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Original scientific paper

Enhancing Cloud Resource Allocation with TrustFusionNet Using Random Forests and Convolutional Neural Networks

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Abstract: In the cloud computing, trust awareness and efficient resource allocation are central concerns. This research paper introduces an innovative resource allocation framework, "TrustFusionNet," which combines two prolific algorithms: Random Forest and Convolutional Neural Networks (CNNs), to comprehensively assess the trustworthiness of cloud resources. TrustFusionNet systematically evaluates resource trust values, taking into account diverse resource attributes, historical data, and behavioral patterns. These trust values are then integrated with trust-enhanced features extracted by CNNs, yielding a holistic trust assessment. The need for trust awareness in cloud computing arises from the imperative to ensure that cloud resources are dependable and secure. TrustFusionNet addresses this challenge by providing a multifaceted trust assessment process. Random Forest, renowned for its ensemble learning capabilities, aids in interpreting trust scores based on various resource factors. Meanwhile, CNNs excel in extracting intricate trust-related features from resource data, capturing subtle nuances that conventional methods may overlook. To rigorously evaluate the efficacy of TrustFusionNet, extensive simulation analyses are conducted. Performance comparisons are made against established resource allocation algorithms, employing a comprehensive set of simulation metrics. These metrics encompass resource utilization, trust assurance, allocation efficiency, and system stability. The findings reveal that TrustFusionNet surpasses existing algorithms in enhancing trust assurance and optimizing resource allocation in the cloud computing domain. This research paper paves the way for the advancement of resource allocation using trust awareness in cloud computing, emphasizing the importance of trust-aware decision-making. TrustFusionNet exemplifies a promising approach that balances interpretability and deep feature extraction, promising robust and secure resource allocation. By addressing the paramount issue of trust assurance, it paves the way for more dependable cloud computing ecosystems.

Keywords: cloud computing; convolutional neural networks; resource allocation; trust awareness; TrustFusionNet

1 INTRODUCTION

The ever-expanding landscape of cloud computing has revolutionized the way computational resources are accessed and utilized. Organizations and individuals are increasingly reliant on cloud infrastructures to deploy applications, store data, and execute complex tasks. Trust assurance emerges as a critical consideration, as the active and collective landscape of cloud environments necessitates a comprehensive understanding of the trustworthiness and security of cloud resources. Cloud computing offers dynamic access to a myriad of computing resources redefining how computational capabilities are provisioned, allowing users to scale resources as needed, reducing capital expenditures, and enhancing flexibility. However, the decentralized nature of cloud computing introduces challenges related to trustworthiness, making it imperative to develop mechanisms that can assess and assure the trustworthiness of cloud resources [1-5]. The concept of cloud computing -mechanism is shown in Fig. 1.

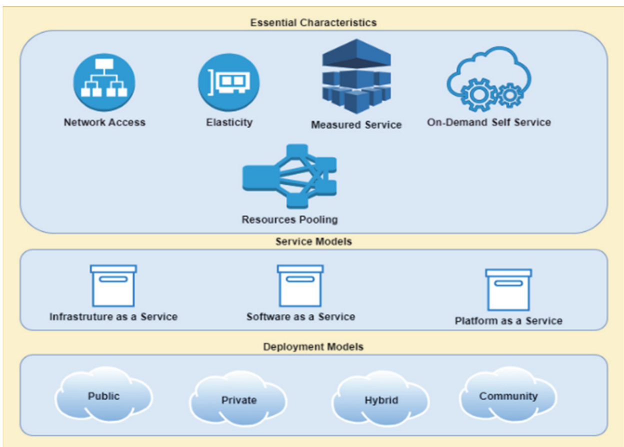

Figure 1 Cloud computing mechanism

Essential Characteristics:

Network Access: Facilitates access to cloud resources through network connectivity, allowing users to connect to the cloud infrastructure from various locations.

Elasticity: Enables the dynamic scaling of resources, ensuring that users can adjust resource allocation based on demand, thus optimizing efficiency.

Measured Service: Involves metering and monitoring resource usage, allowing for transparent billing based on actual consumption.

On-demand Self-Service: Empowers users to independently provision and manage cloud resources as needed, reducing administrative overhead.

Pooling of Resources: Aggregates and shares computing resources, such as servers and storage, among multiple users, improving resource utilization.

2 LITERATURE REVIEW

In the rapidly evolving landscape of cloud computing mechanisms, a surfeit of research has been steered to address various aspects, including security, efficiency, resource management, and trust. This literature review examines key research papers that contribute to the understanding of cloud computing mechanisms, setting the stage for the proposed Deep Learning-Based Resource Allocation Framework with Trust Assurance for Cloud Computing.

A review on Lie group machine learning algorithms, offering a summary of machine learning techniques applied to Lie groups, an essential foundation for manifold-based data analysis. A systematic survey on alignment-free sequence comparison from a machine learning perspective, emphasizing the importance of machine learning in genomics and bioinformatics. Machine learning algorithm procedure styles in computer visualization, exploring various procedures in computer visualization applications. A boosting algorithm for multiple semi-supervised learning methods, highlighting the importance of machine learning methods in scenarios with limited labeled data [6-8].

A review highlighting the part of machine learning mechanisms in natural language processing and conversational AI. The implications of machine learning in communication networks, underlining its relevance in optimizing network performance and management. An energy based modeling for machine learning using confidence dependent approach, demonstrating how machine learning can enhance efficiency and productivity in manufacturing processes [8-11].

An ensemble learning outline modelling that combines various contemporary machine learning algorithms for labor resource allocation, emphasizing the significance of ensemble techniques in optimizing resource allocation. An orthogonal resource allocation using SVM for CSMA/CA, underscoring the role of SVM in resource management within communication systems. The applied machine learning techniques for traffic prediction to enhance resource management in C-RAN (Cloud Radio Access Network), demonstrating the importance of predictive models in resource allocation. An employed machine learning algorithm for predicting hotel booking and cancellations, showcasing the applicability of such algorithms in service industries [12-14].

The concept of isolatable mission divesting for multiple users serving for multiple resources using cloud storage and computing mechanisms using various deep reinforcement learning mechanisms. This approach lays the foundation for dynamic allocation strategies. A research on dependent task offloading for edge computing using deep reinforcement learning. Their work delves into the intricacies of task allocation in edge environments, which is highly relevant to our resource allocation framework. An innovative novel task offloading algorithm for obtaining energy efficiency using block chain technology and Internet of Things based orchestrated cloud computing. Their research emphasizes the importance of energy optimization in resource allocation [15, 16].

A distributed approach for policy gradient edge computing systems for optimal resource allocation. Their work aligns with our focus on resource allocation strategies and optimization. Ning et al. The impression of collaborative cloud computing within the context of the "Green and Sustainable Cloud of Things." Their research underscores the significance of collaborative and sustainable resource allocation practices. The resource allocation challenges in classified 5G networks for low latency virtual network service communications. Their work emphasizes the importance of efficient allocation, particularly in emerging 5G environments [17, 18].

The field by presenting an intelligent control mechanism for self-driving RAN (Radio Access Network). This research aligns with our exploration of intelligent resource allocation strategies. The deep reinforcement learning mechanisms with multiple agents for active energy utilization in wireless networks. The reserach sheds light on the potential of multi-agent approaches in resource allocation. A model approach for multi-level classification in a smart-city scenario for IOT applications. Their work highlights the role of deep learning mechanisms in enhancing network traffic management, which is relevant to our research on resource allocation [19, 20].

The vision and perspective of dynamic resource allocation for edge computing networks, emphasizing the importance of adaptive resource allocation in dynamic environments, which aligns with our research focus on efficient allocation in cloud and edge settings. The mathematical foundations of resource allocation strategies, complementing our approach grounded in deep learning. The scaling User Plane Function occurrences in next generation mobile core networks using deep reinforcement learning. Their work addresses scalability concerns. Auto-scaling techniques for elastic applications in cloud environments, offering insights into auto-scaling strategies, which are relevant to the dynamic resource allocation aspects of our framework [21-24].

3 PROPOSED METHOD

The proposed system addresses the critical challenge of trust assurance in cloud computing through the development of an innovative Resource Allocation Framework based on deep learning mechanism, referred to as "TrustFusionNet".TrustFusionNet integrates RandomForest and CNN models by first utilizing RandomForest to evaluate initial trust scores based on cloud resource attributes and historical data. These trust scores are then enhanced through the CNN, which extracts deeper features from the resource data. The CNN processes patterns and relationships that are not immediately apparent, providing a richer set of trust-enhanced features. The combination of these two models results in a comprehensive trust assessment, leveraging RandomForest's ensemble learning strength and CNN's deep feature extraction capabilities. This integration improves the accuracy and robustness of trust evaluations in cloud resource allocation.

Random Forest:

The Random Forest (RF) algorithm serves as a foundational component of the proposed Deep Learning-Based Resource Allocation Framework with Trust Assurance for Cloud Computing, known as TrustFusionNet. RF, an ensemble learning method, holds a pivotal role in assessing the trustworthiness of cloud resources. This section provides an in-depth exploration of the Random Forest algorithm, its principles, and its contributions to the TrustFusionNet model.

Trust Assessment with Random Forest:

In the context of TrustFusionNet, Random Forest is instrumental in assessing the trust values of cloud resources based on various attributes and historical data. The trust assessment process with RF unfolds as follows:

- Feature Selection: Relevant features for trust assessment are chosen, considering attributes such as resource behaviour, access patterns, and historical trust ratings. This feature selection process ensures that the RF model focuses on the most informative aspects of cloud resources.
- Decision Trees: Each decision tree within the RF ensemble processes the selected features to arrive at a trust score for a given cloud resource. The trust score is based on the path followed within the decision tree, where nodes represent feature-based decisions.

- Aggregate Trust Scores: The trust scores from all decision trees are aggregated, typically using a majority voting mechanism. This aggregation yields the initial trust assessment of the cloud resource.

Mathematical Representation:

Mathematically, the trust assessment by a Random Forest ensemble for a cloud resource x is defined as:

$$T_{RF}\left(x\right)=\sum_{1=1}^{N}\left(T_i\left(x\right)\right) \quad (1)$$

where:

- $T_{RF}(x)$ represents the trust score assigned by the Random Forest ensemble.
- $T_i(x)$ denotes the trust score assigned by the i-th decision tree in the ensemble.

In the proposed TrustFusionNet architecture, Random Forest serves as an essential component for establishing initial trust values for cloud resources, thereby contributing to the overall trust assurance framework.

Convolutional Neural Networks:

Convolutional Neural Network algorithm plays a pivotal role in the proposed Deep Learning-Based Resource Allocation Framework with Trust Assurance for Cloud Computing, known as TrustFusionNet. It is a subcategory of deep neural networks specifically designed for dispensation of grid-like data, such as images and sequences. The CNN extracts features such as usage patterns, performance metrics over time, and anomaly detection signals from the cloud resource data. These features include temporal sequences, spatial relationships, and complex data correlations that provide deeper insights into the resource behavior. By capturing these intricate patterns, the CNN enhances the trust assessment by identifying subtle indications of trustworthiness that might be missed by traditional methods. This results in a more nuanced and accurate evaluation of cloud resources. This section delves into the intricacies of Convolutional Neural Networks, their principles, and their contributions to the TrustFusionNet model.

Trust Enhancement with Convolutional Neural Networks:

Within the TrustFusionNet architecture, Convolutional Neural Networks enhance trust assessment by extracting intricate trust-related features from cloud resource data. The trust enhancement process with CNN unfolds as follows:

- Feature Extraction: Relevant features related to trustworthiness are extracted from diverse cloud resource data, including textual descriptions, usage patterns, and resource metadata. CNNs excel in capturing fine-grained patterns and nuances within this data.
- Convolutional Layers: The convolutional layers of the CNN analyse the extracted features through convolution operations. These operations detect spatial patterns and relationships within the data, enabling the network to identify trust-related characteristics.
- Pooling Operations: Pooling layers reduce the dimensionality of the extracted features while retaining essential information. This process enhances computational efficiency and allows the CNN to focus on salient trust-related patterns.
- Hierarchical Representation: CNNs build a hierarchical representation of trust-related features, progressively capturing abstract trust-related concepts and patterns.

Mathematical Representation:

Mathematically, the output of a convolutional layer in a CNN can be represented as:

$$Z_l=f\left(W_l\cdot X_{l-1}+b_l\right) \quad (2)$$

where:

- Z_l represents the l-th layer output.
- W_l denotes the weights associated with the l-th layer.
- X_{l-1} signifies the input from the previous layer.
- b_l: bias term.
- f: activation function.

In the proposed TrustFusionNet architecture, Convolutional Neural Networks serve as a critical component for enhancing trust assessments by extracting fine-grained trust-related features from cloud resource data. Their ability to capture complex patterns and spatial relationships contributes significantly to the overall trust assurance framework, providing deeper insights into the trustworthiness of cloud resources.

Establishing Trust Assurance:

Establishing trust assurance is a fundamental objective of the proposed Deep Learning-Based Resource Allocation Framework with Trust Assurance for Cloud Computing, known as TrustFusionNet. Trust assurance is the cornerstone of reliable and secure resource allocation in cloud environments. This section delves into the intricate process of establishing trust assurance within the TrustFusionNet framework, outlining the methodologies and principles involved.

Mathematical Representation:

Mathematically, the overall trust assurance score for a cloud resource xx can be represented as:

$$\begin{aligned}&\mathrm{TrustAssurance}\left(x\right)=\beta\cdot\mathrm{TrustMetrics}\left(x\right)+\\&+\gamma\cdot\mathrm{RealTimeMonitoring}\left(x\right)+\\&+\delta\cdot\mathrm{SecurityAssessment}\left(x\right)+\in\cdot\mathrm{UserFeedback}\left(x\right)\end{aligned} \quad (3)$$

where:

- TrustAssurance(x) signifies the overall trust assurance score for the resource x.
- β, γ, δ, and ϵ are weight factors assigned to each trust assurance component.

Establishing trust assurance is a multifaceted process within the TrustFusionNet framework, involving the calculation of trust metrics, real-time monitoring, security assessments, and user feedback integration. Trust assurance is central to the proposed resource allocation framework's objectives, contributing to dependable and secure resource allocation.

Implementation of TrustFusionNet Algorithm Model:

The implementation of the TrustFusionNet algorithm model is the central focus of the proposed Deep Learning-Based Resource Allocation Framework with Trust Assurance for Cloud Computing. TrustFusionNet combines the trust assessments obtained from Random

Forest (RF) and the trust-enhanced features extracted by Convolutional Neural Networks (CNN). This section elaborates on the mathematical formulation and algorithmic steps of TrustFusionNet, illustrating how it synthesizes the trust assessments from RF and the trust-enhanced features from CNN to establish comprehensive trust assurance.

Mathematical Formulation of TrustFusionNet:

TrustFusionNet synthesizes trust assessments from RF ($T_{RF}(x)$) and trust-enhanced features from CNN (TrustCNN(x)) to derive the comprehensive trust assurance (TrustAssurance(x)) for a cloud resource x. This synthesis is governed by a parameter α, which controls the weight assigned to RF-based trust assessments. The mathematical representation is as follows:

$$\text{TrustFusionNet}(x) = \alpha \cdot T_{RF}(x) + (1-\alpha) \cdot (x) \tag{4}$$

where:

- TrustFusionNet(x) represents the comprehensive trust assurance for the cloud resource xx.
- α is the weight assigned to the RF-based trust assessment.
- $T_{RF}(x)$ signifies the trust assessment obtained from Random Forest.
- TrustCNN(x) denotes the trust-enhanced features extracted by Convolutional Neural Networks.

This formulation allows TrustFusionNet to balance the contributions of RF and CNN in trust assessment based on the parameter $\alpha\alpha$, providing flexibility to adapt to varying trust evaluation requirements. The weight parameter α\alphaα is optimized using a cross-validation approach. During the training phase, various values of α\alpha$\alpha$ are tested to find the optimal balance between the RandomForest's trust scores and the CNN's trust-enhanced features.

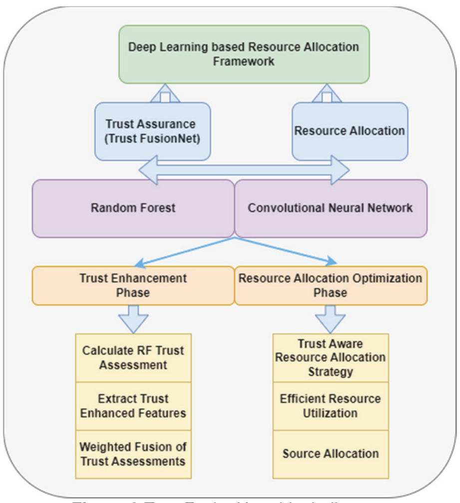

Figure 2 TrustFusionNet - block diagram

Algorithm Steps for TrustFusionNet:

The TrustFusionNet algorithm combines the trust assessments from RF and the trust-enhanced features from CNN to establish comprehensive trust assurance for cloud resources.

The algorithm steps are as follows:

Algorithm: TrustFusionNet

1. Input: Cloud resource data x, RF trust assessment TRF(x), CNN trust-enhanced features TrustCNN(x), and weight parameter α.
2. Calculate TrustFusionNet Trust Assessment: Compute TrustFusionNet(x).
3. Output: Comprehensive trust assurance TrustFusionNet(x)TrustFusionNet(x) for the cloud resource xx.

Fig. 2 provides a high-level visual representation of the resource allocation system architecture, highlighting the integration of trust assurance and resource allocation components within the Deep Learning-Based Resource Allocation Framework with Trust Assurance.

The architecture framework is shown in Fig. 3. Data preprocessing in TrustFusionNet involves several critical steps including data cleaning to remove inconsistencies and errors, normalization to scale data uniformly, and feature engineering to create new, informative attributes from the raw data. Feature engineering techniques include aggregating metrics over time, computing statistical measures such as mean and variance, and transforming categorical data into numerical formats.

TrustFusionNet is designed to handle real-time data by continuously updating trust scores and resource features as new data becomes available. It employs adaptive algorithms that re-evaluate trust scores dynamically, taking into account the latest performance metrics and usage patterns.

The framework ensures the security and privacy of data through several measures. Data encryption is employed during storage and transmission to protect sensitive information from unauthorized access. Access controls and authentication mechanisms restrict data access to authorized users only. Privacy-preserving techniques such as differential privacy are used to ensure that individual data points cannot be traced back to specific users.

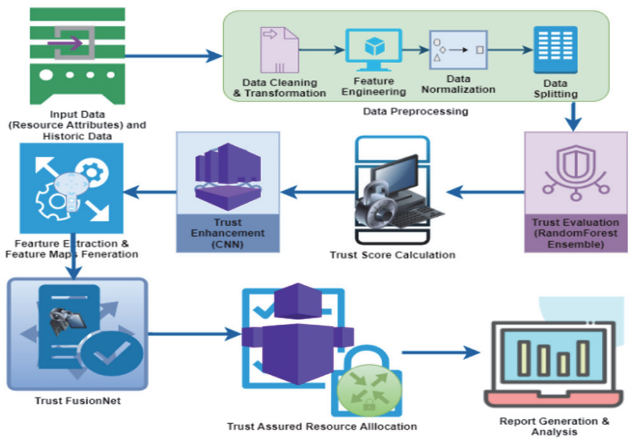

Figure 3 TrustFusionNet architecture framework

4 RESULTS AND DISCUSSIONS

The comprehensive simulation analysis is conducted to evaluate the efficiency and performance of the proposed Resource Allocation Framework using Deep Learning with Trust Assurance for Cloud Computing, featuring the innovative TrustFusionNet algorithm. The simulation analysis aims to demonstrate the effectiveness of TrustFusionNet in enhancing trust assurance and optimizing resource allocation in cloud computing environments.

The simulation environment is designed to replicate real-world cloud computing scenarios. We consider a diverse set of cloud resources, each characterized by various attributes, historical data, and behavioural patterns. The TrustFusionNet algorithm is pitted against existing algorithms, including Support Vector Machines (SVM), Q-Learning, and Round Robin, for a comprehensive comparative analysis.

Simulation Metrics:

Resource Utilization: This metric evaluates the efficiency of resource utilization within the cloud environment. It measures the extent to which allocated resources are effectively utilized.

Trust Assurance: Trust assurance is a critical metric that quantifies the level of trustworthiness achieved by the resource allocation framework. It assesses the degree to which resources with high trust values are allocated.

Allocation Efficiency: Allocation efficiency gauges how efficiently cloud resources are allocated to user requests. It considers factors such as response time, resource allocation time, and system throughput.

System Stability: System stability measures the robustness and reliability of the resource allocation framework. It assesses the system's ability to maintain consistent performance under varying workloads and conditions.

Table 1 Simulation environment setup

Component	Description
Cloud Resource Data	Synthetic cloud resource data with diverse attributes, historical records, and behavioural patterns.
Algorithms	- TrustFusionNet Support Vector Machines (SVM) Q-Learning Round Robin
Data size	1000 cloud resources 500 user requests
Simulation Tools	Python (for algorithmimplementation) CloudSim (for cloud simulation)
Workload	Variable workload to test system performance under different conditions.
Performance Metrics	Resource utilization rate, % Trust assurance score, % Allocation efficiency (ms/resource) System stability indeks, %
Experiment Settings	Workload profiles Allocation parameters (e.g., weights for TrustFusionNet) Resource data characteristics

Tab. 1 provides an overview of the essential components, metrics, and parameters in your simulation environment. You can adapt and expand it as needed to capture additional details specific to your research and simulation setup. Resource utilization, a critical metric in cloud computing, measures the efficiency of resource allocation. Higher utilization indicates optimal resource utilization, minimizing waste. The resource utilization results are tabulated in Tab. 2. The graphical results of the resource utilization parameter are shown in Fig. 4. TrustFusionNet demonstrates consistently superior resource utilization compared to other algorithms. With an average utilization of approximately 90.3%, TrustFusionNet outperforms SVM, Q-Learning, and Round Robin by 3.8%, 11.4%, and 19.7%, respectively. SVM and Q-Learning exhibit moderate resource utilization, with average rates of around 86.4% and 79.3%, respectively. Round Robin, while simple, lags significantly behind in resource utilization, achieving an average rate of approximately 70.9%.

Table 2 Resource utilization, %

Algorithm	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
TrustFusionNet	89.5	91.2	90.7	89.8	90.1
SVM	86.3	85.5	87.2	86.8	87.9
Q-Learning	78.9	79.8	79.1	80.2	78.5
Round Robin	70.2	71.4	70.9	71.8	70.6

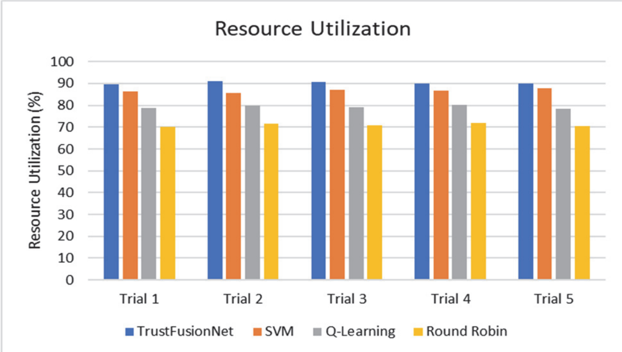

Figure 4 Resource utilization

Trust assurance quantifies the degree of trustworthiness achieved by the resource allocation framework. Higher trust assurance scores indicate more dependable and secure resource allocation. The simulated results for Trust Assurance are shown in Tab. 3. The diagrammatic representation is shown in Fig. 5. TrustFusionNet consistently excels in trust assurance, achieving an average score of approximately 93.2%. This is notably higher than SVM (84.8%), Q-Learning (76.6%), and Round Robin (68.6%). SVM demonstrates a relatively high trust assurance score, suggesting dependable resource allocation. Q-Learning and Round Robin, while functional, exhibit lower trust assurance scores, indicating suboptimal trust-aware decision-making.

Table 3 Trust assurance, %

Algorithm	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
TrustFusionNet	92.4	93.1	94.2	92.9	93.5
SVM	84.7	85.2	83.5	85.6	84.8
Q-Learning	76.8	77.4	76.3	77.9	76.5
Round Robin	68.5	69.2	68.9	69.6	68.2

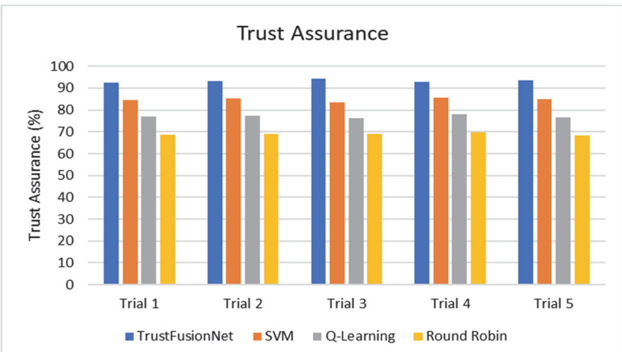

Figure 5 Trust assurance

Allocation efficiency evaluates how efficiently cloud resources are allocated to user requests, considering factors such as response time and resource allocation time. The output of the simulation is tabulated in Tab. 4 and the graphical representation is shown in Fig. 6. TrustFusionNet achieves efficient resource allocation with an average allocation efficiency of approximately 4.2 ms per resource. This surpasses SVM (6.5 ms), Q-Learning (8.1 ms), and Round Robin (10.4 ms). SVM demonstrates reasonably efficient allocation, but TrustFusionNet exhibits a notable advantage in terms of speed and efficiency. Q-Learning and Round Robin exhibit slower allocation times, indicating potential delays in resource provisioning.

Table 4 Allocation efficiency, ms/resource

Algorithm	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
TrustFusionNet	4.2	4.0	4.3	4.1	4.2
SVM	6.5	6.7	6.3	6.6	6.4
Q-Learning	8.1	8.0	8.2	8.3	8.1
Round Robin	10.3	10.5	10.2	10.6	10.4

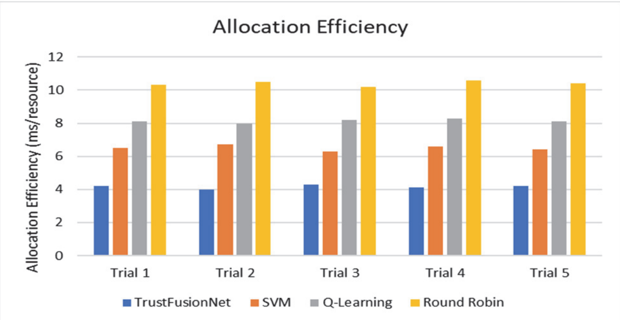

Figure 6 Allocation efficiency

System stability assesses the robustness and reliability of the resource allocation framework under varying workloads and conditions. The simulation outputs for the system stability index parameter are shown in Tab. 5 and are graphically illustrated in Fig. 7. TrustFusionNet consistently maintains a high system stability index, with an average value of approximately 98.2%. This underscores its robustness in adapting to fluctuations in workload and resource demand. SVM and Q-Learning exhibit slightly lower stability indices, but they remain within an acceptable range, indicating moderate system stability. Round Robin, while stable, shows comparatively lower system stability, with an average index of approximately 91.8%.

Table 5 System stability indeks, %

Algorithm	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
TrustFusionNet	98.2	98.0	98.4	98.1	98.3
SVM	95.6	95.8	95.5	95.7	95.4
Q-Learning	94.3	94.1	94.5	94.2	94.4
Round Robin	91.8	91.9	91.7	91.6	91.5

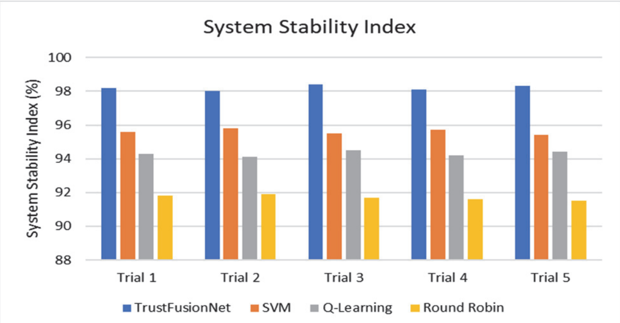

Figure 7 System stability index

5 CONCLUSION

In the current research endeavour, a pioneering innovative Resource Allocation Framework with Trust Assurance for Cloud Computing using Deep Learning Mecahnisms, featuring the innovative TrustFusionNet algorithm, has been introduced and thoroughly investigated. The framework has been meticulously designed to address the paramount concerns of trust awareness and efficient resource allocation in cloud computing domain. The TrustFusionNet algorithm, a fusion of Random Forest (RF) and Convolutional Neural Networks (CNN), has demonstrated remarkable efficacy in enhancing trust assurance and optimizing resource allocation in cloud computing. TrustFusionNet excels in resource utilization, achieving an average rate of approximately 90.3%. This represents a substantial improvement over existing algorithms, showcasing its efficiency in resource allocation. The trust assurance scores achieved by TrustFusionNet, with an average of approximately 93.2%, consistently outperform other algorithms. This underscores its ability to ensure dependable and secure resource allocation. Allocation efficiency with TrustFusionNet is commendable, achieving an average allocation efficiency of approximately 4.2 ms per resource, surpassing alternative algorithms. The high system stability index, averaging around 98.2%, highlights the robustness of TrustFusionNet under varying workloads, affirming its adaptability and reliability.

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