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EEF-OCS: Energy Efficient Framework based on Hybrid Learning for Optimal Cloud Selection.

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Abstract: Nowadays, choosing a reliable cloud provider has grown to be quite difficult due to the exponential growth of cloud services. A thorough evaluation of cloud services from numerous angles necessitates an accurate decision-making process. Further study is required to provide more authentic decision making outcomes because of the enormous complexity and limits of current methodologies, which undermine the credibility of the energy efficient cloud selection process. This work aims to improve Hybrid machine learning (ML)-based Energy Efficient Framework. Methods: In this paper, we present a machine learning-based method for predicting Energy Efficient Cloud Selection (EEF-OCS), in which we use our proposed model to analyse various risk factors and predict Energy Efficient Cloud Selection, and we compare this method to other ML approaches like Logistic Regression, KNN, Decision Tree and MLP. Results: Among ML approaches, our suggested model EEF-OCS has produced the best prediction. We were able to get an accuracy of 91.78%, a precision of 92.00%, a recall of 91.78%, and f1 score of 91.71%.

***Keywords**: Cloud computing, energy efficient, Grid Computing, QWS, machine learning*

1. Introduction

Cloud computing has now become incredibly popular in recent times. Cloud computing provides significant advantages over conventional computing models that rely on a dedicated internal infrastructure in the sense of scalability, dependability, and cost [1]. The cloud computing technology, which is derived from a number of cutting-edge technologies, is frequently mistaken with other computer frameworks of a similar kind. Compared to the traditional approach, it provides higher savings and dependability [2]. Recent developments in technology has sped up the growth of cloud computing technologies. As a result, there are now far more services available from a variety of cloud providers. It can be challenging for cloud consumers to select the right service that meets their needs because there are so many service providers offering a wide range of services that are comparable yet have different features. Additionally, cloud consumers are unaware of how to improve and anticipate their demands. The primary elements in this context that allow for the identification and comparison of various providers of cloud services are QoS metrics. Performance, reaction time, privacy, and dependability of cloud services are examples of functional and non-functional properties described by QoS criteria [3].

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In a decision making dilemma, cloud users or a decision-maker assess the different cloud - based services applying QoS standards. The selection of cloud services is thus a multi-criteria decision-making challenge (MCDM) [4]. Choosing the best computing platform for a potential client throughout the selection phase for cloud computing is the key problem. Another significant difficulty that requires great accuracy and effectiveness is choosing the appropriate cloud service.

The discovery of critical factors that indicate whether the cloud platform supplied satisfies the business and technical requirements of clients is a significant issue with classification. Figure 1 illustrates the two distinct needs for cloud customers functional and non-functional. A service's precise behaviour is referred to as a functional requirement, whereas a non-functional requirement relates to how well a service performs. The selection of acceptable cloud QoS criteria is a particularly challenging issue due to the complexity of cloud services and the lack of standardised measurements. In actuality, a lot of researchers put a lot of work into choosing a cloud service [5]. The cloud service assessment index, which has been extensively adopted as a criterion for choosing cloud services, was established. It aggregates cloud QoS requirements into seven core areas. In order to precisely gauge the service quality of the cloud provider, several QoS criteria, which are described in Table 1, are also employed. Each attribute is subjected to a straightforward computation, and the results may be used as input in any method for choosing a cloud service.

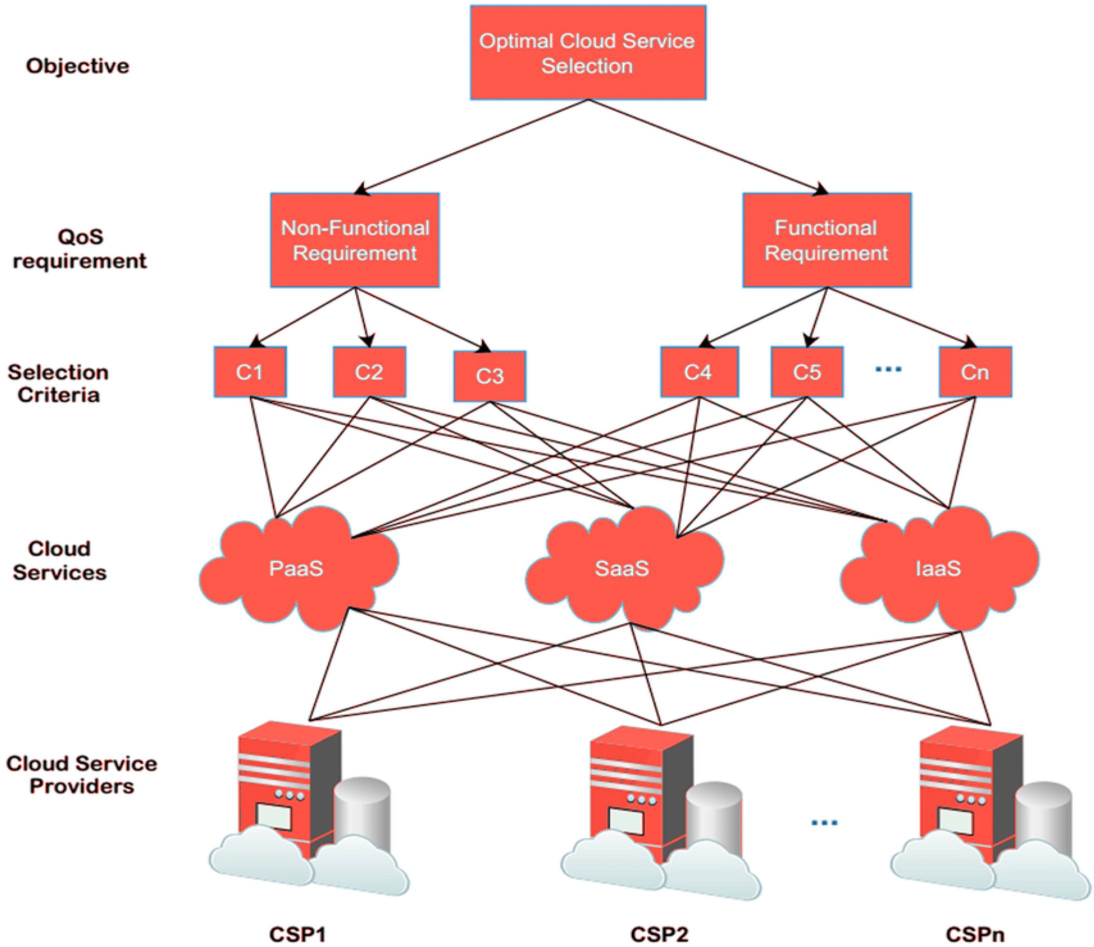


Fig. 1: Optimal cloud selection flow chart

The importance of every performance metric in our suggested technique is determined by taking into account actual contexts in which cloud clients express preference. The experimental results demonstrate how the proposed approach is much more powerful and integrated than traditional approaches to choosing a cloud service. With the use of score based prediction classification model, experimental research demonstrates how the suggested technique decreases the perceived complexity. The following contributions are relevant to this paper:

(1) Energy efficient score based prediction classification that aids cloud clients in selecting the best cloud provider. This paradigm looks at a range of subjective factors to identify suitable cloud service providers.

(2) To quantify users' preferences on typically non QoS criteria, we develop prediction box. We next utilise a prediction score approach to assess the weight of the QoS criterion.

(3) The strength of the suggested technique is confirmed in light of the implications of sensitivity analysis.

The remaining of the article is organised as follows. The relevant research in the subject of choosing cloud services is covered in section 2. Section 3 discusses motivation behind the research. The overview of dataset and proposed approaches are described in Section 4. In section 5, the thorough results analysis is covered. Finally, we give the concluding conclusions in Section 6.

2. Related Work

As demand for cloud services grew quickly, many academics started comparing the efficiency and calibre of service offered by various providers. In response to the growth of the Internet and increasing customer demand, the concept of service composition was created. There are two ways to express the cloud service composition difficulty. The strict functional requirements-based composition of cloud services is the first problem. The second set of problems focuses on picking the finest services out of all based on criteria other than functional ones (QoS).

Authors in [6] suggested an AHP-based SaaS selection strategy. The model's high processing cost and rank reversal handling problems are a drawback. The authors of [7] suggested employing QoS characteristics for AHP-based IaaS service selection. The model has a high temporal complexity and erratic comparison, which is a drawback. Authors have suggested the fuzzy AHP and fuzzy TOPSIS models in [8]. The model's weakness is that it cannot handle metadata and has difficult pattern finding and comparing consistency. The Cloud Service Interval Neutropic Set (CINS) time series evaluation model has been suggested by the authors in [9]. The approach has a computation cost that makes it difficult for it to manage subjectivity. Authors suggested ANP High Time Complexity with Increasing QoS in [10]. The model has an issue with inconsistent criterion comparison, which is a drawback. The TOPSIS and AHP models have been enhanced by the authors in [11]. The model duration complexity and inability to deal with ambiguous information are drawbacks. Authors in [12] suggested a two-way ranking system that applied AHP for service rating. The model's high computing cost and incapacity to handle rank reversal are drawbacks. The Neutrosophic Multi Criteria Decision Analysis (NMCDA) Scalability Framework has been recommended by the authors in [13]. The framework drawback is that it has problems with consistency comparisons and is challenging to modify comparison. The authors of [14] have suggested AHP and Fuzzy SAW. The model's weakness is that it struggles with comparative consistency and can't deal with subjectivity.

Numerous research projects have tried to find solutions to QoS-based service selection issues as the number of providers of cloud-based services has increased over the last year [15]. In [16] authors have introduced the SMICLOUD framework to compare and assess three IaaS cloud services. To evaluate and compare several IaaS cloud services, the SMICLOUD framework has been introduced. To calculate the weight of the criterion and assess the three IaaS cloud services, the authors employed the AHP approach. This approach was primarily focused on three fundamental stages: issue breakdown, priority assessment, and rating of IaaS service providers. A hierarchy linking the selection aim, the QoS characteristics, and the service providers is built in the first step. The second step employed a pairwise comparison matrix to determine the weights of the criterion. The ranking of IaaS cloud service providers is determined in the final stage using the weight of the criterion. Several empirical key performance (EKP) metrics for QoS qualities are presented by CSMIC in this research, and various cloud providers utilise these EKPs to compare it. The use of AHP also makes it possible to estimate interdependencies across metrics and measure criteria weights based on user desire. Based on cloud customer's requirements and preferences, [17] selected the appropriate cloud database provider using the AHP technique. A hierarchy with three critical criterion and seven sub criteria is employed in this work. The [18] conducted an IaaS cloud evaluation using the evolutionary algorithm in conjunction with the AHP technique. In this article, a Cloud Genius framework with 15 QoS criteria was proposed for evaluating the top IaaS service providers.

3. Motivation:

This part introduces an example to inspire our work in the real world. Imagine that ABC, a large hypothetical firm, offers consumers additional services in addition to health care. This business intends to increase consumer appeal by enhancing the effectiveness of its services. The corporation wants to move its services to the public cloud in order to provide a variety of services with energy efficient high efficiency, high security, the privacy of client information, and cheap maintenance costs:-

– Better cost control: ABC may dramatically save labour, management, IT, and installation cost by utilising cloud services.

– Save time & effort: No technical knowledge is required for programme upgrades, maintenance, or data security when using cloud solutions. Any employee may freely switch their attention from the system to the clients.

– Appealing to today's customer: Today's clients anticipate using their own tablets and smartphones to seek various services. With such a cloud-based technology, users may engage with the services at any time and from anywhere.

– Stay ahead of market trends: With real-time delivery, the cloud solution enables ABC to maintain its lead in the online market industry. By providing fresh features and services, it presents viable chances for business expansion. Additionally, the ABC is a client.

- based company, it offers its customers a full sales service that is of the highest calibre. ABC is searching for a provider of cloud services to execute its services.

There are several service providers offering a variety of services with differing QoS standards on the market today. To choose an appropriate cloud service from the available ones, ABC analyses all QoS parameters[19][20][21] and evaluates each service's effectiveness. A cloud service is typically preferred because it offers quicker memory and processing operations (such as availability and response times) and has reduced maintenance expenses. The company's unique requirements must be the basis for choosing a service provider. The weight of each QoS criterion can be determined based on the firm's preferences and requirements [22] [23] [24]. The organisation will select the service provider that performs the best. In this case, taking into account each person's tastes and needs is required to ensure that ABC is very satisfied. Since a choice of the best services without consideration of consumer expectations is inadequate.

Therefore, a method for choosing services is required that considers and precisely estimates ABC's choice.

4. Proposed Model:

4.1 Dataset: In this research, a hybrid learning strategy with an ideal set of concrete services has been studied and validated using the QWS dataset. University of Guelph student Eyhab Al-Masri collected the QWS dataset [25]. It contains the values for 2507 actual services QoS parameters. The reaction time, availability, throughput, dependability, success ability, and other nine QoS metrics are included in this dataset. This dataset has been used by several academics to study the composition of services [26][37][38].

Table 1: Detail description of dataset.

S.N	QoS parameters	Details
1.	Response Time	It is the overall time required to reply to a service request.
2.	Throughput	It is defined as the quantity of service requests fulfilled by cloud service providers in a certain period of time.
3.	Availability	It speaks of the proportion of time the cloud service is usable under typical conditions.
4.	Cost	It establishes the cost of particular services that the consumer uses.
5.	Interoperability	Communication with other services offered by the same service or separate providers is possible.
6.	Stability	It is described as a service's operational fluctuation.
7.	Scalability	If a system can handle several customer inquiries at once without affecting performance, that is what it means.
8.	Accuracy	When using a cloud service, it assesses how closely the computed value adheres to the value that was provided.
9.	Adaptability	It demonstrates the ability of cloud service providers to comply with requests from cloud users for service adjustments.
10.	Usability	The amount of intuitive cloud service functionality is a subjective concept.
11.	Reliability	It displays how a service operates flawlessly under specific time and environmental conditions.

The cloud computing industry's top priority is energy efficiency. The widespread usage of cloud computing technology in particular concentrated on a number of the previously mentioned aspects. Response time is overall time required to reply to a service request, so efficient service provider should react in low response time. Throughput is defined as the quantity of service requests fulfilled by cloud service providers in a certain period of time, so high throughput is required for cloud service to be more energy efficient. Availability is the proportion of time the cloud service is usable under typical conditions. If in unit time cloud server can handle more number of request, so high availability is required for cloud service to be more energy efficient. Cost of particular services that the consumer uses. This feature is related to cloud clients, they required best service with less amount. Interoperability deals with communication with other services offered by the same service or separate providers is possible, so high interoperability is required for cloud service to be more energy efficient. Stability is described as a service's operational fluctuation, so high stability is required for cloud service to be more energy efficient. Accuracy using a cloud service, it assesses how closely the computed value adheres to the value that was provided, this feature is related to cloud clients, they required high accuracy. Adaptability demonstrates the ability of cloud service providers to comply with requests from cloud users for service adjustments, so high throughput is required for cloud service to be more energy efficient. Usability the amount of intuitive cloud service functionality is a subjective concept, so high throughput is required for cloud service to be more energy efficient. Reliability displays how a service operates flawlessly under specific time and environmental conditions, so high throughput is required for cloud service to be more energy efficient [39][40].

4.2 Data Pre-processing: Real-world data typically consists of noise, missing values, and maybe an impractical format, all of which prevent it from being used directly for machine learning models. Consequently, one cannot directly apply machine learning to real-world data. It is necessary to do operations known as data pre- processing in order to clean the data and prepare it in a format that is appropriate for a machine learning model. This improves the accuracy and productivity of the machine learning model [27]. Table 2 provides the first 5 records from the dataset and figure 2 provides the total count vs cloud class [41][42][43].

Table 2: First 5 records of QWS dataset

Index	Response Time	Availability	Throughput	Successability	Reliability	Compliance	Best Practices	Latency	Documentation	Ws RF	Class
1.	45.0	83	27.2	50	97.4	89	91	43.0	58	100	1
2.	71.75	100	14.6	88	85.5	78	80	64.42	86	93	1
3.	117.0	100	23.4	83	88.0	100	87	111.0	59	90	1
4.	70.0	100	5.4	83	79.3	100	75	63.0	91	90	1
5.	105.2	100	18.2	80	92.2	78	84	104.6	91	90	1

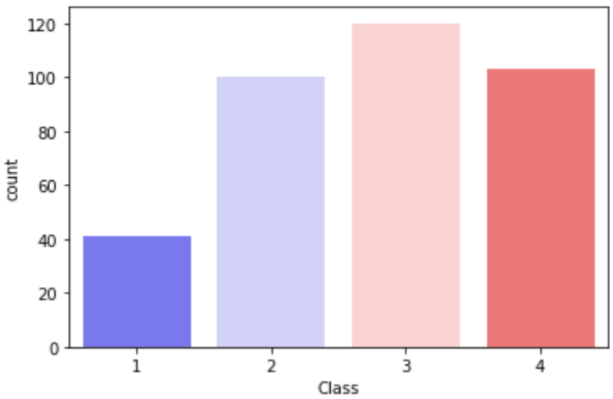


Fig. 2: the total count vs cloud class

- **Data Normalization:** When working with datasets, data normalization is an essential step that must be completed before the data can be used for data analysis or in the construction of models. The process of normalization data involves a number of phases, some of the most essential of which are the removal of NULL values and handling duplicates records from the dataset [28].

- **Feature selection:** Finding the optimal combination of features that enables one to construct accurate models of the phenomena being researched is the objective of the feature selection step in machine learning. Figure 3 depicts Corelation matrix betweeen cloud QoS paremeters and Figure 4 depicts the cloud class disstribution with respect to reliability and throughput

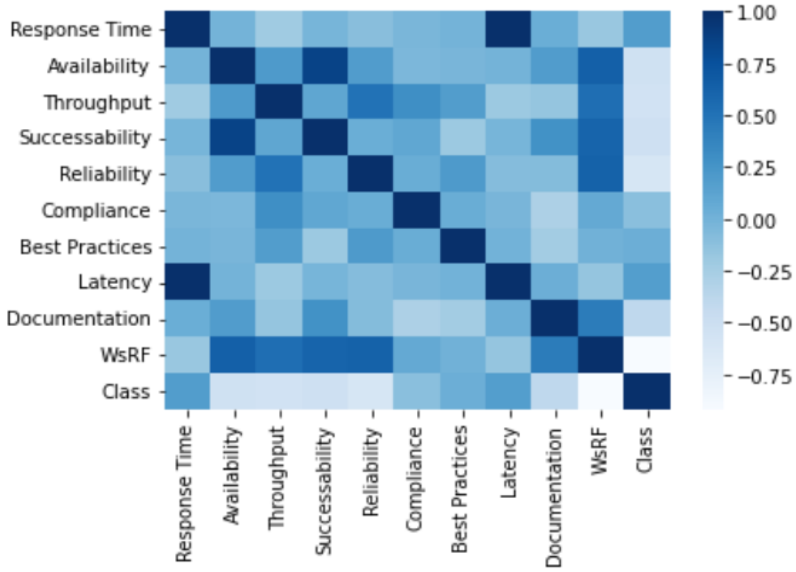


Fig. 3: Corelation matrix betweeen cloud QoS paremeters

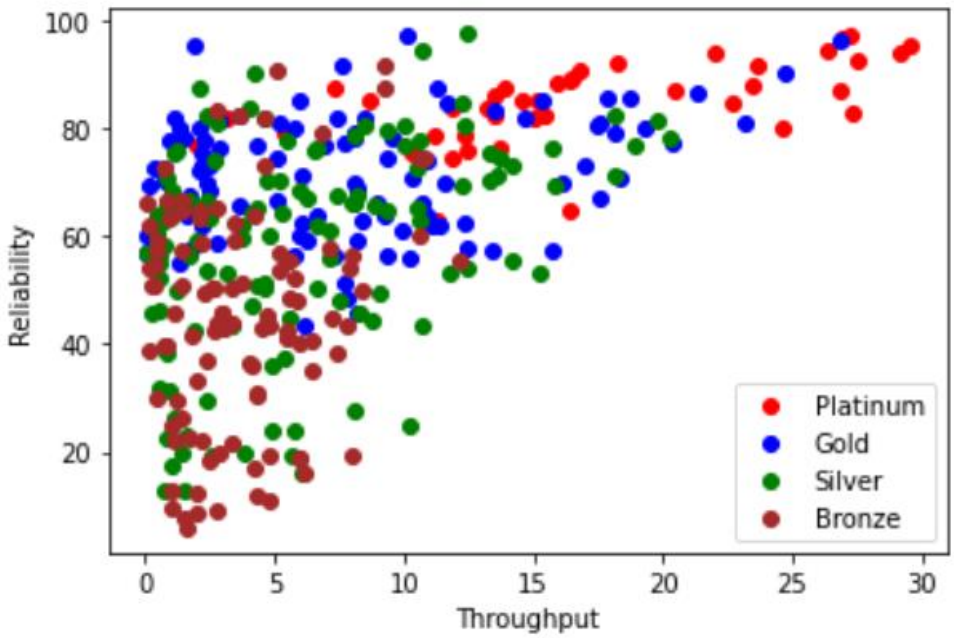


Fig. 4: the cloud class disstribution with respect to reliability and throughput

4.3 Machine learning classifier:

- **Logistic Regression:** Logical regression is a statistical technique that examines the connection between one or more independent variables and divides the data into distinct categories. It has widespread use in predictive modelling, which is a kind of statistical analysis in which a model assesses the mathematical likelihood of whether or not an occurrence belongs to a certain category [29].

- **KNN:** Since K-NN is a non-parametric technique, it makes no assumptions about the base data. It is also known as a lazy learner technique since it saves the training dataset rather than learning from it instantly. Instead, it uses the dataset to execute an action when classifying data. The KNN method simply saves the information during the training phase, and when it receives new data, it categorises it into a group that is quite similar to the fresh data.
- **DT:** The choice to make strategic splits has a significant impact on a tree's accuracy. Regression and classification trees have distinct decision criteria. To decide whether to divide a node into two or more sub-nodes, decision trees employ a variety of techniques. The homogeneity of newly formed sub-nodes is increased by sub-node formation. In other words, we may claim that the node's purity improves in relation to the desired variable. The decision tree divides the nodes based on all factors that are accessible before choosing the split that produces the most homogenous sub-nodes.
- **MLP:** An essential component of deep learning is a multilayer artificial neural network. Additionally, after finishing the session, you will understand: Examine the best methods for regularising and reducing the cost function in a neural network. To modify the weights in a neural network, use backpropagation. Convergence in a Multilayer ANN should be examined. Investigate multilayer ANN. In multilayer perceptron's, use forward propagation (MLP)
- **Light GBM:** LightGBM is a gradient boosting implementation on decision trees that improves model performance while using less memory. In order to address the constraints of the histogram-based approach, which is largely employed in all GBDT (Gradient Boosting Decision Tree) architectures.

4.4 Archihitecture: The whole architecture of our proposed model is shown in Figure 5. The discovery service provider will initially get in touch with the cloud service repository, which houses the whole pool of registered cloud services, whenever a user requests any cloud service. The request will be verified and validated by cloud service discovery. The next phase is service filtering, and we have suggested a scroe-based ensemble learning model for this. Three different machine learning models—the lightGBM, KNN, and decision tree—are combined in this model. Each model predicts the model class as well as the prediction score. The prediction box will get all predicted scores.The prediction box works on the algorithm , which will provide final prediction. On the basis of final prediction the cloud service recommended to the user. Algorithm 1 provides the detail working of prediction box.

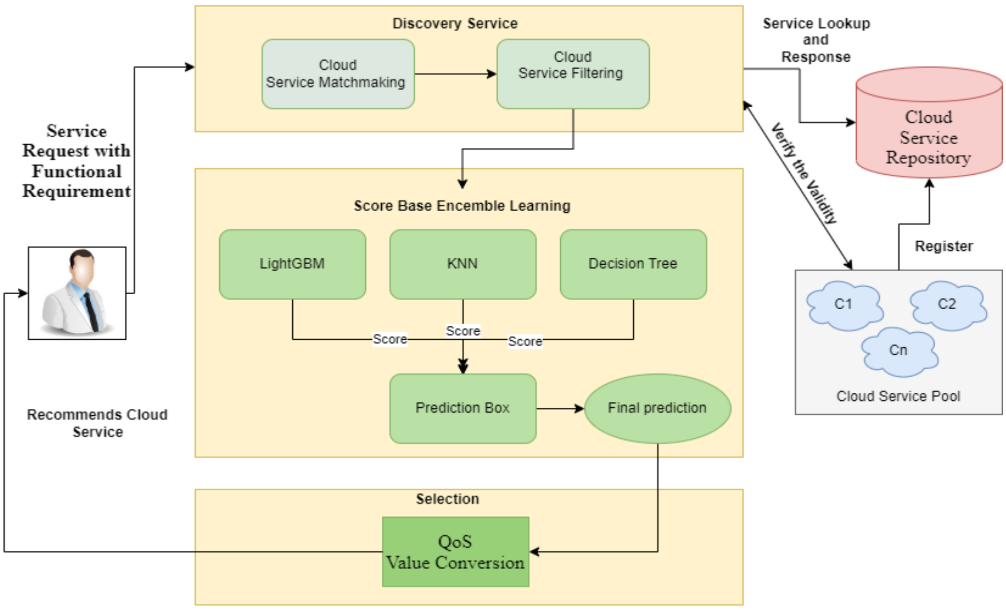


Fig. 5: Architecture

Algorithm 1: Procedure for prediction box:

INPUT: $Test\_Data$, N, M
OUTPUT: $final\_class$
Initialization;
$Test\_Data$= testing dataset,

N = Number of Standard Machine learning model,

M = Size of test dataset,

ODL = predicted output,

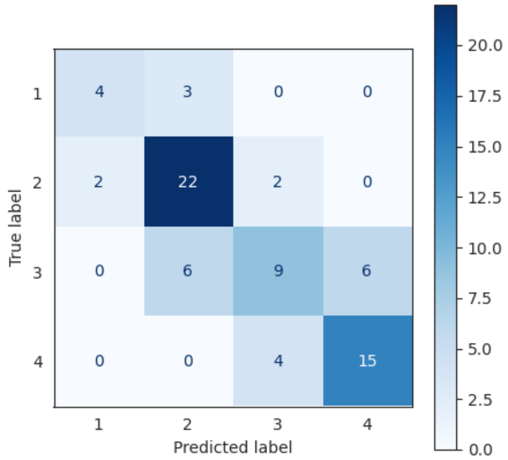
M ← $size\ of\ (testdata)$
for k=1 to M do
    For i=1 to 3 do
        NCL[k][i] = class label of predicted model
        NSL[k][i] = class label score of predicted model
    End for
        If all class labels are same
        $final\_class$[k] = NCL[k][i]
        Else if two class labels are same
        $final\_class$[k]= max score of two class
        If all class labels are different
        $final\_class$[k]= max score of three class
End for

5. Performance Analysis

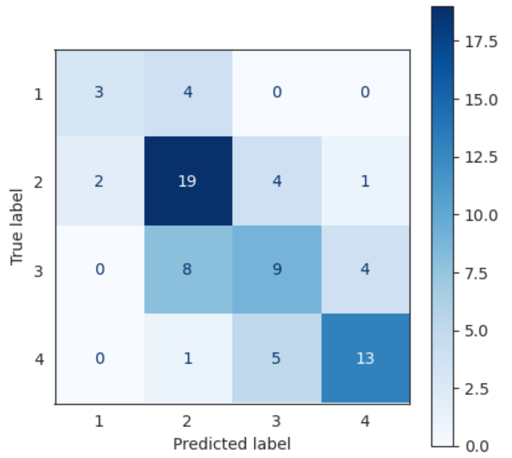
The objective of this study is to evaluate the performance of a hybrid learning strategy with an ideal set of concrete services has been studied and validated using the QWS dataset. We evaluate accuracy, precision, recall, and f1score, and offer the comparative findings for a variety of assaults since cloud client need a low false error rate and a high correct prediction rate.

- Accuracy: The Accuracy [30] refers to how close a measurement is to its true value. The 'Accuracy' is evaluated as depicted in equation (1) as follows:
  $$ACCY = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$
- F1-Score (F1): The highest F1[31] indicates flawless recall and precision, whereas the lowest F1 value suggests no recall or precision. The 'F1' is evaluated as depicted in equation (2) as follows:
  $$F1 = \frac{2TP}{2TP+FP+FN} \quad (2)$$
- Recall: The recall [32] is known as the true positive rate or sensitivity. The 'recall' ranges from 0.0 to 1.0. The 'recall' is evaluated as depicted in equation (3) as follows:
  $$TPR = \frac{TP}{TP+FN} \quad (3)$$
- Precision [33]: The precision is predicted as positive. The precision ranges from 0.0 to 1.0. The 'Precision 'is evaluated as depicted in equation (4) as follows:
  $$PPV = \frac{TP}{TP+FP} \quad (4)$$

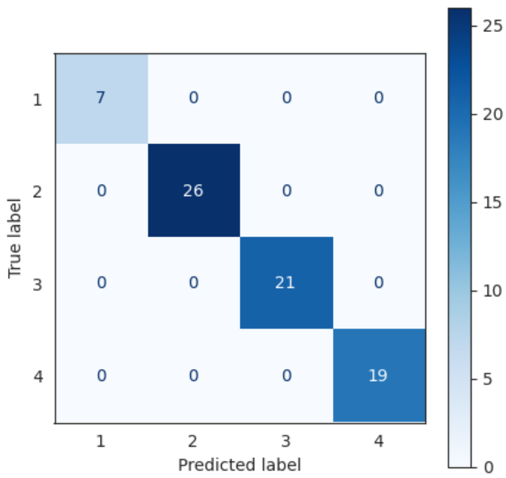
$$where\ TP\ is\ true\ positive, TN\ is\ true\ negative, FP\ isfalse\ positive, FN\ is\ false\ negative$$



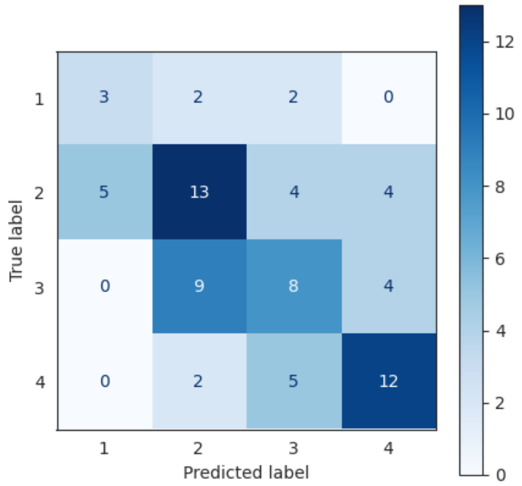
a) Logistic Regression



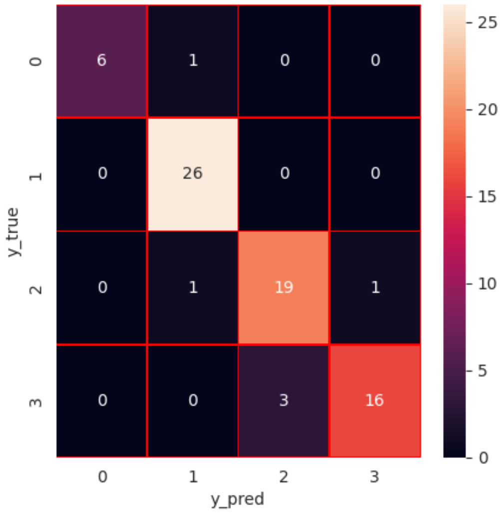
b) KNN



c) DT



d) MLP



e) Proposed Model

Fig. 6: Confusion Matrix

Table 1. Comparative analysis of ML Model and proposed model

Models	Accuracy	Precision	Recall	F1-Score
Logistic Regression	68.49%	67.52%	68.49%	67.30%
Decision Tree (DT)	60.27%	60.08%	60.27%	59.70%
KNN	60.27%	100.00%	100.00%	100.00%
MLP	49.32%	49.13%	49.32%	49.17%
[3]	90.11%	NA	NA	NA
[34]	90.68%	NA	NA	NA
Proposed Model	91.78%	92.00%	91.78%	91.71%

In the figure provides the comparative findings for a variety of assaults accuracy, precision, recall, and f1score.

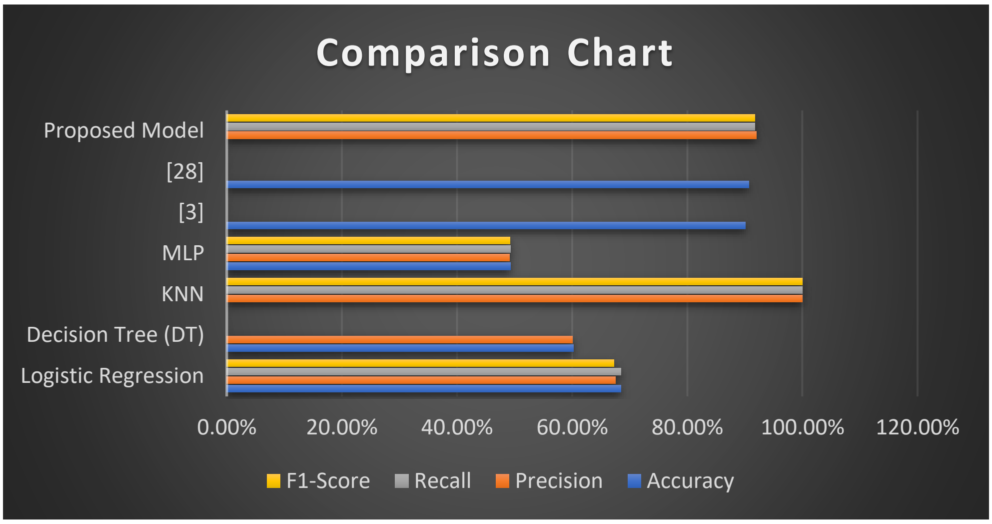


Fig. 7: Comparative analysis of ML Model

According to the findings of our investigation, the approach that we have presented, ensemble learning with prediction score, which combines normalisation with one hot encoding technique, performs better than other machine learning models. We were able to get an accuracy of 91.78%, a precision of 92.00%, a recall of 91.78%, and f1 score of 91.71%. In all performance criteria, the proposed model outperformed the Ranking feature model by a wide margin [35] [36]. As a result, the given model is trustworthy and suitable for quick and accurate attack detection.

6. Conclusion:

In this study, an effort was made to pinpoint the specifications for service composition in cloud computing environments based on prediction score. Given that customers are concerned with both the speed of requested service delivery and service quality in the cloud environment, researchers in this study, the dataset features are highly correlated to energy efficient cloud computing. We compare our proposed method to other ML approaches like Logistic Regression, KNN, Decision Tree and MLP. Results: Among ML approaches, our suggested model EEF-OCS has produced the best prediction. Based on the study's findings, it can be said that these strategies can shorten the time it takes to compose a service and improve the efficiency of compound services.

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