Caring is Sharing – Exploiting the Value in Data for Health and Innovation
M. Hägglund et al. (Eds.)

doi:10.3233/SHTI230326

Technological Assessment of Smart Wearables and 5G-Integrated Edge Computing for Real-Time Health Monitoring

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Abstract. Smart wearables advance to reliably and continuously measure vital signs. Analyzing the produced data requires complex algorithms, which would unreasonably increase the energy consumption of mobile devices and exceed their computing power. Fifth-generation (5G) mobile networks provide low latencies, high bandwidth, and many connected devices and introduced multi-access edge computing, which brings high computation power close to the clients. We propose an architecture for evaluating smart wearables in real-time and evaluate it exemplary with electrocardiography signals and binary classification of myocardial infarctions. Our solution shows that real-time infarct classification is feasible with 44 clients and secured transmissions. Future releases of 5G will increase real-time capability and enable capacity for more data.

Keywords. Health monitoring, 5G, edge computing, smart wearables

1. Introduction

Smart wearables can record a variety of health parameters. One example is electrocardiography (ECG), which is suitable to detect myocardial infarctions (MIs). Cardiovascular diseases, including MI, are the main cause of death worldwide with more than 17 million deaths every year [1]. MI requires an immediate response as every minute delay reduces the chances of fully recovering. Depending on the severity of the MI, affected persons are unable to call for help themselves or might not even notice the MI when the severity is low.

Smart wearables enable continuous and unobtrusive health monitoring, but the continuous measurement of vital parameters produces much data, which additionally must be classified in real-time. Deep learning (DL) methods like convolutional neural networks (CNN) are suitable to classify this data accurately and timely.

The analysis with CNNs is complex and requires performant hardware. Smartphones and other mobile devices usually do not provide the required performance or only at expense of high battery drainage. Cloud computing could provide a solution but raise privacy

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concerns. Multi-access edge computing (MEC) was introduced with the 5G mobile networks and offers high computing capacity close to the clients [2].
Pham et al. [3] provides an overview of MEC's current and future status. However, previous work (including our own [4]) has not yet considered security and scalability, external devices, or trusted cloud computing [4, 5, 6].

2. Material and Methods

We propose an architecture to analyze smart wearables' signals in the edge (see Figure 1). We evaluated our architecture using a mobile phone with a self-developed application, an edge computing device, and CNN-based analysis.

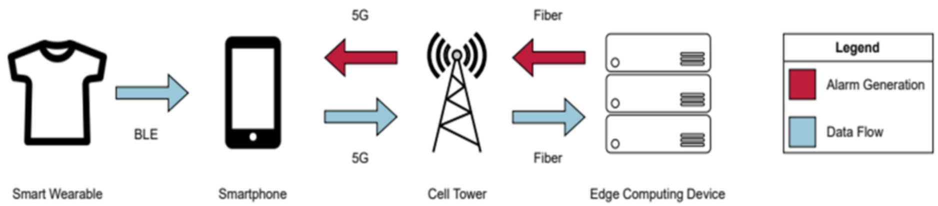

Figure 1. Overview of our proposed architecture.

44 smartphones (Galaxy A52S 5G, Samsung, KOR) generated a simulated ECG signal. All smartphones were equipped with the same business data plan (Business Mobil M, Deutsche Telekom AG, DEU).
A self-developed Android application acquired the data. The app retrieved the current time with the Network Time Protocol (NTP). The smartphone application acted as a Message Queuing Telemetry Transport (MQTT) client and sent the simulated ECG data in batches of eight samples to the server. The Eclipse Paho Android Client library was used for the client implementation.
The edge device was deployed using the far-edge architecture. The data center was chosen based on geographical proximity. *M4.Large* instances served as MQTT brokers (one for secured connection, one for unsecured connection) using Eclipse Mosquitto.
The ECG signals are classified using the 11 layer CNN described in Archarya et al. [7] implemented with Python 3, Tensorflow and Keras and were evaluated with non-specialized hardware without GPU-support. This CNN is provided with single-lead ECG signals and decides binarily whether a MI is detected.

3. Experiment

The experiment aims to analyze 5G for the proposed architecture with respect to latency, data corruption, package loss, inference duration, and energy consumption in consideration of scalability and security-features. The experiment switched between blocks with the Transport Layer Security (TLS)-feature enabled and with TLS disabled. The number of clients decreased logarithmically with three steps per decade: 44, 21, and 9. Values were rounded to the nearest integer. Each block was 15 min long, totaling up to 90 min excluding pauses for reconfiguration and preparation of the next testing block.

4. Results

The study proceeded without any unexpected incidents (e.g.\ application crashes). The system load was low during the experiment. Cell tower connection was monitored by logging their IDs during the experiment to ensure comparability of the data. The study's parameters are evaluated by comparing the client- and server-side log files.
The latencies are computed by aligning the ECG values received on the edge with the values sent by the client and calculating the differences between their timestamps. The latencies are approximately Gaussian distributed (cf. Figure 2). Latency was lowest for nine participants and TLS enabled and highest for 44 participants and TLS disabled.

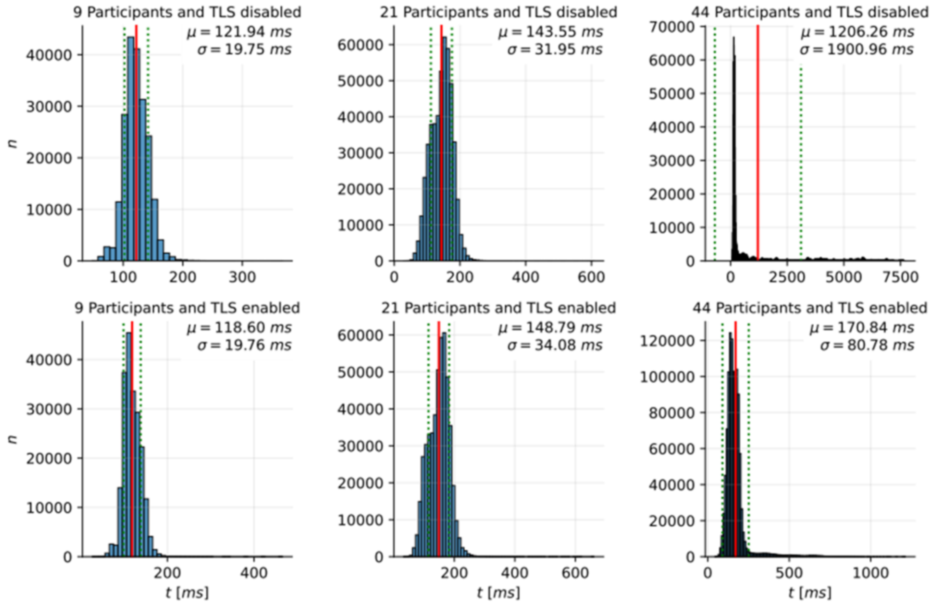

Figure 2. Latencies with their means and standard deviations of transmission from the smartphone to the edge computing device

The data corruption is calculated by aligning the sent and received data. A sliding window can detect missing or unequal values. However, no data corruption was detected in the experiment.
Package loss is calculated by comparing the number of packages sent to the number of packages received. Package loss was lowest for nine participants and TLS disabled and highest for 44 participants and TLS disabled (cf. Table 1).

Table 1. Percentual package loss over the experiment

	9 Participants	21 Participants	44 Participants
TLS enabled	0.001 ± 0.004	0.005 ± 0.013	0.029 ± 0.044
TLS disabled	0.000 ± 0.000	0.002 ± 0.006	0.041 ± 0.079

The inference durations are measured after the experiments. The pre-trained model is fed with the ECG data obtained during the experiment. This data was preprocessed and upsampled according to the algorithm's description [7]. The durations are bimodally distributed (see Figure 3). For all instances the first peak is located within the first few milliseconds and the second peak at approximately 20 ms.

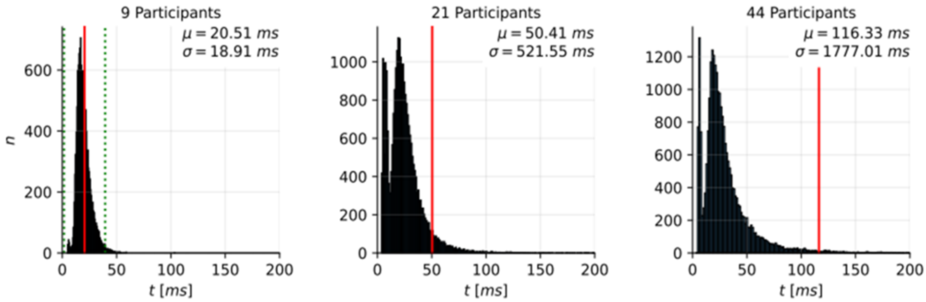

Figure 3. Inference duration with their means and standard deviation.

The energy consumption is logged during the experiments. The battery drainage is 3.221 ± 0.613 % per 15 min when TLS is turned off and 2.978 ± 0.687 % per 15 min when TLS is turned on.

5. Discussion

Our experiments show that end-to-end delays of approximately 500 ms can be realistically achieved even with many patients and encrypted transmissions. This consideration regards that some smart wearables use Bluetooth Low Energy, which achieves delays of up to 50 ms in the worst case [8]. The analysis can be done reliably with low data corruption and low loss, which is below one heart beat per 15 min (0.37 s of loss) and thus clinically irrelevant.

The experiments were conducted with off-the-shelf non-optimized configurations. This essentially means that no other apps ran on the smartphone that could have produced system load or network load influencing the results of our experiment. Also tuning many parameters like the batch size could improve performance without noteworthy drawbacks.

The DL model was trained with a public database, however, this might not be ideal for the detection of MI recorded by mobile ECG sensors. Preprocessing of the data will account for additional delays, which were not considered. The classification of the data then, though evaluated with non-specialized hardware, is quick but GPU-supported classification can further reduce this delay.

The location of the experiment was fixed and the influence of cell tower changes or dead spots was not analyzed concretely. Our proposed architecture will not work in these scenarios and requires fallback solutions like client-side classification, which would cause higher energy consumption and increase inference duration. Third-person devices could have produced concurrent network load negatively influencing our results, which were not compensated. Especially the anomalous distribution of the latency for 44 participants and TLS disabled might be due to cell tower changes. The phones connected to the same tower for only circa 80 % of the time.

Smart wearables providing more sensors could simulate higher data loads and enable other use cases like activity recognition [9], fall detection [10, 11], or detecting deteriorating clinical conditions using the respiration sensors [12].

Finally, 44 patients should not cause high data loads on the mobile network as 5G will support up to 10^6 connections per m^2 [13], but experiments with more volunteers were not possible because of lacking number of devices. The results show that the increasing number of participants only had little impact on the outcomes. Using more multi-lead ECG sensors would also produce further data. This work evaluated 5G in non-standalone mode, which builds upon existing 4G Infrastructure. Future infrastructure will support new modes like ‘ultra-reliable low latency communication’ or by using network slicing [14], the latencies will be reduced further.

6. Conclusion

Smart wearables record many vital parameters, which can be analyzed by MEC in real-time and with respect to privacy concerns. The proposed MEC platform analyzes signals within 500 ms when evaluated with MI detection by single-lead ECG signal continuously produced by a smart wearable. Future releases of 5G mobile networks could further reduce the time required for classification. Besides, we will repeat the experiment to understand the reasons behind the results more thoroughly.

Appendix

The German Federal Ministry of Transport and Digital Infrastructure (BMVI) funded this work under grant #VB5GFWOTUB.

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