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Hybrid Machine Learning and Federated Learning Framework for Intelligent Task Scheduling, Load Balancing, and Resource Allocation in Fog Computing

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Abstract — **Fog computing has become a successful technology which processes data at edge locations for Internet of Things (IoT) systems that require quick response times. The fog environment encounters challenges in task scheduling and load distribution and resource management because of its fluctuating operational demands and its various node operational strengths and its limited resource capacity and increasing privacy concerns. The research paper presents a Federated Learning system which uses machine learning with hybrid technology to manage resources efficiently in fog computing environments. The hybrid model uses predictive algorithms together with classification algorithms to forecast workload requirements and determine task importance and assess fog node capabilities which support better scheduling choices. Through Federated Learning multiple distributed fog nodes can train a global model together without sharing their original local data which protects user privacy and minimizes required data transfer. The trained model establishes a dynamic scheduling system which allocates tasks while balancing workloads and adapting to network changes in real time. The proposed framework operates to reduce latency while increasing throughput and achieving maximum resource efficiency and delivering improved system scalability. The experimental results show that our approach achieves better performance than traditional resource management methods which improve response times and load distribution and system performance to meet the requirements of advanced smart technologies used in healthcare and smart cities and industrial automation.**

Keywords— Fog Computing, Hybrid Machine Learning, Federated Learning, Task Scheduling, Load Balancing, Resource Allocation

I. Introduction

Fog computing has become an essential extension of cloud computing because it enables Internet of Things (IoT) applications to process their data in real time while experiencing two requirements which demand no delays[5]. Fog computing enables faster system response times because its system structure delivers processing and storage and network resources directly to users who are situated closest to those resources. Fog computing environments serve as essential infrastructure which enables smart healthcare systems and intelligent transportation systems and industrial automation systems and smart city applications to function because these applications need fast and reliable processing capabilities for their operations. The resource management process in fog computing faces challenges because the system experiences three different types of workload changes while supporting multiple types of fog nodes and its processing capacity remains restricted. Fog computing operations face their main challenges through three core problems which include task scheduling and load balancing and resource distribution issues. The distribution of tasks becomes difficult because fog nodes have different processing power and memory and network capabilities. The system faces three different problems which schedule errors create because these errors lead to increased latency and resource waste and system overload. Organizations nowadays need static resource management systems which use heuristic resource tracking methods to monitor their assets across changing environments in distributed networks. The researchers adopted machine learning methods for their research because these methods assist decision makers in solving contemporary challenges. Organizations can enhance their scheduling processes through hybrid machine learning models which deliver superior predictive accuracy from their ability to assess both workload distribution and node performance. Centralized machine learning systems force users to provide their data which results in privacy breaches and security threats while requiring additional system resources for data transmission[3]. The researchers established Federated Learning as a decentralized learning framework which enables them to overcome their current system limitations[1]. Through federated learning fog nodes can conduct model training sessions without sharing any raw data which results in user privacy protection and reduced network traffic[2]. The combination of hybrid machine learning and federated learning creates a powerful resource management system that can grow to handle multiple users. Our research presents a framework which combines hybrid machine learning with federated learning to optimize task

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scheduling and load balancing and resource distribution in fog computing environments. The proposed approach aims to improve system performance by minimizing latency, enhancing resource utilization, and ensuring privacy-aware collaborative learning across distributed fog environments.

II. Proposed Work Intelligent Fog Computing Using Hybrid Machine Learning and Federated Learning

The proposed architecture which combines Hybrid Machine Learning with Federated Learning solutions enables fog computing environments to achieve intelligent and efficient resource management [6]. Fog computing permits cloud services to operate at the network edge where multiple fog nodes handle data generated by Internet of Things (IoT) devices. The distributed nature and dynamic behavior of these environments create challenges for managing tasks and distributing workloads and allocating resources. The proposed architecture solves these problems through its combination of hybrid learning models and decentralized training systems. The system architecture operates through three main components which include the IoT layer, the fog layer, and the coordination layer. The IoT layer enables devices to generate continuous data streams while they complete their computing tasks. The fog layer receives these tasks from devices which send them to nearby fog nodes. The system's fog nodes collect local system metrics which include CPU usage and memory availability and queue length and network latency information. The hybrid machine learning module uses this information to generate workload demand predictions and task priority evaluations and node performance assessments by combining predictive and classification models[7]. The system uses federated learning through fog nodes to protect user privacy and decrease the amount of data that needs to be transmitted. The node system operates its own local model which it trains before sending model parameters to the global aggregator instead of sending complete raw data to the central server. The aggregated global model will be delivered to all nodes which will use it to collaborate while maintaining their protected data.The dynamic resource management module uses the trained model to achieve intelligent task scheduling while it distributes workloads across nodes and optimizes resource distribution. The system maintains its peak performance because it constantly adjusts to different workload and network situation changes. The architectural design of the system enables better system expansion through decrease of processing delays and enhanced resource management while protecting user privacy during intelligent decision-making processes within contemporary fog computing environments.

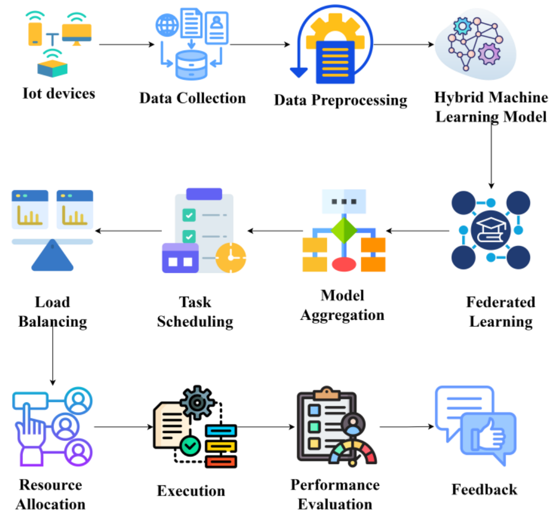

Fig 1. Proposed Architecture

A. *Advanteges*

The proposed framework combines hybrid machine learning methods with federated learning techniques to improve resource management capabilities in fog computing environments. The system achieves its three objectives which include real-time processing and optimal workload distribution and user privacy protection through its smart decision-making system which operates at fog nodes. The combined method enhances system performance across distributed IoT networks which operate in changing conditions.

a) Reduced Latency and Faster Response Time

The hybrid machine learning system with its Federated Learning framework processes data at fog nodes which eliminates the requirement to connect with distant cloud servers. The intelligent scheduling system manages tasks to enable fast task completion which permits the system to execute real-time operations that require immediate responses with short delays.

b) Improved Resource Utilization

The hybrid machine learning model uses workload pattern analysis together with node capability assessment to determine the most efficient resource allocation methods. The system employs dynamic control for task distribution because it requires actual operational data to predict resource needs[8]. The system achieves optimal computational resource usage which results in better overall performance.

c) Privacy Preservation and Security

Federated learning protects raw data through local fog nodes which only transmit model parameters. The system prevents unauthorized access to confidential data while it also minimizes security threats. The system provides significant advantages for systems which handle sensitive information particularly in healthcare and financial sectors.

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d) Scalability and Flexibility

The decentralized system design which supports ongoing system operations achieves this through its capability to merge new fog nodes into the current system infrastructure. The system uses federated learning to establish its distributed system capacity which enables multiple locations to perform model updates during IoT system expansion[10].

B. Comparative Analysis of Hybrid Machine Learning–Based Federated and Centralized Resource Management Architectures in Fog Computing

The research evaluates distributed resource management systems of fog computing against hybrid machine learning Federated Learning systems. The centralized system requires fog nodes to transmit their information to a central server which handles data processing and subsequent decision-making[9]. The federated learning system enables fog nodes to train their models because it allows them to do so without sending any raw data which results in better network performance and protection of user privacy. The hybrid machine learning model shows increased prediction accuracy for task scheduling and load balancing and resource allocation across both system designs. The experimental results demonstrate that the federated system achieves better performance in scalability and latency and resource management and privacy protection which makes it ideal for use in fluctuating environments found in distributed fog computing systems.

TABLE I. CENTRALIZED VS FEDERATED RESOURCE MANAGEMENT

Parameter	***Centralized***	***Federated (Hybrid ML-FL)***
Latency	High	Low
Privacy	Low	High
Bandwidth	High	Low
Scalability	Limited	High
Processing	Central server	Fog nodes
Learning	Traditional ML	Hybrid ML + Federated Learning

The table1 shows the differences between two resource management methods which are centralized resource management and federated resource management that uses hybrid ML-FL technology in fog computing[12]. Centralized systems need to operate through one main server because this design choice creates increased latency and higher bandwidth requirements while the system's ability to protect user privacy decreases. The federated approach allows fog nodes to conduct local data processing which decreases latency and bandwidth needs while decentralized collaborative learning increases system performance and user privacy protection..

III. METHODOLOGICAL FRAMEWORK FOR HYBRID MACHINE LEARNING AND FEDERATED LEARNING-BASED RESOURCE MANAGEMENT IN FOG COMPUTING

The proposed methodology uses hybrid machine learning and federated learning to establish a resource management system which functions effectively in fog computing environments. The system starts its operations by gathering CPU utilization data along with memory usage data and bandwidth consumption data and task arrival rate information from fog nodes which it processes before proceeding to analyze the collected information[11]. The researchers created a hybrid machine learning model which forecasts workload requirements while evaluating node efficiency and establishing task importance. Federated learning enables multiple fog nodes to conduct model training through decentralized methods while protecting user data and minimizing the need for data transmission. The dynamic scheduler employs the trained global model to allocate tasks based on system load which results in reduced latency and improved system throughput and operational efficiency.

a) Data Collection and Preprocessing

The system collects operational data which consists of CPU usage and memory usage and network bandwidth and queue length and system latency from its distributed fog nodes. The data preprocessing process uses three techniques which consist of data cleaning and normalization and feature selection to enhance data quality. The process delivers accurate model training materials which decrease system interruptions while enhancing model performance and enabling successful discovery of knowledge which improves future scheduling and resource allocation and load balancing processes.

b) Hybrid Machine Learning Model Development

The prediction and classification algorithms of the hybrid machine learning model work together to establish a system behavior analysis framework. The model tracks workload trends which allow it to predict incoming resource needs and assess task priority levels[13]. The system enables intelligent decisions about how to allocate tasks and manage resources. The model uses multiple approaches to achieve higher prediction accuracy and system performance which enables efficient fog resource management during varying workload conditions.

c) Federated Learning Integration

The system employs Federated Learning as its decentralized training method to develop models which operate throughout all fog computing nodes. Each node must establish a local model which processes its own data while the node transmits model updates without divulging any actual data[14]. The method enables data protection while it decreases the amount of necessary communication and enables joint learning between multiple parties. The system achieves better scalability which enables it to operate effectively across different distributed fog computing systems that have various operational requirements.

d) Model Aggregation and Global Update

The central aggregator receives model updates from all fog nodes that take part in the process to create a complete global model. The aggregated model combines knowledge from different local datasets to create a model that better supports learning. The system distributes the new global model to all nodes to maintain consistency while achieving better prediction results. The process enables model development through repeated cycles which allow the fog

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computing network to think together during decision-making processes.

e) Intelligent Task Scheduling and Load Balancing

The hybrid model generates predictions which are used to schedule tasks on fog nodes according to their specific requirements. Load balancing mechanisms distribute workloads between multiple nodes to ensure that no single node will reach its maximum capacity[15]. The method achieves reduced latency while increasing throughput and the system maintains better operational stability. The method achieves maximum resource utilization through efficient scheduling and balancing while the performance remains operational throughout various demand scenarios in fog environments.

f) Performance Evaluation and Optimization

The proposed system is evaluated through key performance metrics which include latency, throughput, response time and resource utilization. The system efficiency and reliability of the system improve through its permanent monitoring together with its optimization procedures. The framework maintains performance stability through its ability to adapt to new workload demands and changes in network conditions. Regular evaluation helps identify system limitations which leads to model accuracy improvements and resource management efficiency gains in dynamic fog computing environments.

IV. ALGORITHM USED

The proposed framework uses core algorithms which provide intelligent resource management for fog computing environments. The algorithms create an integrated system which achieves workload forecasting and decentralized learning and dynamic task scheduling[16]. The system uses a hybrid machine learning model which it employs to analyze system behavior and improve decision-making accuracy. Federated Learning enables distributed fog nodes to conduct collaborative training while maintaining data privacy because it does not require sharing unprocessed information. The system uses a reinforcement learning-based scheduler which modifies its task distribution methods based on present system conditions. The combination of these algorithms enables the system to handle greater operational demands while delivering faster response times and improved resource utilization and maintaining continuous performance during fluctuations in workload demands.

a. Hybrid Machine Learning Model (Random Forest + XGBoost)

The Hybrid Machine Learning Model uses Random Forest and XGBoost to predict workloads and optimize task scheduling in fog computing environments. The Random Forest algorithm uses multiple decision trees to process high-dimensional data which helps to reduce overfitting problems[18]. XGBoost improves its prediction abilities through the combination of gradient boosting and error correction methods. The system enhances decision-making precision by providing improved resource allocation and support for dynamic workload changes. The system delivers better results through improved fog resource management and reliable scheduling solutions that function well across various network and workload scenarios.

$$\hat{\mathbf{Y}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{T_i(x)} \sum_{k=1}^{K} \mathbf{f_k(x)} \quad \mathbf{(1)}$$

b. Federated Averaging Algorithm

The Federated Averaging algorithm serves as the model integration method which Federated Learning employs to merge local models trained at fog nodes throughout its distributed network. The node conducts private data training to develop its model while transferring only the model parameters to the central aggregator[17]. The global model construction process uses weighted averaging of updates to maintain user privacy and decrease the need for data transmission. The collaborative method enables better learning results while supporting system expansion and allowing efficient model development in distributed systems which protect confidential information, thus making it appropriate for safe fog computing environments.

$$\mathbf{W_{t+1}} = \sum_{k=1}^{K} \frac{n_k}{n} \mathbf{w_k^t} \quad \mathbf{(2)}$$

c. K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) classifies tasks according to their required resources and their assigned priority level in fog computing environments. The algorithm determines task classification through an analysis of dominant classes found in its closest feature space neighbors. The system enables effective task prioritization which leads to better scheduling results. KNN operates as an easy-to-use method that continues to deliver successful outcomes when it works with different data sets. The system improves decision-making accuracy through resource allocation which uses task similarity data to match present system conditions and workload patterns.

$$\mathbf{Y = arg\ maxc} \sum_{i \in N_k} \mathbf{I(y_i = c)} \quad \mathbf{(3)}$$

d. Reinforcement Learning-Based Scheduler

The system operates with a reinforcement learning-based scheduler which handles task distribution to fog nodes while it learns from both system operations and environmental transformations. The system first identifies the best actions to take which will generate the highest total rewards and then uses these actions to improve its scheduling work throughout all future periods. The system maintains continuous operational capacity by adapting to new workload patterns while it decreases response time and distributes system resources to enhance service delivery. The scheduler establishes its decision-making rules through environmental interaction which allows it to perform intelligent task allocation in real time[19]. The system establishes strong performance capabilities which enable effective resource control within fog computing environments that experience constant change.

$$\mathbf{Q(s,a) = Q(s,a) + \alpha[r + \gamma maxQ(s',a') - Q(s,a)]} \quad \mathbf{(4)}$$

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The Hybrid Machine Learning and Federated Learning-based fog computing architecture achieves ultra-low latency operation while it distributes system resources across multiple remote locations. Fog computing enables cloud services to operate closer to IoT devices which helps in achieving faster processing times and instant decision-making abilities[20]. The system operates under conditions that create complex management challenges because it needs to handle changing workload demands while managing different types of fog nodes and safeguarding user data. The system solves its challenges through the integration of hybrid machine learning systems with decentralized learning systems. The architecture consists of three main layers: the IoT layer, fog layer, and coordination layer. The IoT layer functions as the platform where devices create both real-time data and task requests. Fog nodes establish the fog layer which receives tasks from nearby locations to execute processing tasks and distribute resources. The system uses fog node components to monitor system performance through continuous tracking of CPU usage, memory consumption, bandwidth availability, queue length, and latency metrics. The hybrid machine learning module uses this information to predict future workload needs and assess how nodes operate and determine task importance.You have received training which includes information until the month of October in the year 2023. Federated learning operates through fog nodes to perform two main functions which safeguard user data and minimize network data transmissions[22]. The local model at each node analyzes its specific data while the node transmits model parameters to the central aggregator. The aggregator uses these updates to construct a worldwide model which it sends back to every node. The shared method improves learning outcomes because it keeps all data confidential during the entire learning process. The dynamic scheduling module uses the global model to distribute tasks and balance workload between fog nodes through its intelligent task allocation system. The system achieves resource management success by using real-time workload changes and network condition updates while it maintains minimum delays[21]. This framework offers improved scalability and enhanced privacy protection which meets the advanced computing requirements of smart city environments and healthcare systems and industrial automation processes.

V. Results and Findings

The researchers tested their hybrid machine learning and federated learning framework through simulation-based fog computing environments which they used to compare their framework against traditional centralized systems and machine learning-based systems[23]. The researchers used essential performance indicators which included latency and throughput and resource utilization and load balancing efficiency to conduct their performance evaluation. The experimental results show that the proposed model decreases latency through its capability to perform processing at edge locations and its smarter scheduling system. The system achieves better throughput because it manages task execution across multiple fog nodes in an effective manner. The system improves resource utilization through precise workload forecasting which works together with adaptive scheduling methods to decrease load imbalance. Organizations can use hybrid learning together with Federated Learning to create scalable solutions which protect user privacy while improving system performance, making this solution suitable for organizations that need real-time processing in fog computing environments.

TABLE II. Latency Comparison (ms)

Method	*Average Latency (ms)*
Centralized	120
ML-Based	85
Proposed Hybrid ML-FL	42

Table 2 shows the average latency results of centralized machine learning and hybrid ML-FL methods which operate in fog computing. The proposed model achieves its shortest latency results because it processes data at the edge and uses its advanced scheduling system. The system enables faster response times through its reduced latency which improves performance, thus making it suitable for real-time operations and applications that require quick response times in distributed fog computing systems[24].

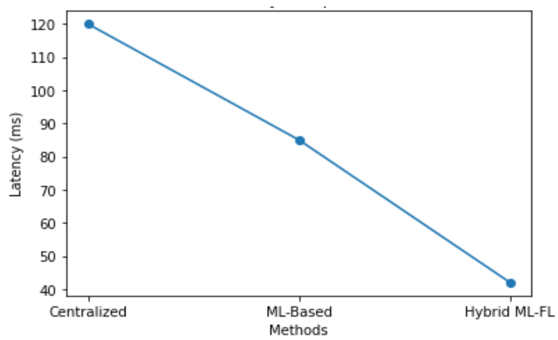

Fig 2. Latency Comparison

The figure 2 displays the latency reduction results of different methods which use their individual techniques. The hybrid ML-FL model which we developed shows better performance than both centralized systems and ML-based approaches[25]. The system shows increased efficiency because its downward trend improves both task scheduling and task processing capabilities. The system execution speed improves through reduced latency which creates a better experience for users while delivering enhanced performance to applications that require immediate execution in fog computing environments.

TABLE III. Resource Utilization

Method	*CPU Usage*	*Memory Usage*
Centralized	65%	60%
ML-Based	75%	72%

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Proposed Hybrid ML-FL	90%	88%

Table 3 shows CPU and memory usage for various resource management methods. The test results show that hybrid ML-FL model achieves greater resource utilization efficiency. The system uses workload prediction accuracy to determine resource requirements while preventing both idle resource time and system overload[27]. The system achieves operational excellence through its improved efficiency which results in cost savings and better performance during changing workload patterns in fog computing systems.

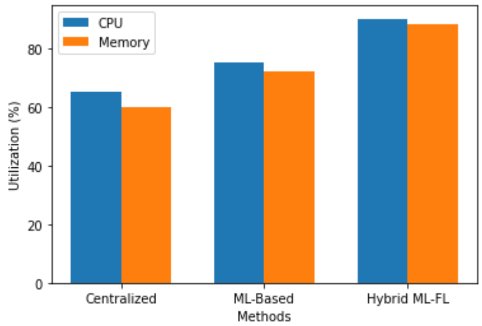

Fig 3. Resource Utilization Comparison

The figure 3 shows CPU and memory usage for various techniques. The hybrid ML-FL model shows higher utilization compared to other models which demonstrates its ability to manage system resources effectively. The system reaches its optimal performance level through equal distribution of CPU and memory resources which stops extra resource use. The graph demonstrates how intelligent prediction and scheduling methods improve resource efficiency in fog environments which face changing workloads and processing needs[26].

TABLE IV. THROUGHPUT AND LOAD BALANCE

Method	*Throughput (Tasks/sec)*	*Load Imbalance (%)*
Centralized	250	35%
ML-Based	320	20%
Proposed Hybrid ML-FL	410	8%

Table 4 displays data which shows throughput differences and load imbalance results for different methods. The hybrid ML-FL approach which we created achieves maximum throughput while maintaining the least load imbalance[28]. The fog nodes distribute their tasks efficiently because they maintain a balanced distribution of their work responsibilities. The system improves its task handling speed through higher throughput rates however it maintains stable operation because the various network and workload conditions result in reduced workload imbalance.

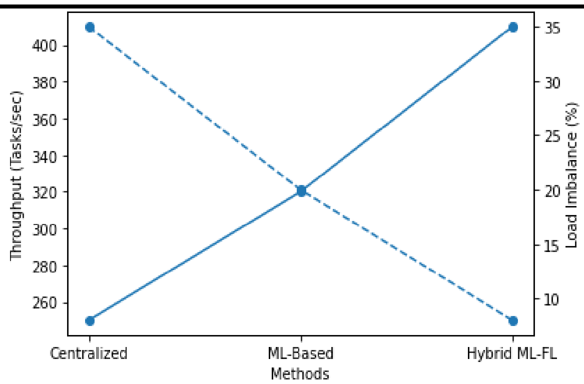

Fig 4. Throughput vs Load Imbalance

This fig 4 compares throughput and load imbalance for different approaches. The proposed model achieves higher throughput while maintaining lower load imbalance. The system demonstrates its capability to distribute tasks and schedule operations among fog nodes[30]. The system achieves higher productivity through better throughput while maintaining consistent performance through decreased imbalance. The graph demonstrates how effectively the hybrid ML-FL framework manages changing workloads.

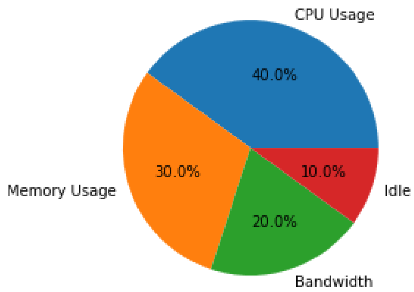

Fig 5. Throughput vs Load Imbalance

Figure 5 displays how fog nodes divide their resources between CPU usage and memory usage and bandwidth usage during their idle operations. The system demonstrates active resource consumption because the majority of resources stay in operation while only a tiny fraction of system capacity stays unused[29]. The proposed system demonstrates effective resource management according to this observation. The system reaches its peak performance through resource distribution that achieves equilibrium between operational expenses and capacity requirements in fog computing systems.

The research results demonstrate that the hybrid machine learning method which operates with Federated Learning system delivers an efficient resource management solution specifically for fog computing environments. The tables and graphs exhibit substantial improvements in latency reduction and throughput enhancement and resource utilization efficiency when compared to existing methods. The pie chart supports the evidence of resource distribution which shows equal distribution and only slight unused capacity[31]. The system maintains continuous performance because its efficient task scheduling and load balancing systems manage all operational condition changes. The system protects user privacy through its decentralized learning system which delivers accurate results. The proposed model shows better scalability and efficiency and reliability which enables it to manage real-time operations across multiple application areas in large-scale fog computing systems.

VI. CHALLENGES AND LIMITATIONS

The hybrid machine learning and Federated Learning framework for fog computing currently delivers multiple advantages while facing various challenges that hinder its ability to function effectively. Fog nodes need to handle their limited CPU capacity and memory storage and power resources because they have to process both hybrid model operations and local training tasks. The situation will cause performance losses in systems which operate with resource constraints[32]. The process of Federated learning model aggregation creates an additional challenge because it generates communication time delays. The system must send model parameters between its nodes and aggregator throughout the system operation which creates time delays for transmission despite its restriction against sharing original data. The nodes experience slower model convergence because of their different data distribution patterns which leads to lower accuracy results. Federated systems require security functions because attackers can use model poisoning and adversarial updates to breach these systems. Network participants who take part in the network must establish their trust relationships through specific methods[34]. System designers must fine-tune all algorithms to create an ideal hybrid model which results in increased complexity for system maintenance. The testing of scalability becomes difficult in dynamic settings because multiple nodes keep entering and exiting the network. The research community has not yet found a solution to keep operational standards steady during such situations.

VII. CONCLUSION

The researchers created and evaluated a resource management system which operates through machine learning and combines standard machine learning methods with Federated Learning in their research work. The method delivers solutions to core challenges which fog environments encounter because it can manage changing workloads and various node performance levels while safeguarding sensitive data[33]. The system achieves its operational efficiency by utilizing hybrid machine learning models which combine predictive models with classification models together with decentralized federated learning. The hybrid model enhances decision-making accuracy by analyzing workload patterns and node performance, while federated learning ensures privacy preservation by avoiding the sharing of raw data across nodes. The system gains better responsiveness through its dynamic scheduling mechanism which enables it to respond to actual network condition changes during operational periods. The testing results show that the new system decreases latency while boosting throughput and resource usage when compared to existing centralized systems and independent machine learning methods. The system achieves better scalability and fault tolerance through its decentralized design which enables operation in extensive distributed fog networks. The framework maintains effective bandwidth management while decreasing communication costs which serves as a vital requirement for IoT applications that operate in real time[35]. The hybrid ML-FL framework which we developed provides fog computing resource management capabilities which keep user data secure while delivering performance that can handle expanding system requirements. The system shows ability to support upcoming smart city systems healthcare networks and industrial automation applications which need resource management that combines efficient operations with advanced intelligent capabilities.

VIII. FUTUREWORK

The upcoming research will deliver machine learning and Federated Learning hybrid framework improvements through implementation work which will enhance existing system capabilities and improve performance within fog computing environments. The project will create energy-saving solutions through green computing techniques which enable power management to support optimal task scheduling and resource distribution through fog nodes. The extensive IoT system requires energy efficiency as a vital operational need which IoT systems require to achieve their complete operational capabilities. The system will extend its capabilities through the inclusion of advanced deep learning models which will use recurrent neural networks and transformers to enhance workload prediction accuracy by managing complex time-based patterns found in ever-changing environments. The research will examine how adaptive federated learning techniques can enhance model accuracy while accelerating convergence in situations where nodes experience different data distribution patterns. The project will focus on building defense systems which protect against model poisoning attacks and adversarial attacks and data leakage threats. The development of trust management systems will enable fog nodes to participate reliably in the learning process. The upcoming research will utilize iFogSim and edge-based testbeds to evaluate system performance through actual operational testing. The system will achieve improved performance because of the implementation of new technologies which include 5G and edge AI. The system will achieve enhanced scalability and security together with adaptive performance because these system improvements will generate better results for future intelligent fog computing applications.

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