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Edge Computing in Centralized Data Server Deployment for Network Qos and Latency Improvement for Virtualization Environment

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Abstract

With the advancement of Internet of Things (IoT), the network devices seem to be raising, and the cloud data centre load also raises; certain delay-sensitive services are not responded to promptly which leads to a reduced quality of service (QoS). The technique of resource estimation could offer the appropriate source for users through analyses of load of resource itself. Thus, the prediction of resource QoS was important to user fulfillment and task allotment in edge computing. This study develops a new manta ray foraging optimization with backpropagation neural network (MRFO-BPNN) model for resource estimation using quality of service (QoS) in the edge computing platform. Primarily, the MRFO-BPNN model makes use of BPNN algorithm for the estimation of resources in edge computing. Besides, the parameters relevant to the BPNN model are adjusted effectually by the use of MRFO algorithm. Moreover, an objective function is derived for the MRFO algorithm for the investigation of load state changes and choosing proper ones. To facilitate the enhanced performance of the MRFO-BPNN model, a widespread experimental analysis is made. The comprehensive comparison study highlighted the excellency of the MRFO-BPNN model..

Keywords- Edge computing; Quality of service; Resource estimation; Virtualization; Machine learning

1. Introduction

With the advancement of Internet of Things (IoT), an ever-increasing number of gadgets, particularly cell phones, continually access the Internet. CISCO will predict 50 billion gadgets will associate with the Internet by 2020 [1]. These gadgets will produce a lot of information toward the finish of the organization, which prompts the augmentation of the weight of cloud server farm. Additionally, the remote distance among the cell phones and cloud server farm makes the transmission postpone increment, which makes some deferral touchy administrations cannot get reaction and handle quickly. IoT administrations, for example, associated vehicle and video web based, require high transfer speed and low idleness content conveyance to ensure QoS. IoT-based administrations are becoming well known quickly. The quantity of associated gadgets has arrived at 9 billion and by 2020, they are supposed to become further up to 24 billion [2]. With such pace of expansion in the quantity of heterogeneous gadgets being important for IoT and creating information, it is absurd any longer for an IoT to productively deal with the information, power, and data transfer capacity. In this manner, a great deal of administration situated undertakings would be acted in the cloud, making mixture of IoT and cloud computing [3]. For this situation, a confined miniature datacenter would be available near the fundamental hubs to offload the errands and preprocess the crude information. That miniature datacenter is known as Fog or Edge. Haze likewise helps in limiting postponements and increment administration quality by consolidating better responsiveness, making it unavoidable for sight and sound web based and other defer touchy administrations. There comes what is happening when the cloud is associated with IoT that creates media information. Fig. 1 defines the infrastructure of edge computing.

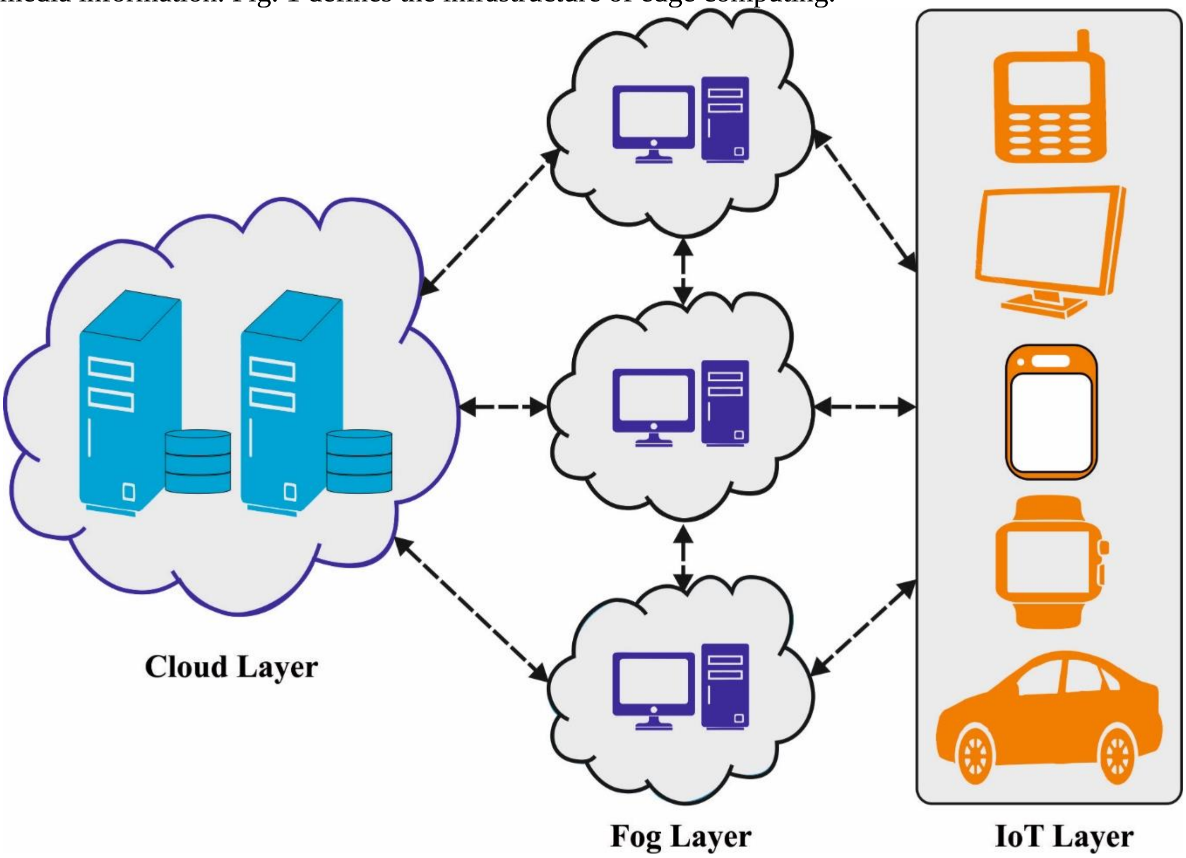

Fig. 1. *Structure of edge computing*

IoT arranged administrations are picking up speed quickly. Number of associated gadgets previously surpassed the quantity of individuals on Earth beginning around 2011. Associated gadgets have arrived at 9 billion and are supposed to develop all the more quickly and arrive at 24 billion by 2020 [4]. With expanding number of heterogeneous gadgets associated with IoT and creating information, it will be unimaginable for an independent IoT to perform power and data transmission hungry undertakings productively. IoT and cloud computing combination has been imagined in such manner [5]. There comes what is happening when cloud is associated with an IoT that creates sight and sound information. Visual Sensor networks or CCTV associated with cloud can be instances of such situations. Since media content consumes seriously handling power, extra room, and booking resources, its administration in cloud will become unavoidable. Moreover, strategic and inactivity touchy IoT administrations require an exceptionally fast reaction and handling. All things considered, conveying through far off cloud, over the Internet isn't doable.

To achieve this and to make edge computing (EC) reality and a triumph, there was a need for a productive source of executives at the edge [6]. Without a doubt, cell phones or IoT gadgets are resource-compelled gadgets, though the cloud has practically limitless yet distant resources. Giving and additionally dealing with the sources at the edge would empower the end gadget to save resources (e.g., put away energy in batteries) and accelerate calculation, and permit utilizing resources it doesn't have. Also, keeping information near where it was produced empowers better control, particularly for protection related issues [7]. At last, being found near the client, EC makes it conceivable to build the nature of offered types of assistance using profiling inside a neighborhood setting, without compromising the protection or taking care of countless clients. This is known as setting variation.

EC assumes a significant part by utilizing network resources close to the nearby organization to give a low inertness administration and further develop QoS [8]. EC was situated among the end gadgets and cloud server farm. Because of the way that edge servers are near end clients, the inertness between cell phones and server farms is decreased. Additionally, resources are near the client that can further develop QoS somewhat. In the IoT climate, the quantity of organization gadgets is expanding continually [9]. The resources with a similar help capability are likewise expanding steadily.

The intricacy of client prerequisites makes resources the executives a test. Among the numerous accessible resources, choosing reasonable resources to address the issues of clients has turned into the primary objective. Albeit the idleness is diminished, the resources in EC are restricted contrasted with cloud computing. The accessibility and transient expectation of resources load have some effect on task planning, application execution, and the QoS of clients [10]. The technique for resource expectation can give the proper resource to clients by investigating the heap of the actual resource. Subsequently, the assessment of Resource QoS is vital for client fulfillment and errand designation in EC.

This study develops a new manta ray foraging optimization with backpropagation neural network (MRFO-BPNN) model for resource estimation using quality of service (QoS) in the EC platform. Primarily, the MRFO-BPNN model makes use of BPNN algorithm for the estimation of resources in the EC. Besides, the parameters relevant to the BPNN model are adjusted effectually by the use of MRFO algorithm. Moreover, an objective function is derived for the MRFO algorithm for the investigation of load state changes and choosing proper ones. To facilitate the enhanced performance of the MRFO-BPNN model, a widespread experimental analysis is made. The comprehensive comparison study highlighted the excellency of the MRFO-BPNN model.

2. Existing Works

Xiang and Zhang [11] modelled an isolation forest-oriented structure including dynamic Insertion and Deletion techniques (IDForest) that could upgrade the forest for identifying anomalies in data. In addition, IDForest will be positioned on power servers simultaneously padding every tree into a sub-task that enables the wild AD on data streams. In [12], an approach for privacy-aware IoV service disposition having amalgamated knowledge in cloud-EC, called PSDF, was devised. Theoretically, joined knowledge will secure the dispersed exercise of placement choice net over every ES through exchanging and aggregating model weights, evading the original data communication. In the meantime, homomorphic encryption was accepted to upload weights previously the prototype accumulation over the cloud.

In [13], the authors initiate the attempt for managing this Edge Data Integrity (EDI) issue from the service vendor’s viewpoint through proposal of an inspection and corruption localized method for EDI called ICL-EDI. This method will let a service seller scrutinize the subject edge data and restrict tainted edge data over many edge servers professionally and precisely. Li et al. [14] endeavours the primary effort to manage this EDI issue. The research workers originally scrutinize the threat method and the audit objects, before suggesting a lightweight sampling-related probabilistic method, specifically EDI-V for aiding app sellers's checking the honesty of their data cached over a big scale of edge servers. The authors advise a novel data construction termed variable Merkle hash tree (VMHT) to generate honesty evidence of person's information copies throughout the audit.

In [15], a drone-aided mobile EC scheme was modelled. The delinquent to cooperatively minimalize the power consumption at the IoT gadgets and the drones throughout task implementation stands deliberate through adjusting the duty unburdening decision, resource allocation system, and drone's route though seeing the computation and communication latency necessities. A non-convex erection of the expressed issue was discovered. In [16], the authors learn the issue of energy-aware edge server assignment and attempt to bargain an extra active settlement system having low energy utilization. Formerly, the authors develop the issue as a multi-objective optimized issue and develop a PSO-related energy-aware edge server assignment method for finding the best solution.

3. The Proposed Model

This study has introduced an effective MRFO-BPNN model for resource estimation using the QoS in the EC platform. Primarily, the MRFO-BPNN model makes use of BPNN algorithm for the estimation of resources in the EC. Besides, the parameters relevant to the BPNN model are adjusted effectually by the use of MRFO algorithm. Moreover, an objective function is derived for the MRFO algorithm for the investigation of load state changes and choose proper ones.

3.1. Resource Estimation Process

In this work, the BPNN algorithm is applied for the estimation of resources in the EC [17]. NNs create an efficient procedure of $y = f(x)$ in the view of the network system. An input vector $\chi = (x^{(1)}, x^{(2)}, \dots, x^{(D_1)})^T$, a feed-forward network with K-l hidden layers (HLs) is defined as:

$$y \approx f_{BP}(x) = g^{(K)}\left(W^{(K)} g^{(K-1)}\left(W^{(K-1)} g^{(K-2)}\left(\dots g^{(1)}\left(W^{(1)} x + b^{(1)}\right)\dots\right) + b^{(K-1)}\right) + b^{(K)}\right) \quad (1)$$

whereas $W^{(k)} \in \Re^{d_k \times d_{k-1}}$ refers to the weighted matrix from k^{th} HL, $b^{(k)} \in \Re^{d_k \times 1}$ stands for the equivalent bias vector, $g^{(k)}(.)$ denotes the non-linear activation function implemented in k^{th} HL, $d_0 = D_1$ and $d_K = D_2$.

Represent the model parameters set by $\theta = \{W^{(k)}, b^{(k)}\}_{k=1}^{K}$. With trained the network based on every trained instance, an optimum network parameter θ is attained. Therefore, it can be minimizing the subsequent error function:

$$E(\theta) = \frac{1}{2}\sum_{i=1}^{N} \| f_{BP}(x_i) - y_i \|_2^2 \quad (2)$$

The easy and effective manner is the gradient descent (GD), and the upgraded formula as:

$$\theta \leftarrow \theta - \eta \nabla E(\theta) \quad (3)$$

whereas $\nabla E(\theta)$ refers the gradient of $E(\theta)$ interms of θ, and the step size η is named as rate of learning.

All the parameters upgrading stage comprises of 2 steps. A primary step estimates the derivate of the error function interms of weighted matrices as well as bias vectors. The backpropagation (BP) system propagates errors backward with network and it is developed in a computationally effective manner to estimate the derivate. The derivate was utilized for adjusting every parameter under the secondary step. Therefore, the MLP has also termed a backpropagation neural network (BPNN). A comprehensive execution, mini-batch GD was generally employed for upgrading parameters for reducing the computation burden.

3.2. Parameter Adjustment Process

At this stage, the parameters relevant to the BPNN model are adjusted effectually by the use of MRFO algorithm. The MRFO is a novel SI optimization technique which simulates the behavior of manta ray foraging for plankton that has the subsequent three foraging behaviors [18]. Fig. 2 demonstrates the flowchart of MRFO.

Chain Foraging (CF)

In this phase, manta rays form a chain to whirl straightforward for the plankton. Excepting the primary one in the foraging chain, all the individuals are upgraded using the preceding and better individuals, correspondingly as follows:

$$\begin{cases} z_1^d(x+1) = z_1^d(x) + r.\left[z_{best}^d(x) - z_1^d(x)\right] + \alpha \cdot [z_{best}^d(x) - z_1^d(x)], \\ Z_{i(x+1)}^d == z_i^d(x) + r.\left[z_{i-1}^d(x) - x_i^d(x)\right] + \alpha \cdot [z_{best}^d(x) - z_i^d(x)], \ i = 2, 3, \ldots, M \\ \alpha = 2r \cdot \sqrt{|\log(r)|}, \end{cases} \quad (4)$$

In Eq. (4), the arbitrary number $r \in [0,1]$, x characterizes the existing amount of iterations, and M characterizes the overall amount of individuals.

Spiral Foraging

In this phase, all the individuals move towards the preceding individual and food in a spiral manner as follows:

$$\begin{cases} z_1^d(x+1) = z_{best}^d(x) + r.\left[z_{best}^d(x) - z_1^d(x)\right] + \beta \cdot \left[z_{best}^d(x) - z_1^d(x)\right] \\ Z_{i(x+1)}^d == z_{best}^d(x) + r.\left[z_{i-1}^d(x) - x_i^d(x)\right] + \beta \cdot [z_{best}^d(x) - z_i^d(x)], \ i = 2,3, \ldots, M \\ \beta = 2e^{r_1 \frac{X-t+1}{X}} \cdot \sin(2\pi r_1), \end{cases} \quad (5)$$

Where the arbitrary vector $r_1 \in [0,1]$ and X characterizes the maximal amount of iterations. The abovementioned behaviors are enhanced for exploration as follows:

$$\begin{cases} z_1^d(x+1) = z_{rand}^d(x) + r.\left[z_{best}^d(x) - z_1^d(x)\right] + \beta \cdot \left[z_{rand}^d(x) - z_1^d(x)\right] \\ z_i^d(x+1) = z_{rand}^d(x) + r.\left[z_{best}^d(x) - z_1^d(x)\right] + \beta \cdot \left[z_{rand}^d(x) - z_1^d(x)\right] \\ z_{rand}^d = Lb^d + r \cdot \left(Ub^d - Lb^d\right), \end{cases} \quad (6)$$

Whereas Lb^d and Ub^d characterize the upper and lower limits, correspondingly.

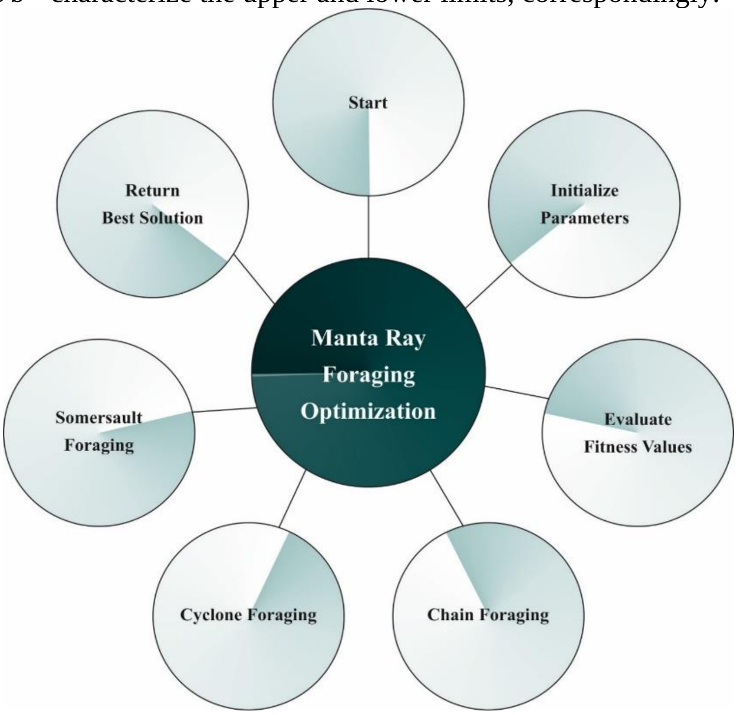

Fig. 2. *Flowchart of MRFO*

Somersault Foraging (SF)
In this phase, all the individuals are upgraded based on the better individual as follows:

$$z_i^d(x+1) = z_i^d(x) + S \cdot \left[r_2 \cdot z_{besi}^d(x) - r_3 \cdot z_i^d(x)\right], i = 1,2,\ldots,M \quad (7)$$

Now $r_2, r_3 \in [0,1]$ indicates random number and $S = 2$ represents the somersault factor.
In this paper, we construct an QoS attribute matrix of resources as the decision matrix.

$$R = (r_{ij})_{n\times m} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix} \quad (8)$$

where r_{ij} is the QoS attribute value of resource.
As the measuring components of QoS features remain different, it was pointless toward developing the matrix straightly [19]. Thus, as per the association among features as well as user satisfaction, here used the subsequent formula for standardizing processing:

$$z_{ij} = \begin{cases} \dfrac{r_{ij} - r_j^{\min}}{r_j^{\max} - r_j^{\min}} & q \text{ is positive feature} \\ \dfrac{r_j^{\max} - r_{ij}}{r_j^{\max} - r_j^{\min}} & q \text{ is negative feature} \end{cases} \quad (9)$$

The above formula designates 2 cases: if QoS feature q was positive feature, if more the worth of feature was, the gratification of users was more. IN contrast, the negative feature specifies the lesser the feature value was, the advanced user gratification was. To assure the objectivity of the predictive outcomes, the author leverages the entropy weighted algorithm for calculating entropy weight w_j and entropy value e_j for the QoS feature of sources. The method was given below:

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} f_{ij} \cdot \ln f_{ij}$$
$$w_j = \frac{1 - e_j}{m - \sum_{j=1}^{m} e_j} \quad (10)$$
$$f_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}}$$
$$\sum_{j=1}^{m} w_j = 1.$$

4. Results Analysis

The experimental assessment of the MRFO-BPNN model is made here. Table 1 and Fig. 3 provide a brief result analysis of the MRFO-BPNN model. The results inferred that the MRFO-BPNN model has the capability of attaining effectual performance. The MRFO-BPNN model has provided $accu_y$ of 93.55%, $prec_n$ of 94.96%, $reca_l$ of 94.81%, F_{score} of 94.63%, MCC of 93.24%, kappa of 94.39%, and $Jaccard_{index}$ of 94.10%.

Table 1 *Result analysis of MRFO-BPNN system with various measures*

Measures	**Values (%)**
Accuracy	93.55
Precision	94.96
Recall	94.81
F-Score	94.63
MCC	93.24
Kappa	94.39
Jaccard Index	94.10

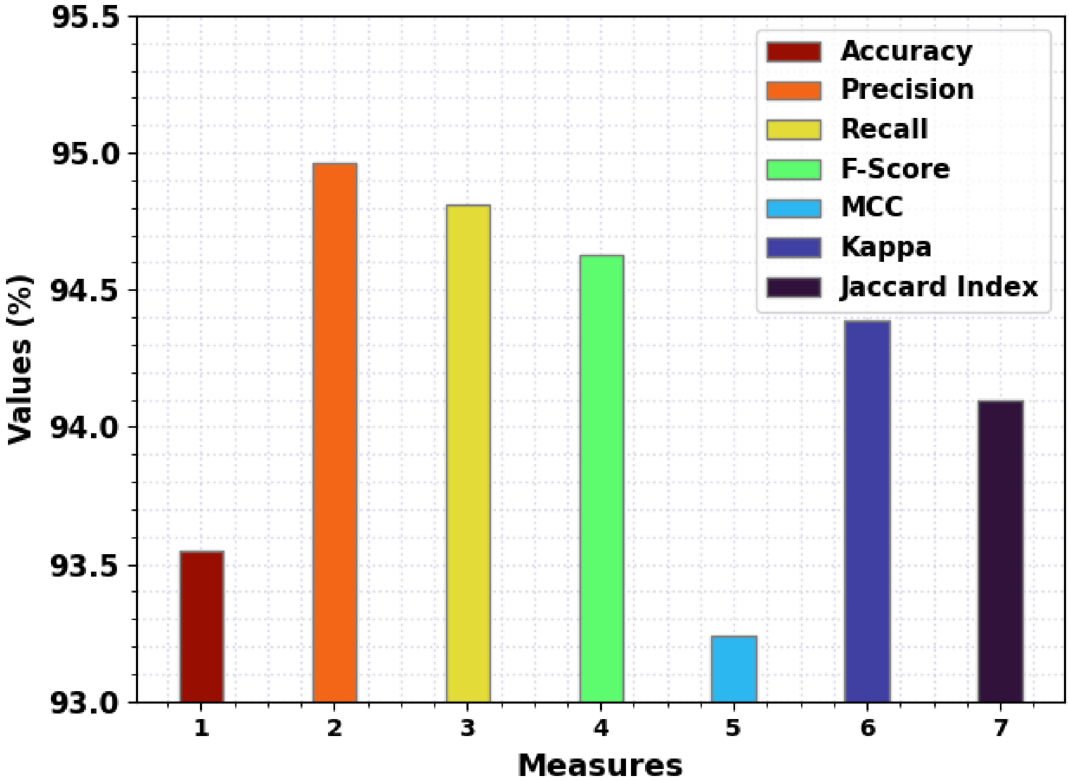

Fig. 3. *Result analysis of MRFO-BPNN system with various measures*

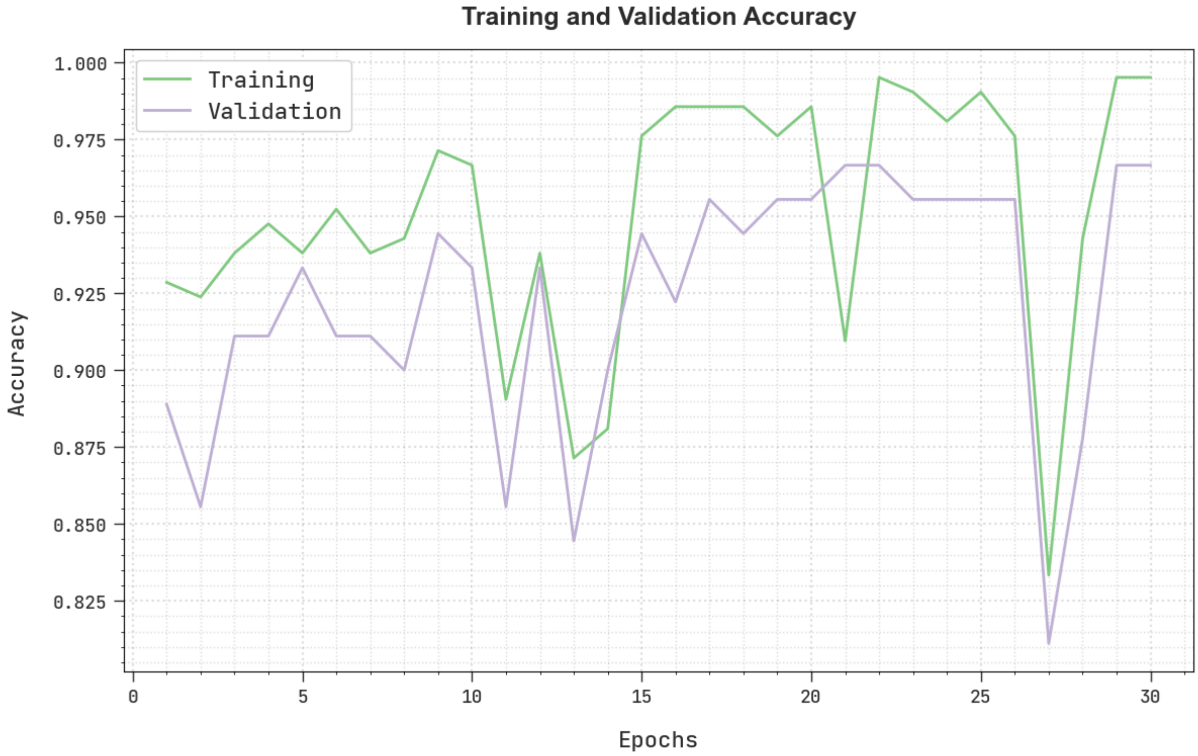

Fig. 4. *TRA and VLA analysis of MRFO-BPNN system*

Fig. 5. *TRL and VLL analysis of MRFO-BPNN system*

The TRA and VLA gained by the MRFO-BPNN technique under test database are exemplified in Fig. 4. The experimental result denoted the MRFO-BPNN method has reached maximal values of TRA and VLA. Predominantly the VLA is greater than TRA.

The TRL and VLL attained by the MRFO-BPNN method under test database are displayed in Fig. 5. The experimental outcome implied that the MRFO-BPNN algorithm has accomplished minimal values of TRL and VLL. Particularly, the VLL is lesser than TRL.

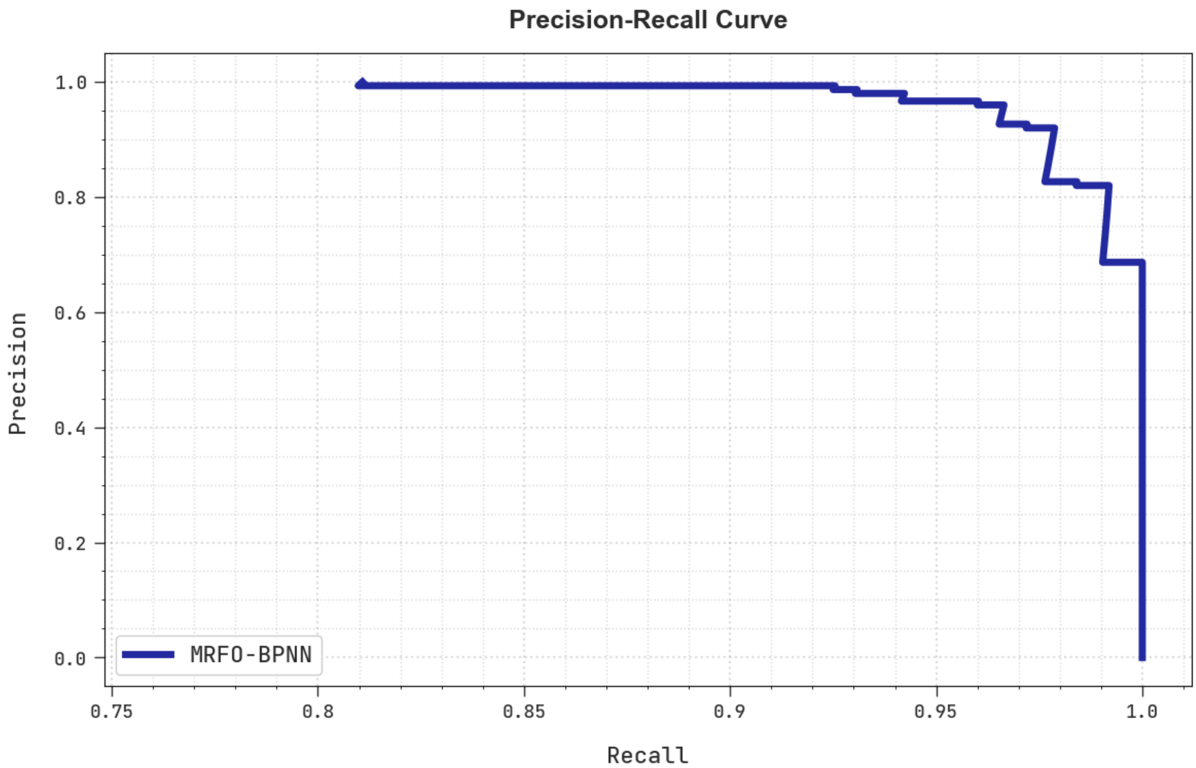

Fig. 6. *Precision-recall analysis of MRFO-BPNN system*

A clear precision-recall inspection of the MRFO-BPNN technique under test database is represented in Fig. 6. The figure shows the MRFO-BPNN system has resulted in enhanced values of precision-recall values under all classes.
A brief ROC study of the MRFO-BPNN approach under test database is shown in Fig. 7. The results symbolized the MRFO-BPNN method has exhibited its capability in classifying different classes in test database.

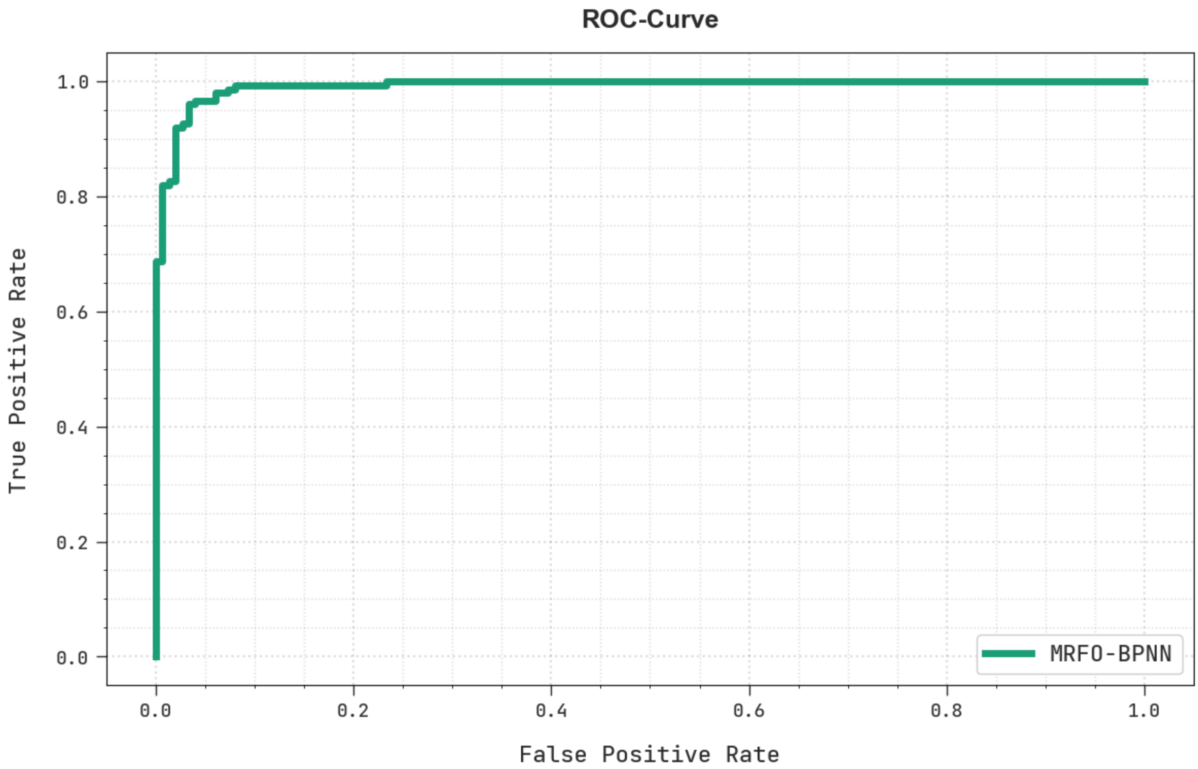

Fig. 7. *ROC analysis of MRFO-BPNN system*

Exclusive comparison outcomes of the MRFO-BPNN model with recent models are given in Table 2 and Fig. 8. With respect to accuracy, the MRFO-BPNN model offered maximum value of 95.45% whereas the similarity matching, SMNP, and SMNG models have attained minimal values of 93.04%, 89.99%, and 87.61% respectively. Also, with respect to F-score, the MRFO-BPNN method presented maximum value of 95.04% whereas the similarity matching, SMNP, and SMNG methods have achieved minimum values of 92.75%, 90.45%, and 87.32% correspondingly.

Table 2 *Comparative analysis of MRFO-BPNN system with recent algorithms*

Methods	**Accuracy**	**Precision**	**Recall**	**F-Score**
MRFO-BPNN	95.45	94.43	95.79	95.04
Similarity Matching Algorithm	93.04	91.73	93.15	92.75
SMNP Method	89.99	89.32	89.96	90.45
SMNG Method	87.61	87.16	87.21	87.32

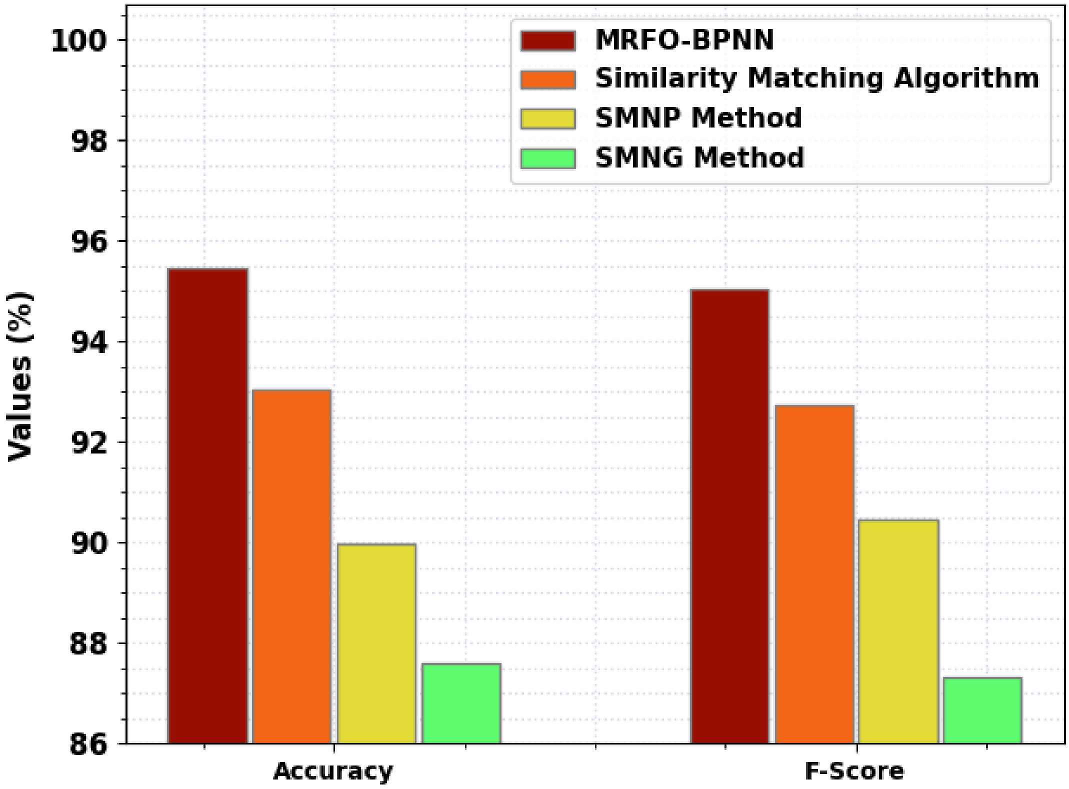

Fig. 8. *$Accu_y$ and F_{score} analysis of MRFO-BPNN system with recent algorithms*

Table 3 *Comparative analysis of MRFO-BPNN system with recent algorithms*

Methods	**MCC**	**Kappa**	**Jaccard Index**
MRFO-BPNN	93.24	94.39	94.10
Similarity Matching Algorithm	89.94	91.57	92.22
SMNP Method	87.85	87.97	90.39
SMNG Method	85.20	84.53	86.69

Brief comparative results of the MRFO-BPNN method with recent approach are given in Table 3 and Fig. 9. With respect to MCC, the MRFO-BPNN method offered maximum value of 93.24% whereas the similarity matching, SMNP, and SMNG models have attained minimal values of 89.94%, 87.85%, and 85.20% correspondingly. Also, with respect to kappa, the MRFO-BPNN technique offered maximum value of 94.39% whereas the similarity matching, SMNP, and SMNG models have achieved minimal values of 91.57%, 87.97%, and 84.53% correspondingly.

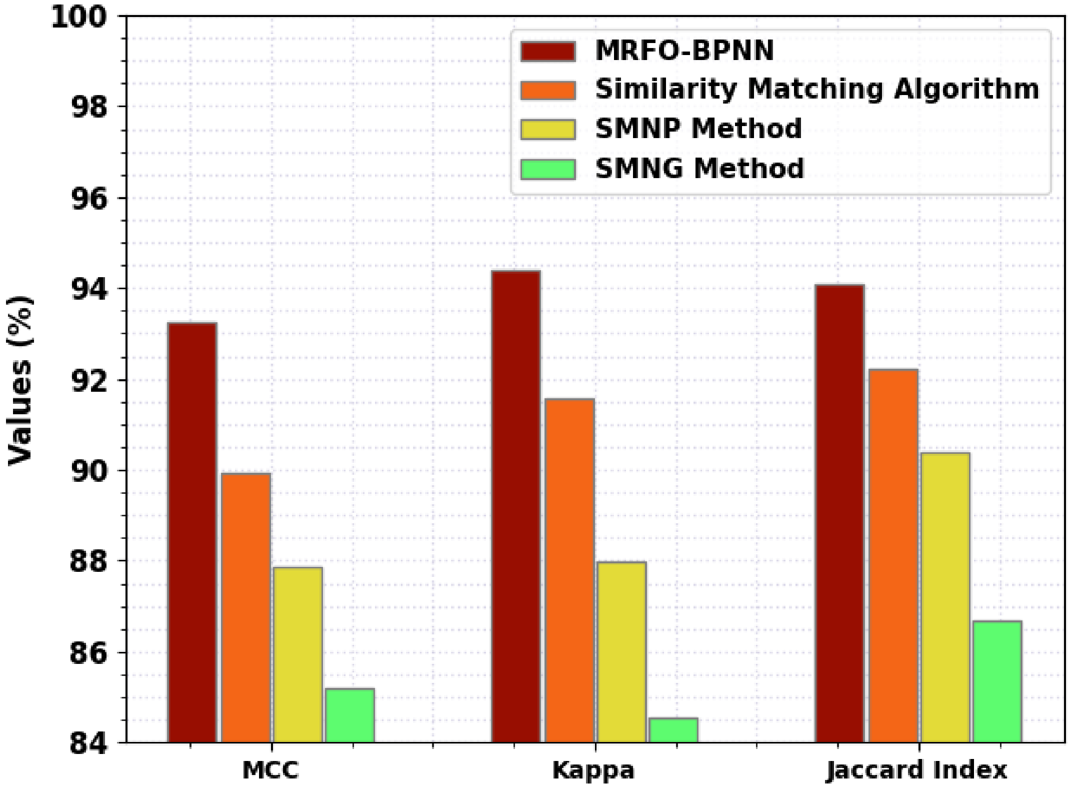

Fig. 9. *MCC, kappa, and JI analysis of MRFO-BPNN system with recent algorithms*

5. Conclusion

This study has introduced an effective MRFO-BPNN model for resource estimation using the QoS in the EC platform. Primarily, the MRFO-BPNN model makes use of BPNN algorithm for the estimation of resources in the EC. Besides, the parameters relevant to the BPNN model are adjusted effectually by the use of MRFO algorithm. Moreover, an objective function is derived for the MRFO algorithm for the investigation of load state changes and choosing proper ones. To facilitate the enhanced performance of the MRFO-BPNN model, a widespread experimental analysis is made. The comprehensive comparison study highlighted the excellency of the MRFO-BPNN model.

Reference

[1] Hartmann, M., Hashmi, U.S. and Imran, A., 2022. Edge computing in smart health care systems: Review, challenges, and research directions. *Transactions on Emerging Telecommunications Technologies*, *33*(3), p.e3710.

[2] Xia, X., Chen, F., Grundy, J., Abdelrazek, M., Jin, H. and He, Q., 2021. Constrained app data caching over edge server graphs in edge computing environment. *IEEE Transactions on Services Computing*.

[3] Zhang, Y., Di, B., Wang, P., Lin, J. and Song, L., 2020. HetMEC: Heterogeneous multi-layer mobile edge computing in the 6 G era. *IEEE Transactions on Vehicular Technology*, *69*(4), pp.4388-4400.

[4] Singh, A., Satapathy, S.C., Roy, A. and Gutub, A., 2022. Ai-based mobile edge computing for iot: Applications, challenges, and future scope. *Arabian Journal for Science and Engineering*, pp.1-31.

[5] Zhao, L., Tan, W., Li, B., He, Q., Huang, L., Sun, Y., Xu, L. and Yang, Y., 2021. Joint Shareability and Interference for Multiple Edge Application Deployment in Mobile-Edge Computing Environment. *IEEE Internet of Things Journal*, *9*(3), pp.1762-1774.

[6] Zhao, L., Li, B., Tan, W., Cui, G., He, Q., Xu, X., Xu, L. and Yang, Y., 2022. Joint Coverage-Reliability for Budgeted Edge Application Deployment in Mobile Edge Computing Environment. *IEEE Transactions on Parallel and Distributed Systems*, *33*(12), pp.3760-3771.
[7] Debauche, O., Mahmoudi, S. and Guttadauria, A., 2022. A new edge computing architecture for IoT and multimedia data management. *Information*, *13*(2), p.89.
[8] Xie, R., Tang, Q., Qiao, S., Zhu, H., Yu, F.R. and Huang, T., 2021. When serverless computing meets edge computing: architecture, challenges, and open issues. *IEEE Wireless Communications*, *28*(5), pp.126-133.
[9] Yang, M., Gao, C. and Han, J., 2022. Edge Computing Deployment Algorithm and Sports Training Data Mining Based on Software Defined Network. *Computational Intelligence and Neuroscience*, *2022*.
[10] Aral, A. and Brandić, I., 2020. Learning spatiotemporal failure dependencies for resilient edge computing services. *IEEE Transactions on Parallel and Distributed Systems*, *32*(7), pp.1578-1590.
[11] Xiang, H. and Zhang, X., 2022. Edge computing empowered anomaly detection framework with dynamic insertion and deletion schemes on data streams. *World Wide Web*, pp.1-21.
[12] Xu, X., Liu, W., Zhang, Y., Zhang, X., Dou, W., Qi, L. and Bhuiyan, M.Z.A., 2022. Psdf: Privacy-aware iov service deployment with federated learning in cloud-edge computing. *ACM Transactions on Intelligent Systems and Technology (TIST)*.
[13] Cui, G., He, Q., Li, B., Xia, X., Chen, F., Jin, H., Xiang, Y. and Yang, Y., 2021. Efficient verification of edge data integrity in edge computing environment. *IEEE Transactions on Services Computing*.
[14] Li, B., He, Q., Chen, F., Jin, H., Xiang, Y. and Yang, Y., 2020. Auditing cache data integrity in the edge computing environment. *IEEE Transactions on Parallel and Distributed Systems*, *32*(5), pp.1210-1223.
[15] Tun, Y.K., Park, Y.M., Tran, N.H., Saad, W., Pandey, S.R. and Hong, C.S., 2020. Energy-efficient resource management in UAV-assisted mobile edge computing. *IEEE Communications Letters*, *25*(1), pp.249-253.
[16] Li, Y. and Wang, S., 2018, July. An energy-aware edge server placement algorithm in mobile edge computing. In *2018 IEEE International Conference on Edge Computing (EDGE)* (pp. 66-73). IEEE.
[17] Alkronz, E.S., Moghayer, K.A., Meimeh, M., Gazzaz, M., Abu-Nasser, B.S. and Abu-Naser, S.S., 2019. Prediction of whether mushroom is edible or poisonous using back-propagation neural network.
[18] Zhao, W., Zhang, Z. and Wang, L., 2020. Manta ray foraging optimization: An effective bio-inspired optimizer for engineering applications. *Engineering Applications of Artificial Intelligence*, *87*, p.103300.
[19] Li, G., Song, J., Wu, J. and Wang, J., 2018. Method of resource estimation based on QoS in edge computing. *Wireless Communications and Mobile Computing*, *2018*.