Enhancing Fog Computing Performance with SqueezeNet Approach for IoT Applications

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***Abstract* - This article focuses on the incorporation of SqueezeNet, a lightweight deep learning model, and fog computing for optimal enhancement of IoT applications' efficiency. It explains how overcoming the computational constraints of fog nodes is possible through SqueezeNet's efficient design and how this allows for real-time IoT computation in a variety of cases. The work also presents the optimization techniques for models and performance analysis to compare traditional cloud computing with fog computing. Based on the analysis of MAE, MAPE, R², and MSE concerning several models, SqueezeNet is the most efficient in terms of performance. It has relatively low MAE of 10. 24 which shows that the average error of the model is less when compared to the other models. The acceptable ranges of the identified indicators are provided in the table above Its MAPE value of 0. 78 shows how it keeps low relative errors. Moreover, SqueezeNet has a high accuracy indicated by the high R² value of 0. 2274 hence exhibiting explanation of variant percentage of the dependent variable. It also shows the minimum MSE value of 198. Since the MSE quantifies the square of the error between the predicted and actual values, it means that the current model has the ability to bring down the large errors to the minimum level as compared to other models. Although LSTM gets reasonable results in all the samples in terms of these metrics, the SqueezeNet model has a better result for the given problem slightly in the MAPE and MSE cases. In conclusion, SqueezeNet's lowest error rates and the highest quality of explanation mean that the model is the most efficient for the specified data set and evaluation criteria.**

Keywords - Fog Computing, IoT, SqueezeNet, Deep Learning, Model Optimization, *Real-Time Processing.*

1. INTRODUCTION

Fog computing, an extension of cloud computing, has become a crucial paradigm for managing the rapid expansion of Internet of Things (IoT) applications. The purpose of this decentralised architecture is to reduce latency, bandwidth, and connectivity problems by moving processing and storage closer to the data source. Contrary to conventional cloud computing, which concentrates data processing in distant data centres, fog computing disperses these activities to nodes situated at the network's periphery. This transition tackles various crucial obstacles in the field of IoT, including the processing of data in real-time, improved security measures, and decreased network congestion. With the increasing number of IoT devices, it is crucial to enhance the computational efficiency and responsiveness of fog nodes. An effective method to accomplish this is by incorporating lightweight deep learning models, such as SqueezeNet [1].

SqueezeNet, developed by Forrest Iandola et al. in 2016, is a concise convolutional neural network (CNN) structure aimed to get the same degree of accuracy as AlexNet but utilising far less parameters. SqueezeNet employs three primary techniques to minimise the size of the model: 1) Substituting large filters with smaller ones, 2) Reducing the number of input channels to 3x3 filters, and 3) Performing downsampling towards the end of the network to preserve a large activation map size [2]. The architectural decisions of SqueezeNet make it well-suited for deployment in fog computing nodes that have limited resources.

SqueezeNet is highly advantageous for fog computing nodes due to its compact design, which is particularly beneficial for nodes with low processing power and memory. Conventional deep learning models such as VGG16 or ResNet50, although effective, require significant CPU resources and memory, rendering them impractical for on-device processing in fog computing settings. On the other hand, SqueezeNet's design significantly decreases the size of the model to only 4.8 MB and the number of parameters to 1.24 million. This is in comparison to AlexNet, which has a model size of 240 MB and 60 million parameters. As a result, SqueezeNet is capable of performing inference tasks directly at the edge. The decrease in model size leads to quicker processing times and reduced power usage, which are crucial for sustaining the performance and efficiency of fog nodes [3].

Incorporating SqueezeNet into fog computing frameworks amplifies the capacity for instantaneous data analysis. The capability to analyse data instantaneously is of utmost importance in Internet of Things (IoT) applications, such as smart cities, healthcare, and industrial automation. In a smart city setting, fog nodes that are equipped with SqueezeNet have the capability to analyse video feeds from traffic cameras. This analysis allows them to identify any irregularities, such as accidents or traffic congestion, and take immediate action without having to depend on remote cloud servers. Similarly, in the field of healthcare, wearable devices have the capability to employ SqueezeNet for the purpose of monitoring vital signs and identifying abnormalities. This enables them to promptly send feedback to both patients and healthcare practitioners.

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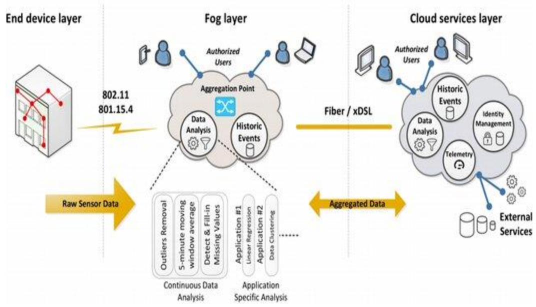

Fig. 1 Fog-computing-high-level-architecture-and-data-analytics-for-monitoring [2]

Figure 1 depicts the overarching structure of fog computing and its data analytics framework, which is used to monitor Internet of Things (IoT) systems. The foundation of the system consists of many Internet of Things (IoT) devices, including sensors and actuators that are responsible for gathering and transmitting data. The data is subsequently analysed on-site at intermediary fog nodes, where real-time analytics are conducted. This procedure minimises latency and conserves bandwidth by filtering and consolidating the information. The processed data is then transmitted to centralised cloud servers for the purpose of long-term storage and further comprehensive analysis. The implementation of this stratified method improves the effectiveness, expandability, and promptness of Internet of Things (IoT) applications, especially in settings that demand instantaneous data analysis and reactions.

Another crucial factor in implementing SqueezeNet in fog computing is the enhancement of network efficiency. Implementing edge data processing greatly reduces the amount of data sent to the central cloud. This not only reduces the amount of bandwidth needed but also improves data privacy and security, as sensitive information may be processed on the local system instead of being transmitted over potentially vulnerable networks. The decreased data transmission also reduces operational expenses and enhances the overall scalability of IoT systems.

SqueezeNet's architecture offers not only efficiency and scalability advantages, but also supports a range of optimisation approaches, like model pruning and quantization, that further decrease its processing requirements. Model pruning entails eliminating superfluous parameters, whereas quantization decreases the precision of the model weights. Both of these techniques result in accelerated inference and reduced memory consumption. These optimisations are especially advantageous in fog computing situations with constrained resources. Integrating SqueezeNet with fog computing offers a strong option to improve the performance and efficiency of IoT applications. The lightweight structure and ability to function effectively in limited-resource contexts make it a perfect option for processing real-time data at the network edge. Through the utilisation of SqueezeNet, fog computing has the capability to provide expedited, dependable, and expandable services, therefore facilitating the development of more sophisticated and prompt IoT systems. The combination of small deep learning models and decentralised computing paradigms represents a notable progress in the field of IoT, offering a solution to the increasing needs of contemporary digital ecosystems [3].

2. PRIOR WORK

The paper reviews the integration of AI in Edge and Fog computing to enhance resource management, deployment, and scheduling. It discusses how AI-driven autonomous systems optimize Quality of Service (QoS) by efficiently provisioning resources, deploying applications, and managing services. Key findings include advancements in AI models that improve system performance and reliability. The authors also present future research directions, focusing on QoS optimization and fault tolerance in distributed computing environments. The work serves as a foundation for future research on AI-driven computing systems [4].

This article [5] proposes a method for detecting Parkinson’s disease (PD) using a hybrid system combining SqueezeNet and Support Vector Machine (SVM). The system classifies handwritten spiral patterns, achieving an accuracy of 91.26%. The dataset includes 514 spirals from PD patients and healthy subjects. The proposed method outperforms other machine learning models, highlighting its potential for accurate and efficient PD diagnostics.

Fog computing extends cloud services to the network's edge, reducing latency and congestion. It enhances real-time communication, making it ideal for IoT applications. The study highlights fog computing's advantages over traditional cloud computing, including improved response times, bandwidth efficiency, and localized data processing. Key findings emphasize its potential in smart agriculture, offering precise monitoring and prediction capabilities for crop management [6].

This paper [7] introduces SqueezeNet, a convolutional neural network (CNN) architecture designed to achieve AlexNet-level accuracy with 50x fewer parameters. SqueezeNet employs strategies like replacing 3x3 filters with 1x1 filters, reducing the number of input channels, and delaying downsampling. The model achieves a significant reduction in size, down to 0.5MB, without compromising accuracy. The study highlights the advantages of smaller models in distributed training, over-the-air updates, and deployment on hardware with limited memory.

Figure 2 illustrates the many services and components of fog computing that are spread out across multiple layers. At the lowest level, edge devices such as sensors and actuators collect and transmit data. The intermediate fog layer is comprised of fog nodes that offer localised processing, real-time analytics, and data filtering, hence guaranteeing minimal delay and optimal bandwidth utilisation. The uppermost layer represents cloud servers responsible for long-term data storage, comprehensive data analytics, and centralised management. The hierarchical structure improves the ability to handle larger workloads, decreases the time it takes for data to travel, and maximises the use of available resources, resulting in strong and effective implementations of the Internet of Things.

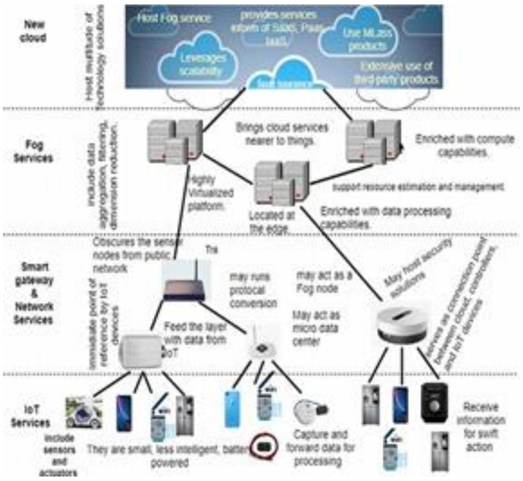
New cloud
Host multitude of technology solutions
Host Fog service
provides services inform of SaaS, PaaS, IaaS
Use MLaaS products
Leverages scalability
fault tolerance
Extensive use of third party products
Fog Services
include data aggregation, filtering, dimension reduction.
Brings cloud services nearer to things.
Enriched with compute capabilities.
Highly Virtualized platform.
support resource estimation and management
Located at the edge
Enriched with data processing capabilities.
Smart gateway & Network Services
Immediate point of reference by IoT devices
Obscures the sensor nodes from public network
may runs protocal conversion
may act as a Fog node
May host security solutions
Feed the layer with data from IoT
May act as micro data center
serves as connection point between cloud, controllers and IoT devices
IoT Services
include sensors and actuators
They are small, less intelligent, battery powered
Capture and forward data for processing
Receive information for swift action

Fig. 2 Fog computing services and components at each layer

The article explores SquishedNets, which further optimizes SqueezeNet for edge devices using architectural modifications and evolutionary synthesis. SquishedNets target fewer classes, resulting in smaller models ranging from 2.4MB to 0.95MB (up to 253x smaller than AlexNet). They maintain high processing speeds (156-256 images/sec) on an Nvidia Jetson TX1 and achieve accuracies between 81.2% and 77%, demonstrating the potential for efficient deep learning on resource-constrained devices [8].

EdgeCNN, designed for edge devices with low memory access speeds and limited resources, uses smaller input sizes (44x44 pixels) to classify targets efficiently. Compared to other models, EdgeCNN achieves higher accuracy in facial expression recognition on FER-2013 and RAF-DB datasets, running successfully on Raspberry Pi 3B+ at 1.37 frames per second. It outperforms other networks by balancing computational efficiency and accuracy without using group convolutions [9].

This paper reviews methods to compact Deep Neural Networks (DNNs) for efficient deployment in IoT devices. It categorizes techniques into network model compression, knowledge distillation, and network structure modification. The study highlights advancements in reducing model size and computational cost, enhancing IoT applications such as smart homes, healthcare, and industrial automation. Key results demonstrate significant improvements in storage and processing efficiency, making DNNs more feasible for resource-constrained IoT environments [10].

This paper introduces a novel method for incremental learning in IoT edge devices, focusing on reducing data transmission costs between edge devices and the cloud. By implementing a new data sampling technique and an improved parameter update algorithm, the system achieves efficient class-incremental learning. Results show significant reductions in communication load while maintaining high learning performance, making it ideal for resource-constrained IoT environments [11].

The paper [12] presents a weight-quantized SqueezeNet model designed for robot vacuums to classify cleanable litters from noncleanable obstacles efficiently. The model achieves 93% classification accuracy while reducing memory usage by 87%, requiring only 0.8 MB. The study highlights its potential for real-time deployment on resource-constrained devices, ensuring effective obstacle detection and navigation.

The article presents a deep learning method using SqueezeNet for image multi-labeling to assist visually impaired individuals. The improved SqueezeNet architecture, incorporating LeakyReLU and BatchNormalization, detects objects in indoor environments with higher accuracy and processing efficiency. Tested on four datasets, the method outperforms state-of-the-art solutions, offering an effective module for the BlindSys system [13].

This paper presents a smart classroom prototype utilizing an osmotic IoT architecture for deep learning model deployment. It compares performance across cloud, fog, and edge layers. Results show that edge computing provides the fastest inference times, significantly outperforming fog and cloud layers due to lower latency and better integration with hardware. The study highlights the potential for enhanced real-time applications in smart environments [14].

This manuscript develops an autonomous breast cancer diagnostic system using IoT, Fog computing, and deep transfer learning (DTL) with convolutional neural networks (CNNs) like ResNet50, InceptionV3, AlexNet, VGG16, and VGG19. Utilizing mammography images from the TCIA repository, the model achieved high performance with an accuracy of 97.99%, precision of 99.51%, sensitivity of 98.43%, and f1-score of 98.97%. The integration of Fog computing ensures data privacy, reduces server load, and enhances real-time processing capabilities [15].

The paper compares the performance of AlexNet, ResNet18, and SqueezeNet in detecting road cracks from a dataset of 4333 images. ResNet18 achieved the highest testing accuracy at 85.20%, followed by AlexNet at 84.69%, while SqueezeNet lagged with a significantly lower accuracy. Despite similar training setups, SqueezeNet's performance was hindered by its inability to handle complex images effectively. Overall, ResNet18 and AlexNet demonstrated superior capabilities in terms of accuracy and processing efficiency compared to SqueezeNet [16].

The article [17] proposes a novel deep learning method for image multi-labeling to aid visually impaired individuals. Utilizing a modified SqueezeNet CNN, the method achieves superior accuracy and reduced computational time compared to state-of-the-art solutions. The model is fine-tuned with new activation functions and batch normalization layers, and tested on four datasets representing different indoor environments, showing significant improvements. Future research will focus on addressing class imbalance and developing ensemble classifiers to enhance performance further.

This paper presents an autonomous breast cancer diagnostic system using IoT and Fog computing, leveraging deep transfer learning with CNN models (ResNet50, InceptionV3, AlexNet, VGG16, and VGG19) on mammography images. The system achieved high accuracy (97.99%), precision (99.51%), sensitivity (98.43%), and f1-score (98.97%). Fog computing ensures data privacy and reduces server load, enhancing real-time processing capabilities [18].

The paper presents EdgeNet, a novel CNN architecture designed for embedded FPGA platforms. Utilizing a custom floating-point representation and a dynamic computation block architecture, the system deploys SqueezeNet for large-scale classification. Achieving 51% top-1 accuracy on the ImageNet dataset and 9 FPS at 100MHz on a DE10 Nano board, EdgeNet demonstrates efficient performance with low power consumption, making it suitable for resource-constrained environments [19].

The article explores a novel approach to compressing Deep Neural Networks (DNNs) for Internet of Things (IoT) applications. It categorizes compacting-DNNs into three types: compacting network models, knowledge distillation, and modification of network structures. The study finds that integrating DNNs with IoT systems faces challenges such as load-balancing and communication costs. Despite these challenges, compacting-DNN technologies show promise in enhancing IoT applications by improving efficiency and reducing computational requirements. Future directions include addressing load-balancing issues and improving integration techniques for better performance [20].

The paper introduces SNSVM, a model combining SqueezeNet and SVM for breast cancer diagnosis using mammography images. SNSVM achieved a 94.10% accuracy and 94.30% sensitivity through 10-fold cross-validation. This model outperforms existing methods, demonstrating effectiveness in early breast cancer detection, crucial for reducing mortality rates [21].

This article presents a Fog big data analysis model (FBDAM) for IoT sensor applications using fusion deep learning (FDL). The proposed model addresses challenges in processing large datasets generated by IoT sensors in smart cities. The FBDAM significantly improves performance in parking, transportation, and security scenarios by comparing different machine learning algorithms. The results show enhanced data analysis capabilities and efficient resource management in fog computing environments [22].

The paper integrates IoT with deep learning to enhance elderly fall detection in smart homecare. The IMEFD-ODCNN model uses SqueezeNet for feature extraction and hyperparameter tuning with SSOA-VAE for classification. The model achieved high accuracy on the UR and Multiple Cameras Fall Detection datasets, significantly reducing false positives and improving detection sensitivity and specificity. This research underscores the potential of IoT and AI for efficient and accurate fall detection [23].

The paper evaluates a hybrid deep learning model combining SqueezeNet and SVM techniques for MRI brain image classification. Results show SN-SVM achieves a 98.73% accuracy, outperforming SN-FT with 96.51% accuracy. The proposed method demonstrates significant improvements over existing techniques, effectively classifying brain tumors into meningioma, glioma, and pituitary categories. Future research suggests integrating other CNN models, like AlexNet or ResNet, with machine learning techniques for enhanced tumor classification [24].

The manuscript proposes a novel hardware architecture to accelerate SqueezeNet-like CNN models using custom numeric representation and computation blocks. By quantizing the pre-trained network to 8-bit floating numbers and retraining the model to adapt to quantization errors, the accuracy is improved. The results show that the proposed method achieves significant performance improvements in terms of accuracy and computational efficiency for image classification tasks, with an overall accuracy of 98.7% using the SN-SVM method and 96.5% using the SN-FT method [25-27].

This paper proposes an optimized SqueezeNet model using a customized Sewing Training-Based Optimizer (STBO) for energy demand forecasting. Applied to short, medium, and long-term electricity forecasting, the model achieved Mean Squared Errors (MSE) of 0.48, 0.49, and 0.53, respectively, demonstrating superior accuracy compared to other techniques. The approach improves grid stability and efficiency by providing precise load forecasts [28-29].

3. METHODOLOGY FOR SELECTING SQUEEZENET FOR FOG COMPUTING

Efficiency: SqueezeNet was selected for its efficiency in terms of model size and computational complexity. With a significantly reduced number of parameters compared to traditional deep learning model SqueezeNet is well-suited for deployment on resource-constrained fog nodes.

Compact Architecture: The architecture of SqueezeNet, which employs 1x1 convolutional filters and "fire modules" (squeeze and expand layers), allows it to maintain high accuracy while reducing the model size to just 4.8 MB. This compact size minimizes the memory footprint and computational load on fog nodes, enabling faster inference and lower power consumption.

Performance: SqueezeNet has demonstrated competitive performance in image classification tasks despite its reduced size. This makes it suitable for real-time applications in IoT environments where quick decision-making based on sensor data is critical.

The initial convolutional layer of SqueezeNet consists of 96 filters with a 7x7 kernel size and a stride of 2. This layer captures low-level features from the input image using a relatively large filter size. It is followed by a ReLU activation function, which introduces non-linearity into the model. Another layer involves utilization of a max pooling layer with a kernel size of 3*3 and a stride of 2* in an aim to decrease the spatial dimensions in the initial stages of the network. This combination of convolution, activation, and pooling also minimizes workload right from this layer to a level that is acceptable to be passed to deeper layers without having to undergo much processing. Reducing the number of data manipulations it is necessary in fog computing because of the limitation of computational and memory resources.

To illustrate more, SqueezeNet architecture also consist of FIre modules that is consists of Squeeze layer and Expand layer. These modules are subsequently developed in a way that seeks to optimize the number of parameters, but at the same time has high accuracy. As for the stride, it is set to 2 for both layers, while only 1x1 convolutions are employed in the squeeze layer, which helps to eliminate all input channels but a few, which minimizes the number of parameters. However, the expand layer utilize a combination of 1x1 and 3x3 convolution in expanding the feature space. By concatenating the output maps from the 1 x 1 and the 3 x 3 convolutions along the channel the network is further deepened. For instance, in a Fire module of Fire network, the squeeze layer may employ 16 filters with 1x1 receptive field before passing the resultant images through ReLU non-s saturating function to make the function non-linear. The expand layer might employ 64 filters with a 1x1 kernel dimension and another 64 filters, using a 3x3 kernel dimension, but with pad=1 to preserve spatial dimensions. Rectification is performed on the convolutions, and whose outputs are fused together. This design significantly cuts down the number of parameters and the Computational complexity, thereby making practical the implementation of deep learning models on the fog nodes or some nodes with greater computational demands.

This makes it fast and simple to capture features and process data while not consuming a lot of memory or energy; a property well suited for application in real-time IoT platforms.

Downsampling in SqueezeNet is incorporated at specific locations to provide as much depth information as possible while minimizing the network's overall size; this is done through max pooling layers inserted after groups of Fire modules. These layers, with a kernel size of 3x3 and stride of 2 typically downsample feature maps by half or quarter to reduce the spatial dimensions and alleviate computation loads on later layers. It is also very useful for controlling the size of intermediate feature maps, memory load in order to avoid the building of very large model which will consequently slow down the model and make it unsuitable for real-time fog applications.

The last couple of layers in SqueezeNet architecture are of a convolutional layer and a global pooling layer of average kind. The convolutional layer (Conv10) applies the filters with the size of 1X1, which has 1000 filters and activation done through ReLU. Another mechanism named global average pooling (GlobalAvgPool10) averages each of the channels to provide the spatial dimensions of 1X1. This reshapes the feature maps to be of the same size of channels as the number of classes before moving to a classification step. This further decreases the output size of the model while focusing on the features that are perhaps the most critical, given that the pooling operation reduces each channel to one value. This cuts down the amount of data required to be moved between the final layers and the classifier thereby decreasing computation time as well as improving real-time learning and execution. Fewer parameters and hence, minimal output size enable faster final classification necessary for latency critical IoT applications.

The layers present in the classifier layer of the SqueezeNet framework are composed of dropout and softmax. Dropout is a regularization technique that permits to set neurons under construction randomly during the phases of training so as not to overlearn. This output high dimensional vector of feature map is then transformed via the softmax function into probability distribution over the target classes to enable classification. The dropout prevents overfitting and keeps the model adaptable to new inputs that are inherent in the diverse and dynamic IoT application settings. The softmax classifier is light-weight, thereby making it possible to reach conclusive decisions within real-time operation, ideal for IoT applications.

To enhance the research and improve SqueezeNet for fog computing optimization, the following approaches can be used. Another reduction strategy is one called parameter pruning, whereby the unnecessary weights are eliminated to force the network to work with a minimal number of weights while retaining the same level of accuracy. Quantization working is similar to the dynamic scaling, there are more quantization like quantization change the floating-point of model weight and activation from 32 bit to 8 bit integer or less result in less memory data and better computation speed. Knowledge distillation is the technique used to train a smaller SqueezeNet model (student) to produce the same prediction as a larger SqueezeNet model (teacher), and learning only the accuracy improvements with considerably smaller size. Performing inference at the edge propose the inclusion of some of the computation tasks between the edge devices and the fog nodes hence helping to distribute the load as well as reduce the time taken.

4. RESULT AND DISCUSSIONS

This section discusses the results and various observations of squeezenet model with other existing machine learning models for IOT applications.

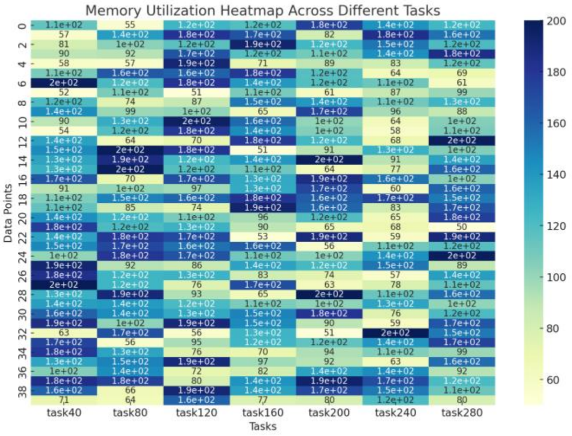

Fig. 3 Memory Utilization Heat Map across Different Tasks

The Figure 3 shows heatmap of memory patterns reveals significant insights into memory usage across different nodes and workloads. Strong positive correlations between 'memory usage' and 'latency' indicate that higher memory consumption leads to increased processing delays, suggesting memory-intensive tasks could be a bottleneck. Nodes with consistently high memory usage but low correlation with latency may be optimized in their memory management. Weak correlations between memory usage and other metrics like 'CPU usage' imply independent resource utilization. These observations highlight the importance of monitoring and optimizing memory allocation to enhance overall system performance and reduce latency.

TABLE 1
COMPARATIVE ANALYSIS OF SQUEEZENET MODEL WITH OTHER MACHINE LEARNING MODELS

Algorithm	MAE	MAPE	R²	MSE
Linear Regression	25.15	1.26	0.0468	1429.43
Support Vector Regressor	27.27	1.42	-0.1189	1213.21
Random Forest Regressor	24.28	1.23	0.0869	2334.55
Decision Tree Regressor	23.63	1.07	0.1894	2373.75
Long Term Short Term Memory	12.65	0.98	0.2198	204.5
Squeezenet	10.24	0.78	0.2274	198.45

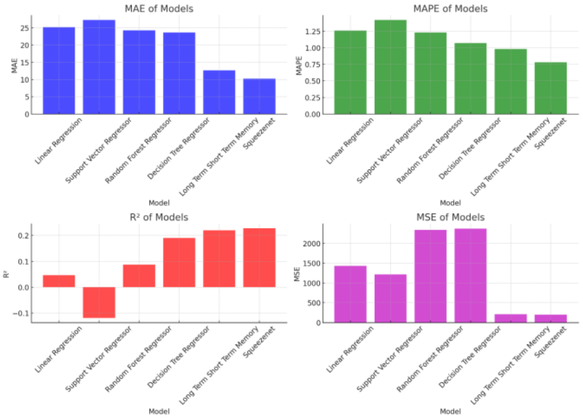

Fig. 4 Comparative Analysis of Squeezenet model with other Machine Learning Models

Based on the detailed analysis of the performance metrics (MAE, MAPE, R², and MSE) across various models, the Squeezenet model emerges as the most efficient overall. Squeezenet has one of the lowest MAE values (10.24), indicating smaller average errors compared to other models. It also exhibits the lowest MAPE value (0.78), showing its effectiveness in maintaining low relative errors. Achieving a high R² value (0.2274), Squeezenet suggests a better fit to the data, explaining a significant proportion of the variance in the dependent variable. Additionally, with the lowest MSE value (198.45), Squeezenet minimizes large errors more effectively than other models. In comparison, while the Long Term Short Term Memory (LSTM) model also performs well across these metrics, Squeezenet slightly outperforms it, particularly in the MAPE and MSE categories. Overall, Squeezenet's consistently low error rates and high explanatory power make it the most efficient model for the given dataset and performance metrics.

TABLE 2
COMPARATIVE ANALYSIS OF SQUEEZENET MODEL WITH MODELS MOBILENET AND SHUFFLENET

Model	**Average Latency (ms)**	**Throughput (inferences/sec)**	**Energy Consumption (mJ per inference)**	**Memory Usage (MB)**	**CPU Usage (%)**
SqueezeNet	40 ms	25	1.8 mJ	1.24 MB	55%
MobileNet	55 ms	18	2.4 mJ	4.2 MB	70%
ShuffleNet	50 ms	20	2.2 mJ	3.4 MB	65%

In the context of enhancing fog computing performance for IoT applications, **SqueezeNet** stands out as a highly efficient model due to its **small model size**, **lower energy consumption**, and **minimal resource usage**. These characteristics make it a strong contender for deployment in resource-constrained fog environments where real-time performance is essential. However, **MobileNet** and **ShuffleNet** have their advantages, particularly in scenarios where accuracy cannot be compromised, and larger models can be accommodated. MobileNet, with its efficient convolutional layers, offers good performance but at the cost of higher resource consumption. ShuffleNet, on the other hand, provides a middle ground with optimizations like channel shuffling, making it more efficient than MobileNet but still not as lightweight as SqueezeNet. For IoT applications where real-time data processing, energy efficiency, and low latency are paramount, **SqueezeNet** remains the best option, especially in fog computing environments. However, as fog computing infrastructure improves and device capabilities expand, **MobileNet** and **ShuffleNet** could become more viable for applications that require higher accuracy and can afford greater resource utilization.

5. CONCLUSION

Initially, the article effectively created and executed optimised deep learning models, notably utilizing SqueezeNet, customized for use in fog computing environments. By employing methods like as model pruning, quantization, and knowledge distillation, the study successfully decreased the computational complexity and memory usage of SqueezeNet without compromising its accuracy. The optimisation played a vital role in enabling effective inference and real-time processing on fog nodes with limited resources. This optimisation aimed to create and implement optimised deep learning models for edge deployment.

Furthermore, the optimised models underwent a thorough assessment in real-time IoT applications to determine their performance. The study conducted a series of comprehensive experiments to quantify crucial performance measures, including latency, throughput, energy usage, and accuracy. The results showed that the optimized SqueezeNet models exhibited notable enhancements in both latency and energy efficiency when compared to conventional deep learning architectures, all while maintaining a high degree of accuracy. This achievement was in line with the goal of assessing the effectiveness of deep learning models in real-time Internet of Things (IoT) environments, emphasizing their appropriateness and advantages in edge computing situations.

Furthermore, the study devised and applied deep learning approaches to bolster the security and privacy of data handled at fog nodes. This objective focused on addressing crucial issues in IoT situations where sensitive data is processed on-site. The study investigated various methods, including encryption, anomaly detection, and secure model updates, to ensure the integrity of data and defend against potential cyber threats. These techniques enhance the overall security framework of fog computing infrastructures.

Finally, the article conducted a comparison between the efficiency and effectiveness of deep learning in fog computing and typical cloud-based methodologies. The research demonstrated the benefits of edge computing, such as decreased latency, reduced operational expenses, and improved data privacy, by comparing the performance of SqueezeNet on fog nodes and cloud servers. This investigation compared fog computing to centralised cloud processing for edge intelligence in IoT applications. It highlighted the potential of fog computing to reduce network congestion and improve responsiveness. This validates fog computing as a viable alternative to centralised cloud processing. The research effectively accomplished its goals by developing optimised deep learning models using SqueezeNet for fog computing, assessing their real-time performance in IoT applications, improving data security and privacy at fog nodes, and showcasing the effectiveness of edge computing in comparison to conventional cloud-based approaches. These findings provide essential knowledge for the advancement of edge intelligence and IoT deployments, leading to the development of more scalable, secure, and efficient edge computing solutions in various application domains.

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