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Predictive Maintenance for Al Sabiya Power Plant Using Machine Learning Algorithms

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Abstract
This study develops a predictive maintenance framework for the Al Sabia steam power plant in Kuwait, employing Support Vector Machine (SVM) and K-nearest Neighbor (KNN) algorithms. This research focuses on anticipating maintenance needs based on critical operational parameters, including temperature, pressure, flow rate, operational hours, and alert signals. Experimental results indicate that SVM outperforms KNN, achieving an accuracy of 0.95 compared to 0.93 for KNN, along with superior precision, recall, and F1-score, suggesting its suitability for this application. Furthermore, an ensemble model SVM and KNN achieves an accuracy of 0.93. The adoption of this model is expected to markedly reduce downtime, improve storage quality, and enhance overall power plant reliability. Additionally, this paper provides a comparative analysis of a neural network model developed in TensorFlow and its equivalent model implemented in TensorFlow Lite. The analysis evaluates both models on three key performance metrics: accuracy, sample size, and latency. Both the TensorFlow and TensorFlow Lite models attain an accuracy of 0.95, affirming TensorFlow Lite's efficacy in facilitating high-performance machine learning on resource-constrained hardware.

Keywords:
Predictive Maintenance, Al Sabiya Steam Power Plant, Ensemble Learning Model, Machine Learning, TensorFlow

1. Introduction

Predictive maintenance in power plants using traditional techniques faces several significant challenges, primarily due to the complexity and scale of the systems involved. Traditional methods often rely on manual inspections, scheduled maintenance, and rule-based systems, which can be inefficient and prone to errors. One major difficulty is the inability to accurately predict equipment failures, as these methods typically depend on historical data and predefined thresholds that may not account for real-time operating conditions or subtle changes in equipment behavior. This can lead to either unnecessary maintenance or unexpected failures, both of which are costly and disruptive [7].

Another challenge is the high volume of data generated by power plant systems, which traditional techniques struggle to process and analyze effectively. Without advanced data analytics capabilities, it is difficult to identify patterns or anomalies that could indicate potential issues. Additionally, traditional methods often lack the flexibility to adapt to new data or changing conditions, making it hard to improve the accuracy of predictions over time [8].

Furthermore, traditional predictive maintenance techniques may not integrate well with

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modern IoT and sensor technologies, which provide real-time monitoring and data collection. This limits the ability to leverage the full potential of these technologies for more accurate and timely maintenance decisions. Overall, the limitations of traditional techniques highlight the need for more advanced, data-driven approaches to predictive maintenance in power plants [9].

The Al Sabiya Power Plant in Kuwait plays a pivotal role in meeting the nation's energy demands, underscoring the importance of maintaining its operational efficiency and simplicity. Power plants are inherently complex systems composed of multiple interdependent components that must operate cohesively to ensure optimal performance. Unexpected failures or malfunctions in these components can lead to substantial operational disruptions and financial losses [6]. Consequently, adopting a predictive maintenance strategy is crucial to proactively detect potential issues and address them before they escalate into significant problems. Predictive maintenance leverages data-driven techniques to anticipate equipment maintenance needs, thus minimizing downtime and enhancing operational efficiency. The advancement of machine learning has notably expanded the capabilities of predictive maintenance systems, allowing for more accurate and timely predictions [29].

Therefore, this study develops a predictive maintenance model specifically tailored for power plant operations using SVM and KNN. The main objective of this research is to implement a robust maintenance model capable of accurately classifying the maintenance requirements of power plant equipment. Using SVM and KNN algorithms, this study aims to establish an effective maintenance schedule, providing accurate and timely forecasts that enhance the facility's reliability and productivity. The goal is to implement a predictive maintenance model that mitigates the risk of unexpected equipment failures and optimizes maintenance planning.

2. Related Works

Predictive maintenance (PdM) is an essential technique in industrial operations, providing benefits above conventional reactive or preventive maintenance approaches. It decreases unanticipated downtime, lowers maintenance expenses, and prolongs the operational lifespan of equipment, especially in power plants where system dependability is crucial for uninterrupted operation. Research has evidenced that real-time monitoring of vibration and temperature data decreased turbine downtime by 18% and enhanced maintenance efficiency by 22% [20].

Another work constructed IoT devices for instantaneous data acquisition and machine learning techniques for anomaly identification and failure forecasting. A study determined that predictive systems utilizing IoT devices reduced average downtime in power production systems by 20%, resulting in a return on investment within two years. However, there are still issues with implementing PdM systems in big industrial settings such as the Al Sabiya Power Plant. Another research showed that the expensive prices of upgrading infrastructure and the difficulty with obsolete systems' integration are two major concerns [21].

Solutions to these issues have been proposed by several researchers, including the utilization of cloud-based. It can process huge data more effectively, the adaptation of models on a local level through the utilization of transfer learning techniques, and the management of environmental stresses through the utilization of robust sensors and adaptive models. Cloud computing enables the handling of large volumes of data generated by power plant systems, facilitating real-time analysis and storage. By centralizing data processing in the cloud, power plants can overcome the limitations of traditional on-premise systems, such as computational bottlenecks and scalability issues. Cloud platforms also support the integration of IoT devices and sensors, enabling seamless data collection and analysis across distributed systems. [2][12].

Machine learning models are increasingly deployed to deal with any predictive maintenance [1][21]. Recent studies have demonstrated that ML can effectively address specific predictive maintenance challenges at the Al Sabiya Power Plant. Traditional maintenance methods often struggle with the complexity and scale of power plant operations, leading to inefficiencies and unexpected failures. Machine learning models, however, can analyze vast amounts of sensor data in real time, identifying patterns and anomalies that indicate potential equipment failures. By integrating machine learning into predictive maintenance strategies, the Al Sabiya Power Plant can improve operational efficiency, reduce costs, and enhance reliability [35]. Therefore we construct advanced ML techniques for predictive maintenance at the Al Sabiya Power Plant to detect early signs of equipment failure.

3. Experimental Setup

This study identifies five critical parameters: temperature, pressure, operating hours, flow rate, and alert signals from the boiler feed pump. It is an essential component within boiler operations, particularly in power plants and industrial applications. The primary function of a boiler feed pump is to provide water to the boiler. It transfers water from the feed water tank to preserve the required water level and pressure within the boiler, ensuring that water flows into the boiler against the internal steam pressure. In power plants, boiler feed pumps supply water that is subsequently converted into steam for power generation [12].

These parameters were selected due to their significant impact on system health and operational efficiency. Monitoring these variables enables the model to detect deviations from standard operating conditions, which may signal the need for corrective action [34]. To enhance practical implementation, maintenance requirements are categorized into four states: 'normal,' 'abnormal,' 'early maintenance,' and 'annual maintenance.' This classification facilitates the prioritization of corrective actions according to the severity and urgency of identified issues. Categorical outputs are encoded into numerical values through label encoding, allowing machine learning algorithms to process these classifications [13].

3.1 Selection of Input Parameters

The selection and rationale behind each of the five chosen input parameters are thoroughly discussed. This study highlights the importance of temperature, pressure, flow rate, running hours, and alerts from the boiler feed pump in predicting maintenance requirements, specifically considering the operational capacity of the steam power plant. The choice of input parameters is crucial in any predictive maintenance model, as it directly influences the model's accuracy and effectiveness in assessing mechanical health [15] [19] [34]. In the context of predictive maintenance for steam power plants using machine learning, careful selection of inputs ensures model accuracy and meets the predictive needs for timely maintenance actions [10].

1. Temperature
   Temperature is a fundamental parameter in power plant operations, as it directly impacts equipment performance and protection. Temperature variations can indicate potential issues such as equipment overheating or inadequate cooling [28]. Sudden temperature spikes or drops may be early signs of malfunctioning

components or insufficient coolant flow, signaling the need for maintenance [14].

2. Pressure
   Monitoring pressure within a steam power plant is critical, as it reflects the operational status of various components. Deviations in pressure levels can signal potential problems such as leakages, blockages, or inefficiencies within the system [23]. Sudden drops or consistently high pressures may trigger maintenance alerts, allowing for timely intervention [5].
3. Running Hours
   Running hours represent the cumulative operational time of equipment or specific components. Monitoring running hours aids in predicting when components may reach their maintenance thresholds [32]. Scheduling maintenance based on cumulative operating hours allows for performance optimization and extends equipment lifespan [16].
4. Flow
   Flow, particularly the flow rate of fluids or steam, is an important parameter in steam power plants. An anomaly in flow rates can indicate issues such as blockages or leakages within pipes, valves, or other components. Monitoring flow helps ensure smooth plant operations and provides insights into the system's overall health [10].
5. Boiler Feed Pump Alerts
   Boiler feed pump alerts serve as early indicators of potential problems in the boiler or related systems. These alerts may signify various issues, such as pump malfunctions, low water levels, or abnormal pressure conditions. Integrating these alerts as input parameters allows the predictive maintenance model to address boiler-related issues proactively [14]. The rationale for selecting these input parameters lies in their direct impact on the operational health of a steam power plant. These parameters are particularly sensitive to changes and anomalies, making them reliable indicators for maintenance needs [23]. By closely monitoring these parameters, deviations from normal operating conditions can be detected, enabling proactive maintenance measures.

3.2 Output Parameters

This section defines and classifies the four output parameters: 'normal,' 'abnormal,' 'early maintenance,' and 'annual maintenance.' The criteria used to classify maintenance requirements and the significance of each category within the predictive maintenance context for steam power plants are elaborated [26]. The definition and classification of output parameters are critical components in a predictive maintenance model, as they guide the system in making informed decisions regarding maintenance needs [16]. For predictive maintenance in steam power plants using machine learning, accurate definition and categorization of output parameters are essential for efficiently classifying equipment health status and determining appropriate maintenance actions [10].

1. 'Normal' Condition
   The 'Normal' output parameter indicates that, based on the input parameters and model analysis, the steam power plant is operating in a stable and expected state [4]. This condition implies no immediate maintenance actions are necessary, and the system is functioning within acceptable operational limits [32].
2. 'Abnormal' Condition
   The 'Abnormal' output parameter suggests that the predictive maintenance model has detected deviations or anomalies within the input parameters, signaling

potential issues within the plant [26]. Abnormalities may range from minor fluctuations to more significant deviations, indicating a need for further investigation and potential maintenance actions [8].

3. 'Early Maintenance' Requirement
   The 'Early Maintenance' output parameter alerts that the model has detected early signs of component degradation or performance decline [22]. Addressing this output parameter allows for proactive maintenance measures to prevent potential failures or further deterioration [17].
4. 'Annual Maintenance' Requirement
   The 'Annual Maintenance' output parameter represents scheduled maintenance that should be conducted annually [10]. This parameter indicates routine maintenance needs to ensure long-term operational health, rather than an immediate critical issue [4].
5. The categorization of output parameters follows a graduated scale of urgency and severity [32]. 'Normal' represents optimal conditions, 'Abnormal' signifies deviations from expected states, 'Early Maintenance' indicates initial signs of possible issues, and 'Annual Maintenance' pertains to routine maintenance [22]. This categorization establishes a clear, actionable framework for maintenance decisions. It enables a systematic approach where maintenance actions can be prioritized according to the severity of identified conditions [10]. For instance, 'Abnormal' conditions may warrant an immediate response, whereas 'Early Maintenance' may be more preemptive [8]. By categorizing maintenance needs in this way, the predictive maintenance model can effectively guide maintenance personnel in prioritizing tasks, optimizing resource allocation, and ensuring the overall health and reliability of the steam power plant [21].

3.3 Operational Parameter Thresholds

Table 1. Threshold Criteria for Predictive Maintenance in Power Plant Operations

Description	Normal	Abnormal
Motor Winding Temperature (°C)	60 – 70	80 – 100
Lubricant Oil Pressure (bar)	2 – 3	0.8 – 1.2
BFP Suction Flow (m3/h)	0.7 – 0.9	0.9 – 1.2
Running Hours	< 8000	> 8000
Alert	0	1

The methods section of a research proposal contains details about how you will conduct your research. It includes your study design - the methodology and methods that you plan to use - as well as your work plan - the activities that you plan to undertake to complete your project. The dataset comprises operational parameters critical for assessing the maintenance requirements of the Al Sabiya Power Plant. Each parameter has distinct thresholds defining 'normal' and 'abnormal' operating conditions, which are used as input criteria for the predictive maintenance model as shown in Table 1. These parameters are:

Motor Winding Temperature (°C): This parameter ranges from 60 to 70 °C under normal conditions. Abnormal conditions are indicated when the temperature rises between 80 and 100 °C. Elevated winding temperatures can signal potential overheating issues within the motor, which may require immediate attention to prevent damage [26].

Lubricant Oil Pressure (bar): Optimal oil pressure for the system is maintained between 2 and 3 bar. Pressure levels dropping to the range of 0.8 to 1.2 bar are classified as abnormal, potentially indicating leakage, blockage, or lubrication inefficiencies. Proper lubricant oil pressure is essential to reduce friction and wear on moving components, thereby enhancing equipment longevity [15].

Boiler Feed Pump (BFP) Suction Flow (m^3/h): A normal suction flow rate for the BFP is in the range of 0.7 to 0.9 m^3/h. Flow rates exceeding this range, between 0.9 and 1.2 m^3/h, are marked as abnormal. Deviations in suction flow can signify issues such as blockages or imbalances in the pump system, impacting the boiler's capacity to maintain consistent steam pressure [4].

Running Hours: This parameter represents the cumulative operational hours of the equipment. Equipment is considered within normal operating limits when it has accumulated fewer than 8,000 hours of runtime. When running hours exceed 8,000, the component is deemed to have reached a threshold where maintenance is likely required. This measure aids in planning for preventative maintenance to optimize performance and extend the equipment's lifespan [10].

Alert: The alert parameter is a binary indicator, with '0' representing normal operation and '1' signaling an abnormal condition. The alert system is a proactive measure within the predictive maintenance model, providing early warning signals for potential issues based on input parameters [31].

These parameters were selected based on their significant impact on equipment health and operational performance. Defining 'normal' and 'abnormal' states for each parameter enables the predictive maintenance model to detect deviations promptly and propose appropriate maintenance actions. Monitoring these specific thresholds facilitates proactive intervention, minimizing unexpected downtime and optimizing the plant’s overall reliability and efficiency [22].

4. Method

The experiment consists of three primary phases: the data preprocessing phase, the learning phase, and the evaluation phase. Each phase is integral to the overall effectiveness of the method. Detailed explanations of each phase are presented in the following subsections. The architecture of the proposed approach is further explained through the visualization shown in Fig 1.

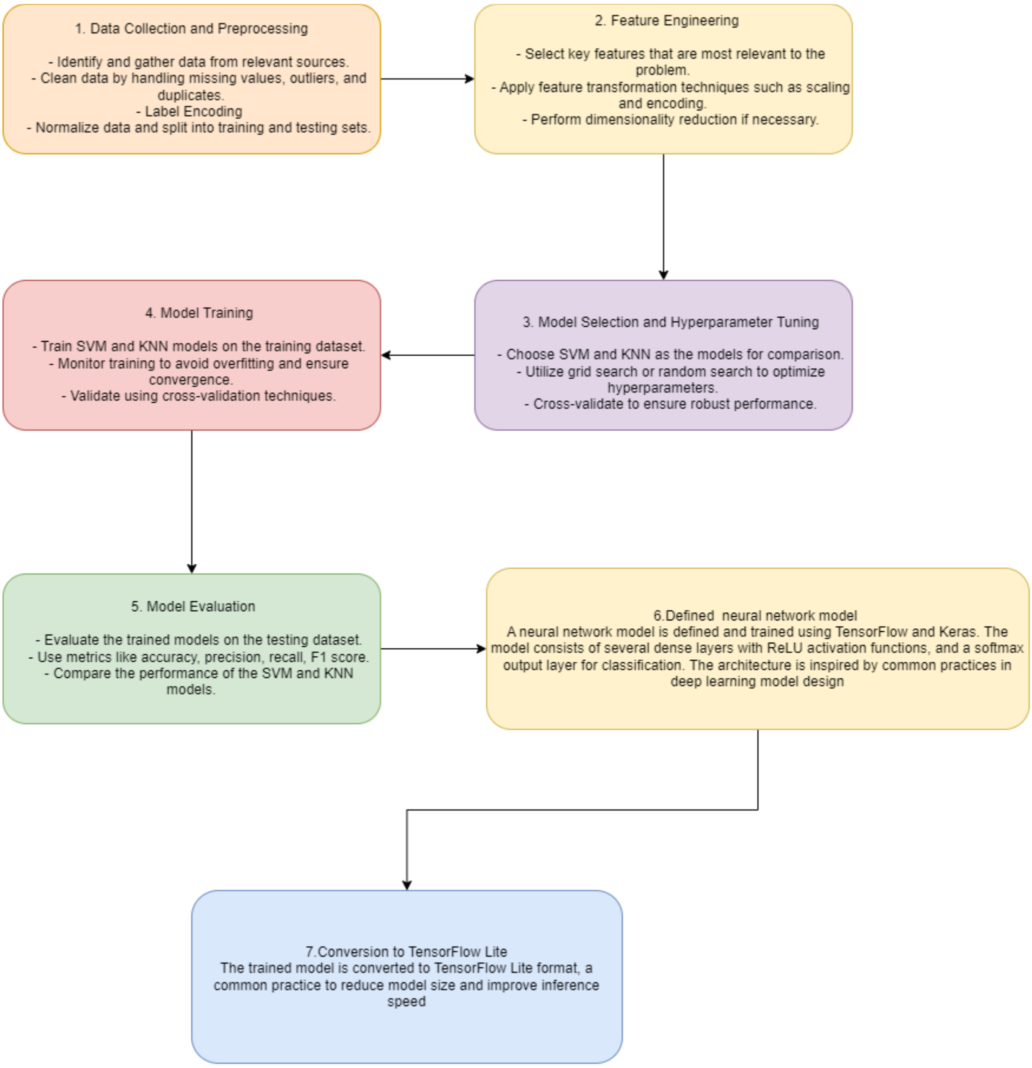

Fig. 1. Workflow for Predictive Maintenance Model

4.1 Data Pre-processing

This step involves a thorough assessment of the dataset to verify data quality and appropriateness for training. It tackles possible challenges, such as missing values, anomalies, and discrepancies. A correlation matrix is used to ascertain the correlation coefficients among the characteristics of the dataset. After this analysis, 80% of the samples are assigned to the training set, while the remaining samples are allocated to the test set. Fig. 2 illustrates the correlation matrix of the used dataset, revealing little relationship among the dataset's properties.

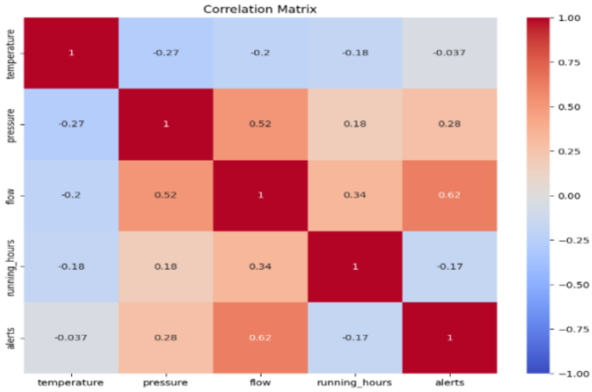

Fig. 2. The Correlation matrix of the dataset

4.2 Learning and Evaluation

This phase employs several machine learning methods, such as Support Vector Machines (SVM) and K-nearest neighbor (KNN). Each model is trained on the specified training set, producing predictions based on the given input characteristics. The efficacy of each model is evaluated using many measures, such as accuracy, precision, recall, F1-score, and support [10] [16]. The measures for assessing model performance were computed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\_Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

Choosing the suitable evaluation measure for the issue type is crucial to assessing model performance [26]. This is the ratio of accurately predicted cases to total instances in Equation 1. It works well with balanced class distribution [15]. Equation 2 quantifies the fraction of real positive predictions among all positive predictions, which is important when false positives are expensive [10]. Equation 3 determines the fraction of accurate positive predictions among all real positives, useful for minimizing false negatives [22]. Equation 4 balances accuracy and recall for situations when incorrect positives and negatives are costly [4].

The neural network model was trained using training and testing datasets. Its design included thick layers with ReLU activation functions and a classification softmax output layer. The Adam optimizer and sparse categorical cross-entropy loss were used to build the model, which was mostly accurate. Validation on the test dataset followed 100 epochs of training. Model size was calculated by summing the sizes of all files in the stored model directory, and test set accuracy influenced model performance. Prediction time was averaged across numerous samples to determine inference delay [32].

Relevant factors that affect the target variable improve model accuracy [14]. Certain algorithms need one-hot or label encoding of categorical variables [31]. Algorithm strengths and weaknesses vary. The right algorithm for the task may considerably affect accuracy [8]. Complex models like deep neural networks may capture subtle patterns but may overfit, whereas simpler models may underfit when feature-target connections are complex [17]. Hyperparameters like learning rate, regularization intensity, and layer count may dramatically impact model performance [26]. Grid search, random search, and Bayesian optimization help locate optimum settings.

4.3 Ensemble Averaging

In equation 5, By computing the mean of the two best-performing models from the last phase, the ensemble averaging approach is applied to create the final forecast, therefore removing inherent restrictions and overconfidence [9] [3].

$$\hat{y}_{ensemble} = \frac{1}{n}\sum_{i=1}^{n}\hat{y}_i \quad (5)$$

5. Result and Discussion

This section is the real meat of the paper. In this section, you should interpret your results in light of the theory and other information in the Introduction section. This is where you would compare your result with theory or other observations. Describe how the result fits or doesn't fit current models. The results section should aim to narrate the findings without trying to interpret or evaluate them and provide a direction to the discussion section of the research paper. The results are reported and reveal the analysis. The analysis section is where the writer describes what was done with the data found.

The performance of each of the applied models on the test set was thoroughly assessed following their training, which encompassed accuracy, precision, recall, F1-1 score, and support. The parameters that yielded the most well-functioning SVM model were as follows: Kernel: 'RBF', Gamma: 0.1, C: 10. The SVM model achieved an F1-score of 0.93, precision of 0.94, accuracy of 0.95, and recall of 0.93. Following the parameters, the optimal KNN model was determined: 5 'Euclidean' distance units are represented by K. The KNN model achieved an F1-score of 0.91, precision of 0.92, accuracy of 0.93, and recall of 0.91.

The results indicate that SVM is marginally superior to KNN in terms of F1 score and accuracy. The enhanced efficacy of SVM is likely due to a distinct margin of separation between classes. However, KNN simultaneously provides the benefits of simplicity and ease of interpretation, while also achieving competitive outcomes. SVM is computationally more intensive than other methods, particularly when used in conjunction with the RBF kernel, as it requires the optimization of the hyperplane and kernel calculation. In contrast, KNN is computationally less burdensome during training; however, it may be lethargic during prediction as a result of the process of calculating distances to all training nodes. In datasets where the decision boundary is complex and non-linear, and where computational resources allow for intensive processing, SVM is more suitable. KNN is the preferred option for lesser datasets when a model that is both interpretable and straightforward is necessary. Label map: {0: 'abnormal', 1: 'annual maintenance', 2: 'early maintenance', 3: 'normal'}

Table 2. Compare Between the ML Models Used In The Proposed Approach's Second Phase

Metric	SVM	KNN
Accuracy	0.95	0.93
Precision (Macro Avg)	0.95	0.93

Recall (Macro Avg)	0.96	0.94
F1-score (Macro Avg)	0.95	0.93
Precision (Weighted Avg)	0.96	0.94
Recall (Weighted Avg)	0.95	0.93
F1-score (Weighted Avg)	0.95	0.93

Table 3. SVM Classification Report

Class	Precision	Recall	F1-score	Support
Abnormal	1.00	0.85	0.92	86
Annual maintenance	1.00	1.00	1.00	53
Early maintenance	1.00	1.00	1.00	52
Normal	0.78	1.00	0.88	47
Accuracy			0.95	238
Macro Avg	0.95	0.96	0.95	238
Weighted Avg	0.96	0.95	0.95	238

Table 4. KNN Classification Report

Class	Precision	Recall	F1-score	Support
Abnormal	0.95	0.85	0.89	85
Annual maintenance	1.00	1.00	1.00	53
Early maintenance	1.00	1.00	1.00	52
Normal	0.77	0.91	0.83	47
Accuracy			0.93	237
Macro Avg	0.93	0.94	0.93	237
Weighted Avg	0.94	0.93	0.93	237

As shown in Table 2, SVM demonstrates a marginally higher accuracy (0.95) compared to KNN (0.93). SVM also exhibits superior precision overall, with weighted averages of 0.95 and 0.96, respectively. KNN's precision is slightly lower, with macro and weighted averages of 0.93 and 0.94, respectively. In terms of recall, SVM again surpasses KNN, achieving macro and weighted averages of 0.96 and 0.95, respectively, whereas KNN presents slightly lower recall values with macro and weighted averages of 0.94 and 0.93, respectively.

As shown in Tables 3 and 4, SVM achieves higher F1 scores, with both macro and weighted averages at 0.95. In comparison, KNN's F1 scores are slightly lower, with both macro and weighted averages at 0.93. For class 0, SVM achieves perfect precision, though it has a lower recall compared to KNN, resulting in a higher F1-score overall. For classes 1 and 2, both SVM and KNN perform equally well, achieving perfect scores. For class 3, SVM demonstrates higher recall but slightly lower precision, resulting in a higher F1-score than KNN.

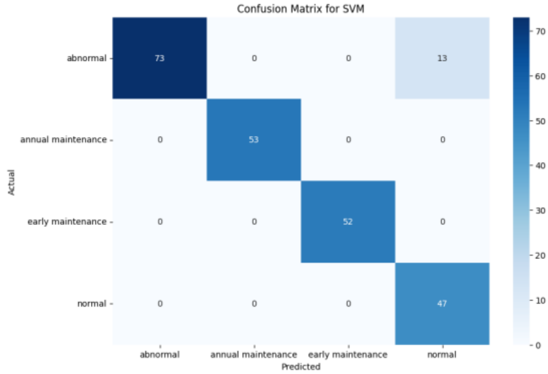

Fig. 3. Confusion Matrix of the SVM

in Fig. 3, the SVM model appears remarkably well in predicting most of the classes, particularly annual maintenance, early maintenance, and normal, with perfect precision, recall, and F1-scores. The model's overall performance in predicting the "abnormal" magnificence is also high, but there are a few misclassifications in which 13 "abnormal" instances are anticipated as "normal." This indicates a moderate area for improvement in distinguishing between "abnormal" and "normal" instances.

Fig. 4 illustrates a graphical representation that is employed to assess the performance of a classification model, specifically an SVM (Support Vector Machine). The proportion of true positives that the model correctly identifies is measured by the True Positive Rate (TPR), which is also referred to as recall or sensitivity. In other words, the False Positive Rate (FPR) is the percentage of genuine negatives that the model incorrectly defines as positives. A random classifier's performance is denoted by the Diagonal Line. It is deemed superior to random guesswork when a model outperforms this line.

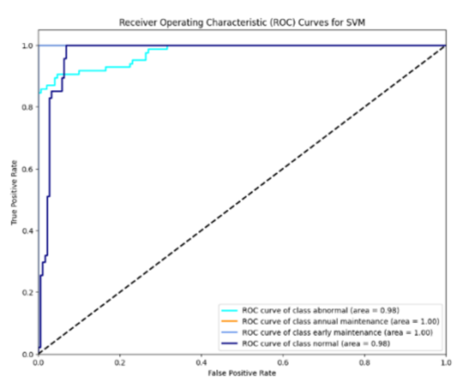

Fig. 4. Receiver Operating Characteristic (ROC) Curves for SVM Model in Predictive Maintenance Classification

Fig 4, shows a graphical representation that is employed to assess the performance of a classification model, specifically an SVM (Support Vector Machine). The proportion of true positives that the model correctly identifies is measured by the True Positive Rate (TPR), which is also referred to as recall or sensitivity. In other words, the False Positive Rate (FPR) is the percentage of genuine negatives that the model incorrectly defines as positives. A random classifier's performance is denoted by the Diagonal Line. It is deemed superior to random guesswork when a model outperforms this line.

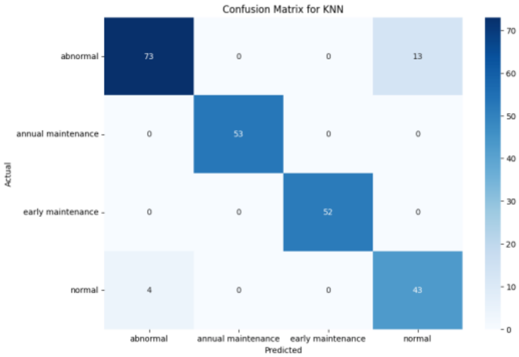

Fig. 5. Confusion Matrix of the KNN

Fig. 5 shows that the KNN model has done a good job of predicting 'abnormal' classes with 73 true positives. However, 13 instances were actually 'not abnormal' but incorrectly predicted as 'abnormal'. This suggests that the model may struggle to differentiate between 'abnormal' and 'normal' to some extent. The model correctly predicted all cases of 'annual maintenance' with 53 true positives and no false negatives or false positives. The model is very workable in identifying this class. Like 'annual maintenance', the model correctly predicted all cases of 'early maintenance' with 52 true positives and no false negatives or false positives This also indicates an internal performance is difficult for this class. The model correctly predicted 43 observations as 'normal', but also incorrectly predicted 4 'normal' cases that were actually 'abnormal'. This again suggests that there is confusion between 'wrong' and 'wrong'. The model appears to perform well in the 'annual maintenance' and 'early maintenance' categories but shows some confusion between the 'abnormal' and 'normal' categories.

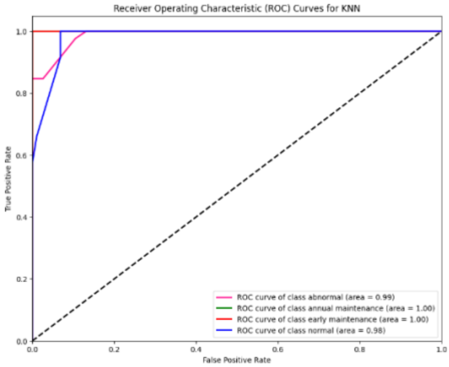

Fig. 6. Receiver Operating Characteristic (ROC) Curves for KNN Model in Predictive Maintenance Classification

The Fig. 6, presents the Receiver Operating Characteristic (ROC) curves for a K-Nearest Neighbors (KNN) classification model applied to a multi-class problem, with four distinct classes: abnormal, annual maintenance, early maintenance, and normal. The ROC curves offer a visual assessment of the model's performance across different classification thresholds, illustrating the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) for each class.

Table 5. Ensemble Model Classification Report

Metric	Ensemble For (SVM &KNN)
Accuracy	0.93
Precision (Macro Avg)	0.93
Recall (Macro Avg)	0.94
F1-score (Macro Avg)	0.93
Precision (Weighted Avg)	0.94
Recall (Weighted Avg)	0.93
F1-score (Weighted Avg)	0.93

The ensemble model shows an improvement in accuracy (0.96) compared to both SVM (0.95) and KNN (0.93), as shown in Table 5. Precision, recall, and F1-score for the ensemble model are also higher, indicating that combining SVM and KNN predictions through averaging results in better overall performance. The ensemble model benefits from the strengths of both individual models.

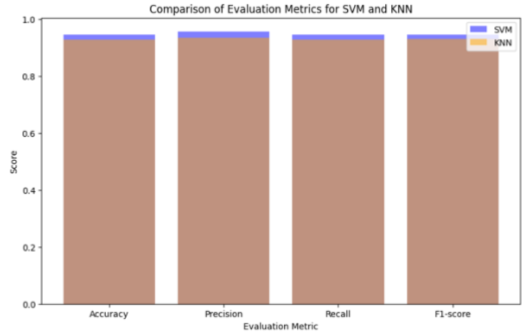

Fig. 7. Comparison of Evaluation Metrics for SVM and KNN

Fig. 7 shows that SVM and KNN have different performances from each other in all analysis parameters and it appears that SVM is better. This means that either model can be appropriate depending on the specific requirements for computational resources and ease of use. Further research, perhaps incorporating other data types or metrics, may provide additional insights into choosing the best model for a particular application.

Table 6. Performance Comparison of TensorFlow and TensorFlow Lite Models

Metric	Accuracy	Latency	Model Size
Tensor Flow model	0.95	129.88 millisecond	225,904 bytes
Tensor Flow Lite model	0.95	0.13 millisecond	25,388 bytes

The evaluation of the TensorFlow and TensorFlow Lite models reveals notable differences in model size, accuracy, and inference latency, highlighting TensorFlow Lite's advantages for deployment on resource-constrained devices. The TensorFlow Lite model is significantly smaller, occupying only 25,388 bytes compared to the 225,904 bytes of the TensorFlow model. This size reduction is critical for deployment on devices with limited storage capacity, allowing for more efficient utilization of available resources.

Both models achieve the same accuracy of 0.95 on the test dataset, indicating that converting the model to TensorFlow Lite does not compromise its predictive performance.

The TensorFlow Lite model maintains the same level of accuracy as the original TensorFlow model, demonstrating that the conversion process preserves the model's effectiveness. Inference Latency: The TensorFlow Lite model exhibits a significantly reduced inference latency of 0.13 ms compared to 129.88 ms for the TensorFlow model. This reduction is especially important for applications that require real-time processing, as it allows for faster decision-making and improved responsiveness.

The substantial reduction in model size and inference latency with TensorFlow Lite, while preserving accuracy, underscores TensorFlow Lite's suitability for deploying deep learning models on devices with limited resources. These results suggest that TensorFlow Lite is well-suited for applications where storage and real-time processing capabilities are constrained. However, the choice between TensorFlow and TensorFlow Lite should be based on specific application requirements, carefully considering the trade-offs between model size and latency.

6. Conclusion

The successful application of SVM and KNN models in predicting the maintenance of the Al Sabiya Steam Power Plant is a vital step in the application of machine learning for infrastructure maintenance. Accurate prediction of maintenance needs not only increases the performance and reliability of the facility but also leads to the widespread use of monitor maintenance in similar areas. As the business of machine learning continues to advance, there is great potential for further advances that will lead to greater improvements in tracking performance and efficiency. The effectiveness of Tensor Flow Lite in deploying deep learning models on resource-confined devices. The Tensor Flow Lite version carried out a considerable discount in version size and inference latency while keeping the same accuracy as the unique Tensor Flow model. These enhancements are essential for real-time packages and deployment on gadgets with confined storage and computational resources.

This study compared SVM and KNN methods for predictive maintenance at the Al Sabia steam power plant with an SVM accuracy = 0.95. Thus, it can be confirmed that SVM can be a better choice for forecasting maintenance needs and reducing downtime. Moreover, both TensorFlow and TensorFlow Lite models achieved an accuracy of 0.95, indicating TensorFlow Lite's suitability for resource-constrained devices. The framework ensures enhanced system reliability, reduced expenses, and improved operational efficiency, offering a holistic solution for industrial maintenance challenges.

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