Cardio Twin: A Digital Twin of the human heart running on the edge

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***Abstract*—We present the Cardio Twin architecture for Ischemic Heart Disease (IHD) detection designed to run on the edge. We classify non-myocardial and myocardial conditions with a CCN. This CNN generates features from the electrocardiograms and performs the classification task. The database used is "PTB Diagnostic ECG Database" from Physio Bank and it comes from 200 different people. Each patient data sample was partitioned into 2.5 second windows for training. The implemented model achieved 85.77% accuracy and used 4.8 seconds for each sample classification. The results show that technology is ready to fully support demanding processes, such as Digital Twin, on the edge.**

Keywords—Digital Twin, machine learning, deep learning, convolutional neural network, edge computing, electrocardiogram, ischemic heart disease, stroke, cardiovascular disease, physio bank.

I. INTRODUCTION

For decades, Ischemic Heart Diseases (IHD) and stroke have been in the top ten causes of death in the world, especially in populations with high level of income. According to the World Health Organization, 56.9 million deaths were registered in 2016, from which 15.2 million were caused by these two diseases [1], accounting for 26.7% of the total.

A Myocardial Infarction (MI) is a type of IHD in which oxygen-rich flow of blood to the heart muscle is interrupted causing damage to the heart itself. Quite often the victims of IHD do not realize they are about to suffer one until it is too late, preventing them from getting proper help. Mortality in this cases is related to a delay in treatment [2], that is why every minute counts from the moment the first symptoms appear until proper treatment is administered. In other words, early detection and reaction is key to survival. Timely detection is not a trivial as it requires the subject to be constantly monitored.

Consider the following scenario: a retired 62-year-old male who is a regular smoker is sitting in the dining room of his house sharing the day with his family when he suddenly suffers a MI. A call to the emergency services and hoping for the best is usually the only thing whoever is present can do for that him at that point; and if he's alone, he will never receive any help. Continuous monitoring by a health professional is a good strategy to prevent this last scenario but it is impossible to monitor all people at risk. Several computer-based solutions have been proposed before as we will discuss later, however, the problem of a universal monitoring model remains unsolved. Hence, we proposed to use a Digital Twin (DT) of the human heart as a mean to reach a possible solution.

A DT is the digital representation of an object or a thing from the real world. By definition, a DT must be an exact copy of its real twin. The concept has its origins in the monitoring of industrial processes and machines, however, in recent years it has been expanded to include living beings as well. A DT of a human use sensors and other data sources to create an exact virtual copy of a human being [3], [4]. El Saddik et al. [5] present an ecosystem of the DT for healthcare and well-being which can be implemented to automatically monitor and assist a person in case of an emergency even if the real twin (the person at risk) is alone and suffers an IHD emergency. In this paper, we present Cardio Twin, a DT of the human heart based on the ecosystem of the DT for healthcare and well-being mentioned above.

Time is critical when dealing with emergencies of IHD or Stroke; this is where the concept of Edge Computing comes into play. Satyanarayanan [6] calls edge computing devices as "cloudlets" and lists the following advantages: highly responsive cloud services, scalability via edge analytics, privacy-policy enforcements and masking of cloud outages. Highly responsive cloud services refer to the almost non-existent latency that comes from the advantage of having most of the computation done in each cloudlet. Scalability via edge analytics frees the bandwidth load of the cloud by only transmitting the necessary data. Privacy-policy enforcement is

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important for Cardio Twin and having it running on the edge contributes to it as the data is in the subject's smartphone. Thanks to edge computing the analytics computing power required to continuous monitoring a subject is always available at subject's reach and service at any time, which translates to continuous monitoring. The use of edge computing also enables the subject to exert total control over the information being collected and processed (privacy). And "masking the cloud outages" pushes the availability of the service into the hands of the subject.

Kazi et al. presents C2PS as a "Digital Twin architecture reference model" in [4]. This is a generic architecture in the sense that it is a reference to implement a DT of anything: animals, vehicles, humans, etc. In his proposal, Kazi considers the DTs to be hosted in the cloud.

The concept of DT for humans is new, however it can be abstracted, to a Cyber-Physical System (CPS) which is a topic that has had a lot of attention over the last years. Some of that work that could be a precedent for a DT for humans is reviewed in the next lines. In [7] Constanzo et al. presents a home-based monitoring CPS that takes advantage of fuzzy rules to calculate a "risk code" corresponding to the current state of the patient. The patient health status can be consulted by treating physicians, family members, etc. The patient data is stored temporarily in the patient mobile device (smartphone) and constantly in a home-based Web Service (WS).

Much of the proposed CPS for healthcare conform to a centralized architecture like the one described in [8] with "n" nodes collecting data and transmitting the data to a central structure (a server or the cloud) to process the data and transmit back the results to the respective nodes like in figure 1. This architecture depends on a centralized "Data Analysis Structure". The disadvantage of this system is that if this layer fails, it fails for all the patients. More examples of CPS for healthcare can be found in [9]–[11], however, a common characteristic of these systems is that they are oriented only to detect and store the state of the subject but not to help the him/her in the event of a MI or even to prevent an IHD.

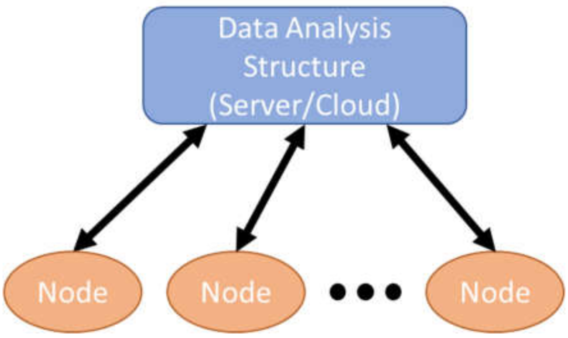


Figure 1. Typical configuration of a centralized structure that pushes data analysis out of the nodes to a centralized structure.

Smartphones have the intrinsic capacity of sensing the user and its context by collecting data from the sensors integrated in the device itself. Then can also be enhanced by adding external sensors taking advantage of its communication capabilities [12]. A plethora of ECG collecting devices with Bluetooth capabilities are available in the market which means that these sensors can be easily attached to a smartphone, this makes them an ideal platform to deploy a DT of humans for healthcare given its extensive use among population of all ages. A smartphone ticks all boxes to host Cardio Twin: edge device, recent models have increased computing capabilities which makes them highly responsive and the fact that are mobile makes easily accessible as they are within hands reach at almost all times. Deep learning classification models can run in modern smartphones.

II. CARDIO TWIN

Cardio Twin is an architecture of a DT for healthcare and well-being running on the edge to help in the event of a IHD situation. Cardio Twin collects data from sensors (body area network), medical records, social networks and external sensors. In turn, this data is processed to detect and help in case the real twin is suffering an IHD or a Stroke. This platform takes advantage of internal sensors already existing in edge devices such as smartphones and their capacity to pair with external sensors in order to collect bio signals through Bluetooth communication. Cardio Twin also capitalizes on the ease of access to social networks of these devices. Figure 2 shows the components of Cardio Twin. Machine learning interprets all the collected data and take appropriate action through the execution of instruction pipelines. Cardio Twin also has communication with external entities such as smart services through the interaction interface. A multimodal interaction layer is considered in the design to render a representation of the human heart using different technologies such as virtual or augmented reality, screens, haptic devices and robotic avatars. This is accomplished thanks to the interaction interface. Cardio Twin is organized in three structures: Data Source, AI-Inference Engine, and Multimodal Interaction Layer.

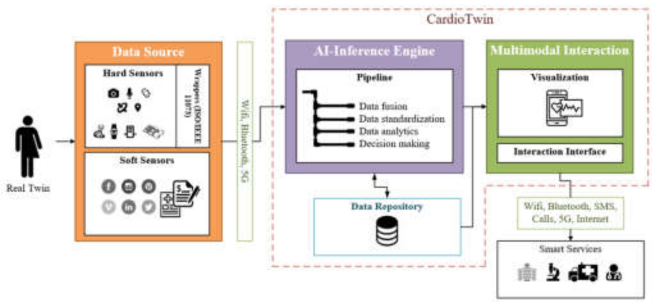


Figure 2. Cardio Twin structures and components.

A. Data Source

Cardio Twin is designed to run on the edge, so it can take advantage of it and collect data from the real twin and its context by pairing with different sensors. First, we have conventional sensors which are electronic devices capable of measuring position, temperature, light and others. Smartphones integrate a subset of those, GPS, gyroscope, accelerometer, camera, microphone, light, proximity, heart rate among them. Other type of sensors are the ones that pair with the smartphone through Bluetooth, USB or another type of port or wireless communication technology. An example of those are digital stethoscopes, heart rate monitors, electrocardiogram devices, surveillance cameras, wearable sensors and custom-made solutions. Arduino and Raspberry Pi are popular platforms to develop custom made sensing solutions with the capability of transmitting their readings to a smartphone.

Social networks are a part of our daily life, whenever a person post an opinion of a restaurant, makes a check-in in a place, a picture or interacts with others, personal information is stored in the cloud. This information can be used to estimate the level of social interaction, views on certain subjects or simply to make sentiment analysis of the user's behavior. In other words, social networks can be considered as other type of sensor. In a way, any kind of documental data could be treated as a sensor; examples of it are financial and clinical records. For practical reasons, Cardio Twin only considers social networks as those are already available through the smartphone and only require the user's authorization.

B. *AI-Inference Engine*

All data collected from social networks, external and internal sensors is concentrated in a data fusion module. This structure is responsible for storing and recover data from the data repository. The data is now available for analysis needed in the AI-Inference Engine.

As mentioned before, Cardio Twin design is based in Digital Twin for healthcare and well-being; in [5], however, for Cardio Twin, the concept of "pipeline" was added to the AI-Inference Engine. This idea was inspired in the pipeline software architecture, in which a pipeline is formed by a series of sequentially executed pipes or processes that take as an input the output of the previous pipe. For Cardio Twin, a pipe is a software object that receives, process and transmits data to the next object in the architecture. At the end of every pipeline, the data object is stored in the data repository and if necessary, transmitted to a smart service or recovered by the next layer (multimodal interaction layer) to represent the real twin's heart. The pipeline is executed as follows:

1. Data fusion: This pipe collects and aggregates data from the different sensors in data source structure and store it in the smartphone storage system (data repository).
2. Data standardization: The data is recovered from the data repository and formatted to fit the appropriate standard. In the case of medical data, the IEEE x73 standard can be used. After formatting the data, it is sent back to the data repository.
3. Data analytics: This pipe recovers standardized data to analyze it and discover "hidden" information from it. Cardio Twin uses Tensor Flow Lite models to classify this data and discover new information about the real twin that is useful to the representation of the real twin's heart and to the next pipe. This information is the stored in the data repository.
4. Decision making: This pipe takes as an input the information from data analytics and decides to communicate with smart services or not depending on the real twin's heart condition.

This component has the potential to detect other health complication simply by modifying the Tensor Flow Lite model or adding more pipes.

C. *Multimodal Interaction & Smart Services*

Each Cardio Twin must be able to interact with the real twin and with the real world. To achieve this, the interaction interface provides communication through Bluetooth connectivity, Wi-Fi/5G networks and conventional messaging services.

Imagine that a doctor wants to see the patient heart's current condition during a visit in the screen of his/her office. The interaction interface and the visualization service will take care of the data transmission and the whole process. With this feature, a patient could be virtually present in the doctor's office regardless of distance and the actual visit might not even be necessary.

The concept of smart service for healthcare and well-being is introduced in this architecture to describe a Cardio Twin compatible service that otherwise would require the intervention of the real twin. For instance, if Cardio Twin detects an anomaly in the heart, it could easily send the data from the past 48 hours to a laboratory by taking advantage of its communication capabilities and, when necessary, it could also book an appointment with a physician. Smart services in Cardio Twin are offered by healthcare providers. In the scenario where a myocardial infarction is detected, a request for an ambulance could be sent to a Smart Service. This is accomplished through the Interaction Interface. All these decisions are made in the "decision making" pipe of AI-Inference Engine.

In the next chapter a proof of concept implementation of the AI-Inference Engine of Cardio Twin to explore the challenges that may arise from implementing this architecture and more specifically the AI-Inference Engine entirely on the edge.

III. PROOF OF CONCEPT IMPLEMENTATION

At this point of maturity, it's not possible to evaluate Cardio Twin on a real situation. In order to compensate for this, the proof of concept implementation is focused in the AI-Inference engine, more specifically, in the data analytics pipe since pairing with external devices (such as sensors), accessing data from social networks, communicating with other devices are intrinsic features of modern commercially available smartphones; said features are building blocks for the Data Source and Multimodal interaction structures.

Thus, this implementation had the objective of proving the performance of the AI-Inference engine but also the viability of

Cardio Twin in real scenarios since doing data analytics is usually done in a centralized server. In this case, the proposed implementation focuses only on monitoring the human heart with the aim of detecting an abnormality in the heart ECG of the real twin.

A MI for instance, will cause an abnormal ECG signal. The deep learning model for the data analytics pipe to run is a CNN trained to classify the first lead of a standard ECG (lead I). The training and test datasets were compiled based on "The PTB Diagnostic ECG Database" (PTBD) which can be found in Physio Bank [13], [14] and described in [15]. The process to compile the train and test dataset was as follows. All the patients suffering MI and healthy controls were identified from PTBD database, 148 patients with MI and 52 healthy controls; 200 patients in total.

The first lead (lead I) of each ECG record of the 200 patients was recovered, scaled and segmented to create 2.5 seconds samples that were fed to the model to ensure that at least one heart beat is present in each sample. According to Edward Laskowski [16], a person in resting state heart rate ranges between 60 and 100 beats per minute. This implies that at the lowest heart rate, a healthy patient in resting state will present a heartbeat per second. The time length for the segments for each sample was determined to guarantee that each segment had at least 2 heartbeats present. In order to properly evaluate the CNN model, the samples of 34 subjects out of the 200 subjects (healthy and non-healthy) were selected as test data. The rest of the samples of the remaining 166 subjects were used to build the training dataset for the CNN model. When working with neural networks, it is recommended that the values in the dataset are scaled to a range of 0-1. Because of that, each 2.5 seconds segment was scaled individually to fit in that range.

Once the training and test datasets were selected, the next step was to create a CNN model and train this model with the training dataset. A heuristic approach was followed towards the construction of the CNN. Two main variables were selected first the number of convolution and pooling layers and second the number of dense layers. The highest accuracy was achieved with a model of 3 pairs of convolution-pooling layers, a flatten layer, 2 dense layers (relu) and 1 output neuron (sigmoid). The model has an accuracy of 85.81%, a sensitivity of 86.29%, a precision of 95.6% and a specificity of 83.87%.

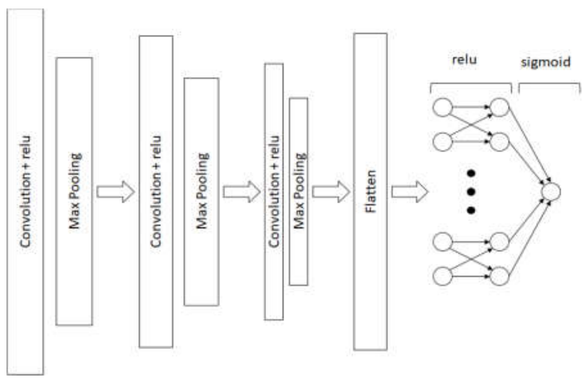


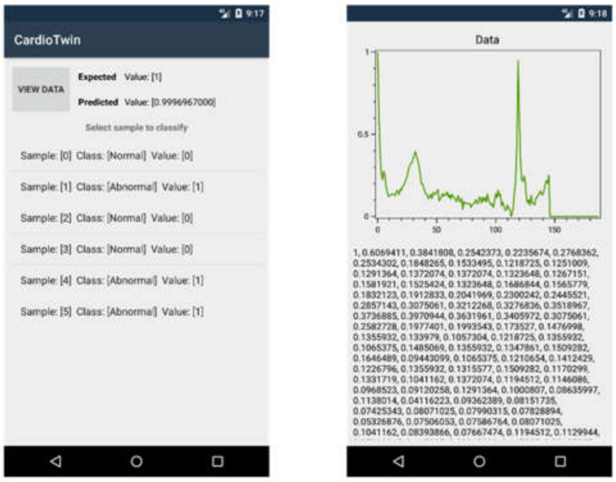
Figure 3. Best performance CNN model abstract diagram.

Figure 3 shows the architecture of the CNN model. The selected activation function was ReLU. Keras and Tensor Flow are libraries for python that assist in the design and training of deep learning neural networks. Keras works on top of Tensor Flow.

Cardio Twin is an architecture that is meant to run on the edge, that is composed of three main components: a data repository, a multimodal interaction component and an AI-Inference engine. Implementing the first two are a trivial task. For example, using most recent relational and NoSQL storage engines available for android and iOS the data repository can be easily implemented. A smartphone is inherently multimodal, thus the resources needed to implement the multimodal interaction component are already in the device. The most challenging component to implement in Cardio Twin is the AI-Inference engine since it requires the device to run classifiers in the device itself. The focus is on having an AI-Inference engine running on the edge that is versatile to run different models that can be improved, update and trained to solve problems of different domains. For example, detecting IHD from an ECG signal or maybe detecting a fall from the accelerometer [17]. A Keras model and ticks these requirements in the sense that neural networks have been used over the years to tackle all kinds of classification problems. By running a Keras model, Cardio Twin is capable of tackling as many classification problems as neural networks have tackled in the past, including deep learning models that had gained a lot of attention from the academic community in recent years. Thus, running Keras models in this proof-of-concept is evidence towards the viability of Cardio Twin architecture running entirely in the edge.

The proof of concept version of Cardio Twin was implemented in two stages. The first stage was to design and train a CNN in Keras obtaining a classifier for ECG segments into MI or non-MI segments. The second stage was to have the data analytics pipe to run the trained model and test its accuracy with the test dataset prepared in the first stage.

To test the data analytics pipe, we used the training dataset previously built and ran it through the pipe alone, registering the predictions for each ECG segment. Figure 4 depicts a prototypical visualization for Cardio Twin in which some samples are shown along with the predicted class (MI or non-MI). The output of the classifier is shown on the "Predicted" label and compare it to the "Expected" value. Cardio Twin visualization also allows to see a graph of the ECG segment by pressing the "View Data" button. However, in this case, Cardio Twin was only tested against a fraction of the test set.



a. Main screen b. Data visualization

Figure 4. Cardio Twin proof of concept visualization.

A second test was done using all ECG segments from the test set. This test set consisted of 13420 ECG segments. To do this, we isolated the Data Analytics pipe to run the test and output a csv file with the results of the classification and the time it took for pipe to process each sample. The cumulative results are shown in table 1.

TABLE I. TFLITE MODEL ACCURACY.

	Predicted Normal	Predicted Abnormal
Healthy	2213	1474
Myocardial	435	9298

Average time (ms)	4.8454545
Total Count	13420
Correct	11511
Incorrect	1909

Accuracy	85.7749627%
Precision	95.5306689%
Recall	86.3163758%

The accuracy of the trained model is 85.77%, which is quite close to the results obtained during the training phase in Keras. This suggest that other models implemented with the Keras framework can go through the same process without suffering significative alterations that could affect performance. Another interesting result is the relatively short amount of time (4.84 ms) needed to classify a single segment. This classification time is short enough to allow real-time processing and classification of ECG segments.

IV. FUTURE WORK

Cardio Twin is a platform conceived as a twin of a human heart with the idea of detecting, preventing and reduce the risk of suffering heart diseases. The human heart is an extremely complex organ and cannot be fully replicated only by collecting ECG data, not even if it is real-time data. Therefore, it is necessary to identify and enable the platform to collect different types of data coming from different sensors. The next step is to assemble all structures and modules and have the data fusion pipe to collect data directly from the sensors and increment the number of sensors to have Cardio Twin take full advantage of the sensing capacities of a modern smartphone. For instance, phonocardiograms in contrast to ECG, clinical data to increase the accuracy of the model to detect heart problems, etc.

In parallel it's also necessary to work on the multimodal interaction structure in order to enable better and more rich visualizations of Cardio Twin. Cardio Twin must be able to visualize in external devices such as TV screens, VR devices and more.

V. CONCLUSIONS

At this point, Cardio Twin focuses on detecting a problem and act accordingly to help the real twin. This is one way to approach this problem, but in the future the platform will be used to help in the prevention of IHD and Stroke by reducing the risk factors associated with these diseases. The suggested approach is to apply persuasive computing to promote healthy habits in the real twin, thus reducing risk factors such as alcohol consumption, smoking, sedentary lifestyle, etc. The AI-Inference engine will be key in achieving this.

The proof of concept implementation of the platform was successful in the sense that even though only ECG data was used for the data analytics pipe, a similar process can be followed in order to integrate other types of data which opens possibility to use Cardio Twin as a test bed to explore other types of data. On the other hand, whenever a model is not accurate enough, the design of Cardio Twin allows to replace or improve any model in the data analytics pipe.

The most challenging structure of Cardio Twin is viable for implementing it in the edge. This would be the first platform of its type that runs on the edge entirely, this pushes the prediction part of the "brains" in deep learning entirely to the edge, which it's a relevant result by itself. In summary, a Digital Twin of the human heart running entirely on the edge is a viable idea that creates new research opportunities to exploit.

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