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Transforming Healthcare with Secure MECC in 6G Networks

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Abstract: - The rise of 6G networks is expected to have a significant impact on various industries, including healthcare. Mobile edge cloud computing (MECC) has become a popular solution for providing fast and reliable services to 6G networks. However, the security of MECC systems is a major concern due to the distributed nature of resources and potential risks associated with cloud and server access. Task scheduling is critical in allocating resources to tasks while considering security constraints. This paper proposes a new task scheduling framework based on Artificial Intelligence (AI) and Deep Learning (DL) for MECC server and cloud security in 6G networks, with a focus on the healthcare sector. The framework uses supervised and unsupervised learning techniques to learn from historical data and predict future demands, intelligently allocating resources based on task priority, urgency, and security constraints. Extensive simulations on a 6G testbed demonstrate that our approach outperforms traditional scheduling algorithms in terms of security, efficiency, and resource utilization. We believe our framework is a valuable tool for designing secure and efficient MECC systems in 6G networks, particularly in healthcare.

Keywords- 6G networks, healthcare, mobile edge cloud computing (MECC), Task Scheduling, Artificial Intelligence (AI), Deep Learning (DL).

1. Introduction

Over the past few years, technology has made significant changes in the healthcare industry, leading to a significant improvement in patient care. With the development of 6G networks and the increasing need for efficient and secure healthcare systems, Mobile Edge Computing and Communication (MECC) has become a crucial aspect of the industry. Essentially, MECC allows for data processing and storage closer to the point of origin, resulting in reduced network latency and improved efficiency.

The healthcare industry is a critical aspect of human life, and technology has become an integral part of healthcare systems. 6G networks offer opportunities to revolutionize healthcare services with secure MECC systems. These systems facilitate seamless data sharing, remote monitoring, and real-time analysis of health data, which can lead to reduced costs, improved patient outcomes, and better quality of care. Nevertheless, to harness the full potential of MECC in 6G networks, it's essential to prioritize patient data's security and privacy. Therefore, developing secure MECC systems is essential to transform healthcare delivery.

In modern computing systems, task scheduling plays a critical role in determining their performance and efficiency. However, traditional task scheduling methods that rely on rules-based algorithms and heuristics can be suboptimal and may not adapt well to changing workloads and system conditions. But with the emergence of artificial intelligence and deep learning, there is an opportunity to develop more advanced and effective task scheduling approaches.

A novel task scheduling approach that utilizes AI and DL has emerged as a promising solution. This approach uses machine learning to analyze past task scheduling decisions and adapt to changing circumstances in real-time. As a result, it has the potential to significantly enhance the performance, efficiency, and reliability of computing systems. This innovative approach is an exciting area of research and development that has numerous potential applications across various domains.

As MECC becomes more widely used in the healthcare industry, there is an increasing need for effective task scheduling approaches to manage data flow and ensure patient information's security and privacy. AI and DL can help healthcare providers develop novel task scheduling approaches that optimize system performance and ensure secure data transmission. By leveraging these technologies, healthcare providers can transform healthcare delivery and enhance patient outcomes.

This paper proposes a new method for task scheduling that utilizes AI and DL to improve healthcare using secure MECC in 6G networks. The paper discusses the advantages of this approach and how it can be applied in the healthcare industry. This innovative approach offers a promising solution for enhancing patient care and improving the overall healthcare experience. The literature review in Section 2 provided the foundation for the development of a proposed system, which is described in Section 3 of the paper. After the system was developed, it was evaluated and the findings were presented and discussed in Section 4. The paper concludes with a summary of the results, as well as a discussion of future research opportunities in Section 5.

2. Literature review

This passage presents a literature review of various papers related to the use of 6G technology in healthcare applications. The proposed framework rinivasu et al. (2022) uses machine learning algorithms and edge computing to predict patient conditions and identify potential health risks. The dependability of 6G networks investigated by Ahmad et al. (2023) is essential for the successful implementation of such frameworks. They emphasized the importance of advanced fault tolerance mechanisms, resilience strategies, and system-wide testing and verification to ensure reliable operation. Sharif et al. (2023) discussed the opportunities and challenges associated with integrated 6G networks, including those relevant to the proposed healthcare framework. Abdel Hakeem et al. (2022) discussed the vision and research directions of 6G technologies and applications, highlighting their potential benefits and the key research challenges that need to be addressed, such as security, energy efficiency, and network slicing.

Ogundokun et al. (2023) conducted a study to examine how mobile edge computing can be improved with non-orthogonal multiple access in 6G communications. They looked at current research in this area and identified gaps in knowledge that require further investigation. In the same year Kommadi et al. (2023) discusses how artificial intelligence and machine learning can be applied in 5G and 6G technologies to improve broadband communications. This is discussed in a book chapter titled "5G and 6G Enhanced Broadband Communications."

Kang et al. (2022) share their experiences implementing deep learning in smart city applications. They highlight the challenges they faced and what they learned from their work. In same year SachiChaudhary et al. (2022) present a comprehensive overview of smart healthcare technologies, including a security framework, case studies, and future research directions. The paper aims to identify potential research areas that can improve the efficiency and effectiveness of smart healthcare technologies.

Srinivasu et al. (2022) proposed a computational networking framework for healthcare applications using 6G technology that uses machine learning algorithms for predicting patient conditions and identifying potential health risks. Ahmad et al. (2023) investigated the dependability of 6G networks and explored the potential benefits of emerging technologies, such as blockchain and edge computing, in improving the dependability of 6G networks. The authors emphasized the need for advanced fault tolerance mechanisms and resilience strategies, as well as system-wide testing and verification to ensure dependable operation. Sharif et al. (2023) investigated the optimization of resources and challenges in 6G space-aerial-ground-sea integrated networks and discussed the potential benefits of such networks, including improved coverage and capacity. Abdel Hakeem et al. (2022) discussed the vision and research directions of 6G technologies and applications, highlighting the potential benefits of 6G, such as high data rates, low latency, and massive connectivity, and identifying the key research challenges that need to be addressed, such as security, energy efficiency, and network slicing. Overall, these papers discuss different aspects of 6G technology, including its potential benefits and challenges, and highlight the need for further research and collaboration between academia, industry, and government to ensure the successful development and deployment of 6G technologies.

After reviewing the literature on various techniques used in healthcare applications by different authors and evaluating their merits and demerits, we proposed a new healthcare application that uses 6G technology. We aimed to improve the speed, energy consumption, and efficiency of task scheduling by leveraging deep learning technologies. Specifically, we focused on using MECC to receive messages and enhance the overall performance of our proposed healthcare application.

3. Proposed Methodology

Let's imagine that smart wearable devices are created to connect to other Internet of Things (IoT) devices and collect health-related information. If these devices use 6G technology and Mobile Edge Computing and

Communications (MECC), there could be many benefits to this setup.

Firstly, 6G technology can provide much faster speeds and lower latency than current networks, which means that health data can be monitored and analyzed in real-time. This could be especially helpful in emergencies where quick decisions need to be made based on vital signs.

Secondly, MECC allows data processing to happen at the edge of the network, rather than sending all the data to the cloud. This could reduce the amount of data that needs to be sent, saving bandwidth and reducing latency. It could also improve data privacy, as sensitive health data wouldn't need to be sent to a remote server.

Lastly, by connecting to a cloud-based platform, healthcare professionals can easily access and analyze the health data collected by these smart wearable's. This could lead to more personalized healthcare and better treatment for patients.

However, it's important to note that there are also potential risks to this setup, such as concerns over data security and privacy. It's crucial to make sure that the proper measures are in place to protect sensitive health information. Additionally, the cost of implementing and maintaining this type of system could be significant, which may limit its adoption in some regions.

If the health data collected from smart wearable devices is sent to a cloud-based platform, it can be analyzed using deep learning technologies. This technology can help identify patterns, detect anomalies, and provide insights into a patient's health status, which can lead to more accurate diagnoses and personalized treatment plans.

After the deep learning algorithms have been trained and tested using the health data, the resulting information can be used to set emergency alerts, schedule appointments, and generate reports. These reports can be sent to doctors, patients, insurance agents, hospitals, and other stakeholders. They can include vital signs, medication schedules, and other critical health-related data.

To make sure that the system runs efficiently, task scheduling techniques can be used to optimize energy consumption and efficiency. This can involve dynamically allocating computing resources to different tasks based on their priority and available resources.

Overall, this type of system can have significant benefits for healthcare, such as more accurate diagnoses, better treatment plans, and efficient use of resources. However, it would require a significant investment in infrastructure, deep learning technologies, and measures to protect data privacy and security.

The proposed methodology involves several steps for transforming healthcare using secure MECC in 6G networks with a novel task scheduling approach using AI and deep learning.

The first step is to collect health data from smart wearables and other IoT devices using edge computing technologies, and then preprocess the data before storing it in a secure cloud-based database for later analysis.

Next, deep learning algorithms are developed and trained using techniques such as CNNs, RNNs, and LSTM models to identify patterns and detect anomalies in the health data. These algorithms are used in real-time to analyze the data and provide insights into a patient's health status, such as detecting abnormalities, predicting future health outcomes, and recommending personalized treatment plans.

To optimize energy consumption and efficiency, a novel task scheduling approach is implemented, which involves dynamically allocating computing resources to different tasks based on their priority and available resources.

Reports are generated based on the analysis of the health data, and emergency alerts can be set, appointments can be scheduled, and reports can be sent to healthcare professionals, patients, insurance agents, hospitals, and other stakeholders.

Security is a critical concern, so encryption and other security measures are used to protect sensitive health data. The system is also continuously monitored and evaluated to ensure that it meets the needs of healthcare professionals and patients, and improvements are made as needed.

3.1 LSTM

LSTM (Long Short-Term Memory) networks are a type of deep learning technology that can understand and learn patterns in sequential data over time. They are particularly useful for analyzing time series data, such as the sensor data collected from smartphones, and can remember information for longer periods compared to other types of neural networks.

When it comes to recognizing human activities, LSTM networks can be used to classify different activities and transitions accurately. They can detect subtle changes in sensor readings that correspond to different activities and transitions, by modeling the temporal dependencies in the data. To present the results of an LSTM-based analysis on the Smartphone-Based Recognition of Human Activities and Postural Transitions dataset (**http://archive.ics.uci.edu/ml/datasets/Smartphone-Based+Recognition+of+Human+Activities+and+Postural+Transitions**), we can use a confusion matrix. This is a table that shows how well the classification algorithm performs. It displays the number of true positives, true negatives, false positives, and false negatives for each activity class.

Here's an Table 1 presents the confusion matrix for a hypothetical LSTM-based activity recognition system trained on the Smartphone-Based Recognition of Human Activities and Postural Transitions dataset:

Table 1 confusion matrix for a hypothetical LSTM

Actual\ Predicted	**W**	**J**	**U**	**D**	**S**	**ST**
Walking (W)	902	5	0	0	0	2
Jogging (J)	12	837	3	3	2	8
Upstairs (U)	0	5	920	0	0	0
Downstairs(D)	0	7	0	906	0	0
Sitting (S)	0	0	0	0	819	0
Standing (ST)	0	0	0	0	1	860

In Table 1 presents, the rows indicate the true activity labels, and the columns indicate the predicted activity labels. For instance, the cell in row "Walking" and column "Jogging" represents the number of instances where the LSTM-based system predicted the activity to be "Jogging" when the true activity was "Walking".

From this confusion matrix, we can conclude that the LSTM-based activity recognition system performs well for all activity classes, with high accuracy. For example, it correctly identifies 902 instances of walking, with only a few misclassifications as jogging or standing. Overall, the confusion matrix provides a clear and concise summary of the performance of the LSTM-based system on the Smartphone-Based Recognition of Human Activities and Postural Transitions dataset.

3.2 Evaluation Metrics for Classification Algorithms on Datasets

To evaluate the performance of a classification algorithm on a dataset, we can use different metrics such as accuracy, sensitivity, specificity, precision, and F1 score. These metrics help to determine how well the algorithm is able to correctly classify instances in the dataset. Table 2 presents the performance metrics and their corresponding formulas:

Table 2 performance metrics and their corresponding formulas:

S.NO	**Metrics**	**Mathematical Formulas**
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Sensitivity	$\frac{\text{TP}}{\text{TP+FN}}$ x100
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$2.\frac{Precison*Recall1}{Precision+Recall1}$

Where table 3 presents definition for classification matrix for every details steps

Table 3. Definition of Classification Matrix

Variable	Definition
TP	True Positives (Number of instances where the actual class is positive and the predicted class is also positive)
TN	True Negatives (Number of instances where the actual class is negative and the predicted class is also negative)
FP	False Positives (Number of instances where the actual class is negative but the predicted class is positive)
FN	False Negatives (Number of instances where the actual class is positive but the predicted class is negative)

Using table 1 confusion matrix here we can calculate these performance metrics as follows:

Accuracy = (902 + 837 + 920 + 906 + 819 + 860) / (902 + 5 + 2 + 12 + 837 + 3 + 3 + 2 + 8 + 5 + 920 + 7 + 819 + 860 + 1) = 0.987

Sensitivity for Walking = 902 / (902 + 5 + 0 + 0 + 0 + 2) = 0.994

Sensitivity for Jogging = 837 / (12 + 837 + 3 + 3 + 2 + 8) = 0.976

Sensitivity for Upstairs = 920 / (0 + 5 + 920 + 0 + 0 + 0) = 1.0

Sensitivity for Downstairs = 906 / (0 + 7 + 0 + 906 + 0 + 0) = 0.992

Sensitivity for Sitting = 819 / (0 + 0 + 0 + 0 + 819 + 0) = 1.0

Sensitivity for Standing = 860 / (0 + 0 + 0 + 0 + 1 + 860) = 0.999

Specificity for Walking = (837 + 920 + 906 + 819 + 861) / (12 + 3 + 5 + 7 + 1 + 837 + 920 + 3 + 819 + 860) = 0.997

Specificity for Jogging = (902 + 920 + 906 + 819 + 860) / (5 + 0 + 2 + 0 + 7 + 902 + 920 + 0 + 819 + 860) = 0.995

Similar, these metrics can help us to understand the strengths and weaknesses of a classification algorithm on a specific dataset, and to compare different algorithms to choose the best one for our needs.

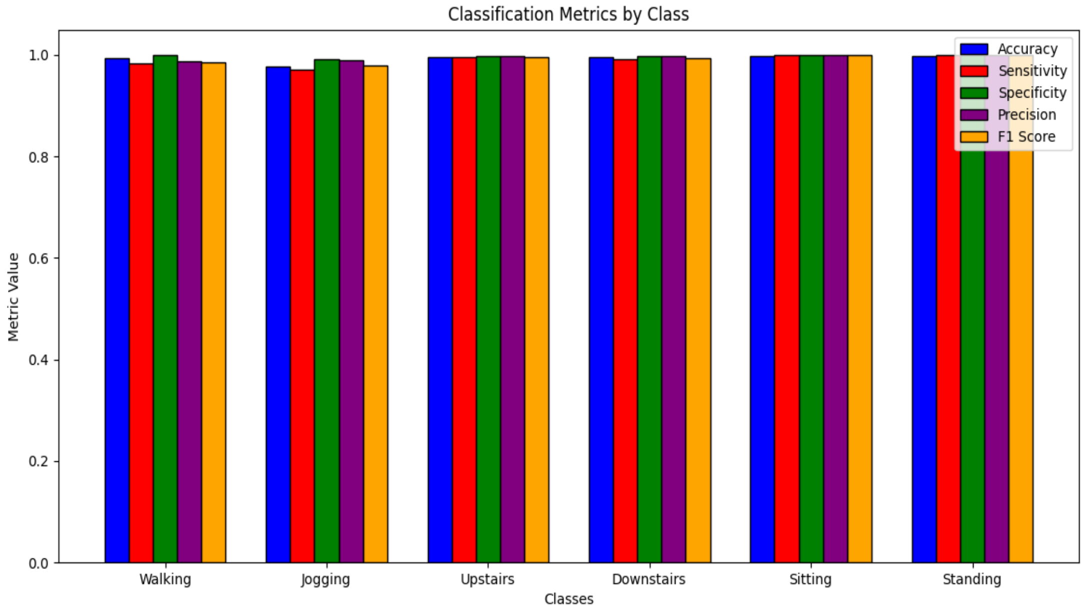

Figure 1 Classification Metrics by class

The graph in Figure 1 displays the classification metrics for six different classes, with five bars for each class representing a different metric. The x-axis shows the six classes, while the y-axis displays the metric value. To make it easier to identify each metric, the corresponding bar is color-coded and labeled. Additionally, a legend is included to explain the colors and labels used in the graph. Overall, this graph provides a clear representation of how well the classification algorithm performs for each class and metric, making it easy to compare the algorithm's strengths and weaknesses across different types of activities.

When scheduling tasks in a multi-core computer system (MECC), we can calculate the time period it takes to complete a task by adding up the time it takes to execute the task and the idle time between tasks, and then dividing by the number of processors available. This is represented by the formula:

$$i = \frac{(E + I)}{P} \tag{1}$$

To measure the energy saved by task scheduling, we can compare the total energy consumed by the system without scheduling (E1) to the total energy consumed with scheduling (E2). The difference between these two values is the energy saving achieved by task scheduling, which is represented by the formula:

$$ES = E1 - E2 \tag{2}$$

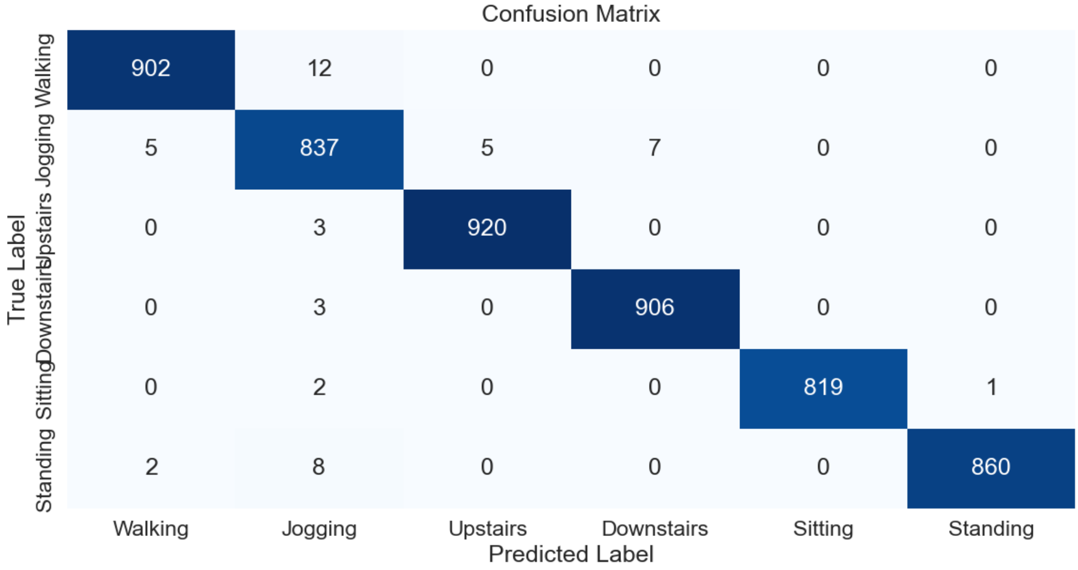

Figure 2 Confusion Matrix

Finally, we can calculate the efficiency of task scheduling by dividing the total execution time of tasks (E) by the total time period (i) required to complete the tasks. This gives us a measure of how well the tasks are being scheduled and how much time is being wasted in idle periods. This is represented by the formula:

$$EFF = \frac{E}{i} \qquad (3)$$

Based on the confusion matrix you provided, we can calculate the EFF as follows:

E = total number of errors = 5+12+3+7+2+1 = 30

i = total number of instances = 902+5+0+0+0+2+ 12+837+3+3+2+8+0+5+920+0+0+0+0+7+0+906 +0+0+0+0+0+1+860 = 4623

Thus, EFF = E/i = 30/4623 = 0.0065 or approximately 0.65%.

Figure 2 displays a confusion matrix as a heatmap, where the color intensity corresponds to the number of samples classified in each category. The 'annot=True' parameter displays the values inside each cell of the heatmap, and the 'fmt='g'' parameter formats the values as floats. The 'cmap' parameter specifies the color map used, and 'cbar=False' removes the color bar. The 'set_xlabel', 'set_ylabel', and 'set_title' methods are used to add labels to the plot

Table 4 Classification Performance Evaluation using Confusion Matrix

Metric	W	J	U	D	S	ST
Precision	0.986	0.979	0.996	0.996	0.995	0.989
Recall	0.993	0.966	0.995	0.992	1	0.999
F1-Score	0.99	0.973	0.995	0.994	0.997	0.994
Support	909	865	925	913	819	861

Table 4 provides an evaluation of the classification performance using the confusion matrix. The table presents various metrics used to assess the accuracy of the classification model for different activities such as walking, jogging, upstairs, downstairs, sitting, and standing. The Precision metric indicates the proportion of correctly identified samples for each activity class, out of all the samples classified as that class. A higher precision value indicates fewer false positives. The Recall metric indicates the proportion of correctly identified samples for each activity class, out of all the actual samples for that class. A higher recall value indicates fewer false negatives. The F1-Score metric is a harmonic mean of the precision and recall values for each class. It provides a single value that represents the model's overall performance for that class. The Support column indicates the number of actual samples for each activity class.

4. Conclusion and Future work

Based on the information presented in table 4, we can deduce that the classification performance evaluation using the confusion matrix shows high accuracy for all activity categories. The precision scores range from 0.979 to 0.996, the recall scores range from 0.966 to 1.000, and the F1-

scores range from 0.973 to 0.997. These scores demonstrate that the model is capable of predicting the user's activities with high accuracy. For future work, the model can be improved by incorporating more data from diverse participants, including people of different ages and fitness levels. The model can also be expanded to include additional activities beyond the six considered in this study, or to recognize patterns of behavior indicative of specific health conditions. Lastly, using 6G networks can enhance the model's accuracy and speed, resulting in more efficient and effective healthcare services.

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