supervised methods that construct models by connecting input variables to target variables.The models were selected based on their capabilities in data classification which is an essential requirement for predictive maintenance. Also, running an analysis using a single technique for prediction could not produce an outstanding outcome. Consequently, performing a study between other techniques can give a better understanding of the prediction, hence the choice of the five models.

Decision tree (DT)

Decision tree has been one of the widely used machine learning algorithms as it could be used in both regression and classification problem. The algorithms is a supervised type of machine learning that employed technique in a tree form where the data features are modeled into root node, branches (internal nodes) and leaf nodes. These tree features are representing the entire dataset, values to make decision and the final output.Decision tree use two major methods to split the dataset; gini impurity or information gain. The splitting continues until a predefined stopping condition is reach. While decision trees are easy to interpret and handle various data types, they are prone to overfitting, which can be mitigated through pruning, setting depth constraints, or using ensemble methods like random forests (Mahmud et al., 2022).

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification by determining the optimal hyperplane that best separates two classes. For linearly separable data, this hyperplane acts as a linear boundary. For non-linear data, a kernel function is employed asthe process of transforming data from a higher-dimensionalspace with theaim of making it linearly separable. The SVM optimization involves minimizing the cost function.

K–Nearest Neighbour (kNN)

k-Nearest Neighbour (k-NN) is a straightforward, non-parametric, and lazy learning technique widely employed as machine learning method. It makes predictions based on the k nearby the intended samples in the feature space, measured by distance metric. For classification, k-NN assigns the class most common among the k nearest neighbors, while for regression, it predicts the average or median value of these neighbors. The algorithm involves storing the entire training dataset and making decisions at prediction time, making it computationally intensive for large datasets. Efficient data structures like KD-trees can help speed up the process.

Random Forest (RF)

Random Forest is among the decision tree ensemble learning method that builds multiple decision trees using a technique called bootstrap sampling. It is designed to improve the predictive performance and robustness of a single decision tree by leveraging the power of ensembles. The random forest prediction function is given by

$$f(x) = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \quad (1)$$

Gradient Boosted Tree (GBT): Gradient Boosted Tree (GBT) is a decision tree ensemble technique that builds an ensemble of weak tree classifiers using the boosting strategy. The boosting method involves iteratively resampling the data and constructing new trees to focus on training cases that previous trees evaluated poorly. This process aims to minimize a specific loss function, such as cross-entropy or the sum of squared errors. Gradient descent is applied to optimize the ensemble. The ensemble function $F_m(x)$ produces a new model by combining the base learner h(x). The algorithm can be expressed as follows:

$$\rho_m = argmin_p \sum_{i=1}^{N}[\zeta(y_i, F_{m-1}(x_i) \; + \rho h(x_i))] \quad (2)$$

$$F_m(x) = F_{m-1}(x) + \rho_m h(x) \quad (3)$$

Various performance metrics are used to compare and evaluate the predictive capabilities of models. In classification problems, the confusion matrix is a common tool to illustrate the predicted classes of test data against their actual true values.

True Negatives: Predicting correctly a “no” as a negative outcome.

True Positives (TP): Predicting correctly a “yes” as a positive outcome.

False Positives (FP): Predicting incorrectly a “yes” when it should a “no” label outcome.

False Negatives: Predicting incorrectly a “no” when it should a “yes” label outcome.

In a perfectly normalized confusion matrix, the values of TN and TP are 1, while FP and FN are 0.

These components are fundamental for deriving evaluation metrics such as accuracy, precision, recall, F1-score, and more, helping assess the performance of classification models. One key metric is accuracy which reflects the model's ability to classify instances correctly and is calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

When the data is balanced across class labels, accuracy serves as a reliable performance measure. However, in cases of imbalanced datasets, relying solely on accuracy can be misleading. To address this, (Tharwat, 2021) defined the F-score as a combination of precision (positive predictive value) and recall (sensitivity), providing a more nuanced evaluation of model performance.

Precision reflects the accuracy of the model which measures the predictive positive instances. In terms of True Positives and False Positives, it is expressed as follows:

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Recall measures the completeness of a model by evaluating its ability to identify all relevant positive instances. In terms of True Positives and False Positives, it is expressed as follows:

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

The F-score is calculated in terms precision and recall as their weighted harmonic mean as depicted below:

$$F - score = \frac{2*Precision*Recall}{Precision+Recall} \quad (7)$$

Table 2 shows the various tuned hyperparameters for each of the ML models used in this work.

Table 2: Hyperparameter Tuning for the ML Models

SVM	DT	RF	GBT	kNN
Kernel function: *linear*	Max. number of splits: *100*	Max. number of splits: *70*	Max. number of splits: *70*	Number of neighbors: *5*
Box constraint level: *1*	Split criterion: *gini index*	Number of learners: *30*	Number of learners: *30*	Distance metric: *Euclidean*
			Learning rate: *0.1*	

RESULTS AND DISCUSSION

These models are used to forecast the maintenance conditions of some equipment in a cement plant. Based on the health of the equipment, five different machine learning algorithms are model to forecast if maintenance will be conducted or deferred.

Table 3 shows the models evaluation results for rotor cable dataset 1, tested on held-out validation. The performance of all models differs slightly. The k-nearest neighbor model performed best with accuracy of 89.47%, precision of 87.82%, recall of 87.82% and F-score of 87.82%.

Table 3: Predictive maintenance model evaluation results for rotor cable dataset 1

Model	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
Decision Tree	78.95	75.65	75.65	75.65
K-nearest neighbor	89.47	87.82	87.82	87.82
Support Vector Machine	84.21	82.86	79.49	81.14
Random Forest	84.21	82.59	79.49	81.01
Gradient Boosted Tree	68.42	68.42	50	57.78

The confusion matrix for kNN model is depicted in Figure 2 which shows that the model classified critical condition 83.3% times and normal condition 92.3% times correctly. These are the values on the diagonal of the confusion matrix. Whereas the remaining entries are classified wrongly.

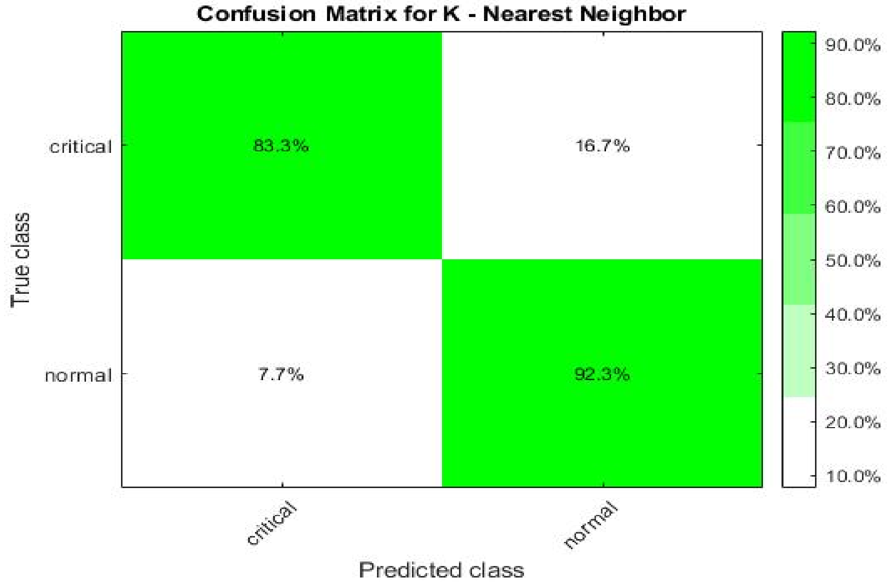

Figure 2: Confusion Matrix for k NearestNeighbor for Rotor Cable Dataset 1

The confusion matrix for GBT model is depicted in figure 3 which shows that the model classified only normal condition correctly at 100% while it got critical condition entirely wrong. This indicate that GBT model will not be good prediction model as it shows poor true negative rate and the equipment fault condition will not be reported as the case may be.

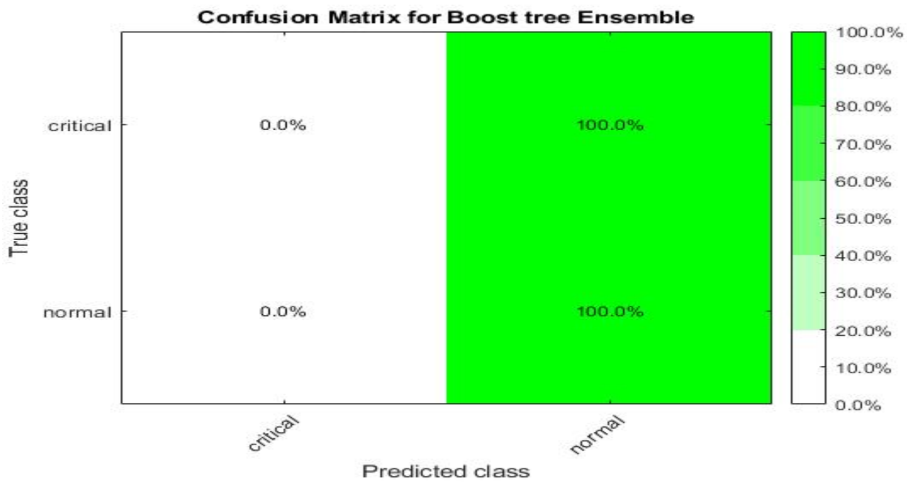

Figure 3: Confusion Matrix for GBT for Rotor Cable Dataset 1

In table 4, the results for rotor cable dataset 2 is shown. The k-nearest neighbor model shown similar pattern with that of dataset 1, with accuracy of 94.74%, precision of 91.67%, recall of 96.43% and F-score of 93.99%.

Table 4: Predictive Maintenance Model Evaluation Results for Rotor Cable Dataset 2

Model	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
Decision Tree	84.21	79.49	82.86	81.14
K-nearest neighbor	94.74	91.67	96.43	93.99
Support Vector Machine	84.21	91.18	70.00	79.20
Random Forest	89.47	93.75	80.00	86.33
Gradient Boosted Tree	73.68	36.84	50.00	42.42

For the second dataset of the rotor cable current, the confusion matrix for kNNmodel is depicted in figure 4. It can be observed from the figure that the model classified critical condition 100.0% times correctly and as normal condition 92.9% of the times correctly. These are the values shown on the diagonal of the confusion matrix. Whereas the remaining entries are classified wrongly.

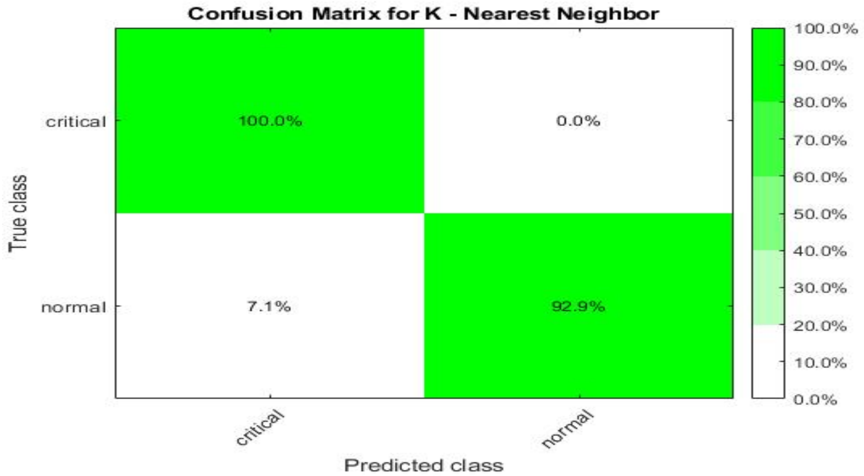

Figure 4: Confusion Matrix for k NearestNeighbor for Rotor Cable Dataset 2

The confusion matrix for GBT model for the second dataset is depicted in figure 5 which shows that the model classified only normal condition correctly at 100% while it got critical condition entirely wrong. This indicate that GBT model will not be good prediction model as it show poor true negative rate and the equipment fault condition will not be reported as the case may be.

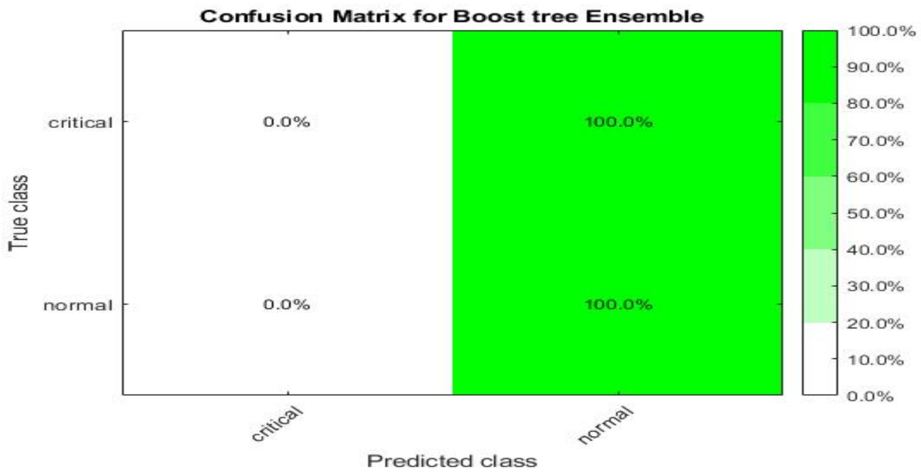

Figure 5: Confusion Matrix for GBT for Rotor Cable Dataset 2

Table 5 shows the model evaluation results for induction regulator dataset, tested on 75:25 held-out validation. All models show a slight difference in performance. The k-nearest neighbor model performed best with accuracy of 95.55%, precision of 95.83%, recall of 88.89% and F-score of 92.23%.

Table 5: Predictive maintenance model evaluation results for induction regulator dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
Decision Tree	91.11	91.67	78.57	84.62
K-nearest neighbor	95.55	95.83	88.89	92.23
Support Vector Machine	82.22	68.25	68.25	68.25
Random Forest	91.11	90.48	91.67	91.07
Gradient Boosted Tree	64.44	46.67	30.00	36.52

For the induction motor regulator dataset, the confusion matrix for kNNmodel is depicted in figure 6 which shows that the model classified critical condition 100.0% times correctly, 100.0% as warning condition and 66.7% as normal condition, these are values on the diagonal of the confusion matrix. It also misclassified normal condition 33.3% as warning, whereas all the remaining entries are classified entirely wrong.

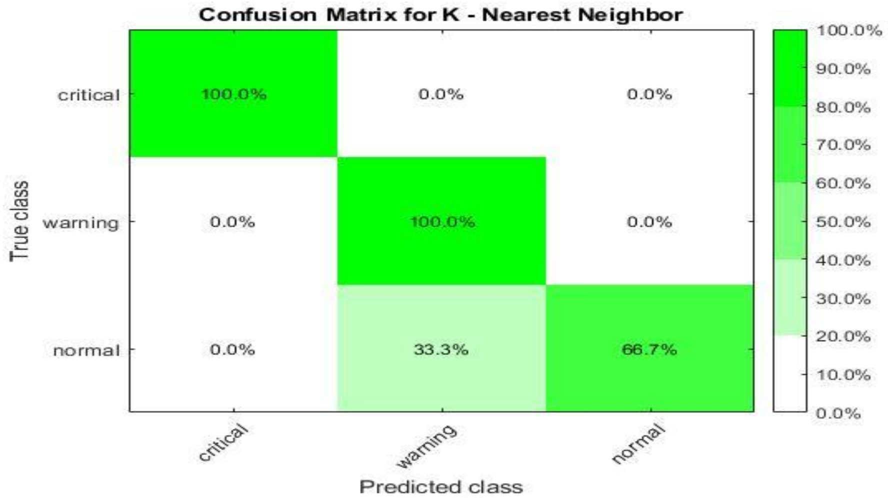

Figure 6: Confusion Matrix for k NearestNeighbor for Induction Regulator Dataset

For GBT model, under the induction motor regulator dataset, the confusion matrix is depicted in figure 7. It shows that the model classified only warning condition correctly at 100%. Whereas all the remaining entries are entirely misclassified. This indicate that GBT model will not be a good prediction model as it shows poor true negative rate and the equipment fault condition will not be reported as the case may be. The true positive rate is extremely low, indicating poor representation of true positive instances. Overall, the GBT will be giving a warning message always even if it is otherwise.

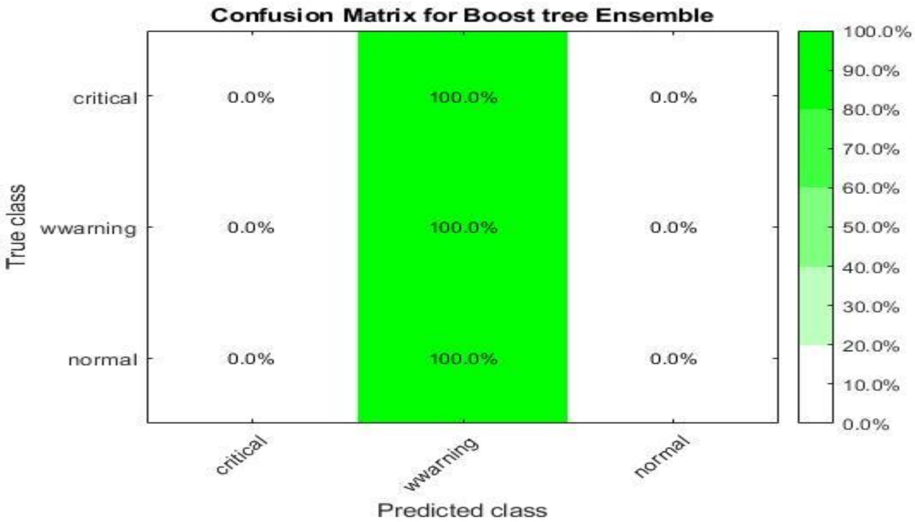

Figure 7: Confusion Matrix for GBT for Induction Regulator Dataset

CONCLUSION

Maintenance datasets from the maintenance department of northern cement company were obtained and used in this research. Predictive maintenance scheme was implemented on the three datasets namely; rotor cable 1, rotor cable 2 and induction regulator. The prediction models used are K-nearest neighbor, decision tree, support vector machine, random forest and gradient boost tree as it was the case in the northern cement company. KNN model performed best with accuracy of 89.47%, precision of 87.82 %, recall of 87.82 and f-score of 87.82% for the rotor cable dataset 1, while GBT has the least performance among the prediction model with accuracy of 68.42%, precision of 68.42%, recall of 50% and f-score of 57.78%. For the second rotor cable dataset 2 and the third dataset which is induction regulator, the performance trend is similar to the one obtained in the first dataset with kNN having the best result and GBT has the least result among the prediction models. The GBT model demonstrated consistently poor performance across all the datasets, as evident in the confusion matrices, suggesting it is unsuitable for predictive maintenance.

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