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# Enhanced Predictive Maintenance for Al Sabiya Steam Power Plant using BiLSTM Attention Networks and Optimization Algorithms: A Comparative Study



**Abstract:** - Predictive maintenance plays a role in optimizing operations as showcased at the Al Sabiya Steam Power Plant Especially in boiler feed pumps . In this research, there are three optimization focused models—PSO BiLSTM Attention, HHO BiLSTM Attention, and CSO BiLSTM Attention—utilizing BiLSTM networks with attention mechanisms were evaluated. The accuracy of these models was examined, with the PSO BiLSTM Attention model standing out for achieving an accuracy score of 1.0 in both two class and four class classification tasks. Particularly noteworthy is that the PSO BiLSTM Attention model accomplished this feat with a training time of around 50.64 seconds for the two-class scenario and 40.48 seconds for the four-class scenario surpassing its counterparts. Following behind is the HHO BiLSTM Attention model with training times of 49.77 seconds for the two-class scenario and 51.59 seconds for the four-class scenario while the CSO BiLSTM Attention model required training time at 117.63 seconds for the two-class scenario and 100.09 seconds for the four-class scenario. This study emphasizes how PSO optimization can effectively enhance both reliability and operational efficiency in BiLSTM networks equipped with attention mechanisms, for maintenance purposes.

**Keywords:** Predictive Maintenance, Boiler Feed Pump, Optimization, Machine Learning, Deep Learning, BiLSTM, Attention Mechanism.

## I. INTRODUCTION

Al Sabiya Steam Power Plant in Kuwait plays a crucial role in meeting the country's energy demand, making its operational efficiency and reliability essential [1]. Steam power plants are complex systems with numerous components that must work in harmony to maintain optimal performance. It is certain that unexpected failure or malfunction in these components can cause significant business disruption and revenue loss [2]. Thus, adopting a predictive maintenance approach is vital to proactively identify potential issues and address them before they escalate into major problems [3].



**FIGURE 1. Al Sabiya Steam Power Plant**

A critical infrastructure in Kuwait, the Al Sabiya Steam Power Plant is designed to meet the nation's growing energy demands. This plant features complex systems and machinery that require continuous monitoring and maintenance to ensure operational efficiency and reliability.

Predictive maintenance leverages data-driven techniques to predict when equipment will require maintenance, thereby reducing downtime and maximizing operational efficiency [4]. The rise of machine learning has significantly enhanced the

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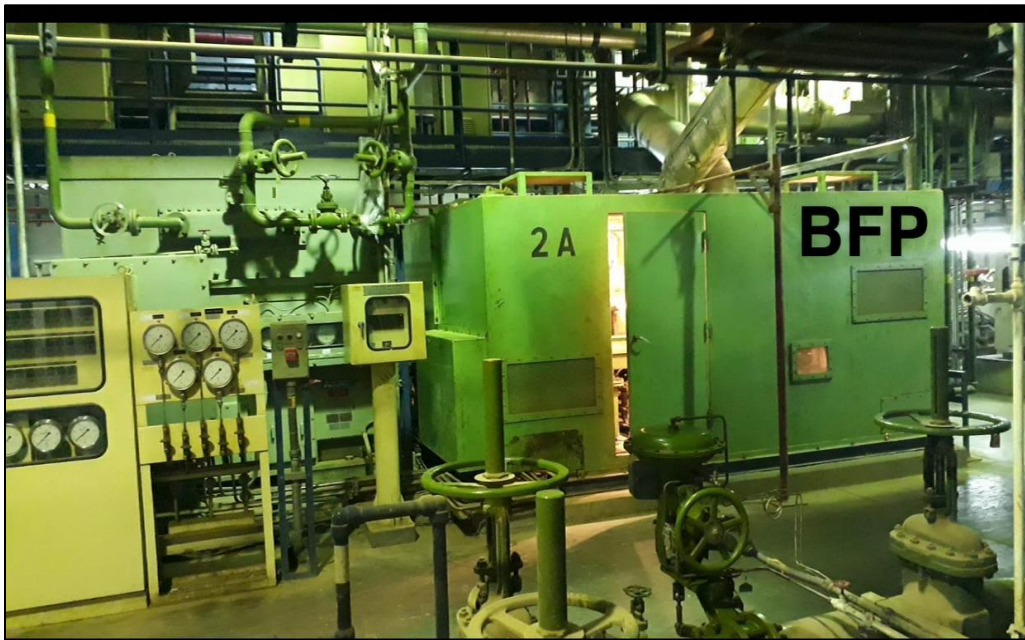
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capabilities of predictive maintenance systems, enabling accurate and timely forecasting [5]. In particular, the Bidirectional Long Short-Term Memory (BiLSTM)[6] network with Attention mechanism[7] has shown great promise in time series prediction and anomaly detection due to its ability to capture temporal dependencies and focus on relevant parts of the input sequence.

This research on Al Sabiya focuses on developing a predictive maintenance model for a steam plant using BiLSTM with Attention, integrated with three advanced optimization algorithms: Particle Swarm Optimization (PSO)[8], Harris Hawks Optimization (HHO)[9], and Cat Swarm Optimization (CSO)[10]. The BiLSTM network processes the input data in both forward and backward directions, providing a comprehensive understanding of the sequence, while the Attention mechanism helps in identifying critical points that are most indicative of potential failures.

The integration of these optimization algorithms with BiLSTM enhances the model's performance by optimizing its parameters, leading to more accurate and reliable predictions. PSO, HHO, and CSO are metaheuristic algorithms known for their efficiency in exploring and exploiting the search space to find optimal solutions. These optimization techniques help in fine-tuning the hyperparameters of the BiLSTM model, thus improving its predictive accuracy and robustness.

Selecting the right input parameters is crucial for the success of any predictive maintenance model [11]. Five key parameters have been identified in this study: temperature, pressure, running hours, flow, and alerts from the boiler feed pump. The boiler feed pump is a critical component in boiler operation, especially in electricity plants and commercial applications. Its primary function is to deliver water to the boiler, and maintaining the desired water level and pressure. The pump must provide water at a pressure higher than the steam pressure in the boiler to ensure continuous water flow against the steam pressure. These parameters significantly impact the operational health and efficiency [12].



**FIGURE 2. Boiler Feed Pump**

Essential for the operation of steam power plants, the boiler feed pump delivers high-pressure water to the boiler. This pump ensures a continuous supply of water, maintaining the necessary pressure and water level for efficient steam generation.

To provide a practical perspective, the maintenance requirements are categorized into four distinct states: normal, abnormal, early maintenance, and annual maintenance. This classification enables prioritized corrective actions based on the severity and urgency of identified issues [11]. Label encoding process translates these categorical outputs into numerical values, facilitating their processing by machine learning algorithms [13].

The main objective of this research is to develop a robust maintenance model that accurately classifies the maintenance needs of steam power plant equipment. By employing PSO, HHO, and CSO algorithms, This research aims to create an efficient maintenance schedule with timely and precise forecasting, thereby enhancing the facility's reliability and productivity. The integration of these optimization techniques in machine learning models not only improves the predictive accuracy but also optimizes the model parameters for better performance [14].

This study addresses the need for a predictive maintenance system in Al Sabiya steam power plant, using advanced machine learning techniques and optimization algorithms to improve plant operational flexibility and performance [15]. By carefully selecting input parameters and applying PSO, HHO, and CSO, we aim to develop a predictive maintenance model that significantly reduces the risk of unexpected equipment failure and optimizes maintenance planning [16].

This paper presents an approach based on the use of three optimization-based machine learning models: PSO-BiLSTM, HHO-BiLSTM, and CSO-BiLSTM. The rest of the paper is organized as follows: Section 2 describes the adopted dataset; followed by Section 3, which discusses the proposed approach; Section 4, which presents the results obtained; and finally, Section 5, which concludes the paper and proposes future directions.

## II. DATASET DESCRIPTION

In this section we provide a detailed overview of the dataset used to develop the predictive maintenance model for the Al Sabiya Steam Power Plant. The dataset plays a crucial role in the accuracy and effectiveness of the model, as it contains the essential parameters needed to predict maintenance requirements. The selected input parameters have been carefully selected based on their importance and impact on the operational condition of the power plant. These parameters include temperature, pressure, flow rate, operating hours, and alerts from the boiler feed pump. In addition, this study identifies and classifies the output parameters into normal, abnormal, early maintenance, and annual maintenance, which enables making informed maintenance decisions.

### A. Selection and Rationale for Input Parameters

The rationale behind each of the selected five input criteria and their careful selection are discussed in detail. The importance of temperature, pressure, flow rate, running hours, and alerts from the boiler feed pump for predicting maintenance requirements [17], considering the capacity of the steam power plant, has been highlighted. The choice of input parameters in any predictive maintenance model is an important decision that affects the accuracy of the model and its maximum effectiveness in assessing mechanical health. In the case of steam power plant predictive maintenance using ML, careful consideration of inputs to ensure model capacity accuracy and predictive needs for timely maintenance is paramount [18].

Temperature is a fundamental parameter in a steam power plant because it directly affects the performance and protection of the gadget [19]. Variations in temperature can suggest potential troubles such as equipment overheating or insufficient cooling [20]. Sudden spikes or drops in temperature can cause early signs of malfunctioning additives or insufficient coolant flow, indicating the need for protection.

Pressure inside a steam strength plant is a critical parameter to monitor, as it reflects the operational state of various additives [21]. Deviations in strain stages can point toward leakages, blockages, or inefficiencies within the machine. Sudden pressure drops or sustained high pressures can trigger indicators for maintenance moves, allowing for timely interventions.

Running hours represent the cumulative operational time of the equipment or specific components. Monitoring strolling hours allows the prediction of when certain parts may reach their protection thresholds. Components that require renovation after a targeted number of working hours can be scheduled for servicing, optimizing their overall performance and extending their lifespan.

Flow, in particular the flow of fluids or steam, is a critical parameter in steam strength plants [22]. Anomalies in flow rates can indicate issues like blockages or leakages in pipes, valves, or other additives. Monitoring flow facilitates in ensuring the smooth operation of the plant and provides insights into the health of the gadget [23].

Boiler feed pump alerts are essential as they often function as early signs of potential problems in the boiler or associated structures [24]. These alerts can include a variety of situations such as pump malfunctions, low water levels, or unusual pressure conditions. Incorporating these signals as an input parameter allows the predictive maintenance model to proactively address boiler-related issues [24].

The intent behind selecting these input parameters is deeply rooted in their direct impact on the operational state of a steam power plant. These parameters are exceptionally sensitive to adjustments and anomalies, which make them reliable indicators of potential preservation needs. By monitoring these parameters carefully, deviations from regular working situations can be detected, allowing for proactive protection measures.

### B. Definition and Categorization of Output Parameters

This sub-section expounds on the right definitions and categorizations assigned to the four output parameters: normal, abnormal, early maintenance, and annual maintenance. The criteria used to categorize maintenance desires and the significance of each category within the context of predictive protection for a steam power plant have been discussed.

The definition and categorization of output parameters in a predictive maintenance model are crucial components that guide the system to make informed decisions regarding upkeep needs. In the context of predictive upkeep for a steam power plant using ML, the proper definition and categorization of output parameters are essential to efficiently classify the health status of the equipment and determine the proper upkeep movements.

The 'Normal' output parameter indicates that, based on the input parameters and model analysis, the steam power plant is in an expected and stable operational state. This condition implies that no immediate upkeep actions are required, and the system is functioning within acceptable operational parameters.

The 'Abnormal' output parameter means that the predictive preservation model has identified deviations or anomalies within the input parameters, indicating a potential issue in the steam power plant. The abnormalities could range from minor fluctuations to more significant deviations, suggesting a need for further investigation and potential upkeep actions.

The 'Early Maintenance' output parameter alerts that the predictive maintenance model has detected early signs of machinery degradation or performance deterioration. Acting upon this output parameter allows for proactive maintenance measures to address the identified issues, preventing potential breakdowns or further deterioration.

The 'Annual Maintenance' output parameter is indicative of routine or scheduled upkeep that should be conducted on an annual basis. This parameter does not indicate an immediate critical issue but rather a regular maintenance requirement to ensure the long-term health and performance of the steam power plant.

The categorization of these output parameters is based on a graduated scale of urgency and severity. 'Normal' represents the optimal running condition, 'Abnormal' indicates deviations from the expected state, 'Early Maintenance' signifies early signs of potential problems, and 'Annual Maintenance' implies routine maintenance. The rationale behind this categorization lies in establishing a clear and actionable framework for upkeep decisions. It allows for a systematic approach where upkeep actions can be prioritized based on the severity of the identified condition. For example, 'Abnormal' conditions may prompt a more immediate response compared to 'Early Maintenance,' which is more preemptive in nature. By categorizing the maintenance needs in this way, the predictive maintenance model can effectively guide maintenance personnel in prioritizing their actions, optimizing resource allocation, and ensuring the overall health and reliability of the steam power plant.

### III. PROPOSED APPROACH

In this section, we present the proposed approach to develop a predictive maintenance model for the Al Sabiya Steam Power Plant. This approach is designed to leverage advanced machine learning techniques combined with optimization algorithms to enhance the predictive accuracy and operational efficiency of a plant maintenance system. We used three optimization algorithms – Particle Swarm Optimization (PSO), Harris Hawks Optimization (HHO), and Cat Swarm Optimization (CSO) – to tune the parameters of the BiLSTM with Attention model. It is known that these algorithms are effective in solving optimization problems and reaching the best solutions at the level of basic algorithms by searching the specified search space and thus improving the model's performance.

Fig. 3 summarizes the methodology of this study, which includes two experimental schemes: (i) binary classification (Normal vs Abnormal) and (ii) four-class classification (Normal, Abnormal, Annual Maintenance, and Early Maintenance). Three optimized BiLSTM Attention models were trained, validated, and tested for predictive maintenance using the Al Sabiya dataset for each classification scheme. The methodology of this research is detailed in the following subsections.

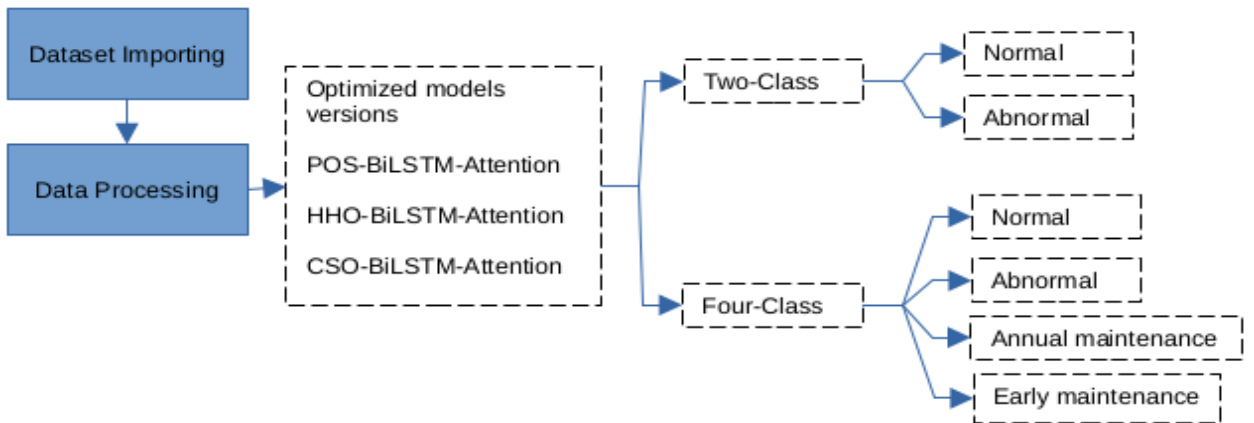
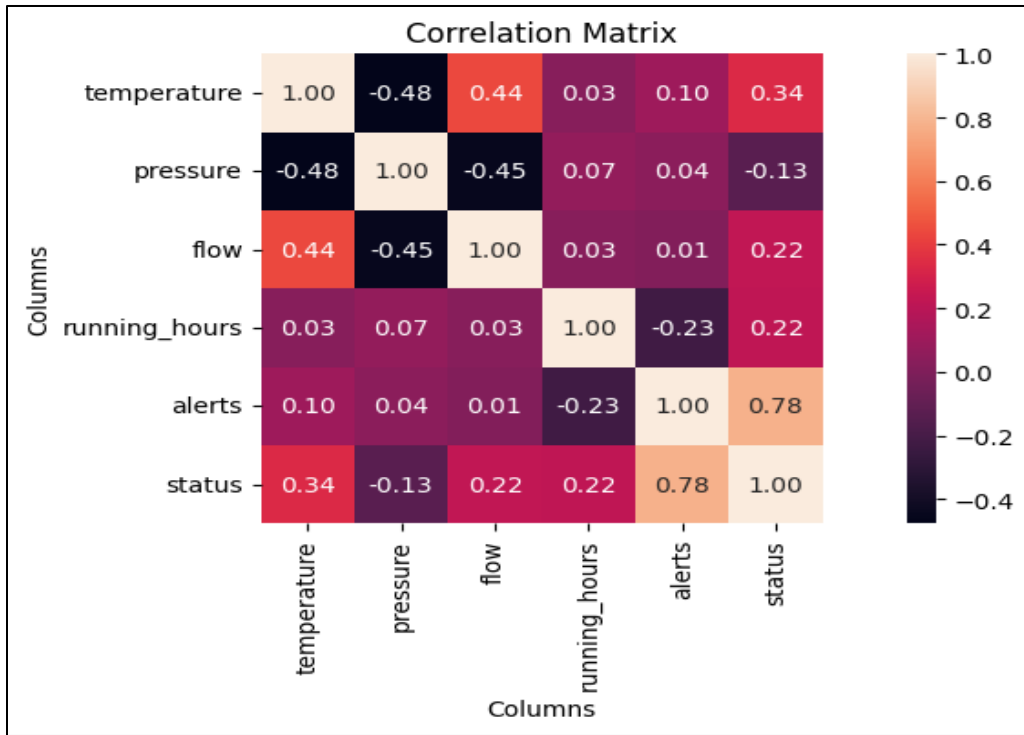


FIGURE 3. Overview of methodology

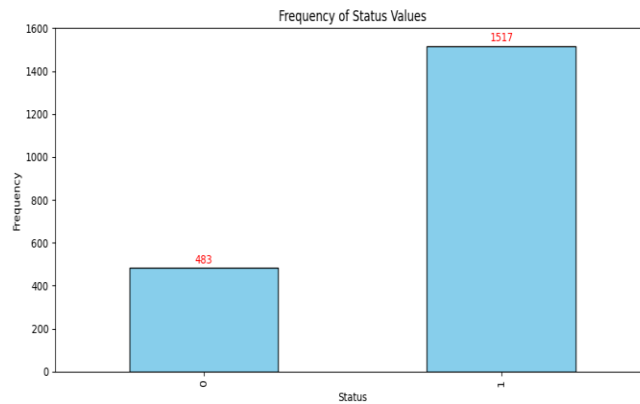
### A. Data Preprocessing

This phase includes a radical exam of the dataset to make sure statistics excellent and suitability for education and to identify capability troubles which includes lacking values, outliers and inconsistencies. Therefore, the correlation matrix became used to find out the correlation coefficients among the dataset's capabilities as it presents in the Fig. 5. After examining the dataset, 80% of the samples have been allotted to the schooling set and the final samples had been allocated to the test set.

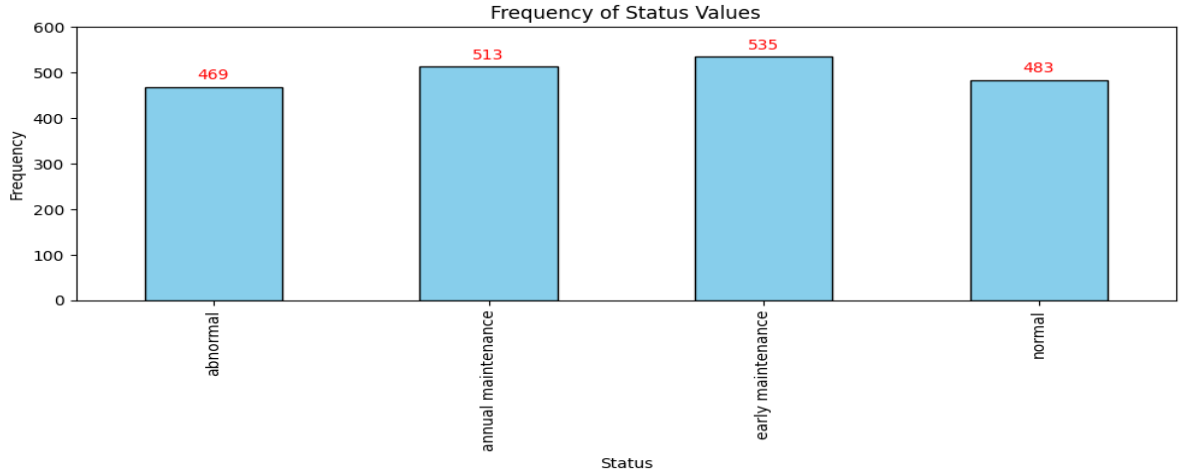


**FIGURE 4.** Heat map of different data inputs and operational status of the steam power plant.

For the Four-class approach Fig. 6 presented the frequency of different maintenance statuses, showing that 'early maintenance' is the most frequent with 535 occurrences, followed by 'annual maintenance' at 513, 'normal' at 483, and 'abnormal' at 469. And for Two-class approach the Fig. 5 presents the 'Abnormal' (which is presented in the Fig. with 1) is the most frequent with 1517 samples and the 'Normal' (presented in the Fig. With 0) at 483 samples this indicates a higher need for proactive and scheduled maintenance actions in the dataset.



**FIGURE 5.** The frequency of values in the Target column in the dataset in Four-class approach

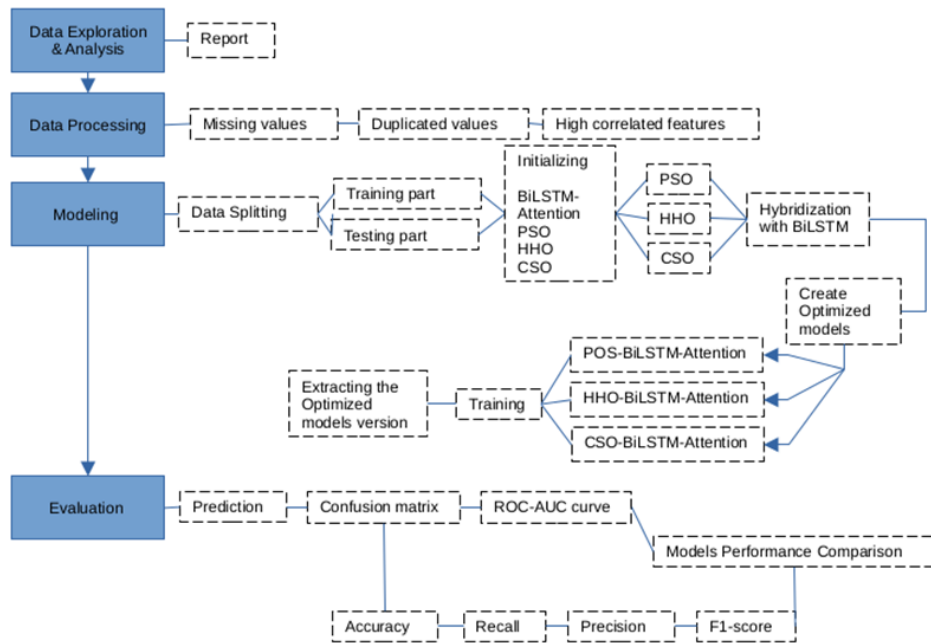


**FIGURE 6.** The frequency of values in the Target column in the dataset in Two-class approach

### B. Model Development

In This section we explain how we developed our predictive maintenance optimized models. We use BiLSTM with Attention mechanism technique and optimization algorithms to improve performance. Our process involved several important steps: preparing the data, designing the model architecture and training and evaluating the models. These steps are essential for making sure our predictive maintenance system is accurate and reliable.

The methodology model, shown in Fig. 7, gives an overview of the entire process, starting from collecting and preparing data to evaluate the final models.



**FIGURE 7.** Methodology Model for Predictive Maintenance

This Fig. outlines our workflow, starting with data preprocessing and initializing the main model and optimization functions. It then shows Hybridization process and model training using the Particle Swarm Optimization (PSO), Harris Hawks Optimization (HHO), and Cat Swarm Optimization (CSO) algorithms. The final steps involve models' evaluation and analyzing their performance to ensure they meet our predictive maintenance goals.

### C. Model Architecture

The core of our predictive maintenance model for the Al Sabiya Steam Power Plant is the BiLSTM-Attention classifier. This model effectively integrates Bidirectional Long Short-Term Memory (BiLSTM) layers with an Attention mechanism to capture complex relationships within the feature set and focus on the most relevant attributes for predicting maintenance needs.

The architecture starts with an input layer designed to handle the five selected features: temperature, pressure, flow, running hours, and alerts. This input layer feeds into a Bidirectional LSTM layer with 64 units. Despite the features not being time-series data, the BiLSTM layer helps in learning intricate patterns and dependencies among the input features in both directions, enhancing the model's ability to understand contextual interrelations.

Following the BiLSTM layer, the output is passed to a custom Attention layer. This layer computes a context vector by assigning different importance levels to various parts of the input feature set. This mechanism enables the model to focus on the most relevant features for making accurate predictions.

The context vector is then flattened and processed through a Dense layer with 64 units and ReLU activation, which further refines the feature representation. Finally, the model includes a Dense layer with SoftMax activation, producing class probabilities for the different maintenance states.

Fig. 8 illustrates the BiLSTM component, highlighting its bidirectional nature, while Fig. 9 shows the Attention mechanism, emphasizing how it selectively focuses on crucial parts of the input features to generate a context-aware representation.

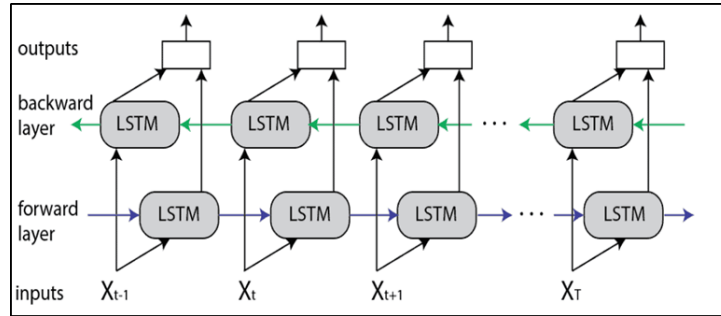


FIGURE 8. BiLSTM model Architecture [30]

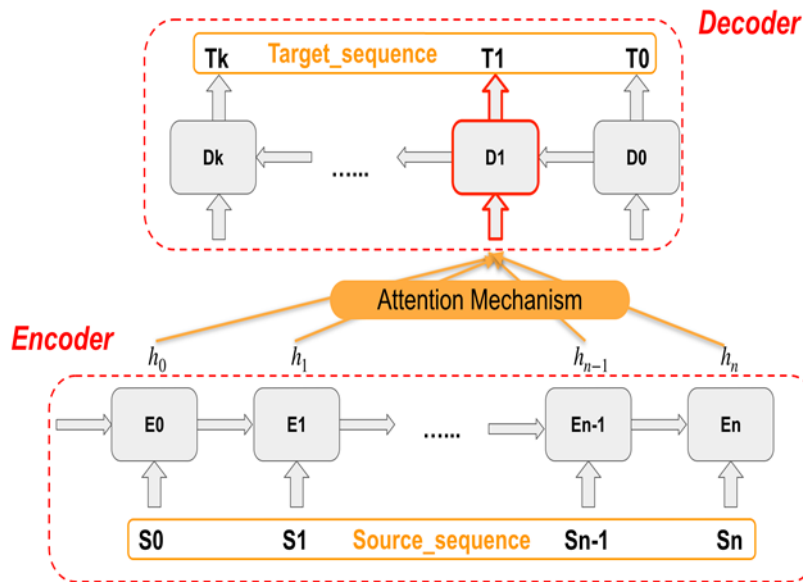


FIGURE 9. Attention mechanism Diagram [31]

Together, these components form robust architecture for predictive maintenance, leveraging the combined strengths of BiLSTM and Attention mechanisms to accurately classify the maintenance requirements based on the given features.

#### D. Optimization Techniques

In this section, we explore the optimization techniques employed to enhance the performance of our predictive maintenance model. Optimization is a critical aspect of machine learning that focuses on finding the best model parameters and configurations to achieve the highest possible accuracy and efficiency. For our BiLSTM-Attention model, we utilized three advanced optimization algorithms: Particle Swarm Optimization (PSO), Harris Hawks Optimization (HHO), and Cat Swarm Optimization (CSO). These techniques were chosen for their ability to efficiently navigate the complex parameter space and identify optimal settings that improve the model's predictive capabilities. By integrating these optimization methods, we aim to refine the model's performance, ensuring robust and reliable predictions for maintenance requirements at the Al Sabiya Steam Power Plant.

#### E. Particle Swarm Optimization algorithm

Kennedy and Eberhardt introduced PSO in 1995 [25]. social biologists believe that a flock that moves together can benefit from the experience of all other members over a single individual, in other words, as a bird flies, for example, in search of food. Of birds in the flock can share their discoveries and help the entire flock have the best catch. While replicating the movement of a flock of birds, we can imagine that the purpose of each bird is to help us to find the optimal solution in a high-dimensional solution space with the best solution. Being found by the herd is the best in space; this is a heuristic solution as we cannot prove that a true global optimum can be found and usually, we do not find that the solution found by PSO is very close to the global optimum.

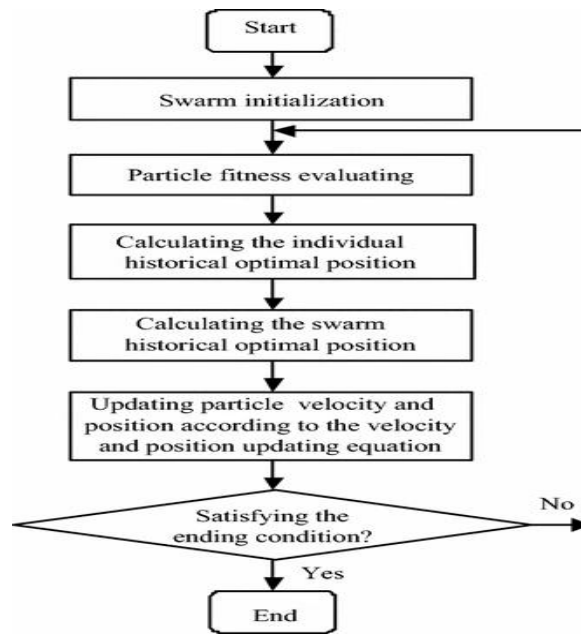


FIGURE 10. Flowchart of the particle swarm optimization algorithm [10]

One of the most positive characteristics of PSO which allow us to use in the predictive maintenance is that it converges faster than GAs [26][27].

#### F. Cat Swarm Optimization algorithm

Cat Swarm Optimization algorithm, introduced by Chu et al. (2006)[28], is inspired by the distinct behaviors of cats, specifically their resting and hunting activities. These behaviors are represented as seeking mode (SM) and tracing mode (TM),

respectively. In SM, cats appear to be resting most of the time, but they remain vigilant and alert, moving slowly and cautiously. Conversely, in TM, cats exhibit high levels of activity, energetically pursuing their targets with speed and precision.

#### Seeking mode

In Seeking Mode (SM), various regions of the search space are examined, corresponding to the positions of cats in SM. However, this search is confined to the vicinity of the seeking cat's position, functioning as a local search around the provided solutions, as illustrated in Fig. 11.

#### Tracing Mode

In Tracing Mode (TM), cats move towards the optimal position by updating their velocity and position based on the best position achieved so far as illustrated in Fig. 12 [28]

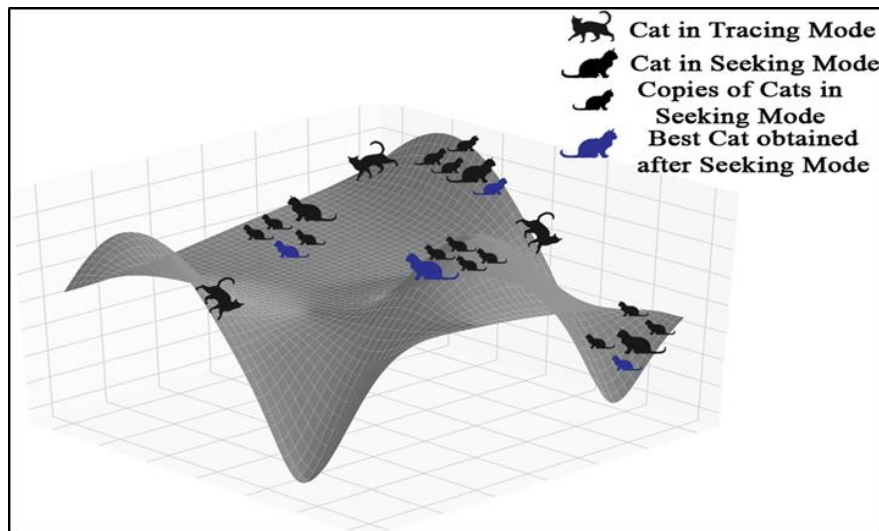


FIGURE 11. Seeking cats [28]

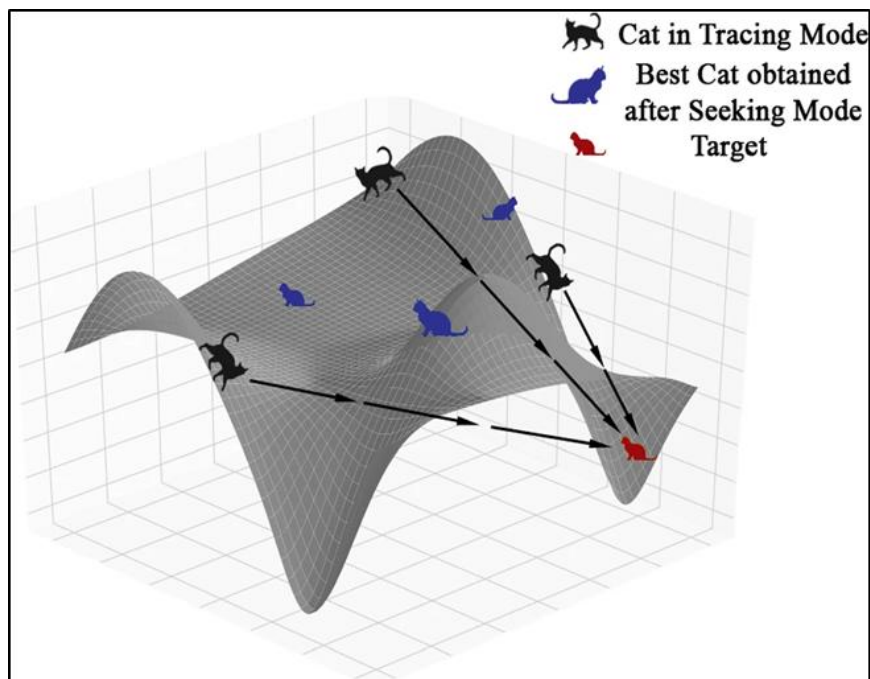


FIGURE 12. Tracing mode of cats [28]

### G. Harris Hawks Optimization algorithm

The Harris Hawks Optimization (HHO) method, introduced by Heidari et al. [29], is a recent addition to population-based optimization techniques. This algorithm emulates the cooperative behavior of Harris hawks in nature, where hawks use strategies like tracing, encircling, approaching, and attacking to surprise their prey. The HHO algorithm logical structure is depicted in Fig. 13. The authors modeled the hawks' behavior through three main steps, capturing the essence of their predatory tactics in the optimization process.

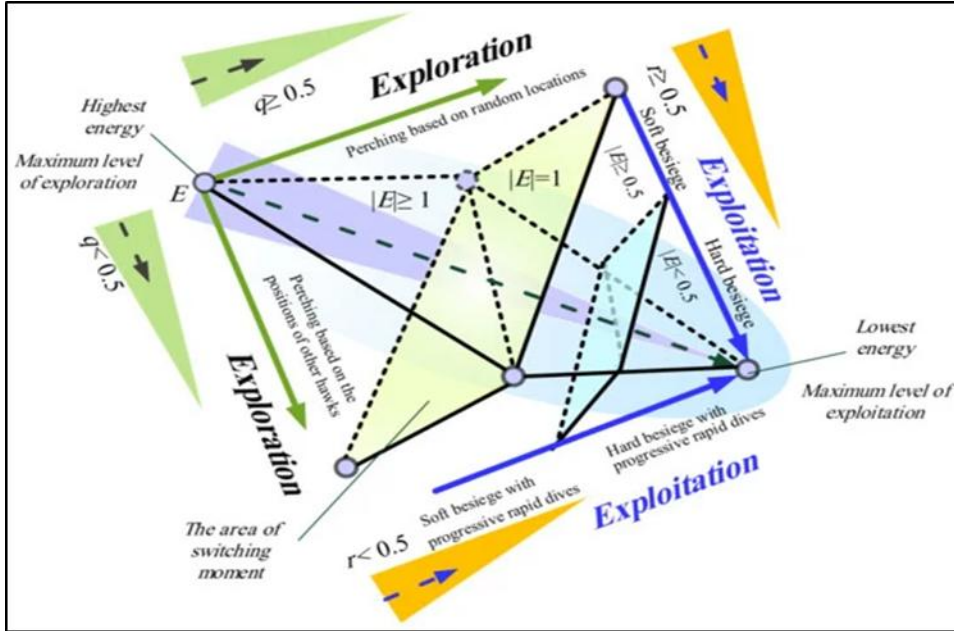


FIGURE 13. The selection processes of exploration and exploitation operators in the Harris' Hawks Optimization metaheuristic [29].

### H. Training and Evaluation

The development of a robust predictive maintenance model involves a comprehensive training and evaluation process. This section outlines the procedures followed to train the BiLSTM-Attention model and the methodologies used to evaluate its performance. Proper training ensures that the model learns effectively from the data, while thorough evaluation ensures that the model performs reliably and accurately in real-world scenarios. We detail the steps taken during the training process and describe the evaluation metrics and techniques used to assess the model's effectiveness.

#### I. Training process

In this section, we delve into the detailed training processes employed for three optimized models: PSO-BiLSTM Attention, HHO-BiLSTM Attention, and CSO-BiLSTM Attention. Each model integrates a BiLSTM with an Attention mechanism designed to enhance predictive maintenance capabilities for the Al Sabiya Steam Power Plant dataset. The training methodologies involve leveraging distinct optimization algorithms Particle Swarm Optimization (PSO), Harris Hawks Optimization (HHO), and Cat Swarm Optimization (CSO) to fine-tune hyperparameters and maximize model accuracy all the training parameters.

#### J. Evaluation process

Several metrics were utilized to evaluate the performance of the predictive maintenance models, including accuracy, F1-score, Sensitivity, Specificity, and Kappa Score. Accuracy measures the proportion of correctly predicted maintenance events to the total number of predictions, providing an overall assessment of model performance. F1-score harmonizes precision and recall into a single metric, crucial for balancing the model's ability to identify both maintenance needs and

operational states accurately. Sensitivity evaluates the model's capability to correctly identify true maintenance requirements, ensuring comprehensive coverage of potential issues. Specificity measures the model's precision in identifying normal operational states, minimizing false alarms and unnecessary maintenance actions. The Kappa Score assesses the agreement between predicted and actual maintenance events, providing a robust measure of model reliability and consistency.

This evaluation framework employs these metrics to comprehensively assess the performance of the predictive maintenance models developed for the Al Sabiya Steam Power Plant. Additionally, confusion matrices (CMs) are used to visualize and analyze the model's classification performance, offering detailed insights into true positives, false positives, true negatives, and false negatives across different maintenance states. By employing these evaluation methodologies, this study ensures that the developed models meet operational requirements, effectively predicting maintenance needs, minimizing equipment failures, and optimizing plant efficiency. This evaluation metric can be calculated using Equations (1)–(5)

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

$$Recall(Sensitivity) = \frac{TP}{TP + FN} \quad (2)$$

$$Precision(Specificity) = \frac{TP}{TP + FP} \quad (3)$$

$$F1_{score} = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

$$Cohen's\ kappa = (po - pe) / (1 - pe) \quad (5)$$

where:

po: Relative observed agreement among raters

pe: Hypothetical probability of chance agreement

#### IV. RESULTS AND ANALYSIS

This section presents the results and analysis of two distinct approaches applied to predictive maintenance at the Al Sabiya Steam Power Plant. The evaluation focuses on optimized models utilizing PSO, HHO, and CSO algorithms with BiLSTM Attention networks. We will provide detailed results for each approach across both two-class (Normal vs Abnormal) and four-class (Normal, Abnormal, Annual Maintenance, and Early Maintenance) classification scenarios.

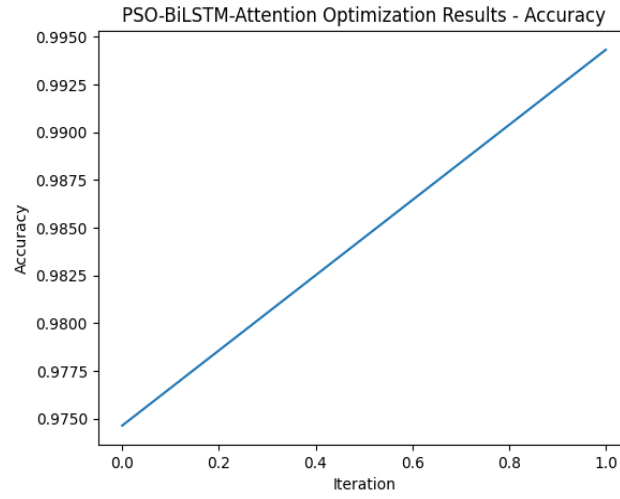
##### A. Binary Classification

In this section we will present the results and analysis of Two-class applied to predictive maintenance at the Al Sabiya Steam Power Plant.

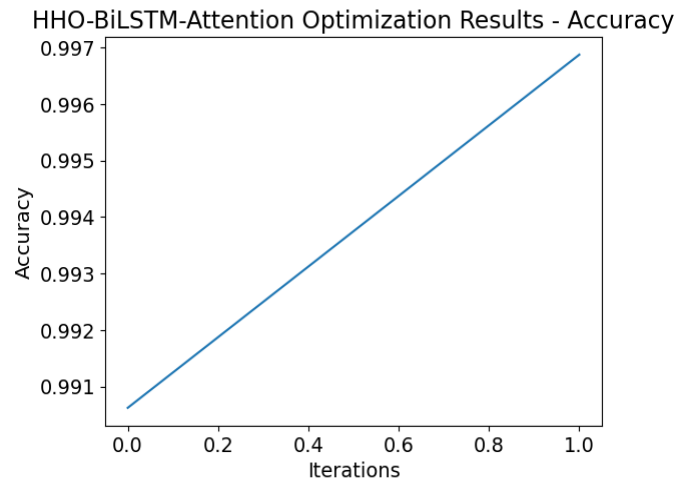
**Table 1. Optimized models classification accuracy in the First Approach.**

|                   | Training Time (s) | Accuracy | F1_Score | Sensitivity | Specificity | Kappa Score |
|-------------------|-------------------|----------|----------|-------------|-------------|-------------|
| <b>PSO-BiLSTM</b> | 50.64             | 1.0      | 1.0      | 1.0         | 1.0         | 1.0         |
| <b>HHO-BiLSTM</b> | 49.77             | 1.0      | 1.0      | 1.0         | 1.0         | 1.0         |
| <b>CSO-BiLSTM</b> | 117.63            | 1.0      | 1.0      | 1.0         | 1.0         | 1.0         |

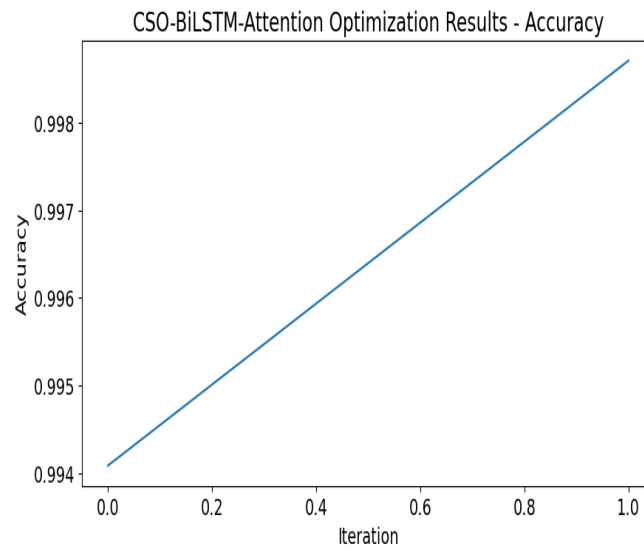
Based on Table 1, we can observe that all the models achieved perfect scores across all metrics. Notably, the HHO-BiLSTM Attention model demonstrated the lowest training time at 49.77 seconds, while the CSO-BiLSTM Attention model had the highest training time at 117.63 seconds. This indicates that while all models are highly accurate, there are differences in their training efficiency.



(a)

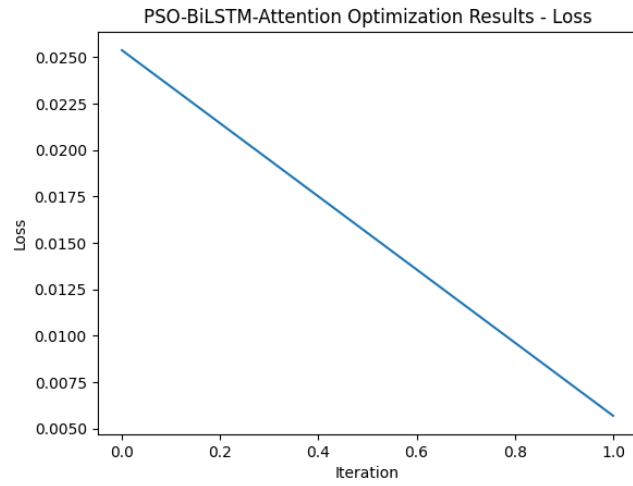


(b)

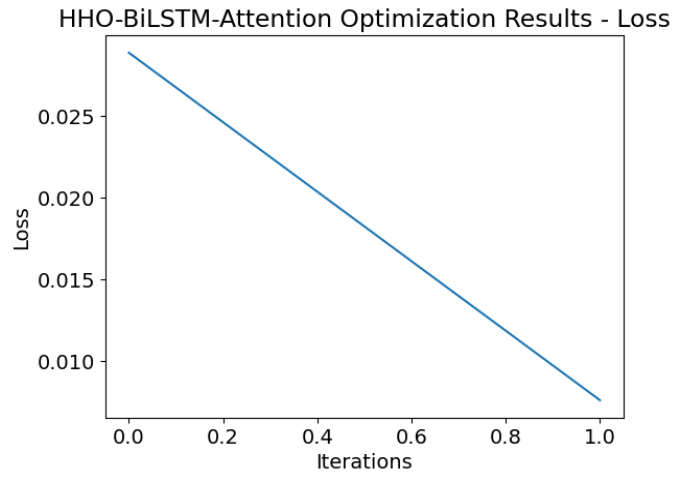


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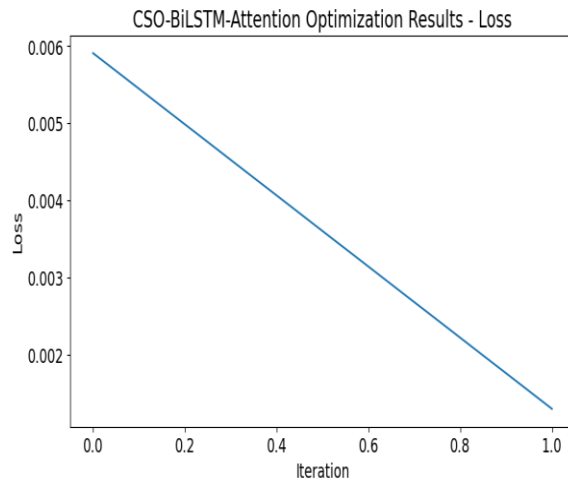
**FIGURE 14. Accuracy Curves obtained for various models: (a) PSO-BiLSTM Attention, (b) HHO-BiLSTM Attention, (c) CSO-BiLSTM Attention**



(a)

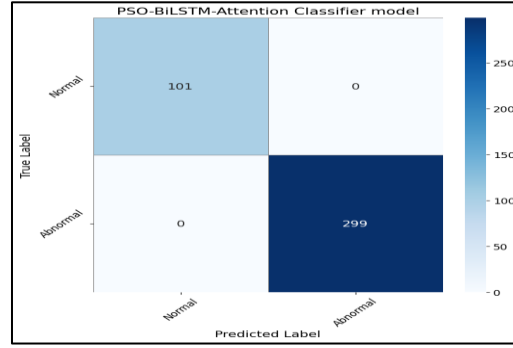


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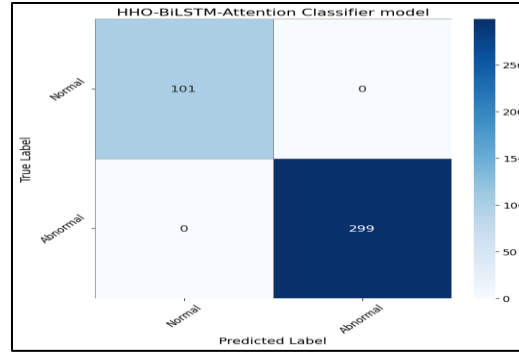


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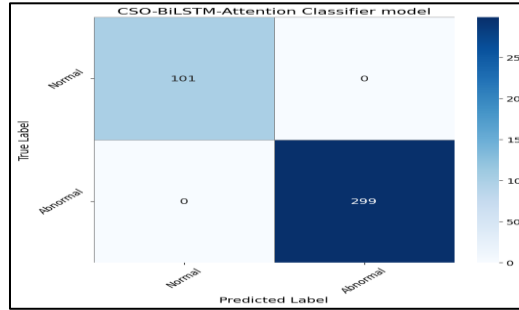
**FIGURE 15. Loss Curves obtained for various models: (a) PSO-BiLSTM Attention, (b) HHO-BiLSTM Attention, (c) CSO-BiLSTM Attention**



(a)



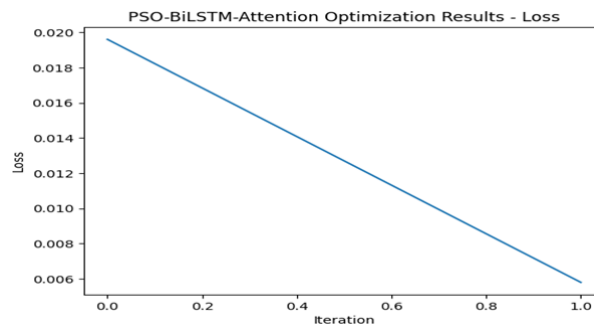
(b)



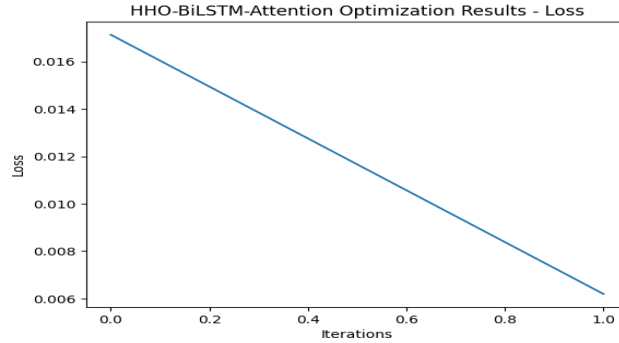
(c)

**FIGURE 16. Confusion matrices obtained for various models: (a) PSO-BiLSTM Attention, (b) HHO-BiLSTM Attention, (c) CSO-BiLSTM Attention**

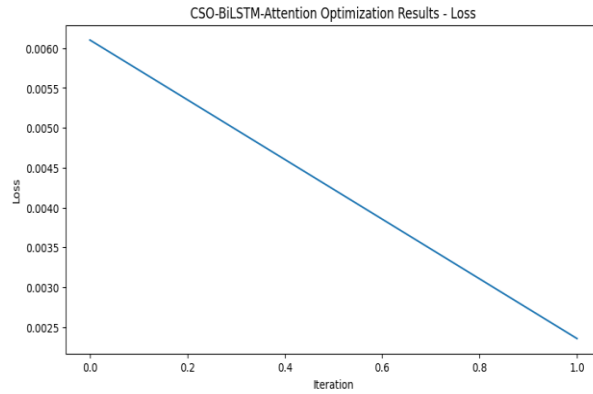
From Fig. 16, It is evident that all the optimized models achieved the highest performance with no misclassifications. This indicates that the models are highly effective in predicting the outcomes accurately in the binary classification scenario.



(a)



(b)



(c)

**FIGURE 17. Loss Curves obtained for various models: (a) PSO-BiLSTM Attention, (b) HHO-BiLSTM Attention, (c) CSO-BiLSTM Attention**

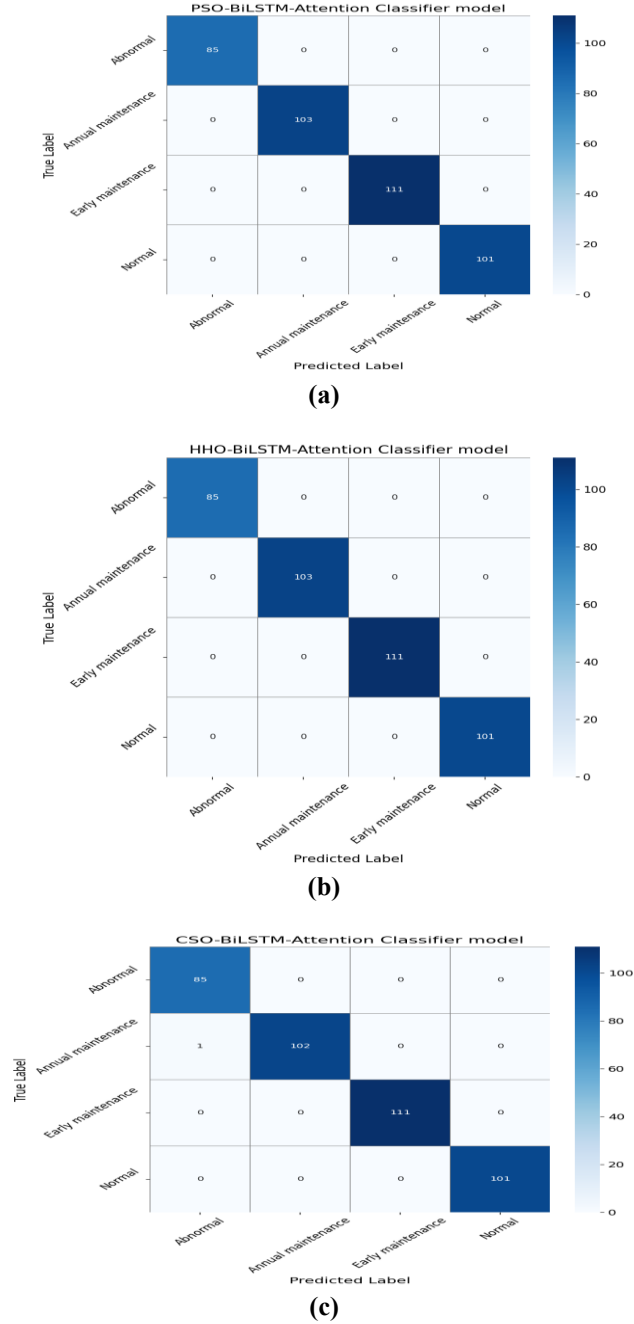
### B. Multi-Classification

In this section we will present the results and analysis of Four-class applied to predictive maintenance at the Al Sabiya Steam Power Plant.

**Table 2. Optimized models classification accuracy in the Second Approach.**

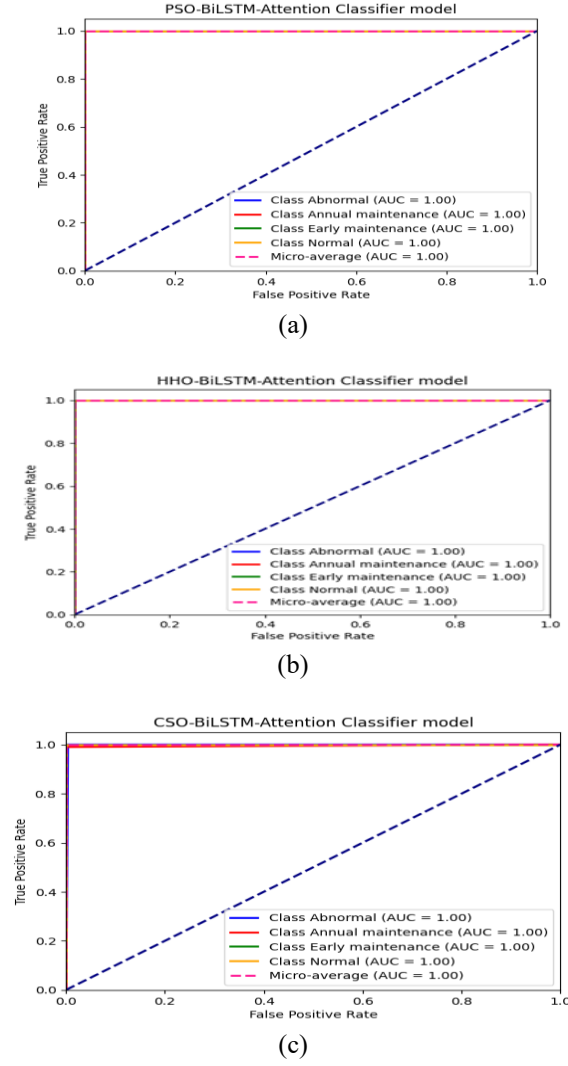
|                   | Training Time (s) | Accuracy | F1_Score | Sensitivity | Specificity | Kappa Score |
|-------------------|-------------------|----------|----------|-------------|-------------|-------------|
| <b>PSO-BiLSTM</b> | 40.47             | 1.0      | 1.0      | 1.0         | 1.0         | 1.0         |
| <b>HHO-BiLSTM</b> | 51.58             | 1.0      | 1.0      | 1.0         | 1.0         | 1.0         |
| <b>CSO-BiLSTM</b> | 100.09            | 0.998    | 0.998    | 1.0         | 0.998       | 0.997       |

Based on Table 2, we can observe that all the models achieved perfect scores across all metrics. Notably, the PSO-BiLSTM Attention model demonstrated the lowest training time at 40.47 seconds, while the CSO-BiLSTM Attention model had the highest training time at 100.09 seconds. This indicates that while all models are highly accurate, there are differences in their training efficiency.



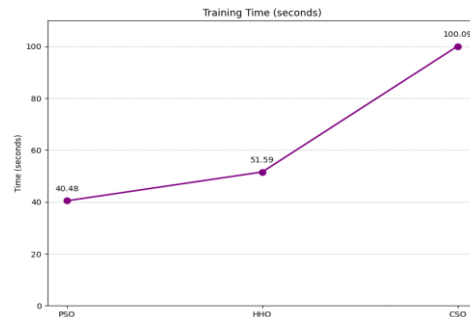
**FIGURE 18. Confusion matrices obtained for various models: (a) PSO-BiLSTM Attention, (b) HHO-BiLSTM Attention, (c) CSO-BiLSTM Attention**

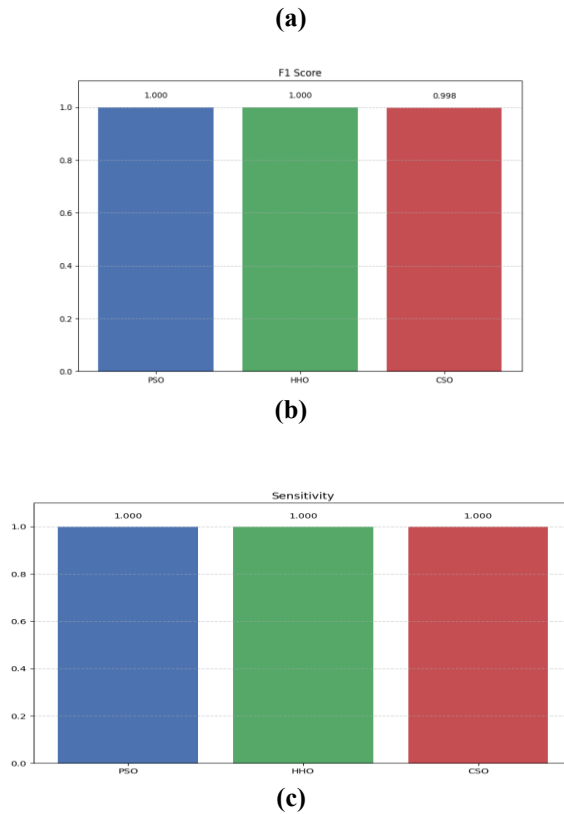
From Fig. 18, it is evident that both PSO-BiLSTM and HHO-BiLSTM Attention models achieved the highest performance with no misclassifications. While the CSO-BiLSTM Attention models have one sample that is misclassified, this model takes the longest Training time. But even though all models still achieved highly effective predictions of outcomes accurately in the Multi classification scenario.



**FIGURE 19. ROC-AUC Curves obtained for various models: (a) PSO-BiLSTM Attention, (b) HHO-BiLSTM Attention, (c) CSO-BiLSTM Attention**

From Fig. 19, we can observe that the AUC-ROC values illustrate the models' performance in distinguishing between classes. All optimized models achieved the highest AUC-ROC scores, indicating superior discrimination ability.





**FIGURE 20. Performance comparison a,b and c Fig obtained for various models: PSO-BiLSTM Attention, HHO-BiLSTM Attention, CSO-BiLSTM Attention in the Four-class approach**

## V. CONCLUSION AND FUTURE WORK

In this study, we introduced and evaluated three optimization-driven models—PSO-BiLSTM Attention, HHO-BiLSTM Attention, and CSO-BiLSTM Attention—for classification tasks. The models were tested on both four-class and two-class approaches, demonstrating exceptional performance across various metrics such as accuracy, precision, recall, F1 score, sensitivity, specificity and Kappa score. Both the PSO and HHO models achieved perfect scores of 1.0 in all metrics, indicating their robustness and reliability. Notably, the PSO model emerged as the most efficient, achieving similar high performance with shorter training times compared to the HHO and CSO models. This highlights the effectiveness of using PSO for optimizing BiLSTM Attention networks in classification tasks.

Future work could focus on further enhancing the efficiency and robustness of these models by exploring advanced hybrid optimization techniques and incorporating additional layers or modules into the BiLSTM Attention architecture. Moreover, testing these models on more complex and diverse datasets could provide deeper insights into their generalizability and performance under different scenarios. Another promising direction would be to investigate the real-time applicability of these models in dynamic environments, leveraging their high accuracy and efficiency for practical deployments in fields such as healthcare, finance, and autonomous systems. Additionally, integrating explainability methods could help in understanding the decision-making process of these models, thereby increasing their transparency and trustworthiness in critical applications.

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