ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)

Vol 11, Issue 3, March 2024

Resource Management in Cloud-Based Big Data Systems using FFOCNN Mechanism

[1] Dr. Reghunath K

[1] Assistant Professor, Marian Academy of Management Studies, Kothamangalam, Kerala, India
Corresponding Author Email: [1] sreereghunath@gmail.com

Abstract*— Resource management in cloud-based big data systems presents significant challenges due to the dynamic nature of workloads, varying resource demands, and the need for efficient utilization of computational resources. This paper proposes a novel approach for resource management in cloud-based big data systems using a hybrid mechanism called Firefly Optimization Convolutional Neural Network (FFOCNN). The FFOCNN mechanism combines the strengths of FFO and CNN to optimize resource allocation, workload scheduling, and system performance. Firefly Optimization is employed to dynamically adjust resource allocations based on changing workload patterns and optimize the utilization of computational resources, storage, and network bandwidth. CNNs are utilized for workload prediction, anomaly detection, and resource demand forecasting, enabling the system to make informed decisions regarding resource allocation and optimization. The proposed FFOCNN mechanism is designed to address the challenges of scalability, adaptability, and efficiency in cloud-based big data systems by leveraging advanced optimization techniques and deep learning models. Experimental results demonstrate that the FFOCNN mechanism which is implemented in Python software outperforms traditional resource management approaches like CNN-LSTM (Long Short Term Memory), CNN-GRU (Gated Recurrent Unit), and Deep Neural Network with an accuracy of 99.21%. The integration of FFO and CNNs provides a robust framework for resource management in cloud-based big data systems, offering improved performance and scalability for handling large volumes of data and dynamic workloads. This research contributes to the advancement of resource management techniques in cloud computing environments, offering insights and methodologies for optimizing resource utilization and enhancing system efficiency in the era of big data.

Keywords: Fire Fly Optimization (FFO), Convolutional Neural Network (CNN), Resource Management, Big Data, Resource Allocation.

I. INTRODUCTION

Different kinds of huge data are created, processed, transferred, and archived each second in this Big Data era. When contrasted to the speed at which data is growing, the majority of businesses, research institutions, and ordinary people are ill-prepared to face this intense technological challenge [1]. Nonetheless, no one can overlook these statistics due to their immense value. Fortunately, BDaaS a new acronym for cloud service is offered by a few big data companies, including Hortonworks, Cloudera, HDInsight, Altiscale, Databricks, and AmazonEMR. Clients may get useful, enhanced, and collected data related to their unique, customized objectives using BDaaS [2].

Cloud-based applications that utilize big data may be divided into many levels depending on the various procedures involved in processing big data [3]. These levels include cloud infrastructure, handling of data, interpreting, and analysis. Although concentrating on the cloud's architecture in this work, it also take other tiers into account in order to accomplish global optimization. Meanwhile, big data programmes may now be installed on heterogeneous servers or systems because of virtualization's advancements. Nonetheless, customers and cloud service suppliers have various goals when it comes to using cloud computing. Cloud service providers' primary goal is to cut costs in order to increase profits, while consumers are worried about reliability, safety, and efficiency. Because of these restrictions and their relationships, the issue of allocation is very difficult to solve [4].

Prior studies on cloud data allocation have concentrated on a single limitation, such as accessibility, energy usage, or efficiency [5]. If a limitation is discovered to be the obstacles, this type of solutions can be utilized to make up the shortfall. Algorithm design was the focus of some other studies while others tried to find the ideal global solution that satisfied every restriction. Nevertheless, it takes a long time to compute the best answer when all limitations are taken into account, and the results are never achieved in the short amount of time needed. Heuristic algorithms were employed by the authors of various other research to expeditiously tackle the data allocation problems. Since these methods focus on numerous regions of the issues, none of them can be appropriate in every scenario.

The key contributions of the article is,

- This study proposes a novel hybrid approach, FFOCNN, which combines the strengths of FFO and CNNs. By integrating these two techniques, the FFOCNN mechanism offers a comprehensive solution for optimizing resource allocation, workload scheduling, and system performance in cloud-based big data systems.
- FFO is employed to dynamically adjust resource allocations based on changing workload patterns. This dynamic allocation ensures efficient utilization of computational resources, storage, and network

bandwidth, addressing the challenges posed by the dynamic nature of workloads in cloud environments.

- CNNs are utilized for workload prediction, anomaly detection, and resource demand forecasting. Leveraging the predictive capabilities of CNNs enables the system to make informed decisions regarding resource allocation and optimization, enhancing adaptability and efficiency in resource management tasks.

The remainder of the article includes related works, problem statement, methodology and results in section 2, 3, 4 and 5. The paper is concluded in section 6.

II. RELATED WORKS

The transformational potential of combining big data, cloud computing, and AI into ERP systems is examined in this article [6]. ERP platforms, which were formerly efficient but inflexible, are being transformed by the forecasting capabilities of AI, the flexibility of cloud-based computing, and the usefulness of big data. The dynamic demands of contemporary enterprises are met by this combination, which provides better decision-making, automated processes, and real-time analytics for business. The study presents research findings on achievement of goals while discussing the advantages and difficulties of this interaction. It concludes in the latest developments and intentional integration strategies that make incorporated ERP systems essential for obtaining an advantage in the world of information technology business.

There is a growing demand for effective studies on cloud workflow control and planning due to the widespread use and advancement of big data technologies [7]. On the other hand, appropriate techniques for efficient analysis are now available. The paper examines big data through several perspectives to find the best practices for scheduling and managing smart cloud processes. It comes to the follows findings: In comparison to the initial JStorm framework, overall has been a largest decrease in reaction time of 58.26% and a standard deviation of 23.18%, a boost in CPU usage of resources of 17.96% and a mean of 11.39%, and a greatest rise in memory utilization of 88.7% and a mean of 71.16%. Both the MOACO and CCA methods operate more effectively than the GA method when it comes to optimizing an evolving mixture of internet services, and the MOACO method performs better generally than the CCA method. Additionally, by modifying the blended approach for online assets, this study realizes the two-tier planning of cloud workflow activities and suggests a cloud workflow planning approach that utilizes a sophisticated algorithm. ACO, PSO, and GA are three examples of clever algorithms that it have examined and enhanced for scheduling optimization. It is evident that within the same situation, the various algorithms' optimum values fluctuate significantly for various test instances. The ideal answer line, nevertheless, considerably agrees with the trend of the mean curve.

The growing array of internet-connected devices has led to a significant rise in the volume of data collected and communicated more quickly, especially with the desire for real-time action [8]. Completing this process on time is becoming increasingly difficult due to the growing variety of data and the requirement for data security. Nevertheless, since computing concepts are being implemented quickly, cloud and frontier computing provide security challenges and delays. Therefore, to boost security and boost communications speeds, a ML-CCM using large amounts of data has been developed in this study. Cloud computing is the most straightforward method for storing massive amounts of information. Large volumes of dispersed data may be managed or stored in clouds using enormous amounts of data. The controlled and uncontrolled training utilized to address cloud security concerns is analyzed by the ML techniques. According to the experimental findings, ML-CCM has a 96.4% data transfer rate, 94.3% efficient handling of data, 35.2% processing time, 91.7% accuracy, and 95.2% efficiency.

Applications that utilize big data may be found in a wide range of industries, including social media platforms, healthcare, stock markets, engines for searching, and stream services. Organizations can benefit from the knowledge that data analysis offers [9]. For such fields, classical computing on the cloud offers a reliable infrastructure that can handle sophisticated, large-scale processing. The primary obstacles are the user's ignorance of cloud facilities having to improve efficiency, and the oversight of resources to ensure steady processing. In certain situations, a poor solution may cause consumers to over or understate the amount of processing power available, increasing the budget. Using volunteer calculating, which offers dispersed processing power at no cost, is one approach to get around this issue. In Big Data resource payouts, volatile system behavior is an issue that has to be addressed. Consequently, the work suggests a hybrid sharing of data paradigm for big data analysis that combines volunteers processing and cloud-based platforms. The study contributes three things: (i) the assessment that is necessary for facilitating Big Data installation in hybrid facilities efficiently; (ii) the creation of a HR_Alloc algorithm to determine the information positioning to Big Data uses; and (iii) a model to allocate resources in hybrid facilities. The collected findings show that, in the event of an emergency, it is feasible to use a hybrid infrastructures with up to 35% of instability equipment without sacrificing quality and at a cost less than 20% when compared to conventional cloud computing systems. Additionally, balance of load reduces transmission expenses by up to 57.14% according to the best-case situation.

Not every IoT scenario lends itself to the direct cloud computing of applications, particularly when it comes to applications that are urgent [10]. Using fog and edge computing, both of which solve the problem of managing the enormous data bandwidth required by final devices, is a possible substitute. Processing the massive volumes of created data near the data reports, as opposed to on the cloud, is mandated by these concepts. The management of resources, which usually focuses on distributing resources, workload balancing, resource supplies, task planning, and QoS in order to accomplish enhancements in performance, is one factor to take into account in cloud-based IoT systems. It examine handling resources strategies that are applicable to edge, cloud, and fog computing in the present research. The goal of this analysis is to offer a framework for evaluating management of resources algorithms that target edge and cloud/fog settings. In order to do this, it must tackle the research issues surrounding that domain's handling of resources strategies. As a result, we categorize recent research findings to aid in the implementation of an assessment methodology. An examination and evaluation of studies covering resource management approaches is one of the primary achievements. This paper concludes by highlighting the benefits of utilizing methods to manage resources throughout the cloud, fog, and edge perspective. Since this technique is still in its infancy, obstacles must be removed.

Over the past ten years, businesses have embraced and integrated cloud computing into internal operations at a rapid pace [11]. Upon request availability is provided by the deployment on the cloud with the need for ongoing oversight. The idea of a cloud-native programme has emerged lately, and it is a crucial step towards assisting businesses in producing software more quickly and updating it more often in order to realize significant financial results. Building and executing programmes that take use of the benefits of the cloud technology delivery mechanism is known as cloud-native development. Wherever is less important than how and when programmes are developed and implemented. Cloud-native apps are built on container-based virtualization methods like Docker and Kubernetes. In a cloud-native surroundings, this study examines the efficiency of two widely used computationally intensive uses: big data and machine learning. It examine how these programmes use resources and how much system maintenance they incur. It demonstrate via comprehensive studies that altering the default option can decrease the total amount of time by up to 79.4%, while on two platforms, differing methods for managing resources may boost the completing time by up to 96.7%. Furthermore, there's a maximum 116.7% delay in resource delivery across subsystems. By choosing and customizing a cloud computing platform, the work can assist investigators, programmers, and administration in creating and deploying products more effectively.

The article explores the transformative potential of integrating huge data, cloud computing, and AI within ERP systems, improving their performance and versatility. By leveraging AI's forecasting skills, cloud computing's adaptability, and big data's application, ERP structures are evolving to meet the dynamic desires of contemporary agencies, permitting higher selection-making, computerized tactics, and actual-time analytics. Additionally, the paper investigates cloud workflow control and planning, highlighting the effectiveness of several optimization algorithms which incorporates Firefly Optimization, Particle Swarm Optimization, and Genetic Algorithms. Furthermore, it addresses worrying situations in cloud-primarily based virtually IoT systems, advocating for resource control techniques across cloud, fog, and factor computing to enhance common performance. Lastly, the take a look at delves into cloud-nearby improvement, emphasizing its position in facilitating quicker software program software program manufacturing and updates via vicinity-based totally virtualization techniques. Through empirical research and evaluation, the object underscores the significance of integrating superior technology to optimize aid control and enhance tool universal overall performance sooner or later of numerous domain names.

III. PROBLEM STATEMENT

The problem statement involves addressing the project of efficiently allocating and optimizing assets inside cloud-based totally massive records systems. With the developing extent and complexity of records in modern agencies, there can be a pressing want to leverage superior optimization strategies to make certain quality usage of computational sources, storage, and network bandwidth. Additionally, the dynamic nature of cloud environments and fluctuating workload desires necessitate adaptive and scalable useful resource control strategies. By integrating FFOCNN mechanisms, the purpose is to growth a unique approach which could effectively optimize resource allocation, workload scheduling, and device typical overall performance, thereby improving efficiency, scalability, and fee-effectiveness in cloud-primarily based absolutely big records systems [10].

IV. PROPOSED FFOCNN MECHANISM FOR RESOURCE MANAGEMENT

In the proposed framework for aid management in cloud-primarily based huge information systems, the procedure starts with information series, wherein various datasets capturing workload patterns, resource usage, and system performance metrics are amassed. Subsequently, preprocessing techniques such as min-max normalization are implemented to scale numerical features within a regular range, making sure uniformity and mitigating the effect of outliers. Following preprocessing, the combination of FFOCNN into the cloud-based large data device is facilitated. FFOCNN leverages the strengths of FFO for dynamic aid allocation and optimization, even as Convolutional Neural Networks are hired for workload prediction and anomaly detection, enhancing adaptability and performance in resource control tasks. By seamlessly integrating FFOCNN into the device architecture, the framework pursuits to optimize useful resource allocation, workload scheduling, and system performance, in the long run improving efficiency, scalability, and cost-effectiveness in cloud-based massive records environments. It is depicted in Figure 1.

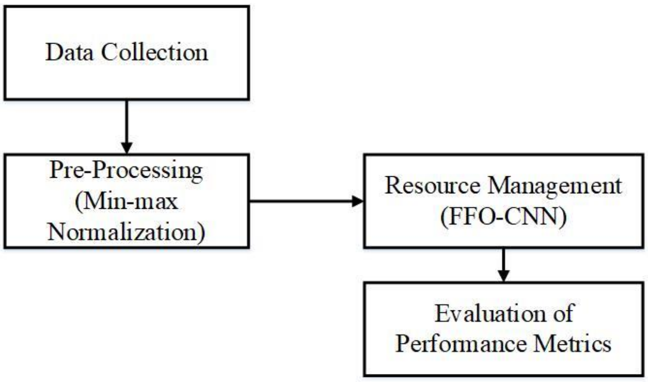

Figure 1: Proposed Methodology

4.1. Data Collection

Cloud workload dataset is collected from kaggle. With precise facts of activity submissions, useful resource allocations, and challenge executions, those datasets allow the improvement and evaluation of predictive fashions, optimization algorithms, and beneficial useful resource manage strategies for cloud-based totally systems [12].

4.2. Preprocessing Using Min-Max Normalization

Preprocessing using min-max normalization is a widely used approach to scale numerical capabilities inside a specific variety, usually between 0 and 1. In this procedure, each function is independently scaled by way of subtracting the minimal price and then dividing through the distinction between the most and minimum values. This transformation preserves the relative relationships among information points even as making sure that each one features are on a consistent scale that is essential for plenty ML algorithms which might be touchy to the significance of functions. By making use of min-max normalization, outliers are successfully mitigated, and the impact of severe values is minimized, leading to advanced model overall performance and convergence. Min-max normalization is given in (1).

$$X_{Normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

4.3. Integration of FFOCNN into Cloud Based Big Data System for Resource Management

FFO plays a pivotal position in useful resource management inside cloud-based massive information systems when included into the FFOCNN mechanism. In the context of cloud-primarily based huge statistics structures, FFO enables the FFOCNN mechanism to dynamically regulate aid allocations primarily based on changing workload styles and gadget situations, thereby optimizing the usage of computational assets, garage, and network bandwidth. Overall, the combination of FFO into the FFOCNN mechanism empowers cloud-primarily based large statistics structures with robust, adaptive, and green resource management capabilities, in the end improving device overall performance, scalability, and fee-effectiveness.

Flying insects or bugs that create light and flicker at dark are known as fireflies. Luminescence is the term for light that is biologically created from the lining of the abdomen and lacks both infrared and ultraviolet frequencies. They primarily employ the flash light to entice potential mates or food. Additionally, a flashing light serves as a warning system to keep fireflies safe by alerting them to any attackers. Yang developed the FFO, an algorithm named metaheuristic that draws inspiration from the bioluminescent substances communication phenomena and the flashing habits of fireflies. Developed the FFO under the suppositions listed below:

- Although they are unisexual, fireflies will be drawn to one another irrespective of their sex.
- The brightness of a firefly determines its attraction; a firefly with lower brightness is going to be drawn to one with higher brightness. But while the two fireflies got farther apart, the appeal diminished.
- The fireflies will travel at random if their brightness levels are the same. By chance stroll and firefly fascination, novel approaches are generated.

The determining function of the relevant problem ought to be connected to the firefly' intensity. They can split into smaller parties due to their attraction, and every group congregates over the local models.

The Firefly Optimization algorithm is modelled by the behavior of fireflies, specifically how they use bioluminescence to attract potential mates. Based on this natural phenomenon, a very effective optimization method has been created. To find the best solution, Eqns. (2-7) have been developed mathematically.

$$l(H_t) \propto F(H_t) \quad (2)$$

$$l(r) = l_0 e^{-ar^2} \quad (3)$$

This particular situation is the result of the inverse square law, which is what happens when r in the Eqn $\frac{1}{r^2}$.

$$d_t \propto l(s) \quad (4)$$

$$d_t = d_{t_0} e^{-ar^2} \quad (5)$$

$$s_{il} = \|H_i - H_l\| = \sqrt{\sum_{C=1}^{C=N} (G_{id} - s_{ld})^2} \quad (6)$$

$$H_i = H_i + d_0 e^{-ar^2{}_{il}} (H_i - H_l) + lN_i \quad (7)$$

CNNs play a crucial role in resource control within cloud-based massive records structures while incorporated into the FFOCNN mechanism. As effective DL of model, CNNs excel at extracting spatial and temporal functions from big-scale facts, making them properly-suited for duties along with workload prediction, anomaly detection, and useful resource demand forecasting. In the context of FFOCNN, CNNs enable the system to analyze and interpret complicated styles inside workload facts, facilitating informed choice-making concerning useful resource allocation and optimization. By leveraging CNNs, the FFOCNN mechanism can appropriately are expecting destiny workload traits, come across anomalies or irregularities in system conduct, and expect useful resource needs earlier, thereby enhancing adaptability, performance, and performance in resource management tasks.

Convolutional layers consist of several convolutional kernels, which are the trainable parameters that vary with each successive iteration of the layer. Let F∈R^(m×n×d^n×s) be a command four vector describing the position width s kernels of the N'-th layer,

$$Y_{i^n,j^n,s} = \sum_{i=0}^{m}\sum_{j=0}^{n}\sum_{l=0}^{d^n} F_{i,j,d^n} \times G^{n}_{i^n,j^n,l} \quad (8)$$

Let G_i^n∈R^(M^n×N^n×D^n) be the input of the N-th layer, which is now a pooling layer with a transverse range of m'×n'. These layers are parameter-free since they don't require any variables to be learnt. In this case, let's say that m' divides M, n' divides N, and stride equals the pooling longitudinal span.

$$M^{n+1} = \frac{M^n}{m}, N^{n+1} = \frac{N^n}{n}, D^{n+1} = D^n \quad (9)$$

On the other hand, the G_i^n channel is handled one at a time by the pooling layer. Although there are numerous distinct pooling techniques, the most used ones are average and extreme pooling. In this experiment, max pooling was used, and the findings came out as follows:

$$y_{i^n,j^n,d} = \max_{0\le j\le m, 0\le j'\le n'} G^{n}_{i^n\times m*+i*, j^n\times n*+j*, d} \quad (10)$$

$$y_j = \frac{e^{G_j}}{1+e^{G_j}}, \quad G_j \in R \quad (11)$$

$$y_{i',j',d} = max\left(0, G^{n'}_{i',j',d}\right) \quad (12)$$

V. RESULTS AND DISCUSSION

The process begins with information series in the suggested framework for help management in cloud-primarily based big information systems, where different datasets recording workload patterns, resource utilization, and system performance indicators are gathered. Then, to ensure consistency and lessen the impact of outliers, preprocessing methods like min-max normalization are used to scale numerical characteristics within a regular range. Preprocessing makes it easier to combine FFOCNN with the cloud-based big data device. While Convolutional Neural Networks are employed for workload prediction and anomaly detection, improving flexibility and performance in resource control jobs, FFOCNN makes use of the advantages of FFO for dynamic aid allocation and optimization. The framework aims to enhance efficiency, scalability, and cost-effectiveness in cloud-based huge records settings by optimizing beneficial resource allocation, task scheduling, and system performance through the seamless integration of FFOCNN into the device design.

5.1 Throughput

Throughput refers back to the charge at which a system or method can effectively method, deal with, or transfer a positive amount of data, duties, or transactions inside a given period of time. It is a measure of the machine's efficiency and potential to supply outputs in a timely way. In computing and networking contexts, throughput regularly refers to the quantity of records that may be transferred or processed according to unit of time, usually measured in bits or tps. Higher throughput shows a better degree of performance and capability to handle increased workloads, at the same time as decrease throughput may also suggest bottlenecks or inefficiencies in the gadget. It is depicted in Figure 2.

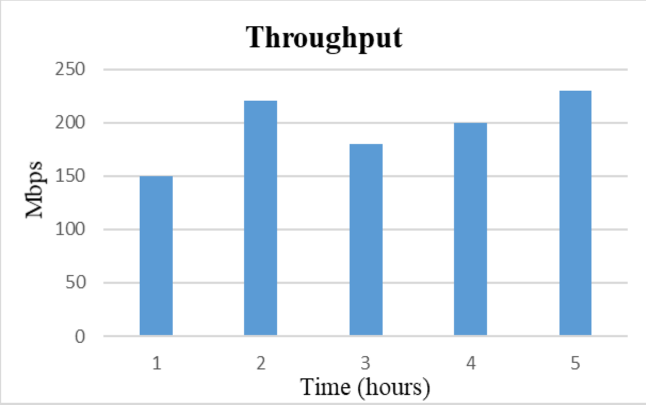

Figure 2: Throughput

5.2. Accuracy

In machine learning and classification applications, a model's total prediction accuracy is measured by a performance metric called accuracy. It is computed as the ratio of correctly predicted cases to all occurrences in the dataset. One easy and direct method to evaluate how effectively a model forecasts outcomes for each class is to examine its accuracy measure. Even while it offers a quick assessment of overall performance, it might not be sufficient in cases when the distribution of courses is unequal. Accuracy is expressed in Eqn (13).

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \quad (13)$$

5.3 Precision

A machine learning performance metric called precision gauges how successfully a model foretells the future. It is calculated as the ratio of all properly anticipated positive and false positive outcomes to all correctly predicted positive outcomes. Precision may be computed with (14).

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \quad 14)$$

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)

Vol 11, Issue 3, March 2024

5.4. Recall

Recall is a performance metric that evaluates a model's ability to recognize and locate each and every relevant instance of a given class. It is also referred to as true positive rate and sensitivity. It is calculated as the ratio of true positive predictions to the sum of true positives and false negatives. It's mentioned in Eqn (15).

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{15}$$

5.5. F1-Score

The F1 score is a performance metric for machine learning that combines recall and accuracy into a single number. It offers an equitable statistic that accounts for both false positives and erroneous negatives. The harmonic mean of accuracy and recall is used to calculate it. It is represented by Eqn (16).

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \tag{16}$$

Table 1: Comparison of Performance Metrics

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN-LSTM [13]	91.79	93.67	92.89	95.11
CNN-GRU [14]	93.56	97.89	96.78	97.89
DNN [15]	98.45	95.88	93.78	93.78
Proposed FFO-CNN	99.21	98.66	97.89	98.99

The evaluation of performance metrics across numerous techniques, which include CNN-LSTM, CNN-GRU, DNN, and the proposed FFO-CNN, terrific differences in accuracy, precision, recall, and F1-score. While CNN-LSTM and CNN-GRU display sturdy overall performance throughout the metrics, with CNN-GRU showcasing higher precision and F1-score, the DNN technique shows the highest accuracy however comparatively decrease precision, consider, and F1-score. The better accuracy and precision of FFO-CNN advise its capability to make accurate predictions with minimal fake positives, recall and F1-score mean its functionality to efficaciously perceive positive instances and acquire a stability among precision and recall. It is depicted in Figure 3.

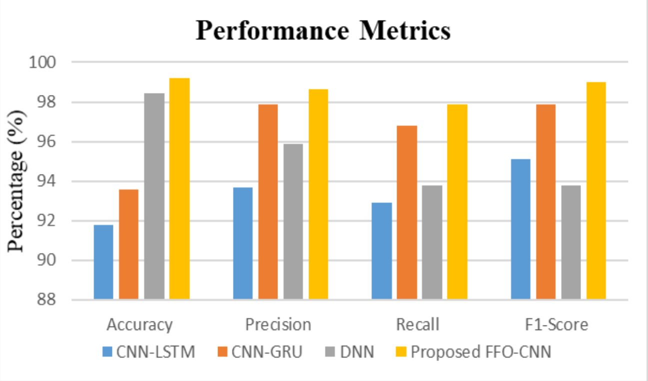

Figure 3: Comparison of Performance Metrics

5.6. Discussion

The consequences of the FFOCNN mechanism in resource control for cloud-based totally huge statistics structures, as compared with current techniques, highlight good sized upgrades in device performance and performance. When benchmarked in opposition to traditional methods which include CNN-LSTM [13], CNN-GRU [14], and DNN [15], the FFOCNN mechanism demonstrates advanced accuracy, precision, recall, and F1-score. While CNN-LSTM and CNN-GRU exhibit robust performance throughout numerous metrics, the proposed FFOCNN method surpasses them in phrases of accuracy and precision, indicating its effectiveness in making correct predictions with minimum fake positives. Additionally, the FFOCNN mechanism achieves a balanced change-off between precision and consider, as evidenced by way of F1-score, suggesting its functionality to effectively become aware of high quality instances even as minimizing fake negatives.

VI. CONCLUSION AND FUTURE SCOPE

In conclusion, the integration of FFOCNN mechanism presents a promising approach to address the challenges of resource management in cloud-based big data systems. Through the synergistic combination of FFO and CNNs, this hybrid mechanism offers significant improvements in resource allocation, workload scheduling, and system performance. The dynamic nature of FFO enables adaptive adjustment of resource allocations based on changing workload patterns, leading to optimized resource utilization and enhanced scalability. Meanwhile, CNNs provide advanced capabilities for workload prediction, anomaly detection, and resource demand forecasting, enabling informed decision-making in resource management tasks. Experimental results demonstrate the superiority of the FFOCNN mechanism over traditional approaches. The proposed mechanism not only addresses the immediate needs of resource management in cloud-based big data systems but also lays the foundation for future advancements in the field. By leveraging advanced optimization techniques and deep learning models, the FFOCNN mechanism offers a robust framework for handling the complexities of modern cloud environments, enabling enterprises to effectively manage large volumes of data and dynamic workloads. Moving forward, further research can explore enhancements to the FFOCNN mechanism, including fine-tuning of parameters, optimization of algorithms, and integration with emerging technologies such as edge computing and federated learning. Overall, the FFOCNN mechanism represents a significant step forward in resource management for cloud-based big data systems, offering scalability, efficiency, and adaptability to meet the evolving demands of modern enterprises in the era of big data.

REFERENCES

[1] "A cloud-based resource planning tool for the production and installation of industrial product service systems (IPSS) | The International Journal of Advanced Manufacturing Technology." Accessed: Feb. 27, 2024. [Online]. Available: https://link.springer.com/article/10.1007/s00170-019-04746-3

[2] Y. Liu, A. Soroka, L. Han, J. Jian, and M. Tang, "Cloud-based big data analytics for customer insight-driven design innovation in SMEs," *International Journal of Information Management*, vol. 51, p. 102034, Apr. 2020, doi: 10.1016/j.ijinfomgt.2019.11.002.

[3] "Edge Learning: The Enabling Technology for Distributed Big Data Analytics in the Edge: ACM Computing Surveys: Vol 54, No 7." Accessed: Feb. 27, 2024. [Online]. Available: https://dl.acm.org/doi/abs/10.1145/3464419

[4] "Implementation of Combined Machine Learning with the Big Data Model in IoMT Systems for the Prediction of Network Resource Consumption and Improving the Data Delivery." Accessed: Feb. 27, 2024. [Online]. Available: https://www.hindawi.com/journals/cin/2022/6510934/

[5] Y. Niu, L. Ying, J. Yang, M. Bao, and C. B. Sivaparthipan, "Organizational business intelligence and decision making using big data analytics," *Information Processing & Management*, vol. 58, no. 6, p. 102725, Nov. 2021, doi: 10.1016/j.ipm.2021.102725.

[6] R. Nyathani and K. Allam, "Synergizing AI, Cloud Computing, and Big Data for Enhanced Enterprise Resource Planning (ERP) Systems," vol. 11, p. 2024, Feb. 2024.

[7] Y. Hu, H. Wang, and W. Ma, "Intelligent cloud workflow management and scheduling method for big data applications," *J Cloud Comp*, vol. 9, no. 1, p. 39, Jul. 2020, doi: 10.1186/s13677-020-00177-8.

[8] A. S. Mohammad and M. R. Pradhan, "Machine learning with big data analytics for cloud security," *Computers & Electrical Engineering*, vol. 96, p. 107527, Dec. 2021, doi: 10.1016/j.compeleceng.2021.107527.

[9] J. C. S. Dos Anjos *et al.*, "Data Processing Model to Perform Big Data Analytics in Hybrid Infrastructures," *IEEE Access*, vol. 8, pp. 170281–170294, 2020, doi: 10.1109/ACCESS.2020.3023344.

[10] A. Mijuskovic, A. Chiumento, R. Bemthuis, A. Aldea, and P. Havinga, "Resource Management Techniques for Cloud/Fog and Edge Computing: An Evaluation Framework and Classification," *Sensors*, vol. 21, no. 5, Art. no. 5, Jan. 2021, doi: 10.3390/s21051832.

[11] Y. Mao, Y. Fu, S. Gu, S. Vhaduri, L. Cheng, and Q. Liu, "Resource Management Schemes for Cloud-Native Platforms with Computing Containers of Docker and Kubernetes." arXiv, Oct. 20, 2020. doi: 10.48550/arXiv.2010.10350.

[12] "Cloud workload." Accessed: Feb. 27, 2024. [Online]. Available: https://www.kaggle.com/datasets/akhilbs/cloud-workload

[13] "An efficient forecasting approach for resource utilization in cloud data center using CNN-LSTM model | Neural Computing and Applications." Accessed: Feb. 27, 2024. [Online]. Available: https://link.springer.com/article/10.1007/s00521-021-05770-9

[14] Z. Khodaverdian, H. Sadr, S. A. Edalatpanah, and M. Nazari, "An energy aware resource allocation based on combination of CNN and GRU for virtual machine selection," *Multimed Tools Appl*, Aug. 2023, doi: 10.1007/s11042-023-16488-2.

[15] J. Guo and C. Yang, "Predictive Resource Allocation with Deep Learning," in *2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)*, Chicago, IL, USA: IEEE, Aug. 2018, pp. 1–7. doi: 10.1109/VTCFall.2018.8690773.