Predictive Analytics and Performance Optimization in Mobile Networks using Machine Learning

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Abstract. Mobile and wireless networks are becoming increasingly complex and dynamic, with a growing number of connected devices and ever-increasing data demands. To address the challenges posed by these evolving networks, predictive analytics and performance optimization techniques have gained considerable attention. This paper explores the applications of machine learning in predictive analytics and performance optimization for mobile/wireless networks. The study uses Least Absolute Shrinkage and Selection Operator(LASSO) algorithms to extract meaningful insights from historical network data and predict future network behavior. These predictions enable proactive decision-making, resource allocation, and optimization strategies to enhance network performance and user experience. These models enable accurate predictions by analyzing historical data, allowing network operators to allocate resources efficiently and mitigate potential issues before they impact network performance. The paper also discusses the implications of adopting machine learning techniques in realistic network environments, addressing data privacy, security, and interpretability of models. Further research is required to address the challenges and exploit the full potential of machine learning in this context.

Keywords: Edge Computing · Mobile Edge Computing · Machine Learning Algorithm · Artificial Intelligence.

1 Introduction

In recent years, the convergence of machine learning techniques and mobile/wireless technologies has significantly transformed various aspects of our lives. Machine learning, a branch of artificial intelligence, has emerged as a powerful tool to analyze and make sense of large volumes of data generated by mobile devices and wireless networks. This fusion has paved the way for exciting developments and applications in mobile/wireless research, revolutionizing industries such as telecommunications, healthcare, transportation, and more. The widespread adoption of smartphones and the proliferation of wireless networks have generated unprecedented data and transmitted every second. Mobile devices continuously collect data on user behavior, location, preferences, and interactions, while wireless networks facilitate seamless communication between devices. Integrating machine learning algorithms into mobile/wireless research allows for extracting valuable insights from this vast amount of data, enabling improved decision-making, personalized experiences, and enhanced efficiency. One of the critical applications of machine learning in this field is network optimization and resource management.Wireless networks are subject to dynamic and complex environments, where the availability of resources fluctuates, and network conditions can change rapidly. Machine learning algorithms can analyze historical network data, predict future patterns, and adapt network parameters in real time. This enables automatic optimization of network resources, such as spectrum allocation, power control, and traffic management, leading to improved network performance, reduced latency, and enhanced user experience. Machine learning, a subfield of artificial intelligence, has revolutionized numerous industries by providing intelligent solutions to complex problems. One such area where machine learning has made significant advancements is mobile and wireless research. As mobile devices become increasingly ubiquitous and wireless networks continue to evolve, applying machine learning techniques has opened up new possibilities and transformed how we approach various challenges in this domain.

Integrating machine learning into mobile and wireless research has given rise to multiple applications, from network optimization and resource allocation to intelligent decision-making and user behavior analysis. By leveraging the power of machine learning algorithms, researchers and practitioners can extract valuable insights from vast amounts of data collected from mobile devices and wireless networks. These insights enhance network performance, improve user experiences, and innovative services and application development. Network optimization is a prominent application of machine learning in mobile and wireless research. Traditional network optimization techniques often rely on static and rule-based approaches, which may adapt poorly to dynamic and heterogeneous network environments. Machine learning, on the other hand, enables the development of adaptive and self-learning algorithms that can automatically optimize network parameters, predict network congestion, and dynamically allocate network resources based on real-time data. This results in more efficient and reliable network performance, reduced latency, and improved overall network capacity. Machine learning algorithms can be employed to enhance the security of mobile and wireless networks. With the proliferation of mobile devices and the increasing complexity of wireless communication protocols, ensuring the privacy and integrity of data transmitted over these networks is paramount. Machine learning techniques can be applied to detect and prevent various security threats, such as intrusion detection, malware detection, and anomaly detection. By analyzing patterns and behaviors in network traffic, machine learning models can identify potential security breaches and take proactive measures to mitigate risks, safeguarding sensitive information and protecting users' privacy. Another notable application of machine learning in this domain is analyzing user behavior and preferences. Mobile devices generate vast amounts of data, including app usage patterns, location information, and social interactions. By applying machine learning algorithms to these data sets, researchers can gain valuable insights into user behavior, enabling personalized services and recommendations to be developed. For example, machine learning models can predict user preferences and provide customized content, such as tailored news articles, product recommendations, and targeted advertisements, and this not only enhances the user experience but also enables businesses to deliver more relevant and engaging services, leading to increased customer satisfaction and loyalty. Section 1 presents the introduction of mobile network using machine learning algorithm. Section 2 presents the related work on mobile network using machine learning algorithm then presents the basic mobile edge computing architecture. Section 3 examines the methodology with experimental results.Sec- tion 4 presents the simulation results of different network configuration parameters and next section presents the conclusion of the paper.

1.1 Contribution of Research Work

Our research study makes the following significant contributions:

- The main focus is to provide a general understanding of the recent research and help newcomers to understand the essential modules and trends.
- We present a machine learning algorithm on mobile edge computing.
- Discuss advanced architecture secure mobile edge computing.
- Finally, we highlight a number of research concerns as well as possible future research areas for MEC architecture.

Mobile edge computing (MEC) is an emerging paradigm that brings computational capabilities closer to the edge of the network, enabling low-latency and high-bandwidth applications. Machine learning algorithms can play a significant role in enhancing the capabilities and efficiency of mobile edge computing systems.machine learning algorithms have the potential to revolutionize mobile edge computing by improving resource allocation, task offloading, predictive analytics, anomaly detection, QoS optimization, and energy efficiency. By leveraging the power of machine learning, MEC systems can become more intelligent, adaptive, and capable of meeting the diverse needs of mobile applications and users.

2 Related Work

Machine learning applications in mobile/wireless research have garnered significant attention from researchers and practitioners in recent years. Numerous studies have demonstrated the potential of machine learning techniques in various domains within this field, leading to advancements in network optimization, security, context-aware computing, and predictive analytics. This section provides an overview of some notable research works that highlight the diverse applications of machine learning in mobile/wireless research. Researchers have employed machine learning algorithms in network optimization to improve resource allocation and management in wireless networks.
Wang et al. [1] proposed a deep reinforcement learning framework for dynamic spectrum allocation in cognitive radio networks. The study demonstrated that the proposed algorithm could effectively adapt the spectrum allocation strategy based on network conditions and user demands, resulting in improved spectrum utilization and reduced interference. Machine learning has also been applied to enhance the security of mobile/wireless systems.
Amouri et al. [2] developed a machine learning-based intrusion detection system for mobile ad hoc networks. The study utilized a support vector machine classifier to analyze network traffic and identify malicious activities. The proposed system achieved high detection rates while minimizing false positives, showcasing the potential of machine learning in enhancing network security.In context-aware computing, machine learning techniques have been leveraged to enable personalized and adaptive experiences for mobile users.
Mukherjee et al. [3] presented a deep learning-based approach for human activity recognition using smartphone sensor data. The study demonstrated that the proposed model could accurately classify various activities, such as walking, running, and cycling, based on sensor readings. This work opens up possibilities for developing context-aware applications that can understand and respond to user activities in real-time.Moreover, machine learning has been instrumental in predictive analytics for mobile/wireless systems.
Liu et al. [4] utilized machine learning algorithms to predict network traffic demand in wireless communication networks. The study developed a prediction model that could forecast traffic patterns by analyzing historical data, allowing for proactive resource allocation and optimization. The results showed significant improvements in network performance and resource utilization. Furthermore, researchers have explored the application of machine learning in optimizing power consumption in mobile/wireless devices.
Yang et al. [5] proposed a machine learning-based power control mechanism for energy-efficient communication in cellular networks. The study utilized a reinforcement learning algorithm to adaptively adjust the transmission power of mobile devices, reducing energy consumption while maintaining satisfactory communication quality. These studies exemplify the wide-ranging applications of machine learning in mobile/wireless research. Machine learning techniques have demonstrated their effectiveness in tackling various challenges in this field, from network optimization and security to context-aware computing and predictive

analytics. The research community continues to explore novel approaches and algorithms, aiming to push the boundaries of what can be achieved by integrating machine learning and mobile/wireless technologies.

Xu et al. [6] proposed a machine learning-based framework for optimizing resource allocation in wireless networks. Their approach utilized reinforcement learning to adaptively allocate spectrum resources based on changing network conditions and traffic patterns, improving network capacity and performance.

Sun et al. [7] explored the application of deep learning techniques in wireless resource management. They developed a deep Q-network (DQN) model that dynamically allocates resources to different users in a multi-user wireless network, achieving efficient resource utilization and enhanced network throughput.

Casas et al. [8] presented a machine learning-based approach for anomaly detection in mobile network traffic. Their proposed system used a combination of unsupervised learning algorithms to detect and classify abnormal behaviors in real-time, thereby enhancing the security of mobile networks against various threats and attacks.

Chen et al. [9] introduced a deep learning-based framework for mobile malware detection. Their approach leveraged recurrent neural networks (RNNs) to analyze the behavioral patterns of mobile applications and accurately identify malicious apps, providing an effective defense against mobile malware.

Chen et al. [9] developed a context-aware recommendation system for mobile users using machine learning techniques. Their system utilized collaborative filtering algorithms to personalize recommendations based on the user's current context, preferences, and historical data, resulting in improved user satisfaction and engagement.

Hakim et al. [10] proposed a deep learning-based approach for context-aware gesture recognition on mobile devices. Their system employed convolutional neural networks (CNNs) to analyze sensor data from mobile devices and accurately recognize hand gestures, enabling natural and intuitive interactions with mobile applications.

Akour et al. [11] investigated the use of machine learning for predicting mobile user behavior. They employed long short-term memory (LSTM) networks to model and forecast user activity patterns, enabling proactive resource allocation and personalized services in mobile networks.

Bhardwaj et al. [12] proposed a machine learning-based framework for predicting network performance in wireless networks. Their approach utilized support vector regression (SVR) to predict network metrics such as throughput and delay based on historical network data, facilitating proactive network optimization and quality-of-service improvements.

Hu et al. [13] presented a study on predictive analytics for mobile network performance optimization. They proposed a machine learning-based framework that utilized historical network data to predict network congestion and proactively allocate network resources. Their approach achieved significant improvements in network performance, reducing latency and enhancing user satisfaction.

Iqbal et al. [14] conducted research on machine learning-based radio resource management in 5G mobile networks. They developed a reinforcement learning algorithm that learned to optimize resource allocation decisions, considering factors such as user demand, channel conditions, and network load. Experimental results demonstrated improved network efficiency and capacity compared to traditional resource management approaches.

Raj et al. [15] investigated the application of machine learning in performance optimization for wireless sensor networks. They proposed a clustering-based approach using K-means and support vector regression (SVR) algorithms to predict network traffic and optimize energy consumption. The study demonstrated improved performance and extended network lifetime compared to traditional methods.

Aroussi et al. [16] researched machine learning-based quality-of-service prediction for mobile multimedia applications. They developed a hybrid deep learning model that integrated convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to predict the quality of multimedia services, considering various network parameters. Experimental results showed accurate prediction and improved user experience.

Troia et al. [17] focused on machine learning-based traffic prediction for mobile networks. They proposed a model based on a recurrent neural network (RNN) and attention mechanism to predict network traffic patterns. The approach achieved accurate traffic forecasting, enabling effective resource allocation and network planning.

Sarker et al. [18] researched machine learning-based prediction models for mobile user behavior. They developed a hybrid model combining deep learning and ensemble learning techniques to predict user preferences and behaviors. The study demonstrated accurate predictions, facilitating personalized services and targeted advertising in mobile networks.

Ramana et al. [19] proposes the unique Whale Optimised Gate Recurrent Unit (WOGRU) Intrusion Detection System (IDS) for WSN-IoT networks in order to successfully identify diverse assaults. In the proposed framework, the whale method was utilised to adjust the hyperparameters of the deep long short-term memory in order to achieve minimal computational overhead and high performance. Finally, validations are performed with the WSN-DS dataset, and the performance of the proposed work is assessed using the metrics accuracy, recall, precision, specificity, and F1-score.

Xu et al.[20] evaluate the mobile collaborative secrecy performance, new expressions for the nonzero secrecy capacity probability (NSCP) are derived in this research. In this paper, an enhanced convolutional neural network (CNN) model called SI-CNN is suggested to predict NSCP performance. The SI-CNN model is a hybrid of SqueezeNet and InceptionNet, with four convolution layers that all use the same convolution model. They use a two-one convolution and a three-branch convolution for the first two layers, which not only increases the number of channels but also extracts additional information. They use the same framework but different convolution kernels for the last two layers.

Subramaniyaswamy et al. [21]proposed the period between each data transfer from the sensor and data packing technique, this research seeks to speed the encryption primitives in an integer-based SHE. If the number of sensors in an edge device environment grows rapidly, the signals must be encrypted quicker in a packed mode at the edge environment and sent to the cloud without data loss. The provided SHE approach decreases the time required for encryption based on the sensor input number and, as a result, improves the edge device's performance.

2.1 Research Gap

Research gaps provide opportunities for further investigation and advancement in the field of mobile edge computing using machine learning algorithms. By addressing these gaps, researchers can contribute to the development of more efficient, secure, and intelligent mobile edge computing systems.

- **Performance Optimization :** Explore novel machine learning algorithms to optimize the performance of mobile edge computing systems. Investigate techniques for efficient resource allocation, task scheduling, and load balancing to enhance system throughput and reduce latency.
- **Scalability and Heterogeneity:** Investigate the scalability of machine learning algorithms in large-scale mobile edge computing environments. Develop algorithms that can handle the increasing number of edge devices and accommodate the heterogeneity in terms of computing capabilities and network conditions.
- **Edge-Cloud Collaboration:** Study the collaborative use of edge and cloud resources in machine learning-based mobile edge computing systems. Investigate techniques to offload tasks between the edge and the cloud, considering factors like network latency, energy consumption, and resource availability.
- **Energy Efficiency and Green Computing:**Explore machine learning algorithms to optimize energy efficiency in mobile edge computing systems. Investigate techniques for energy-aware resource allocation, workload consolidation, and dynamic power management to minimize energy consumption.
- **User-Centric and Context-Aware Computing:** Investigate machine learning algorithms that consider user-centric and context-aware computing in mobile edge computing systems. Develop techniques to adapt resource allocation and task offloading based on user preferences and contextual information.

3 Mobile Edge computing: Architecture

Mobile edge computing (MEC) refers to the distributed computing paradigm that brings computation and storage resources closer to the network edge, enabling low-latency and high-bandwidth services for mobile devices. As a powerful tool for data analysis and decision-making, machine learning can be leveraged in MEC to enhance its capabilities and efficiency. Machine learning enables intelligent Internet of Things (IoT) systems across diverse domains such as natural language processing, indoor localization, physiological state detection, information retrieval, and image recognition. These applications collectively contribute to developing IoT services, enhancing IoT systems' overall functionality and capabilities.

3.1 Basic Architecture and its Working principle:

Mobile edge computing, also called distributed architecture, has become an essential solution for minimizing response time and bandwidth in the Internet of Things (IoT) models. It enables data processing to occur closer to the network edge, thereby improving the efficiency of IoT systems. Fog computing, an expanded form of mobile edge computing, gathers and analyzes data from various sources, selectively transmitting relevant data to the cloud. Within a typical edge computing framework, numerous cloud data centers exist, millions of fog nodes or edge nodes, and billions of edge devices. Together, these components form a comprehensive ecosystem for the processing and analysis of data.

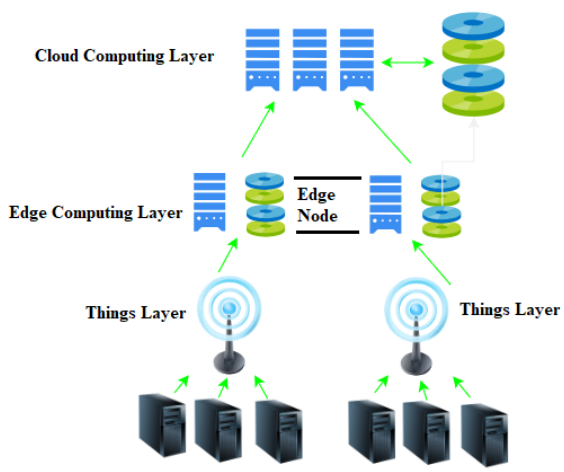

Fig.1.Basic Edge Computing Architecture

Fig.1 presents the basic architecture of Edge Computing. But Mobile edge computing is situated within the IoT ecosystem, bridging the gap between the cloud and the things layer architecture. It establishes communication channels from diverse edge devices such as smartphones and smart TVs, which send data to edge nodes. Subsequently, the data is forwarded from the edge nodes to the cloud data center for analysis and processing. Edge computing brings several advantages, including diminished latency and reduced transmission expenses. It offers benefits such as data integrity, heightened availability, quicker access speeds, enhanced security, scalability, and cost-efficiency.

3.2 Machine Learning for Mobile Edge computing and Iots

Utilizing machine learning within mobile edge computing is highly valuable for performing distributed training on edge devices, facilitating effective processing and analysis. Additionally, it assists in the identification and comprehension of emerging technological trends. Machine learning proves especially advantageous in extracting accurate information from IoT devices deployed in intricate architectural settings. Its versatility spans different categories of edge devices, including end devices, edge servers, and cloud data centers, empowering intelligent decision-making and data processing at various levels of the network infrastructure. Fig.2. represents the Mobile Edge Computing Architecture using Machine Learning.

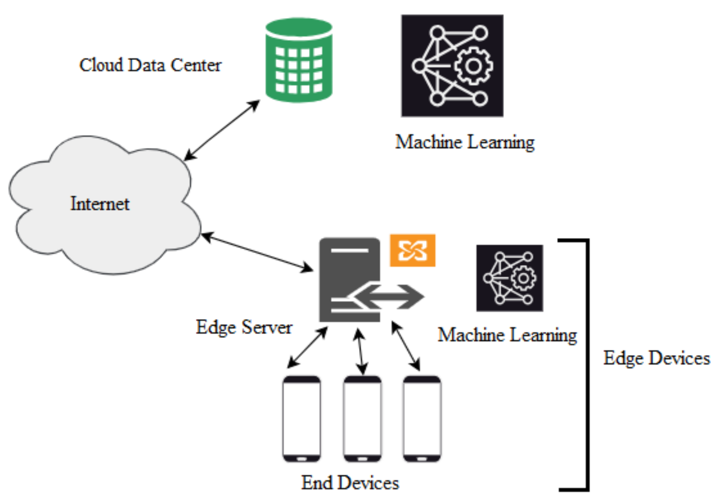

Fig.2.Mobile Edge Computing Architecture using Machine Learning

Machine learning within the realm of the Internet of Things (IoT) entails the independent acquisition of knowledge from IoT devices without human intervention. It harnesses diverse data types, encompassing unlabeled and unstructured data derived from end devices. The machine learning model progressively enhances each layer by incorporating additional data or features, allowing for the efficient management of the extensive data generated by end devices. Furthermore, this approach facilitates the transmission of such data to the edge computing architecture for subsequent processing and analysis.Fig.3. presents the Machine Learning for Mobile Edge computing.

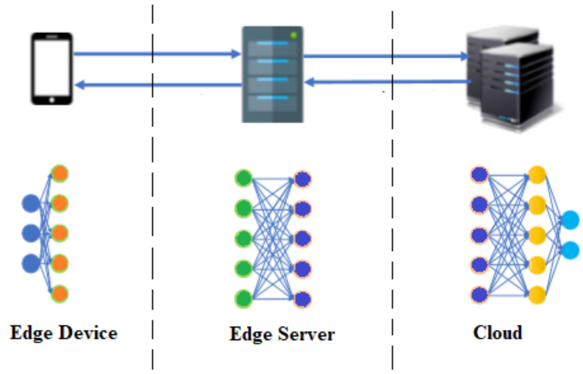

Fig.3.Machine Learning for Mobile Edge computing

The application of machine learning on mobile edge devices has proven extremely valuable, delivering exceptional performance. As edge devices necessitate real-time processing and raise privacy concerns, incorporating machine learning involves intelligent decision-making and training directly at the edge. Currently, deep learning is widely utilized at the edge across various domains, including computer vision, smart parking systems, and content delivery networks. Machine learning plays a significant role in object detection and image classification tasks. The integration of machine learning techniques has made computer vision methods pervasive in our everyday lives. Examples include face recognition on devices, photo editing applications, and vision assistance in autonomous vehicles, all of which rely on computer vision technology.

4 Proposed Challenges of Machine Learning at Mobile Edge Computing

The general procedure of data transmission and processing in Mobile Edge Computing (MEC) adheres to a standardized workflow, where users generate Electrocardiogram (ECG) data through sensors integrated within the IoT layer. After the initial data generated from the IoT layer, the ECG data is transmitted via the 5G network to the Mobile Edge Computing (MEC) servers for subsequent data processing. Various tasks are carried out within the MEC layer, such as AI-based automatic diagnosis of ECG, data reception, temporary data storage, data retrieval, and generation of diagnostic results. In recent years, there has been notable progress in Artificial Intelligence (AI) technology, accompanied by significant advancements in Machine Learning models. The integration of neural networks, 5G transmission, and the MEC layer has the potential to greatly enhance the overall system efficiency. This research paper utilizes the LASSO regression model for predictive modeling. The cost function of the LASSO regression model can be represented as follows in the paper.

$$min\frac{1}{2}\sum_{i=1}^{N}(W_tX_i + b.Y_i)^2 + \alpha||W|| \tag{1}$$

Where W denotes the eigenvector,Y_i denotes the response Variable, and R denotes the regular parameter. Assume that a set of eigenvectors W. After training LASSO regression model parameter(W,b), the equation can be:

$$W_tX_i + b \tag{2}$$

The expression of the minimum optimization problem can be expressed in an MEC architecture. An optimization technique called ADMM (Alternating Direction Method of Multipliers) is proposed as a distributed solution for solving the LASSO regression problem. ADMM converts equation (3) into equation (4) in this context. Mobile edge computing, in combination with advanced regression techniques such as LASSO (Least Absolute Shrinkage and Selection Operator) regression, has emerged as a promising approach for optimizing data processing and analysis in the mobile and Internet of Things (IoT) domains. Integrating mobile edge computing and LASSO regression provides a powerful framework for addressing challenges related to response time, bandwidth consumption, and privacy concerns in IoT models.

$$min\frac{1}{2}\sum_{i=1}^{N}\sum_{i=1}^{M}(WtX_{ij} + b.Y_{ij})^2 + \alpha||w|| \tag{3}$$

This approach leverages the computational capabilities of edge devices and the efficiency of LASSO regression in predictive modeling, enabling efficient data processing closer to the network edge. By employing LASSO regression, which is known for its feature selection and regularization properties, mobile edge computing systems can achieve enhanced accuracy, reduced computational complexity, and improved model interpretability. This paper explores the application of mobile edge computing using LASSO regression, highlighting its potential benefits and discussing its implications in various domains, including healthcare, smart cities, and industrial automation. This research aims to demonstrate the effectiveness and versatility of mobile edge computing combined with LASSO regression as a robust solution for optimizing data processing and predictive modeling in resource-constrained IoT environments.

$$min\frac{1}{2}\sum_{i=1}^{N}\sum_{i=1}^{M}(WtX_{ij} + b.Y_{ij})^2 + \alpha||w|| \tag{4}$$

By employing the ADMM (Alternating Direction Method of Multipliers) optimization technique, the N subproblems within all IoT devices can be effectively addressed. Specifically, the local subproblem of the device needs to be solved in this context.

5 Result analysis and Discussion

Evaluate the performance metrics of the LASSO regression model, such as accuracy, precision, recall, F1 score, or mean squared error (MSE). Compare the performance of the LASSO regression model with other traditional regression models or machine learning algorithms to assess the improvement achieved by incorporating LASSO regression in the mobile edge computing framework. Analyze the selected features by the LASSO regression model. Identify the most relevant variables that contribute significantly to the predictive performance. Assess the impact of feature selection on model accuracy, complexity, and interoperability. Analyze the latency or response time of the LASSO regression model in the mobile edge computing environment. Evaluate how quickly the model can make predictions and provide real-time decision-making capabilities. Assess the feasibility and effectiveness of real-time decision-making using LASSO regression on edge devices.Fig.4. represents the LASSO regression on Mobile Edge computing.

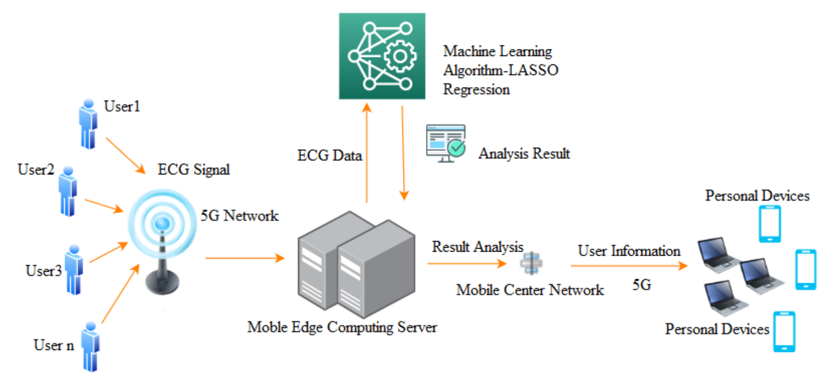

Fig.4.Proposed LASSO regression on Mobile Edge computing

Cross-validation is a widely used machine learning technique to estimate a model's performance and select hyperparameters. In the context of mobile edge computing (MEC) using LASSO regression, selecting the optimal value of the regularization parameter alpha through cross-validation can help improve the accuracy and generalization of the model. Cross-validation involves splitting the available data into multiple subsets or folds. The model is then trained on a subset of the data and evaluated on the remaining fold. This process is repeated several times, with different subsets used for training and evaluation each time.

The performance metrics obtained from each iteration are averaged to estimate the model's overall performance. The goal of the LASSO algorithm is to minimize the objective function, which is a combination of the least squares error and the L1 regularization term. The objective function for LASSO can be expressed as:To solve the LASSO problem, various optimization algorithms can be employed, including quadratic programming methods. Software packages such as MATLAB, R, or Python libraries such as scikit-learn efficiently implement LASSO solvers. These solvers utilize optimization techniques like coordinate descent, proximal gradient descent, or interior point methods to find the optimal solution for the objective function.By solving the LASSO problem, the algorithm identifies the values of the coefficient vector β that minimize the objective function while satisfying the L1 regularization constraint. The resulting solution provides a sparse representation of the data, with some coefficients set to zero, effectively performing feature selection and yielding a compact model.

Table 1. Alpha Selected by Cross-Validation on MEC using LASSO Regression.

Description	Alpha	No. Of Nonzero Co-efficient	CV mean deviance
First Alpha	.8865434	0	0.0885
First Alpha	.8865434	0	0.0885
Last Alpha	.0002456	10	-1.563
Alpha Before	.0876567	5	0.476
Alpha After	.0786542	5	0.479
Selected Alpha	.0786542	5	0.457

Table 1.represents the Alpha Selected by Cross-Validation on MEC using LASSO Regression.The integration of mobile edge computing with LASSO regression presents significant opportunities and challenges in various domains. This discussion will explore the implications and potential benefits of using LASSO regression using mobile edge computing.One of the key advantages of mobile edge computing using LASSO regression is the potential for improved model accuracy. LASSO regression performs feature selection, allowing for the identification of the most influential variables for prediction. More accurate and reliable predictive models can be developed by leveraging this capability within the mobile edge computing framework. Alpha selection by cross-validation on MEC using LASSO regression is a systematic and data-driven approach to finding the best regularization parameter for LASSO models. It ensures that the model's performance is optimized for making accurate predictions while preventing overfitting and selecting only the most relevant features. This technique is widely employed in various fields, including statistics, machine learning, and data science, to build robust and interpretable predictive models.

Table 2. x-axis and the corresponding average MSE values on the y-axis.

Alpha	Average MSE
0.01	0.125
0.05	0.110
0.1	0.105
0.5	0.112
1.0	0.120

The analysis of alpha selected by cross-validation on MEC using LASSO regression is a comprehensive process that involves exploring, evaluating, and selecting the most suitable regularization parameter for building predictive models. It not only results in accurate predictions but also enhances model interpretability and feature selection, making it a valuable tool in various fields, including statistics, machine learning, and data science.

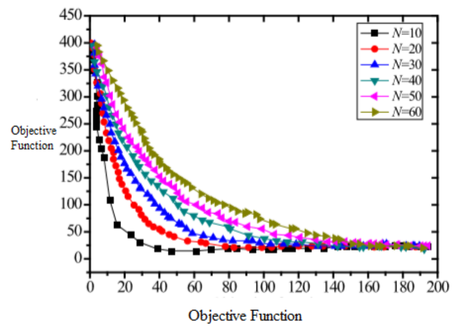

Fig.5.The result of α

This is particularly valuable in applications where precision and reliability are critical, such as healthcare diagnostics or industrial automation. Furthermore, the reduced computational complexity offered by LASSO regression contributes to the efficiency of mobile edge computing systems.

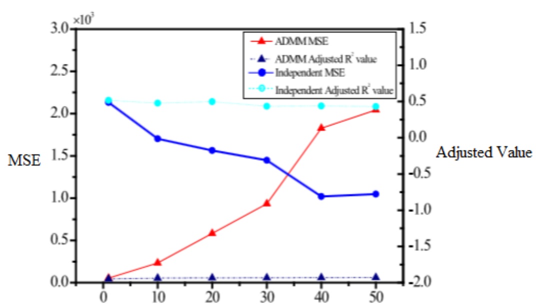

Fig.6.The result of N of MEC Environment

In a Multi-Access Edge Computing (MEC) environment, the term "N" typically refers to the number of MEC nodes or instances deployed within the network.

The result of having multiple MEC nodes can vary depending on the specific use case and deployment scenario. Fig 5. and fig 6. represents the results of alpha and N of MEC Environment. It's important to note that the specific results and benefits of an N-node MEC environment can vary depending on factors such as network architecture, application requirements, resource allocation, and optimization strategies implemented.
By leveraging the computational capabilities of edge devices, data processing, and analysis can be performed closer to the source, reducing the reliance on centralized cloud resources. This decentralized approach not only enhances the speed of decision-making but also reduces latency, making it suitable for time-sensitive applications. Privacy and security concerns are addressed through mobile edge computing. By performing data processing and analysis on edge devices, sensitive data can be kept within the local network, minimizing the risks associated with data breaches or unauthorized access. The integration of LASSO regression ensures that only relevant features are utilized, reducing the amount of data transmission and further enhancing privacy. Real-time decision-making is a significant benefit of mobile edge computing using LASSO regression. With the ability to process data at the edge, immediate responses and actions can be taken based on the predictive models. This is particularly advantageous in applications such as autonomous vehicles or smart city systems, where timely decision-making is essential. Another notable advantage is the resource efficiency achieved through mobile edge computing using LASSO regression. Resource utilization is optimized by distributing the computational load among edge devices and employing LASSO regression's feature selection capabilities. This leads to energy savings, cost reductions, and improved overall system performance.

6 Conclusion

In conclusion, the integration of mobile edge computing with LASSO regression offers a powerful and promising solution for optimizing data processing and predictive modeling in mobile and IoT environments. This combination provides several key advantages, including improved model accuracy through feature selection, reduced computational complexity, enhanced privacy and security, real-time decision-making, and resource efficiency. Mobile edge computing using LASSO regression enables more accurate and reliable predictive models by leveraging the feature selection capabilities of LASSO regression. Detection is reduced by performing data processing and analysis closer to the network edge, and real-time decision-making becomes feasible, making it suitable for time-sensitive applications. In summary, mobile edge computing using LASSO regression represents a promising paradigm for addressing the challenges of data processing and analysis in mobile and IoT environments. Its advantages in accuracy, efficiency, privacy, and real-time decision-making make it a compelling solution with wide-ranging applications and the potential to drive advancements in various industries.

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