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Developing an Innovative Machine Learning Integrated Cloud Monitoring System for Cloud-Based Services

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Abstract: A cloud monitoring system is an integrated solution for monitoring as well as managing the performance, availability along with the security of cloud-based infrastructure and services. It employs a variety of tools and methods to gather, analyze and present data on resource use, application activity and user interactions. By monitoring critical parameters in real-time, it allows proactive problem identification and resolution, resource allocation optimization, as well as adherence to service-level agreements. In this research, we developed an innovative machine learning (ML) integrated cloud monitoring system named Sea Horse fine-tuned Extreme Gradient Boosting (SH-XGBoost). Initially, we collected a dataset that includes various types of cloud environment scenarios to train our proposed approach. We utilized the Robust Scaling (RS) algorithm to pre-process the gathered raw data. We employed the Sea Horse Optimization algorithm to enhance the primary characteristics of the proposed XG-Boost algorithm. The suggested approach is implemented in Python software. The finding evaluation phase is performed with multiple metrics such as,F1-score (98.49%), Recall (98.38%), Precision (98.53%) and Accuracy (98.43%) to assess the proposed SH-XGBoost approach with other conventional approaches. The experimental findings illustrate that the proposed SH-XGBoost approach performed better than other existing approaches for novel cloud monitoring systems.

Keywords: *Cloud Monitoring System, Cloud infrastructure, Machine Learning, Sea Horse fine-tuned Extreme Gradient Boosting (SH-XGBoost).*

1. Introduction

The cloud monitoring tool is essential for ensuring the stability, efficiency as well as safety of cloud servers and services. Currently, businesses are relying more on services offered in the cloud to innovate and improve efficiency, making the demand for strong monitoring tools essential [1]. A cloud monitoring service is primarily created to offer immediate insight into the condition along with the efficiency of cloud-based applications, apps and network elements [2]. The system tracks many measures like CPU usage, memory consumption, network information, delay and error rates to spot anomalies, pinpoint areas of congestion and avert possible problems before they become severe [3]. Organizations can enhance the user experience and reduce downtime by consistently monitoring these indicators to ensure the optimum efficiency, scalability and accessibility of their cloud-based systems [4]. Analytic engines, warning systems, surveillance visuals, and information agent collection are common components of cloud surveillance systems. Conveniently positioned gathering agent are used in the design of the cloud to gather information and manage multiple sources, including servers, networks, packages, and database [5]. The agents transmit the gathered data to a centralized tracking system for immediate analysis, processing and display through easy-to-use summaries and panels. Notifying solutions

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notify admins and DevOps teams of any anomalies or reduced effectiveness, enabling them to react swiftly and preempt any issues [6]. Modern analytical engine identify relationships, patterns, and correlations in data by applying machine learning and artificial intelligence techniques. This results in valuable information that may be used for planning capacity, handling resources, and efficiency improvement [7]. There are many benefits in using cloud monitor systems. Initially, it enables businesses to maintain a high level of service accessibility and dependability by promptly recognizing and fixing issues that could impact efficiency or disrupt operations [8]. Managing KPIs and creating threshold can help companies meet Service Level Agreements (SLAs) and avoid interruptions in service. It optimizes resource consumption and expense management by evaluating the use of resources, detecting underused assets, and redistributing resource based on demands. [9,10].

This not only decreases operational costs but also optimizes a return on investment (ROI) for cloud computing implementations. It improves safety through surveillance for unusual behavior, illegal entry attempts and breaches of compliance in the cloud system [11]. Organizations can promptly identify and address security concerns by linking safety incidents with productivity KPIs, protecting sensitive information and adhering to legal requirements [12].

The study aims to develop an improved cloud tracking system that uses innovative ML approaches to optimize the management of services that are cloud-based by including sea horse fine-tuned Extreme Gradient Boosting (SH-XGBoost).

The remaining portions of this study are outlined as follows: part 2, literature review, part 3, methodological framework, part 4, outcomes and part 5: conclusion.

2. Related works

The study [13] proposed an “Intelligent Monitoring System (IMS) for Photovoltaic (PV) systems” which utilized inexpensive components and small programs. There were many benefits for utilizing cloud monitor services. Businesses could maintain excellent reliability and accessibility by promptly recognizing as well as resolving issues that might have impacted productivity or disrupted operations. Companies could ensure adherence and minimize the chance of service disruptions by tracking KPI and setting certain thresholds. That aided in optimizing resource utilization and cost management by analyzing resource usage, identifying underutilized resources and distributing resources according to demands.

The study [14] developed AI algorithms to forecast blood sugar levels every 30 minutes, integrating cloud services, IoT and CGM wearables for personalized estimates. The sequence RNN-RBM deep learning (DL) model, which combines recurrent neural networks (RNNs) with restricted Boltzmann machines (RBM), was recognized as an advanced DL method used in modern technology for higher prediction accuracy. The research showed that the RNN-RBM, DL model outperformed traditional RNN methods and other comparable models in terms of accuracy in predicting.

The article [15] proposed the implementation of a "Cloud Intrusion Detection System (CIDS)" to safeguard the public cloud from any threats. The suggested CIDS comprised five primary components to track the network, record the flow of traffic, extract characteristics, evaluate flow, identify intrusions, react and document actions. An improved bagged ensembles system consisting of three DL models was used to anticipate incursions. The PSO-based hyper parameter choice technique outperformed all other alternatives.

The study [16] aimed to forecast early defects in an IoT setting to guarantee the integrity, precision, dependability and consistency of IoT-enabled products. The defect model for forecasting was assessed using decision tree, (KNN), Gaussian NB and random forest methods. The random forest approach demonstrated the highest accuracy among the models on the dataset. The findings demonstrated that the proposed model was effective, achieving the maximum accuracy comparable with a different model.

The study [17] introduced the Health Cloud system, which utilized ML and cloud computing to track the health state of patients with hearts. Heart illness could be forecasted using machine learning methods like SVM, KNN, "Neural Networks, Logistic Regression and Gradient Boosting Trees". The article assessed various ML techniques to determine the best precise model while adhering to Quality of Service (QoS) standards. The experimental findings suggested that logistic regression outperformed other models in terms of speed and accuracy.

The research [18] proposed a health surveillance system for a cloud-based IoT system. That predicted diseases by analyzing patients' physiological information through IoT devices and healthcare data. A disease diagnostic system was utilized to assess the health records of patients to provide a comprehensive health/medical recommendation. Once the medical staff verified the results, they were then transferred to the patient. The results showed that the suggested approach offered a practical situation for successful disease forecasting and early diagnosis, as well as delivering precise health and medical advice for patients.

The article [19] presented a control-loop efficiency surveillance system that operated in the cloud as a single entity to globally supervise data from numerous industrial facilities in different places. The Packet control unit (PCU) surveillance system was outlined, detailing its basic elements and their progression towards a cloud-based setup. The outcomes of applying cloud-based tracking to multiple important control loops, which encompassed a combination of optimal operating circumstances and various sorts of malfunctions, validated its usefulness.

The study [20] focused on cloud-based Intrusion Detection Systems (IDSs) chosen to safeguard the safety of valuable data and operations. IDS effectively identified irregularities in intricate network scenarios and ensured the safety of networks. "Deep Convolution Network (DCN)", IDS had a gradual learning rate and inadequate classification accuracy. DL techniques were commonly applied in various security information processes, images and signal analysis tasks, such as learning transfer limitations, module reusability and integrations. Results were additionally contrasted with modern vector-based SVM and recursive search of Neural Network (NN) weaknesses. The suggested model had superior performance overall.

3. Methodology

In this paper, we gather a cloud computing performance metrics dataset. We apply data preprocessing techniques, such as min-max normalization, to prepare the dataset for further analysis and modeling. We propose Sea Horse fine-tuned Extreme Gradient Boosting (SH-XGBoost) to enhance the predictive accuracy of our model on the cloud computing performance metrics dataset.

3.1 Dataset

The data set contains measurements of performance in a cloud computation setting. The characteristics encompass Central Processing Unit (CPU) utilization, utilization of memory, traffic on the network, electrical consumption, the number of processed directions, time required for execution, the efficiency of energy, type of job, task importance and task state. The data set is designed to analyze the effects of ML optimization methods on energy consumption and implementation time in cloud-based settings. The information contained in this dataset was gathered from a replicated cloud-based computing system. The values encompass a broad spectrum of potential states and circumstances inside a system that uses cloud computing [21].

3.2 Robust Scaling (RS) algorithm

Two commonly utilized data scaling methods include the Min-max algorithm and the Z-score algorithm. The present investigation utilized Min Max Normalization.

3.2.1 Min Max Normalization

Min Max Normalization enhances data normalization by ensuring consistent evaluation throughout different data sets. This strategy allows organizations to improve the security framework, mitigating hazards and safeguarding connections from unforeseen cyber threats. We provide the Min-Max Normalization method to address significant data value inconsistencies resulting from varying dimensions as shown in equation (1).

$$X = \frac{x - Min}{Max - Min} \tag{1}$$

The labels Min and Max reflect the highest and lowest values for each dimension, correspondingly.

Min-Max normalization process scales data to a range of 0 to 1 while preserving the linear relationship of the initial information, which enhances both the precision and the rate of resolution in the model.

3.3 Sea Horse Optimization (SHO)

SHO enhances cloud monitoring with resource allocation, anomaly detection and sea horse behavior modeling for optimized service delivery and cost efficiency.

3.3.1 Seahorse mobility behaviours

Seahorse movements can be categorized into two scenarios: one is the spiraling movement of the seahorse's tail in response to ocean currents, while the other is the random motion of the seahorse's tail caused by waves.

Initial case: The seahorse rotates in the vortex of the sea. The seahorse moves in a spiraling manner to maximize its efficiency and a Levy flight is employed to model the Seahorse's movements. This technique prevents the SHO approach from converging on a locally ideal outcome by utilizing the Seahorse's distinctive spiral movement to continuously adjust the angle of rotation and broaden the search space around the current localized solution. This is accomplished by statistical methods as follows in equation (2).

$$W_{new}^{1}(s+1) = W_j(s) + levy(\lambda)(\left(W_{elite}(s) - W_j(s)\right) \times w \times z \times y + W_{new}^{1}(s)) \quad (2)$$

Where w, z and $y$denotes the vector in three-dimensional space (w, z, y) in the rotational movement.

Here w, z and y are the dimensional vector variables w, z, y in the spiral movement.

The seahorse exhibits Brown's law of motion as it moves with the waves in case two in equation (3).

$$\sigma = \frac{\Gamma(1+\lambda)\times \sin(\frac{\pi\lambda}{2})}{\Gamma(\frac{1+\lambda}{2})\times\lambda\times 2(\frac{\lambda-1}{2})} \quad (3)$$

On the opposite side of the $q_1$threshold, Brown's law is utilized to imitate the size of the steps of the sea horse's movements to enhance the exploration of the area of search for SHO. The expression for this simulation is in equation (4):

$$W_{new}^{1}(s+1) = W_j(s) + rand \times k \times \beta_s \times (W_j(s) - \beta_s \times W_{elite}) \quad (4)$$

The value of the coefficients, denoted as$k$, is fixed to k = 0.05 in this paper.

3.3.2 Seahorse hunting behaviour

Sea horses are picked upon in two different situations: either success or failure. This article provides an arbitrary value q_1 to imitate both instances. The seahorse's attack rate that is achieved in real life is 90%. Therefore, we establish a critical value as $q_{1>0.1}$ to indicate the effective capture of the prey by the seahorse. Conversely, if the prey escapes due to being more quickly compared to the seahorse during predatory behavior, its capture is not successful. This scenario is represented by the following computational structure as shown in equation (5).

$$W_{new}^{2}(s+1) = \begin{cases} \propto\times\left(W_{elite} - rand \times W_{new}^{1}(s)\right) + (1-\propto) \times W_{elite} q_{1>0.1} \\ (1-\propto) \times (W_{new}^{1}(s) - rand \times W_{elite}) + \propto\times W_{new}^{1}(s) q_{1\le 0.1} \end{cases} \quad (5)$$

W_{new}^{1}represents the updated location of the seahorse at time$s$. q_2 Is an arbitrary number between 0 and 1, utilized to modify the seahorse's movement distance during hunting, decreasing proportionally as each iteration advances.

3.3.3 Seahorse mating behaviour

Male seahorses grow older in the natural world. In the SHO method, superior values for fitness are selected as male groups for development, while the values that remain are used as female populations to generate future generations with improved traits. The formula for this is as follows in equation (6-7)

$$father = W_{sort}^{2}\left(1{:}\frac{pop}{2}\right) \quad (6)$$

$$mother = W_{sort}^{2}\left(\frac{pop}{2} + 1{:}pop\right) \quad (7)$$

W_{sort}^{2}Denotes the fitness score of all W_{sort}^{2}arranged in descending order based on predatory behavior, whereas both parents refer to the male and female people, correspondingly. The SHO method simplifies the process by generating one child for each pair of seahorse mating at random, as expressed below in equation (8).

$$W_j^{offspring} = q_3 W_j^{father} + (1 - q_3) W_j^{father} \quad (8)$$

q_3 is an arbitrary number among 0 and 1.j is a positive number from $[1, pop/2]$. W_j^{father} and W_j^{father}represent individuals selected at random from male and female groups.

3.4Extreme Gradient Boosting (XGBoost)

XG-Boost is well-suited for improving the efficiency of a clouds monitoring tool for stored in the cloud services. XG-Boost utilizes advanced ensemble learning techniques to analyze large volumes of data from cloud services instantly, allowing for precise anomaly forecasts and identification. XG-Boost has been employed to obtain an effective model characterized by rapid computing speed and effectiveness. The formula utilizes a combination approach to generate predictions by modeling the expected errors of decision trees to optimize subsequent forecasts.

The production of this model includes the reporting of the value of each feature's influence in calculating the prediction of the final building performance score. This feature value signifies the impact that every attribute has on predicting learning outcomes in general terms. XG-Boost facilitates parallelization by concurrently generating decision trees. The algorithm possesses the significant characteristic of distributed computing, enabling it to effectively process extensive and intricate models. The analysis of large and diverse datasets characterizes it as an out-core computing. The management of utilization of resources is effectively executed using this analytical approach. To minimize the mistake, it is necessary to incorporate a different model at each iteration.

The goal of the function of XG-Boost at iteration s is Equation (9):

$$K(s) = \sum_{j=1} K(y_{out_i}, y_{out_j^{(s-1)}} + e_s(w_j) + h(g_s) \quad (9)$$

The variable y_{out_i} represents a known real value obtained from the training dataset. The combined component can be denoted as $e(w + dw)$, wherein x is equal to$x = y_{out_j^{(s-1)}}$. It is necessary to employ the Taylor approximate. Consider the most basic linear approximate of the function $e(w)$ as in equation (10).

$$e(w) = e(a) + e(a(w - a)dw = f_s(w_j) \quad (10)$$

In this context, the loss equation$K$, denoted as $e(w)$, is being evaluated. The variable$a$ represents the expected outcome from the previous procedure $(s - 1)$, while e_s refers to the additional learning that needs to be incorporated in step$s$. The second-order Taylor approximation can be defined as follows in equation (11-12)

$$e(w) = e(a) + e(a)(w - a) + 0.5e'(a)(x - a)^2 \quad (11)$$

$$K(s) = \sum_{j=1}[K\left(y_{out_i}, y_{out_j^{(s-1)}}\right) + g_j e_s(w_j) + 0.5 l_j e_s{}^2(w_j)] + h(e_s) \quad (12)$$

Upon removing the constant components, we are left with the eliminated objectives that need to be minimized at step$s$ in equation (13).

$$K1(s) = \sum_{j=1}[g_j e_s(w_j) + 0.5 l_j e_s{}^2(w_j)] + h(e_s) \quad (13)$$

3.4.1 Integrating Hybrid Sea Horse Algorithm with extreme Gradient Boosting (SH-XGBoost)

A cutting-edge approach for enhancing cloud monitoring systems for cloud-based services involves the integration of the hybrid SHO with XG-Boost. This combination utilizes the flexible features of the Sea Horse optimization, which mimics the unpredictable habits of sea horse colonies, to effectively handle and adjust to the intricate as well as constantly changing characteristics of cloud-based settings. The combined system combines the advanced forecasting abilities of XG-Boost, known for its effectiveness in managing massive data sets with high dimensions, to provide enhanced precision, scaling and real-time adaptability to track different aspects of cloud services along with the infrastructure. This combination allows for early identification of irregularities, efficient allocation of resources and enhancement of system stability, ultimately boosting the effectiveness of cloud surveillance to ensure outstanding efficiency and user contentment. Algorithm 1 depicts the process of SH-XGBoost.

Algorithm 1: SH-XGBoost

```
Initialize sea_horse_population

Initialize xgboost_model

for each iteration in max_iterations:

  Evaluate sea_horse_population using a fitness function

  Select top performers for reproduction

  Generate offspring through crossover and mutation

  Update sea_horse_population with new offspring

  Train XGBoost model on sea_horse_population

  Evaluate the XGBoost model on the validation set

  if XGBoost performance improves:

    Update best_model_weights

    Save best_model_weights

  if convergence_criteria_met:

    break

Return best_model_weights
```

4. Result and Discussion

The recommended task is executed on open-source Anaconda 2024, Python (3.12.1) and Mandatory for co-installation using Python to execute the process. In this section, the effectiveness measurement of the "proposed approach involves assessing it in terms of Accuracy, Precision, Recall and F1-score as well as conducting a comparative analysis with other existing methods, including Long short-term memory (LSTM) [22] and fuzzy information system Long short-term memory (FLSTM) [22]". Table 1 depicts the prediction outcomes.

Table 1. Prediction Outcomes

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
LSTM	95.07	95.07	95.06	95.07
FLSTM	98.04	98.03	98.04	98.03
SH-XGBoost [Proposed]	98.43	98.53	98.38	98.49

The accuracy metric is a vital indicator of the cloud monitoring tool efficacy for cloud computing services. It reflects the system's ability to precisely and correctly assess the performance. Fig 1 and Table 1 illustrate a comparative assessment of accuracy between the proposed and conventional approaches. When compared to existing approaches like LSTM and FLSTM with accuracies of 95.07% and 98.04%, the suggested SH-XGBoost attains an accuracy level of 98.43 %. Our proposed method has demonstrated superior results compared to existing approaches, to accurately monitoring cloud-based services.

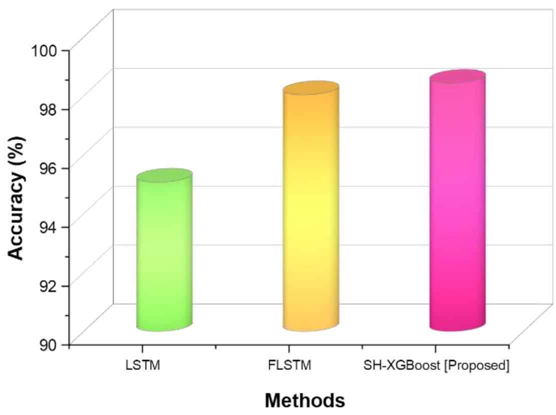

Fig 1. Accuracy

Precision is a measure of accurately identifying and notifying significant events or abnormalities in monitoring information. Precision refers to the proportion of correctly identified faults among all the faults that were detected. Fig 2 and Table 1 present a comparative analysis of precision. In contrast to existing methods like LSTM and FLSTM, which exhibit precisions of 95.07% and 98.03% respectively, the proposed SH-XGBoost demonstrates a higher precision at 98.53%. The proposed methodology for efficacy in accurately monitoring and managing cloud-based services has shown superior results compared to existing approaches.

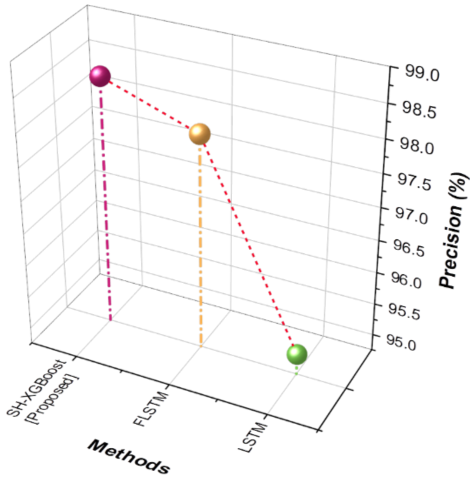

Fig 2. Precision

A web-based visibility method's recall metric for cloud computing services relates to the method's ability to accurately identify and alert users to significant events or anomalies in the cloud's design. Fig 3 and Table 1 demonstrate the comparative analysis of recall for the proposed techniques and other existing methodologies. Our proposed SH-XGBoost performed better than existing methods like LSTM and FLSTM, which produce recall rates of 95.04% and 95.06%, correspondingly. A greater accuracy value of 98.38% is obtained with the proposed SH-XGBoost. The approach that has been suggested has shown to be remarkably effective in improving the accuracy of the cloud tracking system for services that use the cloud.

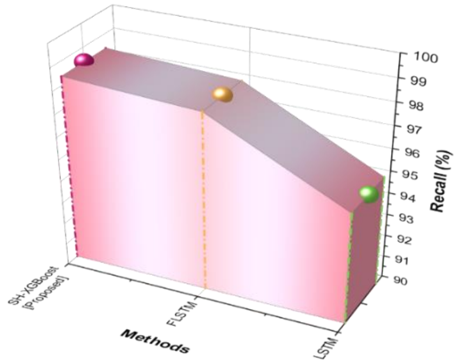

Fig 3. Recall

The F1-score metric is vital for analyzing the usefulness of a strategy in task categorization, particularly in spotting abnormalities along with efficiency maintenance. Fig 4 and Table 1 present a comparative analysis of the F1-score of the suggested method compared to different existing methods .Compared with techniques such as LSTM and FLSTM, that yield F1-score values of 95.07% and 98.03%, correspondingly, the suggested SH-XGBoost achieves 98.49%. The proposed method performed better than current methods in terms of enhancing the cloud surveillance platform's accuracy for cloud-based services.

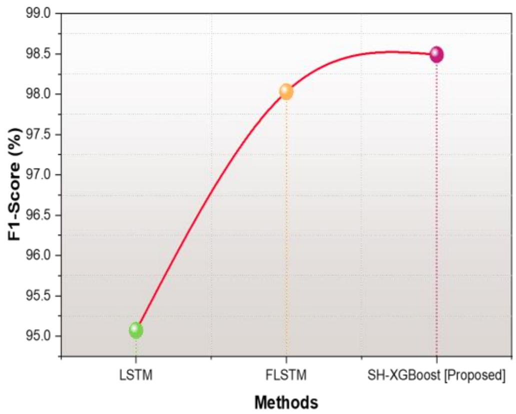

Fig 4. F1- score

5. Conclusion

Optimizing both reliability and performance is crucial in the ever-changing realm of services that use the cloud. In this research, we presented an innovative method; Sea Horse fine-tuned extreme Gradient Boosting (SH-XGBoost), which accurately monitors and analyzes the performance of cloud-based services. Experimental results showed F1-score (98.49 %), Recall (98.38%), Precision (98.53%) and Accuracy (98.43%). The proposed strategy was compared to previous techniques, and assessments showed that it was better for monitoring cloud systems in the cloud. Cloud surveillance systems are designed to handle big and complex architectures but may encounter scalability challenges as clouds grow in size and complexity. In future research, As cloud environments get more intricate, there will be an increasing need for automatic and synchronized functionalities in systems for monitoring. This can include automating repetitive processes, coordinating reactions to occurrences and enhancing resource allocation.

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