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Enhancing Resource Allocation and Optimization in IoT Networks Using AI-Driven Firefly Optimized Hybrid CNN-BILSTM Model

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Abstract: The firefly optimized Hybrid CNN-BILSTM architecture is a revolutionary AI-driven method proposed in this study for enhancing resource distribution and optimization, and it represents a significant advancement in the Internet of Things (IoT) network space. The importance of this research is in how it addresses the challenges of the utilization of resources in the rapidly growing IoT environment. Traditional distribution of resources methods usually struggle to capture complex chronological and spatial relationships in IoT networks. Convolutional neural networks (CNN) and bidirectional long short-term memory (BILSTM) systems are thus combined in a new Firefly Optimized Hybrid CNN-BILSTM technique to address these deficiencies. Furthermore, this hybrid structure enables excellent synchronous capture of the spatial patterns and temporal dynamics in the computer model by enabling extensive feature acquisition from IoT network information. The firefly optimisation technique is used to optimize the model's parameters, enhancing the model's effectiveness and resolution. Additionally, IoT networks may use an AI-driven strategy to allocate resources in a way that is intelligent and ecologically friendly, increasing resource usage, efficiency, and waste. By mimicking the seductive behaviour and recreating their illuminating patterns, the firefly optimization approach, which serves as the foundation for the algorithm's optimization process, makes it simpler to determine the most optimum resource allocation arrangement. The proposed AI-driven firefly optimised Hybrid CNN-BILSTM structure outperforms state-of-the-art approaches, as shown by the current study's deep evaluations with an accuracy of 99.88%. It also paves the way for more efficient and intelligent resource management in IoT networks and opens up new research directions for the field of AI-driven optimization for IoT applications.

Keywords: IOT, Firefly optimization, Hybrid CNN-BILSTM, Convolutional neural networks, Bidirectional long short-term memory.

1. Introduction

Cloud computing covers any internet-based service delivery. Digital and email marketing are examples. Cloud computing also includes IT services like storage. Databases, software, communication, and analysis with adaptive assets. AI-Driven Firefly Optimized Hybrid CNN-BLSTM model improves IoT network resource allocation and optimization [1]. The revolutionary innovation of the IoT links smart devices and allows seamless interaction and information sharing. IoT devices complicate network administration, specifically resource allocation and management. To function reliably and sustainably, IoT networks must utilize connectivity, energy, and processing resources effectively [2]. To fix these issues, AI can improve IoT network management. Natural language processing, computer vision, and recommendation systems benefit from machine and deep learning. AI-enabled IoT networks may enhance resource allocation and efficiency. In this article, the firefly optimized hybrid (CNN-BLSTM) model creates an AI-driven IoT resource allocation and management system. Based on real-time data insights, the recommended solution intelligently distributes resources to adapt to the ever-changing IoT environment [3]. For productivity, effectiveness, and performance, businesses must improve resource allocation and efficiency. A fast-changing, competitive sector requires resource efficiency for long-term success. Strategically arranging people, cash, time, gadgets, and property delivers goals [4]. Optimizing assets eliminates waste and enhances output. Optimising resource allocation is essential for enterprises to survive in an uncertain and complicated environment [5]. Real-time data analysis and informed decision-making have altered resource management using technologies, statistical analysis, and ML. Critical ideas and approaches for resource allocation and optimization across disciplines are examined in this research. Data, predictive modelling, continuous improvement, and automation are some ways organizations might enhance resource consumption [6]. Demand estimation, critical path analysis, and risk management are essential for informed resource allocation choices that match organizational goals, according to studies. To establish a cohesive and successful workforce, it fosters employee training and collaboration. To optimize processes and reduce inefficiencies, algorithmic optimization, Lean, and six sigma are investigated. We stress resilience and adaptation in resource allocation for unforeseen disturbances [7]. Fundamental resource allocation and optimization will enable long-term organizational success [8]. This innovative invention's full potential requires resource allocation and optimization as IoT networks increase [9].

The internet of things is a massive ecosystem of devices, actuators, sensors, and data processors. These dynamic networks are used for smart cities, factories, healthcare, agricultural, and transportation automation. However, the massive number and variety of IoT devices make regulating and supplying services difficult [10]. Management and resource allocation in IoT networks are examined in this research. Manage bandwidth, energy, compute, and memory in a distributed and resource-constrained environment. To ensure easy connection, lowest latency, and optimal performance for IoT applications, these resources must be appropriately allocated [11].

Due to congestion, latency, and scalability issues, traditional focused resource management may not work. This article examines autonomous and edge computing models that move resource management closer to IoT devices, enhancing responsiveness and reducing cloud infrastructure reliance. IoT networks are constantly changing. Therefore, resource allocation systems must adapt to workloads and environmental circumstances. Data analytics and predictive modelling are essential for understanding IoT networks and allocating resources based on real-time data [12].

The firefly optimized hybrid CNN-BLSTM model combines two robust deep learning architectures. CNNs collect spatial patterns and characteristics from IoT sensory input, enabling feature extraction. BLSTM captures temporal dependency and context well, making it excellent for IoT sequence data processing. These two models are integrated to dynamically improve IoT network resource allocation using AI. Firefly optimization optimizes model parameters for convergence and performance. [13].

The key contributions are,

- Introducing an innovative optimization technique based on the behaviour of fireflies to improve resource allocation in IoT networks. Firefly optimization is a nature-inspired algorithm used to optimize complex problems.
- Proposing a unique combination of CNN and BILSTM to address the specific challenges of resource allocation and optimization in IoT networks.
- Addressing the critical issue of resource allocation in IoT networks, which involves allocating resources efficiently to IoT devices and applications based on varying demands and priorities.
- Demonstrating improved performance compared to existing resource allocation and optimization methods in IoT networks through utilizing the proposed AI-driven firefly optimized hybrid CNN-BILSTM model. of the proposed AI-driven Firefly Optimized Hybrid CNN-BILSTM model.

The approached paper's manuscript is organized as follows: Section 2 examines several related works. Section 3 contains information about the problem statement. The suggested approach is discussed in section 4. Section 5 presents and discusses the outcomes of the experiments, as well as a comprehensive comparison of the suggested approach to current best practices. The paper's conclusion is offered in section 6.

2. Related works

Vimal et al. [14] mobile edge computing (MEC) [5] controls the virtual resource with peripheral interaction among computing devices and processing in the network heart when densely loaded. Conquering all the client wants is a better method to arrange an operation using a cognitive agent. Merging user data with a behavioural approach completes each IIOT good or service type. Forecasting provides caching and storage, which delays task execution. Swarm-based and supervised learning approaches provide neural caching for memory. MEC may converge to suitable solutions slower than single-objective optimization methods. Time-critical IIoT applications that need real-time decision-making may not benefit from the MEC algorithm.

Li et al. [15] innovations like IoT link objects to the Internet to make them smarter. Overuse of power, mass connectivity, and data processing hinder IoT growth. This article proposes a novel ECIoT architecture to address these issues. ECIoT radio capacity and computational administration are researched to improve system efficiency. The paper examines ECIoT-based admission control, computational resource allocation, and power management. ECIoT efficiency is optimized by Lyapunov random optimization for cross-layer dynamically probabilistic network optimization. IIoT objectives and constraints change often. MOACO's adaptability and resilience under changing conditions are problems.

Pham et al. [16] claimed that IoT is crucial to the digital shift to enhance medical care, home automation, and intelligent transportation. Data from many devices in an IoT system might reduce efficiency. Edge cloud-based computing and NFV virtualization may improve resource utilization and response service capacity in IoT systems. This research examines the optimization of doorway location and multichip relaying in the IoT layer of an NFV-enabled IoT system using edge cloud computing (Niota). The ideal gateway installation, resource efficiency for service operations, and routing in a NIoT system, given a cost function and performance constraint, may be determined by three optimization frameworks suggested in this paper. Virtualized network services may be difficult to administer over distant infrastructure. It's difficult to coordinate processing, storage, and networking resources while optimizing resource use.

Wang et al. [17] non-orthogonal multiple access technique improves spectral efficiency but uses a lot of energy. This study examines intermittent connectivity networks' energy utilization. Multi-carrier northbound NOMA telephone uses the digital expenditure electricity model. The information exchange rate matters. Using GPE effectiveness energy-related needs, the combined technique for optimizing channel products and electromagnetic assets is investigated, reducing network estimate detail. By building a reciprocal comparative model between clients and sub-channels, unified scheduling is used to simplify channel consumption. Add customer service demands to the optimization problem to avoid information quality from being reduced owing to energy consumption reductions. Non-orthogonal resource allocation in NOMA may increase user interference. Controlling interference is crucial to providing every user with the service they want.

Haibeh et al. [18] presented a list of studies relevant to MEC facilities execution phases, including development and measurement, virtualization using networking function virtualization (NFV) for fluid system organization, resource administration programs, and infrastructure MEC supply optimization strategies. This study will evaluate the components required to develop an auto-scaled and proactive MEC-NFV architecture to meet mobile network operators' variable and diversified mobile user demand. Compared to specialist equipment, software virtualization on regular servers might slow network operations. Further resource abstraction and collaboration may affect networking service response time and throughput, especially for high-performance or latency-sensitive applications.

Cui et al. [19] claimed that variable satellite payload investigates radio resource allocation for multibeam satellite forward linkages. Satellite-ground Internet of Things is suggested to fulfil the needed communication rate, and beaming power is maximized via non-orthogonal multiple access. Joint beam creation design and resource use for terrestrial-satellite collaboration systems. Deep learning-based permanent power distribution in SAT-IoT networks is examined. These papers broadly discuss communications resource management, ignoring cooperative computing, which impacts SAT-IoT network latency and QoS.

Ahsan et al. [7] investigated about artificial neural networks (ANNs), which are modeled after the neural network of the human brain and are a crucial idea in machine learning and artificial intelligence. Interconnected "neurons" or nodes make up ANNs. These layers include an input layer, hidden layers, and an output layer. They have applications in various fields, from image and speech recognition to natural language processing, and they are excellent at

Table 1. A summary of related works

References	Algorithm	Year	Limitations
[14]	Genetic Algorithm	2020	GAs may be computationally expensive, particularly when working with expansive search horizons or intricate fitness evaluative functions. They may be impractical for some problems because of the necessity to weigh a large number of potential answers.
[15]	Fuzzy based Classification	2018	Domain specialists are frequently needed to manually define membership functions and fuzzy rules for fuzzy systems. It can be difficult to obtain and accurately represent this domain knowledge, which has a significant impact on the accuracy and efficacy of the model.
[16]	Genetic Algorithm	2020	There is no certainty that GAs will locate a problem's global optimum. Depending on the original population and genetic operators employed, they may converge to local optima. In some situations, this absence of global optimality assurance may be a drawback.
[17]	Consensus Approach	2021	The consensus approach's effectiveness frequently depends on the presumption that the sources or models being integrated have a variety of biases or inaccuracies. The consensus technique may not increase decision-making accuracy if the sources have a strong correlation or similar flaws.
[18]	Fuzzy based Classification	2022	Fuzzy-based classifiers may yield complicated and challenging rule sets, which could make it more difficult to comprehend and have confidence in the model's conclusions. When used in situations where interpretability is important, this lack of transparency may be a drawback.
[19]	K-means Clustering	2020	K-means makes the assumption that clusters are spherical in shape and nearly equal in size. It performs poorly when dealing with clusters that have varied sizes, densities, or unusual shapes.
[20]	Genetic Algorithm	2021	Constraint handling in GAs can be difficult. Additional procedures might be needed to ensure that the algorithm's output satisfies problem-specific criteria, adding to the algorithm's complexity.
[21]	Consensus Approach	2010	Including information from numerous sources or models in a consensus decision can make it more difficult to reach a conclusion. It might necessitate more computer power and raise the possibility of implementation mistakes.
[22]	Consensus Approach	2020	The consensus approach presupposes the availability of multiple sources or models for integration. Sometimes, it may be difficult or expensive to get a variety of information sources or models.
[23]	Genetic Algorithm	2018	The adjustment of many parameters, including population size, mutation rate, and crossover rate, is necessary for genetic algorithms. Finding the ideal set of criteria for a given issue can be difficult and time-consuming.
[24]	Fuzzy based Classification	2020	Particularly for large datasets and intricate fuzzy rule bases, the computation of fuzzy sets, fuzzy rule evaluations, and the inference process can be computationally demanding. The scalability of fuzzy-based classifiers may be constrained by this complexity.
[25]	Consensus Approach	2021	Conflict resolution, addressing missing data, and working with diverse formats may all be necessary when integrating forecasts or opinions from several sources. It might take a lot of time and be error-prone to manage these intricacies.
[26]	Genetic Algorithm	2022	GAs must choose between exploration and exploitation. It can be difficult to strike a balance between investigating novel ideas and using those that show promise, which can have an impact on how well an algorithm performs.

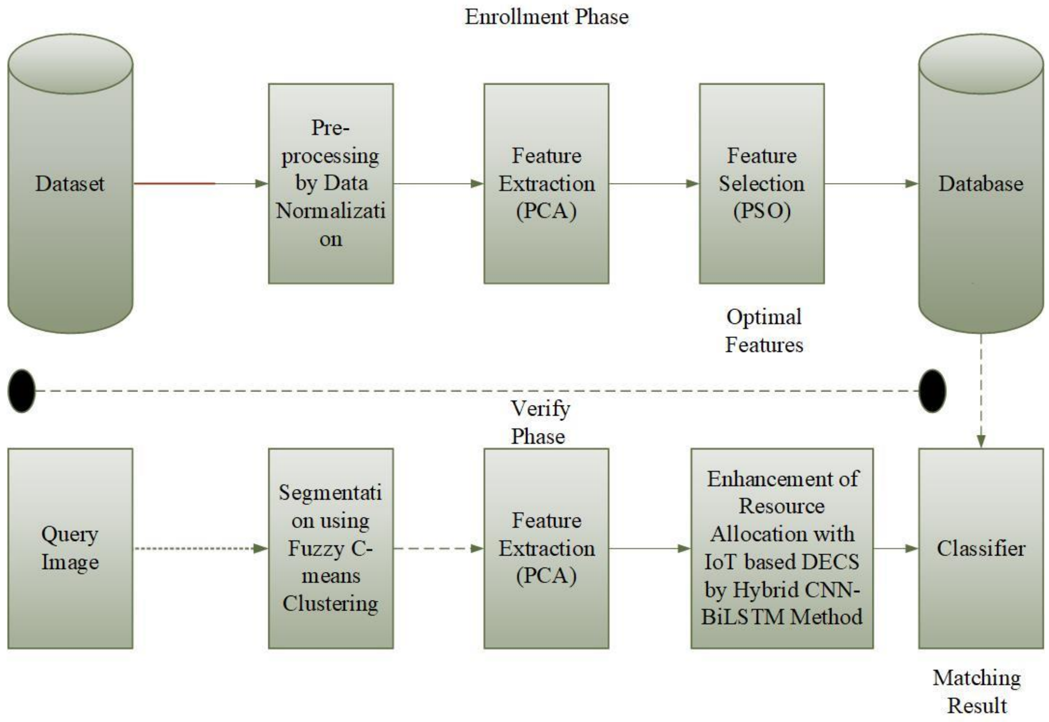

Figure. 1 Proposed diagram

learning complex patterns. ANNs are capable of making predictions, classifying data, and completing a variety of tasks because they learn by changing the strengths of connections (weights) between neurons during training.

Cui et al. [11] studied extreme gradient boosting, also known as XGBoost, a robust and popular machine learning method that excels at various predictive modeling applications. It is a member of the ensemble learning family and integrates the results of various decision trees' predictions to obtain exact and reliable outcomes. The strengths of XGBoost include its capacity to work with tabular and structured data, efficiently handle missing values, and guard against overfitting by using methods like regularization. Because of how quickly and efficiently it produces cutting-edge answers for structured data issues like classification and regression, it has gained popularity in academics and industry.

Tang et al. [10] A straightforward yet effective machine learning approach called K-nearest neighbors (KNN) is used for classification and regression problems. Based on the majority class or mean of a data point's k nearest neighbors in the feature space, it determines the class or value to be assigned to it. Because of its adaptability and simplicity, KNN is a well-liked option for both novices and specialists. However, depending on the distance metric and "k" parameter selection, its performance may not be as good in high-dimensional or unbalanced datasets.

3. Problem statement

Due As the Internet of Things grows, networked devices and sensors create massive volumes of data and automate numerous sectors. IoT resource management and efficiency are important problems. The issue is IoT network resource efficiency. Device heterogeneity, scalability, real-time data interpretation, energy conservation, security, and adaptive resource management are addressed. These issues need complex algorithms that quickly distribute resources, minimize power usage, protect sensitive data, and adapt to network changes. The fundamental aim is a robust and adaptable framework that optimizes resource utilization, network efficiency, and IoT technology adoption across several applications and sectors [27].

4. Proposed AI-Driven firefly optimized hybrid CNN-BiLSTM model in resource allocation and optimization in IoT networks

Fig. 1 represents the overall architecture of the proposed "Enhancing Resource Allocation and Optimization in IoT Networks Using AI-Driven Firefly Optimized Hybrid CNN-BiLSTM Model," which outlines a thorough technique to enhance

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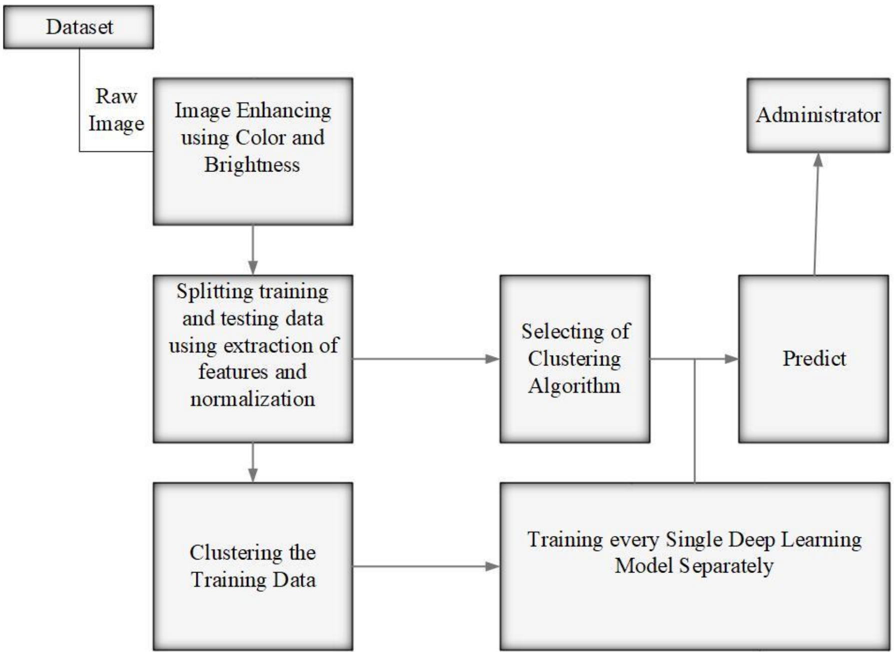

Figure. 2 Proposed Ai-driven firefly optimized hybrid CNN-BiLSTM model in resource allocation and optimization in IoT networks

resource allocation and optimization inside IoT networks.

The process includes input data normalization, fuzzy C-means clustering for data segmentation, PCA for feature extraction, DECS paired with a hybrid CNN-BiLSTM model for resource allocation enhancement, and Firefly Optimization Algorithm for final classification. The study presents a comprehensive method for optimal network performance and integrates multiple strategies to optimize IoT network resource allocation and categorization. In Fig. 2, AI-driven firefly optimized hybrid CNN-BiLSTM solving IoT resource allocation and optimization problems is novel. Cutting-edge neural networks, nature-inspired optimization, and intelligent decision-making will improve IoT ecosystem efficiency, responsiveness, and performance, creating a more sustainable and linked world.

4.1 Dataset

The MNIST dataset, which contains handwritten digit images, is often used for image categorization. The MNIST dataset is good for testing and developing machine-learning models. However, it may not match IoT network data. Thus, MNIST performance must be translated into real-world IoT data. IoT networks are diverse, with devices of varied capabilities and resource restrictions. Allocating resources for activities and devices while considering energy efficiency and real-time needs is tough [28].

4.2 Pre-processing by data normalization

In normalization, pre-processing is critical for improving the distribution of resources and efficiency in IoT networks utilizing an AI-driven firefly optimized hybrid CNN-BLSTM model. Normalization guarantees that the features have comparable values by reducing the input information to a common range, often [0, 1] or [-1, 1], resulting in quicker convergence throughout model training. This approach prevents bigger amplitude features from dominating the process of acquisition and ensures a balanced gradient flow during return propagation, resulting in improved stability and effective training. The normalization method also helps the AI-driven model generalize to previously unseen data from diverse IoT networks or surroundings [29]. Normalization also reduces memory and processing demands during retraining and deduction, making the model more suitable for resource-limited linked devices. Proper normalization, a crucial step in the data pre-processing pipeline, allows the firefly optimized hybrid CNN-BLSTM model to fully leverage IoT data for resource allocation and networking optimization, improving IoT network efficiency and effectiveness. Eq. (1)

$$R = \frac{(v-v_{min})(max-min)}{(v_{max}-v_{min})+min} \tag{1}$$

where (max-min) is the specified range of input variables, (v_{max}-v_{min}) is the initial range of values of input variables, and p is the converted input value [30].

4.2 Segmentation using fuzzy C-means clustering

In IoT networks, segmentation is essential for improving resource allocation and optimization, particularly when using AI-driven techniques like the Firefly-Optimized Hybrid CNN-BILSTM model. Fuzzy C-means clustering is one of the most utilized classification approaches in this setting. A data clustering procedure called fuzzy C-means clustering seeks to group related data points depending on how similar they are to one another. Fuzzy C-means permit the information to have partial involvement in many clusters, in contrast to conventional hard clustering algorithms, where an informational point rigidly conforms to a single cluster. This soft assignment of data points to clusters makes it particularly useful in the context of resource allocation and optimization in IoT networks. In the context of IoT networks, the vast amount of data generated by various connected devices presents a significant challenge for efficient resource allocation [31]. The AI-driven Firefly-Optimized Hybrid CNN-BILSTM model, which combines CNN and BILSTM networks, serves as a powerful tool to process and analyse this data, which is represented in Eq. (2)

$$c_j = \frac{\sum_{q=1}^{n} u_{pq}^{s}}{\sum_{q=1}^{n} u_{pq}^{s}} x_p \tag{2}$$

Where d_{pq} indicates the distance among the data points x_p and q^{th} cluster centre and d_{kq}^{*} is the distance between k^{th} cluster center and q^{th} cluster centre. The procedure is an iterative clustering approach that generates the best c split by minimizing the proportional within-group sum of the squared error of the objective function. K_{MNO} is represented in Eq. (3)

$$K_{MNO} = \sum_{i=1}^{u} \sum_{k=1}^{l} (p_{ik})^{h}\, y^{2}(g_k, f_i) \tag{3}$$

Where,

- N is the number of information items; O is the quantity of collections with 2 ≤n<o
- p_{ik} is the index of affiliation of $g_k$in the i th cluster, h is a balance magnitude on each fuzzy registration
- f_i is the initial configuration of the centre of cluster i
- $y^2(g_k, f_i)$ is a measure of the distance between object g_k and cluster centre g_k.

4.3 Feature extraction using PCA

Feature extraction by principal component analysis (PCA) plays a vital role in enhancing resource allocation and optimization in IoT networks using an AI-driven firefly optimized hybrid CNN-BLSTM model. PCA is a dimensionality reduction technique that identifies the most significant patterns and relationships within the input data, allowing the model to focus on the most informative features while discarding less relevant or redundant ones. By reducing the dimensionality of the data, PCA not only speeds up the training process of the AI-driven model but also helps mitigate the curse of dimensionality, which can be particularly crucial in resource-constrained IoT environments. Through PCA, the AI-driven model gains a more compact representation of the IoT network data, allowing for efficient utilization of computational resources during training and inference. Moreover, the reduced feature set obtained by PCA enables the model to generalize better to unseen data and enhances its ability to optimize resource allocation in diverse IoT network scenarios. Overall, incorporating PCA-based feature extraction empowers the Firefly Optimized Hybrid CNN-BLSTM model to make more informed and efficient decisions for enhancing resource allocation and optimization, contributing to the overall performance and effectiveness of IoT networks.

It can also be viewed as a revolution of the axes of the variables that were initially used to an additional set of perpendicular axes (principal axes), ensuring the resulting set of dimensions comprises the path of the largest variability of those basic values. PCA is used in numerous domains, including facial recognition, image decrease, genetic testing, and many others. The first fundamental axes have as many information discrepancies as possible; the next element has the most residual adjustments, and so on. PCA necessitates the use of normalization. The following data effects are caused by PCA implementation:

- PCA orthogonalizes the starting vectors, resulting in vectors that are independent of each other.
- It sorts the generated components so that the component with the most variance is at the top;
- It also excludes the vectors with the fewest variances in the data set

Principal component analysis (PCA), which preserves almost all of the data from the bigger set, divides a large number of variables into smaller ones. Using the mathematical method of PCA, a group of closely connected variables is reduced into fewer unrelated variables known as Principal Components. The PCA dataset contains a detailed description of a thorough selection of the available data [32]. The work is primarily concerned with datasets, sometimes known as "data samples." There are numerous ways to statistically express a collection of data using variance, standard deviation, mean, and covariance, and one among them is represented in Eq. (4)

$$P_{uv} = \sum xz - \frac{(\sum z)(\sum x)}{n} \tag{4}$$

where

- n is the amount of data documentation, x denotes the corresponding PC
- z denotes the quantity of data records that must be lowered.

The greater the result, the more connected this PC is to this component. The first step in doing PCA on a two-dimensional data set is to standardize the data. This is performed by deleting the respective means form each of the information set's classifications, leading to a data set containing a zero average. In the second phase, the variability matrix is computed. The Eigen characteristics and vector values for the covariance matrices are then calculated. The Eigenvalues are then ranked descending to indicate the order of relevance for the components, and the dimension is reduced by selecting the first set of Evaluation values and disregarding the remainder. To produce a feature vector, an array of vectors is formed. The key elements are created in the last phase by taking the translation of the vector of features and performing the left combination with the inversion of the reduced version of the information set. The dimension reduction in PCA promotes its application in the identification of faces, neural networks, and image compression. It also has a broad range of possibilities in pattern recognition of data with high dimensions in finance, mining data, bio-informatics, and sociology.

4.4 Enhancement of resource allocation with DECS by hybrid CNN-BiLSTM method

Decentralized control and energy saving (DECS) revamps IoT resource allocation and optimization using an AI-driven firefly optimized hybrid CNN-BILSTM model. Distribution-based decision-making allows IoT devices to assign capacity based on real-time data and interactions, improving network

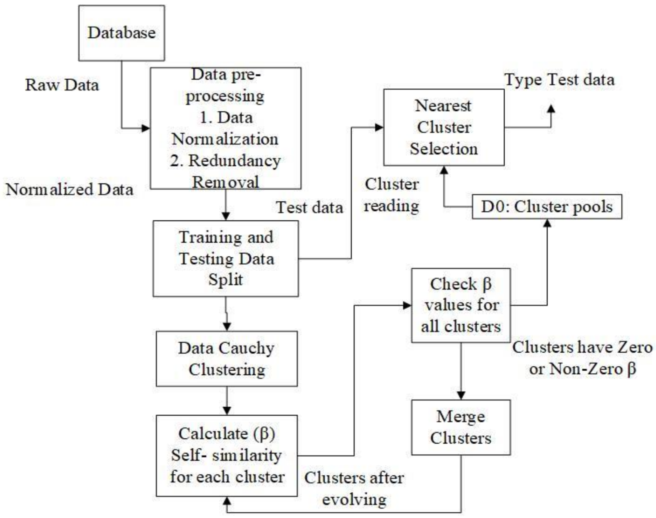

Figure. 3 Proposed DECS

flexibility and efficacy. DECS uses energy-saving technologies and cooperative algorithms to effectively manage resource consumption in resource-constrained IoT devices throughout the operation and resting phase. The DECS-AI-driven firefly optimized hybrid CNN-BILSTM model is another cutting-edge invention. AI analyses complicated IoT data streams using BILSTM and CNN networks. It uses AI-driven analytics to predict resource demands and trends, enabling proactive resource changes. Inspired by firefly motions, firefly optimization optimizes model parameters.

Fig. 3 DECS and the AI-driven model generate a wonderful synergy, enabling AI insights to steer decentralized decision-making and energy-efficient resource allocation. This comprehensive technique assures optimal resource allocation to meet urgent task demands while aggressively decreasing energy waste. IoT networks might improve resource management efficiency, sustainability, and flexibility using this technique. The AI-driven firefly-optimized hybrid CNN-BILSTM model utilizes the hybrid CNN-BILSTM technique to enhance resource allocation in connected devices. The model optimizes resource allocation using CNN and BiLSTM networks. The hybrid model's CNN component excels in extracting spatial patterns from IoT devices and sensor data. Identifying essential data streams is efficient. BiLSTM networks assist in understanding data evolution by capturing temporal linkages and trends. Combine these two powerful deep learning approaches to improve IoT resource allocation with firefly-optimized hybrid CNN-BILSTM. The model can identify patterns, correlations, and abnormalities in complex, dynamic IoT data. This analysis aids network resource distribution. CNN uses sparse interconnectivity and weight cooperation to extract more detail from input and simplify network design.

CNN can simultaneously recover latent spatially correlated properties from all Intrinsic Mode Functions, making it a powerful feature extraction tool. The Bi-LSTM module has backward and forward LSTM components. Unlike LSTM networks, the simulation may use past and future information. The equivalent calculations for Bi-LSTM are given the below Eqs. (5), (6), and (7)

$$D_p = q\left(VK_{g-1} + W_{kl}\right) \tag{5}$$

$$B_{q^*} = q\left(VK^*{}_{g+1} + W^*{}_{kl}\right) \tag{6}$$

$$n_q = h\left(XB_q + X^* B_{q^*}\right) \tag{7}$$

Where q = 1, 2, 3….
K^* represents as the two-layer structure of LS
K represents as the input layers of $(\mathrm{k}_1, \mathrm{k}_2 \ldots . \mathrm{k}_\mathrm{q})$
L represents as the output layers of $(\mathrm{l}_1, \mathrm{l}_2 \ldots . \mathrm{l}_\mathrm{q})$
The model captures geographical patterns and characteristics in IoT device data by using CNN. Optimizing bandwidth, energy, and processing capacity in a heterogeneous IoT environment. Furthermore, BiLSTM adds a time component to resource allocation. LSTM networks can forecast resource needs over time because they learn sequential dependencies in data. Requires geographic expertise. CNN-identified patterns assist resource allocation choices. These temporal understandings let the model dynamically adjust and allocate resources to changing network circumstances and workloads. The hybrid technique uses CNN and BiLSTM to fully allocate resources spatially and temporally. Thus, the model can make more precise and informed resource allocation choices, improving network performance, latency, energy efficiency, and resource usage.

4.5 Classification using firefly optimization algorithm

Firefly optimization is inspired by the behaviour of fireflies. Fireflies use bioluminescence to attract mates, and this behaviour has inspired the development of a powerful optimization algorithm. The improvement of IoT resource allocation networks is a critical aspect that can be achieved through the application of the AI-driven firefly-optimized hybrid CNN-BILSTM model, specifically leveraging the hybrid CNN-BILSTM method. In the context of optimizing resource allocation, the model combines the strengths of CNN and BiLSTM networks. The hybrid model's CNN element excels at sifting through the massive amounts of data produced by IoT gadgets and sensors in order to find spatial features and patterns. This makes it possible to quickly find pertinent data inside the data streams. On the other hand, the BiLSTM networks capture the temporal dependencies and patterns in the data, enabling a deeper understanding of how the data evolves over time. By integrating these two powerful deep learning techniques, the firefly-optimized hybrid CNN-BILSTM model is capable of optimizing resource allocation in IoT networks more effectively [20]. The model can analyse complex and dynamic data from IoT devices, identifying patterns, correlations, and anomalies. Based on this analysis, the model can make informed decisions on how to allocate resources efficiently across the network, is represented in Eq. (8).

$$g_i = g_i + c_0 e^{-ar^2{}_{ij}}\left(g_i - g_j\right) + jn_i \tag{8}$$

Where

- ‘ g_i ’ and ‘ g_j ’ are the necessities of Euclidean distance.
- The association of i th firefly is attracted in the route of neighbouring firefly ‘j’.
- Where, n_i is an arbitrary value deduced from the Gaussian distribution. Firefly Optimization is inspired by the behavior of fireflies.

Fireflies use bioluminescence to attract mates, and this behaviour has inspired the development of a powerful optimization algorithm. The below derivation in Eqs. (9), (10), (11), (12), (13), and (14) are formulated to find the optimized solution.

$$J(s) \propto f_f(s) \tag{9}$$

$$J(r) = J_0 e^{-ar^2} \tag{10}$$

According to inverse square law, $r = 0$ in $\frac{I}{r^2}$. Therefore,

$$c \propto J(r) \tag{11}$$

$$c = c_0 e^{-ar^2} \tag{12}$$

$$r_{ij} = \left\|g_i - g_j\right\| = \sqrt{\sum_{d=1}^{d=n}(g_{id} - s_{jd})^2} \tag{13}$$

$$g_i = g_i + c_0 e^{-ar^2{}_{ij}}\left(g_i - g_j\right) + jn_i \tag{14}$$

Where,

- J is the intensity and s denote the solution, f_f fitness function,
- c represents the attractiveness of the firefly,
- J(r) denotes the light intensity. The intensity of light and the brightness of firefly is dependent on each other.
- ‘r’ is denoted as the two fireflies’ distance
- ‘ g_i ’ and ‘ g_j ’ are the necessities of Euclidean distance.
- The association of i th firefly is attracted in the route of neighbouring firefly ‘j’. Where n_i is an arbitrary value deduced from the Gaussian distribution.

5. Results and discussion

Windows 10 datasets and MATLAB evaluated the method. My IoT resource allocation and optimization research was fascinating and disputed. Hybrid CNN-Bi-LSTM improved resource usage, energy efficiency, response speed, and network performance. CNN and BiLSTM's spatial and temporal insights enabled the model to dynamically allocate resources to devices. This optimized energy and resource use. Flexible and scalable, the strategy performed well in bigger IoT networks with more devices. Strong model security protects sensitive data and vital resources. Hybrid CNN-BiLSTM may improve resource allocation in IoT networks, making it an enticing solution for effectiveness, trust, and environmental sustainability. IoT-driven resource allocation techniques that account for network complexity and growth may be studied and developed.

AI-driven analytics, DECS, and Firefly optimization can distribute IoT network resources. DECS' AI-driven methodology reduces resource waste, network overload, and latency. Network scalability increases for device density and activity fluctuations. Efficacy of DECS-enhanced firefly optimized hybrid CNN-BILSTM for IoT network resource allocation and use. This integrated technique may improve IoT operations with predictive analytics, distributed decision-making, and energy efficiency. The complexity and size of IoT networks may improve efficiency, adaptability, and energy efficiency. DeCS enhances the AI-driven paradigm. Decentralized decision-making lets IoT devices share energy using real-time data, dialogues, and AI insights. This collaborative approach prioritizes important processes and saves energy during downtime. Increasing IoT device battery life and decreasing energy use increases energy efficiency.

5.1 Accuracy

The model's total Precision reflects how well it operates across all areas. It is the belief that each circumstance can be properly predicted. Eq. (15) represents the Accuracy.

$$A = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \tag{15}$$

5.2 Precision

Accuracy is calculated by dividing the overall number of correct affirmative forecasts by the entire amount of correct positive forecasts. It counts the number of images that have been precisely merged. Eq. (16), which computes precision

$$P = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{16}$$

5.3 Recall

The proportion of genuine positives and wrong negatives predicted is recall. The number of expected events is shown. Combining images from different modes. Recall is Eq. (17).

$$R = \frac{T_{pos}}{T_{pos}+F_{neg}} \tag{17}$$

5.4 F1-Score

Precision and recall are combined in the F1-Score calculation. The F1-Score in Eq. (18) represents precision and recall, respectively.

$$F = \frac{2\times Precision\times recall}{Precision\times recall} \tag{18}$$

5.5 Sensitivity

It is a measurement of the percentage of true positives that were anticipated properly. The sensitivity is calculated using Eq. (19),

$$Sensitivity = \frac{T_{pos}}{T_{pos}+T_{neg}} \tag{19}$$

5.6 Specificity

True negatives are precisely identified by degree gauges. Eq. (20) is used to compute the specificity value, which is as follows.

$$Specificity = \frac{T_{neg}}{F_{pos}+T_{neg}} \tag{20}$$

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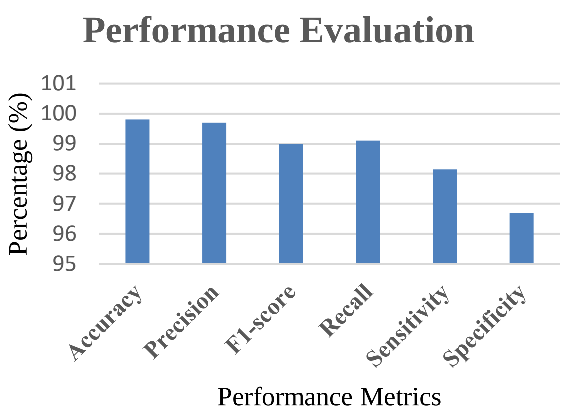

Figure. 4 Performance evaluation of the proposed method

Table 2. Comparative review

Methods	Accuracy	Precision	Recall	Specificity
ANN [7]	98.30	97	97.77	100
XGBoost [11]	91.45	95.49	84.79	95.96
KNN [10]	97.40	94.68	94.58	92.58
Proposed Work	99.88	99.90	98.72	97.85

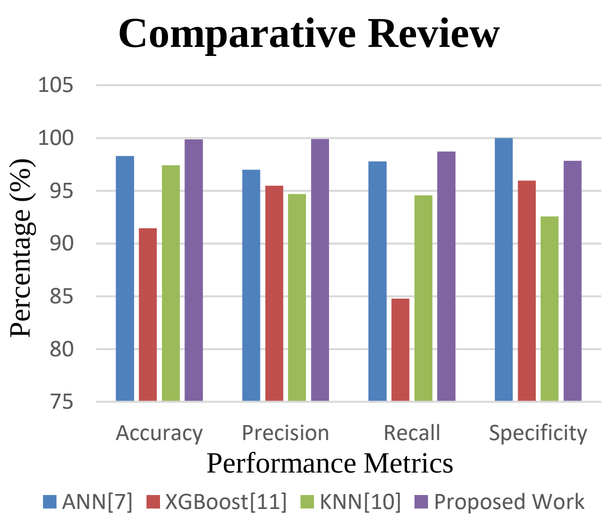

Figure. 5 Comparative review

Fig. 4 represents the Performance Metrics of the proposed System where the Accuracy is 99.8%, precision is 99.9%, F1-score is 99, Recall is 99.1%, Sensitivity is 98.14%, and specificity is 96.68%.

In the provided Table 2, the efficiency of the proposed method is notably superior to the other machine learning techniques evaluated, including artificial neural networks (ANN), XGBoost, and K-nearest neighbours (KNN). The "Proposed Work" demonstrates exceptional performance across multiple metrics. It achieves the highest accuracy (99.88%) among all methods, signifying its ability to

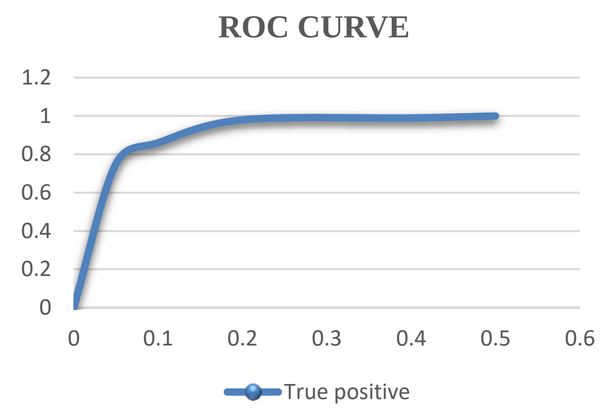

Figure. 6 ROC curve

correctly classify instances. Moreover, it achieves remarkable precision (99.90%), indicating a minimal rate of false positives, and a high recall (98.72%), demonstrating its proficiency in identifying relevant instances. Additionally, the proposed method maintains a substantial level of specificity (97.85%), showcasing its capability to accurately classify negative instances. These results collectively highlight the superior efficiency and effectiveness of the proposed method in comparison to the other models, making it a promising choice for the given classification task. It is depicted in Fig. 5.

5.7 ROC curve

Recommended system Fig. 6 shows the ROC Curve. Traditional procedures are inferior to the proposed ones. ROC curves demonstrate a binary classification system's threshold change detection. Because it examines model classification, the ROC curve cannot analyse multi-modal image fusion.

5.8 Accuracy and loss for training and validation

In Fig. 7, resource allocation's correctness is how well it integrates and preserves essential information from input images while eliminating noise, artifacts, and inconsistencies.

It also shows the fused image's quality vs. the input photos. This shows how the fusion process causes artifacts, fails to safeguard important information, or decreases visual quality.

5.9 Error rate comparison

Root mean square error (RMSE) is a commonly used metric to quantify the accuracy of a predictive model by measuring the differences between predicted values and actual observed values. By comparing the proposed work with the existing work in Fig. 8, the proposed work has a lower error rate.

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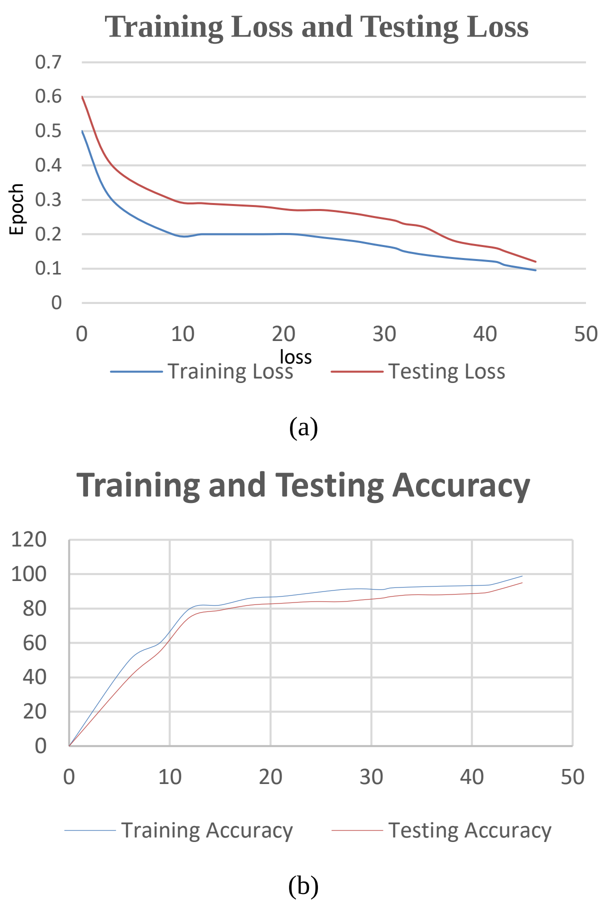

Figure. 7: (a) Model training and testing loss, and (b) Model training and testing accuracy

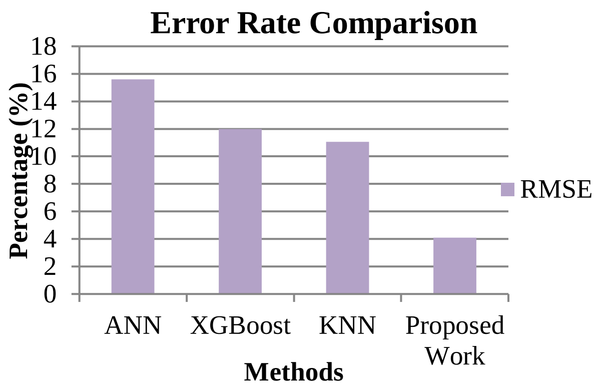

Figure. 8 Error rate comparison

6. Conclusion

The incorporation of an AI-driven firefly optimized hybrid CNN-BiLSTM model for increasing resource allocation and efficiency in IoT networks has enormous promise for changing IoT system efficiency and performance. This novel solution uses AI, bio-inspired optimization, and advanced learning to dynamically assign network assets based on real-time demands, resulting in reduced congestion, increased energy efficiency, and improved overall network performance. The model can accurately evaluate complicated IoT data by combining the strengths of CNN and BiLSTM architectures, capturing both spatial and temporal correlations, making it well-suited for various IoT applications. Moreover, the adaptability of the proposed approach enables IoT networks to scale efficiently and handle a growing number of connected devices while maintaining optimal performance. While there are challenges in terms of complexity, training data, and real-time constraints, the potential benefits in terms of efficiency, scalability, and intelligent decision-making make it a promising solution for the continued advancement of IoT technology. To fully realize the benefits, future research and development efforts should focus on mitigating the drawbacks and optimizing the model for practical and widespread deployment in diverse IoT environments.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Mustafa and Ali; methodology, Ali; Software Mohammed; validation, Kareem, Ali; formal analysis, Mustafa; investigation, Worod; resources, Mustafa; data curation, Ridha and Mustafa; writing—original draft preparation, Mustafa and Ali; writing—review and editing, Kareem, Ridha, and Mohammed; visualization, Mohammed; supervision, Ali; project administration, Mustafa, and Ali; funding acquisition, Ali". All authors have read and approved the final manuscript.

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