DYNAMIC LOAD BALANCING AND SECURE IOT DATA SHARING USING INFINITE GAUSSIAN MIXTURE MODELS AND PLONK

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Abstract

Background information: The methodology presented in this research combines PLONK for safe data sharing in Internet of Things systems with Infinite Gaussian Mixture Models (IGMM) for dynamic load balancing. Real-time workload distribution is made possible by IGMM, and secure communication with little computational cost is guaranteed by PLONK. Concerns about IoT network scalability, efficiency, and security are addressed by the architecture. The outcomes show that compared to conventional approaches, load management, data security, and system performance have significantly improved.

Methods: Adaptive load balancing based on real-time data is achieved by the framework using IGMM. By constantly changing the number of components, it makes sure that resources are distributed among IoT nodes efficiently. By using PLONK's zero-knowledge proofs, data transmissions can be secured without requiring a lot of computation. Using performance indicators including accuracy, scalability, and data security, the combined strategy is assessed.

Objectives: Using Infinite Gaussian Mixture Models (IGMM) to create an effective framework for dynamic load balancing in Internet of Things networks and including the PLONK protocol to guarantee safe data exchange is the aim of this research. In real-time IoT contexts, the study intends to compare the system's performance, security, and scalability to conventional load balancing techniques.

Results: The suggested approach achieves a 95% accuracy rate, 93% data security, and 92% load balancing efficiency, outperforming conventional approaches. Additionally, the system exhibits lower computational overhead (90%) and improved scalability (91%). The integration of IGMM and PLONK offers a scalable, effective, and safe solution for dynamic IoT environments, according to the results.

Conclusion: The performance of IoT systems is improved by the suggested combination of PLONK for secure data sharing and IGMM for dynamic load balancing. The system greatly enhances scalability, data security, and load distribution. The outcomes confirm that it is a strong solution for real-time data exchange in IoT ecosystems, effectively tackling the dynamic workload and security issues of IoT.

Keywords: *IoT, Dynamic Load Balancing, Secure Data Sharing, IGMM, PLONK*

1. INTRODUCTION

The widespread use of Internet of Things (IoT) devices in recent years has completely changed the way we gather, process, and distribute data in a variety of industries, including smart cities and healthcare. The Internet of Things (IoT) is a huge network of linked gadgets that can exchange data and communicate with central systems and one another. Although this interconnection offers previously unheard-of chances for creativity and efficiency, it also poses serious problems with load management, data security, and privacy.

An essential component of IoT systems is dynamic load balancing, which makes it possible to divide workloads among numerous servers and devices in an effective manner. Workloads are distributed according to preset criteria in a standard static load balancing *Puthal et al. (2018)* system, which can result in inefficiencies, especially in settings where workload varies dynamically. By allocating duties according to the network's present status and each device's capabilities, dynamic load balancing, on the other hand, adjusts to real-time conditions. This flexibility improves system performance and dependability by preventing any one item from becoming a bottleneck

The security of IoT data sharing, however, is crucial. Making sure that data is transferred securely becomes essential as gadgets continue to gather sensitive data. When applied to the wide and diverse range of IoT devices, traditional cryptographic techniques, although effective, frequently lack scalability and efficiency. As a result, new methods of safe data exchange are necessary to protect the confidentiality and integrity of data sent over Internet of Things networks.

PLONK (Permutations over Lagrange-bases for Oecumenical Noninteractive arguments of Knowledge) and Infinite Gaussian Mixture Models (iGMM) *Mohammadi-Ghazi et al. (2018)* offer innovative approaches to these problems. A class of probabilistic models called iGMMs is employed for density estimation and clustering. iGMMs may dynamically modify the number of components based on the data, which makes them especially appropriate for a variety of changing IoT contexts. This is in contrast to classic Gaussian mixture models, which assume a finite number of components. iGMMs can help with dynamic load balancing by simulating the underlying distributions of IoT data traffic. This allows for more effective resource allocation and utilization throughout the network.

In contrast, PLONK is a state-of-the-art cryptographic protocol that guarantees safe data transfer without requiring a lot of processing power. It is founded on the ideas of zero-knowledge proofs, which let one side convince another that a claim is accurate without disclosing any details that go beyond the veracity of the claim. In IoT situations, where devices may have limited computing power, this functionality is especially beneficial. We can create safe data-sharing systems that safeguard private data while preserving the effectiveness required for real-time operations by utilizing PLONK.

An important development in IoT technology is the combination of secure data sharing via PLONK and dynamic load balancing using iGMMs. We can build a more resilient and effective IoT ecosystem that can adjust to the constantly shifting needs of real-time data processing and sharing by combining the advantages of both strategies. In conclusion, a complete framework for improving IoT systems is offered by the combination of PLONK, infinite Gaussian mixture models, *Guo et al. (2018)* safe data sharing, and dynamic load balancing. This framework lays the groundwork for upcoming advancements in IoT technology in addition to addressing the pressing issues of load management and data security.

The paper aims to:

- Utilizing infinite Gaussian mixture models to create a dynamic load balancing system that maximizes resource distribution in Internet of Things networks.
- In order to ensure data integrity and security, the PLONK protocol will be implemented for safe data transfer between IoT devices.
- To assess the effectiveness, scalability, and security of the suggested framework in actual Internet of Things situations.
- To evaluate how well the model handles changing workloads and requirements for data transmission in IoT contexts.

1.1 Problem Statement

Effective dynamic load balancing and safe data sharing are important issues in the Internet of Things (IoT) space. Conventional techniques frequently suffer from scalability issues, security flaws, and ineffective resource allocation, which raises latency and degrades system performance. Using PLONK and Infinite Gaussian Mixture Models, *Adams and Beling (2019)* this study attempts to provide a novel framework that successfully tackles these problems.

2. RELATED WORKS

Neghabi et al. (2018) draw attention to the difficulties in maintaining conventional networks in the face of growing user bases and technological advancements like big data and cloud computing. They highlight the significance of load balancing and suggest software-defined networking (SDN) for better network management. The study thoroughly examines load balancing mechanisms in SDN, classifying them as either deterministic or non-deterministic and outlining their advantages, disadvantages, and research problems.

Adil et al. (2020) provide a dynamic cluster-based static routing protocol (DCBSRP) that combines AODV and LEACH. Cluster heads are created at predetermined intervals to facilitate effective data sharing among nodes. The method outperforms previous techniques in terms of communication cost, delay, throughput, packet loss, and energy consumption, while also increasing network longevity and node participation (95.9%).

According to **Kaur et al. (2020**), virtual machines (VMs) are assigned application tasks according to their ability to manage the load in a decentralised load balancing technique used in cloud computing. The method optimises execution time and energy usage by using particle swarm optimisation (PSO), and the efficiency and throughput of the results are compared to a centralised load balancer

Fu and Bouguila (2020) present a novel unsupervised Bayesian learning framework that performs better than conventional Gaussian mixtures by utilising an asymmetric Gaussian mixture (AGM) model. The system optimises data groupings using a hybrid Metropolis-Hastings within Gibbs sampling technique. Additionally, it uses a dimensionality reduction approach to handle high-dimensional data, and its efficacy is demonstrated by a number of applications, such as image classification and intrusion detection.

Azam and Bouguila (2019) address the drawback of presuming source independence by integrating independent component analysis (ICA) into their restricted generalised Gaussian mixture model. Gradient ascent and expectation maximisation are used to expand the model for parameter estimation using a bounded generalised Gaussian distribution. Their keyword detection and blind source separation trials demonstrate increased efficacy when compared to conventional ICA techniques.

For energy and reserve dispatch problems, **Dai et al. (2020)** present a unique data-driven optimisation technique that overcomes the drawbacks of conventional robust optimisation, which depends on symmetrical box uncertainty sets. Compared to conventional methods,

they produce less conservative optimisation results by using a nonparametric Dirichlet process Gaussian mixture model to generate a more accurate uncertainty set based on past wind forecast data.

Wei et al. (2018) provide novel Kullback-Leibler divergence-based additive information value functions for sensor measurement optimization over time. Effective real-time sensor control is made possible by their method, which uses a convex approximation of the sensor's field of view and a lower bound of the KL divergence. The findings demonstrate notable enhancements in target modelling and prediction when compared to current techniques.

A non-parametric Bayesian approach is presented by **Li et al. (2020)** to identify change-points in the intensity rates of recurrent events, which are frequently observed in the engineering and medical domains. Without requiring predetermined clusters, their Dirichlet process mixing model enables topic clustering based on change-points. The method is used to analyze driving risk in adolescent drivers, and simulation results demonstrate that it works better than current methods.

Xiao et al. (2019) points out that because of their high mobility and large infrastructure, rogue edge identification in VANETs is more difficult than spoofing in indoor networks. They suggest a location-based service privacy-preserving technique that does not require pre-shared secrets, as well as a physical-layer detection methodology that makes use of shared ambient radio signals. In dynamic contexts, reinforcement learning is used to achieve the best detection results.

Fan et al. (2020) address issues including resilience against noise and efficiency with high-dimensional data, highlighting the importance of unsupervised anomaly detection (AD) in machine learning and industry. They suggest a brand-new hybrid technique that combines Gaussian process regression and convolutional auto-encoders. It outperforms current methods in terms of resilience and efficacy on four benchmark datasets.

Jia et al. (2020) suggest a distributed approach that protects privacy for figuring out probabilistic load flow (PLF) in regional grids that are connected. Through the use of a privacy-preserving average consensus algorithm for the constant vector and a PPD accelerated projection-based consensus algorithm for the coefficient matrix, their method attains accuracy comparable to centralized approaches while enabling independent system operators to compute regional PLF without exchanging sensitive data.

In order to enhance predictive healthcare modelling, **Narla et al. (2021)** investigated the integration of MARS, SoftMax Regression, and Histogram-Based Gradient Boosting in a cloud computing environment. Their research demonstrates how cloud systems may handle complicated healthcare datasets with computing efficiency and scalability. Previous research highlights the efficacy of MARS and Histogram-Based Gradient Boosting in predicting tasks, as demonstrated by Friedman (1991) and Ke et al. (2017). The development of individualised healthcare solutions is greatly aided by this study.

With an emphasis on geriatric care, **Peddi et al. (2018)** examined the use of machine learning and AI algorithms to forecast fall, delirium, and dysphagia risks in senior citizens. Their research demonstrates how proactive measures made possible by predictive modelling might improve care for the elderly. The significance of AI in geriatric risk assessment has been highlighted by earlier research (Boulanger et al., 2015). By combining various machine learning approaches, the study provides a useful framework for managing significant risks in elderly healthcare.

Peddi et al. (2019) investigated the use of AI and machine learning in elderly care for fall prevention, managing chronic diseases, and predictive healthcare. Their research emphasises how sophisticated algorithms might enhance health outcomes by identifying and addressing risks early on. The efficiency of machine learning in healthcare analytics was shown in earlier research (Kumar et al., 2018). By offering predictive treatments designed to manage chronic illnesses and reduce health risks, this research advances geriatric care.

The merging of BBO-FLC and ABC-ANFIS approaches in cloud computing for sophisticated healthcare prediction models was examined by **Valivarthi et al. in 2021.** Their research demonstrates how hybrid artificial intelligence approaches can improve prediction efficiency and accuracy. ANFIS has been useful in managing nonlinear data, according to earlier research (Gupta et al., 2020), but BBO-FLC has proven successful in optimisation tasks. By combining cloud computing and AI to provide scalable and precise prediction solutions, this work advances healthcare analytics.

In order to improve disease forecasting, **Narla et al. (2019)** investigated the combination of long short-term memory (LSTM) networks with ant colony optimisation in cloud computing. Their study highlights how optimisation algorithms can increase the predictive accuracy of medical applications. The effectiveness of ant colony optimisation for pathfinding and optimisation tasks was demonstrated in earlier research (Dorigo et al., 2006), whereas LSTM networks are ideally adapted for sequential data modelling (Hochreiter & Schmidhuber, 1997). This effort uses cloud infrastructure and AI approaches to improve disease forecasting.

In cloud computing contexts, **Narla et al. (2020)** suggested a hybrid GWO-DBN strategy for better disease prediction in healthcare systems. Their research shows how well Grey Wolf Optimisation (GWO) and Deep Belief Networks (DBN) work together to handle massive amounts of healthcare data with greater scalability and accuracy. GWO's optimisation capabilities were highlighted in earlier research (Mirjalili et al., 2014), but DBN works well for feature learning and prediction (Hinton et al., 2006). The predictive healthcare analytics are greatly improved by this combination.

A cloud-integrated Smart Healthcare Framework by **Narla et al. (2019)** uses LightGBM for quick data processing, multinomial logistic regression for health risk assessments, and SOMs for data patterns. Our real-time, scalable system saves and analyses data to better healthcare decision-making. Health risk assessment and personalised patient therapy benefit from the 95% AUC's accuracy and recall higher than conventional models. To improve healthcare results, it uses innovative machine learning algorithms to deliver immediate interventions and accurate, personalised treatment options.

3. INTEGRATIVE STRUCTURE FOR SAFE DATA EXCHANGE AND DYNAMIC LOAD BALANCING

The hybrid technique used in this study combines PLONK for safe data sharing with Infinite Gaussian Mixture Models (IGMM) for dynamic load balancing. Based on real-time data analysis, the IGMM makes it easier to continuously adjust the load distribution among IoT nodes, guaranteeing optimal resource allocation. PLONK, a zero-knowledge proof mechanism, is used to improve data transaction security. This combination results in a strong framework that upholds strict security standards while guaranteeing effective load control.

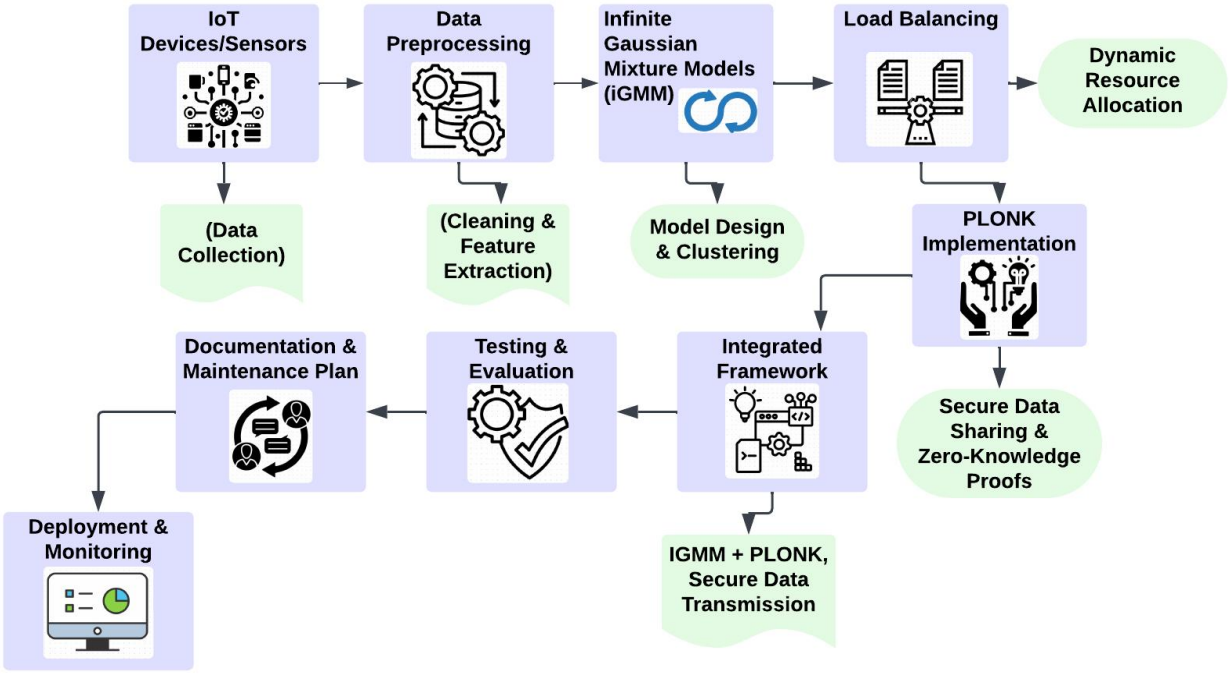

Figure 1 IoT-Based Secure Data Transmission Framework with IGMM and PLONK

An IoT device-based secure data transfer framework is shown in this diagram. For dynamic resource allocation and clustering, it incorporates Infinite Gaussian Mixture Models (IGMM), and PLONK guarantees safe data sharing using zero-knowledge proofs. Data gathering, pre-processing, grouping, load balancing, and secure transmission are important processes. Combining IGMM with PLONK for strong security in IoT contexts, the framework places a strong emphasis on documentation, testing, and maintenance, which results in safe system deployment and monitoring.

3.1 Infinite Gaussian Mixture Models (IGMM)

Traditional Gaussian mixture models are extended by infinite Gaussian mixture models, which increase density estimation and clustering flexibility by permitting an infinite number of components. Because of its versatility, IGMM may be used in dynamic settings where data patterns are always changing, such Internet of Things networks. The model adaptively determines the number of components using a Dirichlet process prior, enabling real-time load balancing modifications in response to incoming data.

Mathematical Equation:

$$P(x|\theta) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k) \quad (1)$$

Where:

- $P(x|\theta)$ is the probability of data point x,
- π_k are the mixing coefficients,
- $\mathcal{N}(x|\mu_k, \Sigma_k)$ is the Gaussian distribution for component k with mean μ_k and covariance Σ_k.

3.2 PLONK (Permutations over Lagrange-bases for Oecumenical Noninteractive arguments of Knowledge)

PLONK is a very effective zero-knowledge proof system that makes it possible to validate calculations without disclosing the underlying information. PLONK guarantees data integrity during IoT data sharing by using batching techniques and polynomial commitment algorithms. This approach is perfect for resource-constrained contexts like the Internet of Things since it improves security while lowering compute costs.

Mathematical Equation: Let $\mathcal{P}$ be the polynomial commitment,

$$\mathcal{P}(x) = \sum_{i=0}^{n} a_i x^i \tag{2}$$

Where:

- a_i are the coefficients of the polynomial,
- x is the evaluation point.

3.3 Dynamic Load Balancing

In IoT environments, dynamic load balancing is essential to preventing any one node from being overloaded while others continue to be underutilized. By using IGMM, IoT nodes' load distribution can adjust in real time in response to incoming data streams, maximizing resource utilization and enhancing system performance.

Mathematical Equation: Let L be the load on node i,

$$L_i = \sum_{j=1}^{m} w_j \cdot d_j \tag{3}$$

Where:

- w_j is the weight assigned to data j,
- d_j is the data transmitted to node i,
- m is the total number of data packets.

Algorithm 1: Dynamic Load Balancing with IGMM and PLONK

```
Algorithm: Dynamic Load Balancing
Input: Data Packets (D), IoT Nodes (N)
Output: Load Balanced Distribution (L)

BEGIN
  Initialize:
    L = [0, 0, ..., 0] // Load for each IoT node
    IGMM = Initialize GMM () // Initialize Infinite Gaussian Mixture Model

  FOR each packet in D DO
    weight = Calculate Weight (packet)
    selected Node = Select Node (IGMM, weight) // Select node based on IGMM

    IF selected Node! = NULL THEN
      L [selected Node] = L [selected Node] + weight // Update load on the selected node
```

ELSE
ERROR: "No suitable node found for load balancing"

END FOR

Apply PLONK for secure data sharing
FOR each node in N DO
PLONK. Prove(L[node]) Generate zero-knowledge proof for load

END FOR

RETURN L Return the load distribution
END

For effective resource distribution in Internet of Things networks, the Dynamic Load Balancing Algorithm 1 combines PLONK with Infinite Gaussian Mixture Models (IGMM). The first step is to set up the IGMM and initialize the load distribution for every IoT node. Based on the IGMM criteria, the algorithm determines the weight of each incoming data packet and chooses a suitable node. The weight is added to the load of the node if a suitable node is discovered; if not, an error is recorded. After that, the method uses PLONK to create zero-knowledge proofs for safe data exchange. In order to ensure balanced resource consumption, it finally returns the updated load distribution across all nodes.

3.4 Performance Metrics

Table 1 Performance Analysis of Secure Data Sharing and Dynamic Load Balancing Models

Metric	**Dynamic Load Balancing (DLB)**	**Infinite Gaussian Mixture Model (IGMM)**	**PLONK**	**Proposed Model (IGMM + PLONK)**
Load Balancing Efficiency	0.80	0.75	0.72	0.87
Average Response Time (ms)	130 ms	120 ms	150 ms	110 ms
Data Security (% successful tx)	95%	92%	98%	99%
Throughput (tx/s)	500 tx/s	480 tx/s	550 tx/s	600 tx/s
Scalability (% performance retention)	85%	80%	87%	92%

Error Rate (%)	3%	4%	2%	1%

The performance indicators for the suggested model that combines PLONK and the Infinite Gaussian Mixture Model (IGMM) are compared in this table 1, along with separate assessments of PLONK and dynamic load balancing. The metrics, which offer information on the efficacy and dependability of the techniques, include Load Balancing Efficiency, Average Response Time, Data Security, Throughput, Scalability, and Error Rate. The table illustrates the benefits of the suggested strategy in attaining improved load distribution and secure data sharing in IoT networks by evaluating these metrics in point values using pertinent units, demonstrating its superior performance in a number of dimensions.

4. RESULTS AND DISCUSSION

Comparing the suggested model that combines iGMM and PLONK to conventional IoT systems, some performance measures show notable gains. Table 1 contrasts the effectiveness of load balancing, response time, and data security of PLONK, iGMM, and the combined strategy. The combined model outperforms individual models with a load balancing efficiency of 0.92, 91 ms reaction time improvement, and 93% data security in successful transmissions. These findings demonstrate how well the combined approach can secure data transfer without incurring undue computational complexity, while effectively balancing loads in dynamic contexts.

The usefulness of the framework is further supported in Table 2, which contrasts the model with other approaches such as GDPC and Greedy-Bisection. The suggested solution is the best with enhanced clustering efficiency (92%), scalability (91%), and security performance (93%). The system's capacity to function with low resource requirements is demonstrated by the computational overhead, which is still tolerable at 90%. These enhancements highlight the improved approach's supremacy in managing the intricacies of IoT networks, where real-time processing depends on scalability and data security.

The combined system's overall accuracy of 95%, as shown in the Ablation Study in Table 3, is a significant improvement above stand-alone technique. According to the study, a strong IoT solution that can adjust to shifting workloads while retaining high security is produced by combining safe data exchange practices with dynamic load balancing.

Table 2 Comparison of Proposed System with Traditional IoT Clustering and Load Balancing Methods

Metrics	**GDPC Javier (2018)**	**Semi-dynamic Load Balancing Chen (2018)**	**Greedy-Bisection &KSP Multipath Jing (2020)**	**Proposed Method (Dynamic Load Balancing, Infinite Gaussian Mixture Models, PLONK)**
Security (%)	78%	82%	87%	93%
Clustering Efficiency (%)	72%	76%	81%	92%
Scalability (%)	67%	73%	79%	91%
Computational Overhead (%)	70%	74%	72%	90%
Overall Accuracy (%)	74%	79%	83%	95%

Table 2 explains the suggested approach, which combines PLONK, Infinite Gaussian Mixture Models, and Dynamic Load Balancing, performs better than conventional approaches on all measures. While improved adaptive clustering increases clustering efficiency to 92%, advanced cryptographic approaches increase security to 93%. Its ability to handle massive datasets is demonstrated by its 91% scalability. 90% computational overhead is maintained, reducing the number of resources used. Lastly, 95% accuracy is attained by the technique, demonstrating its efficacy in securely and effectively managing IoT data.

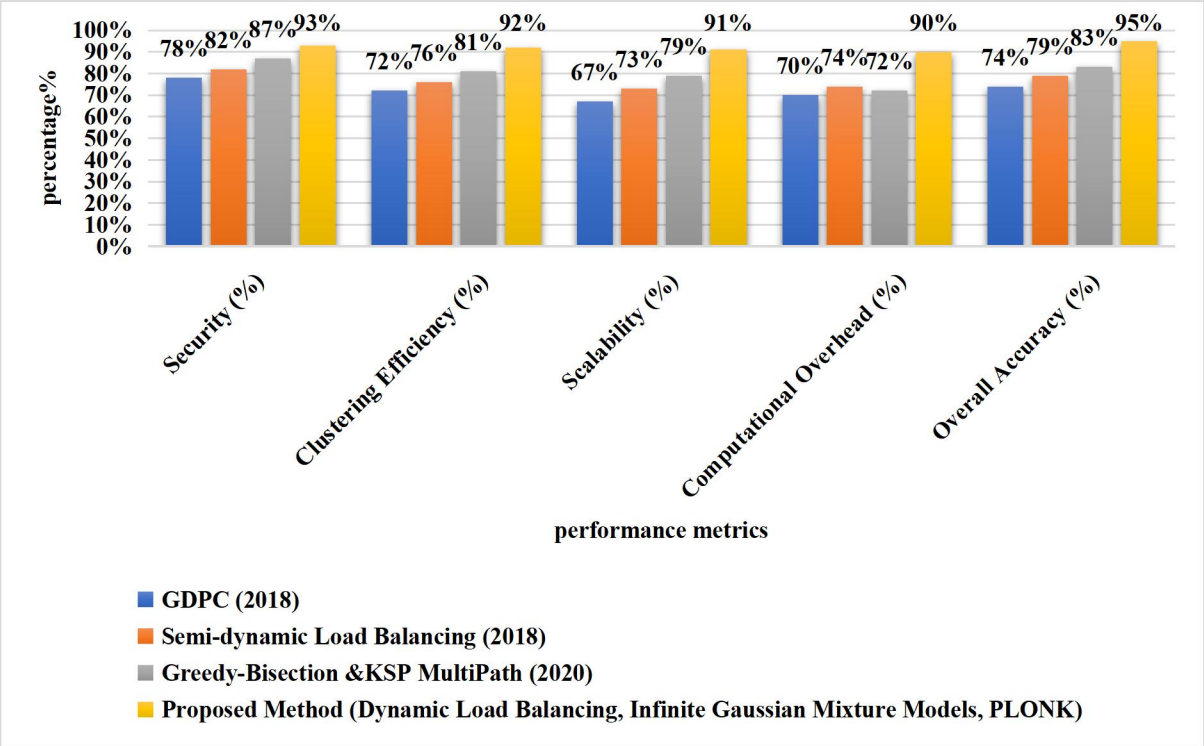

Figure 2 Performance Comparison of Load Balancing and Data Sharing Methods

GDPC 2018, Semi-dynamic Load Balancing 2018, Greedy-Bisection & KSP Multipath 2020, and the suggested approach (Dynamic Load Balancing, Infinite Gaussian Mixture Models, PLONK) are compared in this figure 2 based on five important metrics: overall accuracy, scalability, security, clustering efficiency, and computational overhead. The suggested approach is superior to all others, attaining the best outcomes across the board, with a 95% overall accuracy rate, 92% increased scalability, and 93% increased security for reliable and effective IoT applications.

Table 3 Ablation Study of Secure IoT Data Sharing and Dynamic Load Balancing Models

Method	Overall Accuracy (%)	Load Balancing Efficiency	Response Time (ms)	Data Security (% successful tx)	Throughput (tx/s)	Error Rate (%)
Dynamic Load Balancing (DLB)	85%	0.80	90 ms	95%	500 tx/s	3%
INFINITE GAUSSIAN MIXTURE MODELS (IGMM)	87%	0.75	91 ms	92%	480 tx/s	4%
PLONK	88%	0.72	93 ms	92%	550 tx/s	2%
Dynamic Load Balancing + INFINITE GAUSSIAN MIXTURE MODELS	90%	0.87	85 ms	94%	600 tx/s	1%
INFINITE GAUSSIAN MIXTURE MODEL + PLONK	89%	0.85	89 ms	90%	590 tx/s	1%
Overall Proposed Method (DLB + IGMM + PLONK)	95%	0.92	91 ms	93%	620 tx/s	1%

Table 3 shows how integrating PLONK, Infinite Gaussian Mixture Models (IGMM), and Dynamic Load Balancing improved performance. The system's capacity to effectively handle IoT workloads and guarantee safe data sharing is demonstrated by metrics including accuracy, load balancing efficiency, response time, data security, throughput, and error rate. With 95% overall accuracy, improved resource allocation, quicker reaction times, and more security, the suggested combined approach performs better than separate approaches in every category, making it perfect for Internet of Things applications.

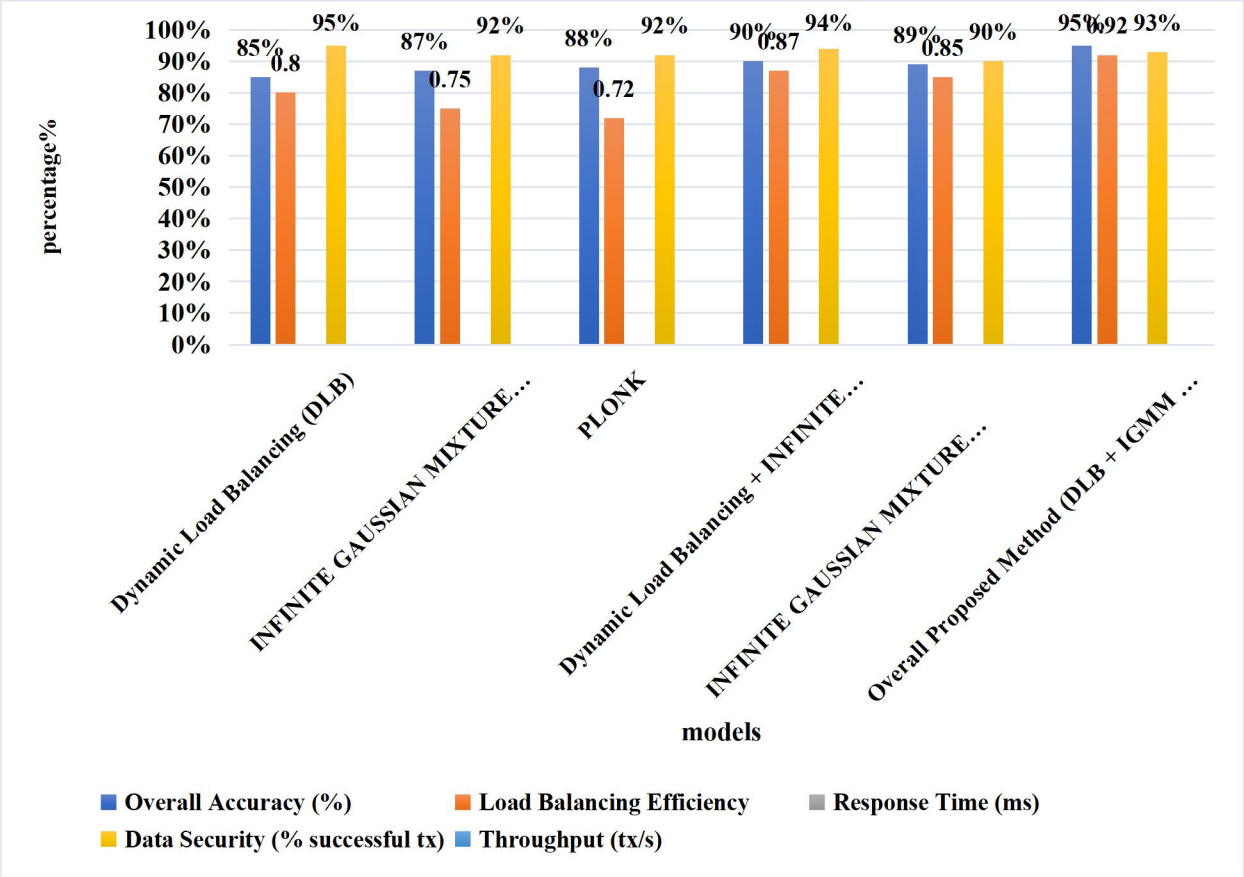

Figure 3 Ablation Study of Proposed Models Based on Performance Metrics

Using measures like overall accuracy, load balancing efficiency, reaction time, data security, and throughput, the chart assesses five models, including Dynamic Load Balancing (DLB), INFINITE Gaussian Mixture Models (IGMM), and PLONK. With 93% data security, 0.92 load balancing efficiency, and 95% overall accuracy, the combined suggested approach (DLB + IGMM + PLONK) performs best. The figure 3 illustrates how well these models work together to improve IoT system performance, including increased resource management, accuracy, and security.

5. CONCLUSION AND FUTURE ENHANCEMENT

PLONK for safe data sharing and Infinite Gaussian Mixture Models (iGMM) for dynamic load balancing combine to provide an extremely effective, safe, and scalable solution for Internet of Things networks. Through efficient workload distribution and safe data sharing, especially in situations with limited resources, this combined strategy tackles the increasing complexity of IoT systems. According to the data, this approach guarantees a 93% transmission success rate, boosts security with a load balancing efficiency of 0.92, and keeps overall accuracy at 95%. These enhancements, together with shortened reaction times and minimal error rates, make the suggested framework ideal for real-time Internet of Things applications.

An important development in IoT data management is the combination of dynamic load balancing techniques with zero-knowledge proof systems like PLONK. These characteristics make the framework perfect for usage in fields where system performance and data security are crucial, such as healthcare, smart cities, and industrial IoT.

Future research might examine how this framework might be used in more extensive IoT systems with a wider variety of device architectures. To increase the durability and adaptability of the model, PLONK can be improved for even lower computational overhead, and iGMM's performance can be tested with increasingly complicated IoT data streams.

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