DeepEmote: Towards multi-layer neural networks in a low power wearable multi-sensors bracelet

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Abstract— Wearable smart sensing is a promising technology to enhance user experience that has already been exploited in sport/fitness, as well as health and human monitoring. Wearable sensing systems not only provide continuous data monitoring and acquisition, but are also expected to process, and make sense of the acquired data by classification in similar ways as human experts do. Supporting continuous operation on ultra-small batteries poses unique challenges in energy efficiency. In this paper, we present an ultra-low-power bracelet with several sensors that is able to run multi-layer neural networks learning algorithms to process data efficiently. The design combines low-power design, energy efficient algorithms and makes this bracelet suitable for long-term uninterrupted usage with small coin batteries. We demonstrate in-field measurement results that prove that neural networks applications can fit within the mW power and memory envelope of a commercial ARM Cortex M4F microcontroller. We show that a fully connected network of 26 neurons achieve an accuracy of 100% on emotion detection, using only 2% of memory available. Field trials demonstrate that the wearable device can achieve a 2-month lifetime while performing one emotion detection classification every 10 minutes.

Keywords—wearable, neural networks, ultra-low-power, health monitoring, sensors, smart sensing.

I. INTRODUCTION

Wearable sensors and related technologies have enjoyed considerable success, as demonstrated by the increasing number of "smart" devices in use. From bracelets to glasses, from smartphones to smart shoes, from smart devices in home automation to professional healthcare systems, the commercial success of these smart objects is the result of vast improvements in electronics that has led to an increase in performance, while reducing the operational power as well as by the availability of ubiquitous wireless connectivity[1][2]. The clear trend is toward billions of smart sensors, in the "Internet of Things" (IoT) vision. In fact, IoT creates formidable challenges for academic and industrial research. In particular, these billions of smart devices with sensors will produce a mind-boggling quantity of data that need to be processed to provide useful information. In fact, the data by themselves are not able to provide value unless they are not processed. Big-data mining techniques allow us to gain new insights by batch-processing and off-line analysis. However, this is not sufficient: in-situ real-time feature extraction, analysis, classification, and local decision-making are essential for a truly scalable and robust IoT infrastructure.

Machine learning technologies, are extensively used with great success in many application domains to solve real-world problems in entertainment e-health, automatic surveillance, assisted living, and assistant driving among many others [1][3]. More and more researchers are tackling classification and decision-making problems with the help of brain-inspired algorithms (i.e. neural network or convolutional neural network), featuring *many stages* of feature extractors and classifiers with lots of parameters that are optimized using the unprecedented wealth of training data that is currently available [4]. These brain-inspired techniques are also knows as multi-layer neural networks [5]. In recent years, neural network has achieved results that exceed those achieved by humans [5] on very challenging problems and datasets, and routinely surpass more mature ad hoc approaches. Neural network algorithms are extremely flexible and applicable to various data sources. They perform at best when information is spatially or temporally well localized, but still has to be seen in a more global context. However, neural networks approaches are still not suitable for wearable, ultra-miniaturized IoT devices, because, in their current embodiments, they require massive amounts of computational power [3][6].

This paper aims to push beyond the current power walls for neural networks and move toward micro-power neural network. This requires working on algorithms, architecture, circuits as well as design methods for neural network under extreme constraints: tiny energy buffers (batteries), miniature energy harvesters, low-power and low-cost logic and memory devices. Specifically, in this paper, we describe the design experimental characterization of an ultra-low-power bracelet that combines bio-sensors, low-power hardware and software co-design. A full-featured prototype has been built and operated to demonstrate that practical neural networks algorithms can be a realized within the power envelope of such a system and an emotion detection application has been tested in-field. The main contributions of the paper are:

- The hardware and software co-design of an ultra-low-power of a wearable multi-sensor device able to run artificial neural network (ANN) [7] applications to classify data on-board. The designed node uses several sensors and low-power design to implement an emotion detection algorithm which achieves high-accuracy

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- Implementation and analyses of an artificial neural network-based classifier that can run on an ARM Cortex M4 Processor
- Using in-field experimental results to demonstrate the performance of the proposed solution in terms of accuracy, scalability of the neural network and energy autonomy.
- Evaluation of a set of neural network algorithms that were never implemented on an ARM Cortex M4 before.

II. RELATED WORKS

Academic and industrial research on wearable and mobile sensor systems has been very prolific in recent years with a variety of solutions in a wide range of application scenarios [6][8]. Especially, many examples of wearable devices attempting to achieve intelligent sensing has been presented to monitor human activities [9][10]. Unlike a few years ago, where the main challenge was to get reliable data from the sensors, today, the main challenge when designing wearable devices, is to achieve long operating lifetime and to enhance usability, maintenance, and mobility, while keeping a small and unobtrusive form factor. In fact, despite other system with sensors, wearable devices have to provide continuous data monitoring, acquisition, processing, and classification, supplied only by tiny batteries. Thus, unique challenges in energy efficiency, low power design and power management are posed [6][11]. On the market, there are many successful example of bracelet that are lasting for days or weeks as reported in [1], however none of them is able to process neural networks and host a such complete set of bio sensors still keeping the battery size as a coin battery for month as our device.

The other major emerging challenge in wearable smart device is to be able to understand the world in a similar way as humans do [10]-[13]. Machine learning approaches, and in particular multi-layer neural network techniques, show great promise toward achieving this goal. Embedding neural network classifiers in distributed sensor systems seem a natural direction of evolution [14]. However, at the moment, most of the state-of-the-art neural networks are currently not only trained, but also deployed for classification on high performance computing (HPC) workstations and data centres and until now could not be implemented within the ultra-tight power constraints of IoT smart sensing devices without major improvements in energy efficiency. In this paper, we present a smart wearable device that is able to perform on-board classification based on multi-layer neural networks within a mW range power envelope and can give a classification in few µs.

Some ultra-low-power solutions based on different brain-inspired models, such as spiking neural networks, have been announced, such as the Qualcomm Zeroth processors for brain-inspired computing [15] or the IBM SyNAPSE chip [16]. Early academic work on spiking neural networks has claimed that conceptually these models are potentially more power-efficient than neural networks because of their asynchronous event-driven operation [17]. However, spiking networks are not yet competitive with neural network in terms of classification performance. Furthermore, even highly optimized spiking networks implementations have not yet demonstrated major improvements in terms of power consumption at the system level.

A similar approach of implementing an artificial neural network in a microcontroller has recently been presented in [19]; however, the authors are not presenting any performance evaluation in terms of execution time, power and memory usage. Moreover, the network is quite simple and uses only one sensor. To the best of our knowledge, this is the first paper that shows extensive results on artificial neural network algorithms that are running directly on a wearable device and an ARM cortex M4F processor with multiple-sensors while being supplied by a small size Li-Ion battery. In [20] the benefits to use convolutional neural network in wearable devices is demonstrated. Despite our approach, the authors use an ultra-low power accelerator coupled with an ultra-low power microcontroller. In our work, we demonstrate that also commercial microcontroller can perform neural network with an mW power consumption.

III. SYSTEM ARCHITECTURE

Fig. 1 shows the block diagram of the wearable bracelet. The primary design aim of the presented system is to acquire bio signals from humans and perform ultra-low-power classification using ANN algorithms. In this way, the data from the sensors is processed directly on-board by an ARM Cortex M4F processor to save overall power by reducing communication power and latency. The system also contains a Bluetooth low-energy interface that is able to send an alert and if needed, the system is able to stream data for further processing off-board. A third communication path is established via the human body over an intra/extra body communication. As the system is designed to be wearable, and long-lifetime is expected even when supplied by a coin battery, the hardware design has to be optimized for energy efficiency.

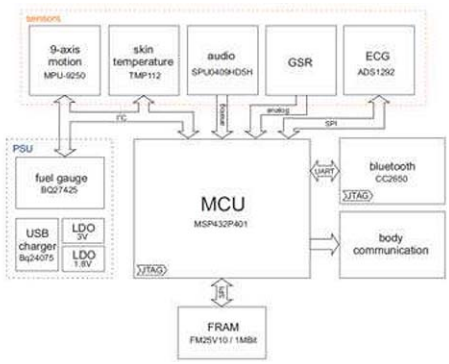

Fig. 1. Block diagram of the wearable bracelet

a. *Microcontroller and non-volatile RAM*

The core of the hardware is the Texas Instruments MSP432 mixed-signal microcontroller, which is based on an ARM 32-Bit Cortex M4F processor running up to 48MHz. The

MSP432 MCU is a novel microcontroller that allows several low-power applications, while providing plenty of computation resources with its DSP and floating point units. The microcontroller consumes only 95µA/ MHz in its active mode, a figure that reduces to only 850nA in low-power mode with RAM retention and real-time clock wake-ups. Low active power consumption, negligible sleep power consumption and performance are useful for wearable devices for health monitoring to achieve long-term monitoring. Finally yet importantly, the MSP432 also provides a low-noise, low-power 14-bit Analog Digital Converter (ADC), which is very useful for data acquisition from analog sensors, used for health monitoring applications.

b. Low Power Sensor for Vital Signs

The application used throughout this paper, uses physically measurable biological signals to detect the emotional state of the wearer. Such a system needs access to an array of sensors to be successful and the bracelet presented in this paper includes several sensors that have been selected with the best power-accuracy tradeoff. All sensor interfaces are designed to be switched off when acquisition is not necessary to save power. The following sensors has been included in our design:

ECG sensors: Meaningful and easily obtained features of the ECG signal and skin conductivity are the heart rate and the heart rate variability, which decreases with an increasing stress level. Many other useful features can be extracted from the ECG signal, such as the ratio of certain peaks in the signal or other more complex frequency based features as stated in [13]. The analog front-end in this sensor is based on the ADS1292R chip, which is a 24-bit analog front-end for bio-potential measurements. This chip can acquire signals from two separate channels with a rate of up to 8 Ksample/s, has a lead-off detection and includes a respiration-impedance measurement function. The digital output of the ADS1292R is connected to the MSP432 through SPI.

Galvanic Skin Conductivity: The galvanic skin response sub circuit consists of a precision voltage source and an amplifier, as seen in Fig 2. The shunt voltage source in combination with the voltage divider R37 and R38 provides a constant voltage at the positive input pin of the operation amplifier of V+ = 0.5V. The nets EL_GSR1 and EL_GSR2 are connected over the varying resistance of the skin, which can vary from a few ohms up to several hundred kOhms. If the two probes are shorted, the positive supply voltage limits the output, which is also the maximal input voltage of the MSP432 ADC.

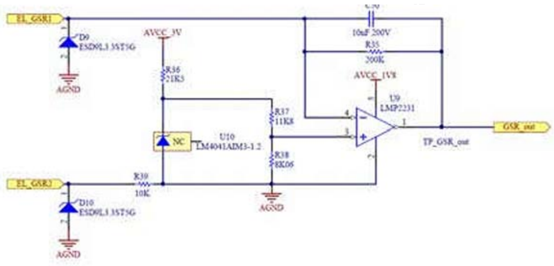

Fig. 2. Galvanic skin conductivity acquisition circuit.

Microphone: The audio sub-circuit consists of a MEMS microphone and a discrete micro-watt amplifier. The output of the amplifier is directly connected to an ADC pin of the MSP432 microcontroller.

***Motion sensor*:**
Important information on activities and other human status comes from the motion data. The included MPU-9250 combines in an ultra-low power multi-chip module a 3-axis accelerometer, 3-axis gyroscope and a 3-axis magnetometer.

Skin temperature: Skin temperature is a key indicator on the status of the human and its correlation with other parameter can lead to detect several diseases.

c. Wireless Interface

The system includes CC2650, an ultra-low power Bluetooth low energy chip by Texas Instruments for communication with the host device. The CC2650 is directly supplied with 1.8V and its internal voltage regulators are disabled. The chip consumes only 6mA when transmitting data to 10-20 meter distance +0dBm as well as only 1µA when in idle mode. Moreover, although not exploited in this paper, the device embeds a body communication subsystem using on-off keying on an 8MHz carrier signal to exchange data with other sensors on the body.

d. Power Subsystem Unit (PSU)

The power supply is designed with two goals in mind. 1) Provide charging via USB and provide battery level indication, a function commonly found in many wearable applications and 2) act as a stable and highly efficient supply for the entire board while the bracelet is worn by the user without the need of an additional supply. The 1.8V and 3V supply for the microcontroller and sensors are generated with two low-dropout (LDO) low-power linear voltage regulators. LDO regulators are used instead of switching regulators to reduce noise during on biophysical signal acquisition. The supervision of the battery is done by a BQ27425 connected through the I2C bus.

IV. ULTRA-LOW-POWER DEEP-LEARNING

The main contribution of this paper is to show that deep learning, and in particular, ANNs can be realized in ultra-low power microcontrollers as well. We have ported the Fast Artificial Neural Network (FANN) library and created software components for data visualization, data logging and training of neural network [21]. The FANN library allows us to create, train and test multilayer artificial neural networks on a PC. In its original composition, it is not possible to run this library on an embedded platform without file system support because the configuration of a trained neural network is saved in an external file. Therefore, the library has to be optimized for use on the MSP432 microcontroller, using the CMSIS library and TI-Driverlib to maximize the performance in the ARM Cortex M4F microcontroller. Fig. 3 shows a generic neural network that has 1 input layers, 2 hidden layers and 1 output and 16 neurons in total. After the network is generated on the FANN tools on the PC, it can be trained with training dataset and the PC can evaluate the weight of neurons. Therefore, the weight is used in the on-line classifier implemented in the MSP432. With the right training set the network can be trained to detect several different classless with different features from the sensors (i.e. fall detection, activity recognition, and disease detection for e-health and so on).

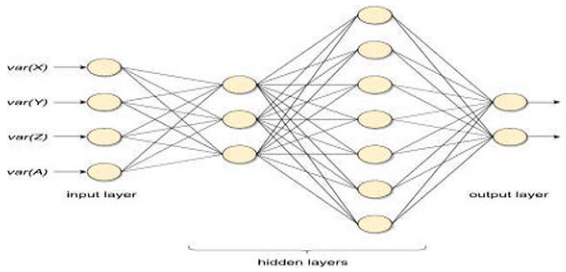

Fig. 3. A generic neural network with 1 input layer (4 neurons features of sensors) 2 hidded layers and 1 output layer with two neurons.

a. Emotion detecion.

In this paper, we implement an emotion detection in order to evaluated the network [7], to evaluate the accuracy of the algorithm and especially the performance of the MSP432 to perform on-line classification. For this example, we chose two output classes (joy and sadness) to be detected, selecting the minimal size of the neural network to achieve 100% accuracy. The Augsburg Dataset [18] was used for the compilation of the training and test dataset. In this dataset, music was used to induce four specific emotions (joy, anger, sadness, pleasure) to several people. Four-channel biosensors were used to record electromyogram (EMG), Electrocardiogram (ECG), skin conductivity and respiration change. Overall, twenty-five recordings were collected for each emotion over a period of twenty-five days. The length of each collected sensor stream is two minutes. ECG was sampled at 256 Hz, the other signals at 32 Hz. We have evaluated different network topologies using varying number of input features. As shown in Fig. 4, the best accuracy was achieved with eight features

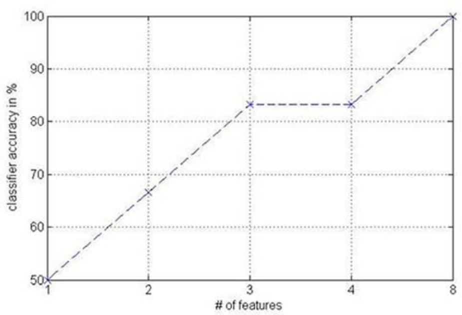

Fig. 4. Evaluated accuracy of the emotion detection accordin with the number of features.

The selected features are the following explained using figure Fig. 5: 1) ecgR-mean: mean of R-R interval in ECG signal; 2) ecgR-median: median R-R interval in ECG signal 3) ecgR-min: min value of R-R interval in ECG signal; 4) ecgR-max: max value of R-R interval in ECG signal 5) ecgRampl-mean: mean of R amplitude in ECG signal; 6) ecgP-max: max value of P-P interval in ECG signal 7) ecgQ-min: min value of Q-Q interval in ECG signal 8)ecgQ-max: max value of Q-Q interval in ECG signal

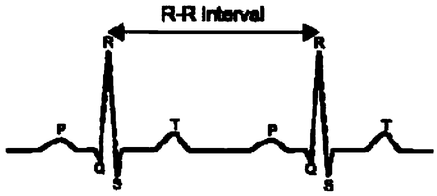

Fig. 5. : ECG peaks and values used for the features extraction.

Training and testing was done with FANN library. The Augsburg dataset was divided into twenty-two subsets (days) for training and three subsets (days) for testing. Furthermore, the sensor streams of the emotions joy and sadness were used for training and testing of the neural network. Finally, the fully connected and trained network has been implemented in the microcontroller and the measurements were collected.

V. Experimental Resutls

The prototype of wearable device seen in Fig. 6 has been implemented to carry out experimental evaluation in terms of power consumption, functionality, sensor acquisition quality and neural network performance and scalability. First, measurements of power consumption are shown. Data acquisition and processing of the ECG sensor are presented while the other sensors are omitted for space reasons. Moreover, performance of the neural network presented in section IV.a is shown, including measured data on the execution time of the whole algorithm and the usage of memory. Furthermore, measured data on bigger networks are presented to show the scalability of the neural network on the MSP432.

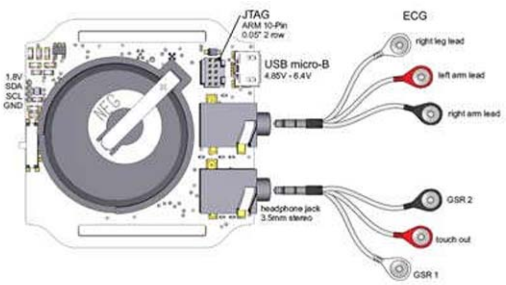

Fig. 6. The prototype of the bracelet designed and implemented.

TABLE I. shows the current and power consumption of the designed wearable device. There are three main voltage domains (3.7V supplied by a Li-Ion battery, 3V and 1.8V) as explained in the previous sesction. The overal current consumption of whole system depends on the task of its components. The low-power design results in a quiescent current of only 250µA which is mainly due to the LDO used because of its low noise. This low quiescient current is very important to guarantee long battery lifetime. The active current consumption is in the order of mW including the sensor data acquisition that allows the system to achieve several hours of continuous working and several days/weeks with duty cycling. It can also be noted that the power consumption of the Bluetooth low energy module is around four times the power consumption of the MSP432 while processing the data, which demonstrates that on-board data processing effectively reduces energy consumption effectively improving the lifetime of the device.

TABLE I. CURRENT AND POWER CONSUMPTION OF SUBSYSTEMS

circuit	voltage	current active	current idle	power active	power idle
fuel gauge	3.7 V	118 µA	23 µA	437 µW	85 µW
USB charger	3.7 V	6.5 µA	6.5 µA	241 µW	241 µW
power multiplexer	3.7 V	55 µA	55 µA	204 µW	204 µW
LDO	3.7 V	170 µA (I_q)	170 µA	629 µW	629 µW
gyroscope	3 V	3.2 mA	8 µA	9.6 mW	24 µW
accelerometer	3 V	450 µA	-	1.35 mW	-
magnetometer	3 V	280 µA	-	840 µW	-
ECG	3 V	237 µA	0.33 µA	710 µW	1 µW
GSR	3 V	10 µA	10 µA	30 mW	30 mW
memory	3 V	1 mA	6 µA	3 mW	18 µW
intra/extra body communication	3 V	3.2 mA	21.3 µA	9.6 mW	64 µW
MSP432	1.8 V	3.8 mA	1 µA	6.84 mW	1.8 µW
Bluetooth	1.8 V	12.2 mA	1 µA	22 mW	1.8 µW
temperature sensor	1.8 V	15 µA	1 µA	27 µW	1.8 µW
audio	1.8 V	1.65 mA	1 µA	2.97 mW	1.8 µW
Total 3.7 V (without LDOs)		238 µA	84.5 µA	881 µW	529 µW
Total 3 V		8.38 mA (I_{o3V})	45.6 µA	25.1 mW	138 µW
Total 1.8 V		17.7 mA ($I_{o1.8V}$)	1 µA	31.8 mW	1.8 µW

Fig. 7 shows an example of ECG signal and the respiration rate calculated in the MSP432. There is practically no noise in the signal, due to the low-power front-end in combination with the LDOs that supply the entire wearable device. For space reasons, we are unable to show the performance results of other sensors, all tested in-field.

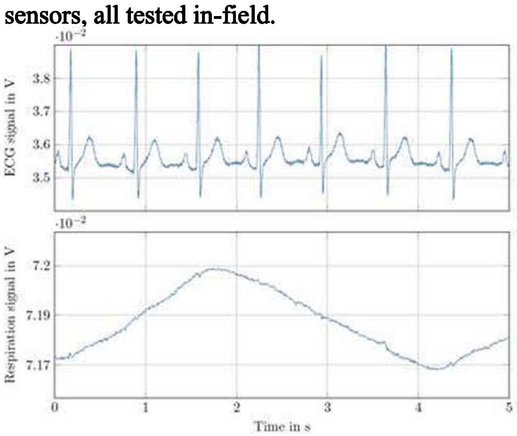

Fig. 7. Example data acquired by the wearble device and send by blutooth log energy to the logger data.

Feature extraction performance: As we presented above, the used features are mainly based on distances between specific peaks in the ECG signal. For a meaningful feature set, at least three heartbeats are necessary to be captured by the ECG. Assuming a person at rest has a heart beat rate of 60 beats per minute, this gives a minimal window size of 3s. A preliminary algorithm was implemented on the MSP432 that extracts the R-peak related features (ecgRampl-mean, ecgR-mean, ecgR-min, ecgR-max, ecgR-median). For the computation of the median, the quicksort algorithm qsort of the stdlib library was used. The feature extraction was tested on MSP432 on the data of 4, 8 and 16 second long sensor streams of ECG sampled at 250 Hz (TABLE II.). The execution time scales up linearly with the window size. The extraction of the remaining 3 features (ecgP-max, ecgQ-max, ecgQ-min) is associated with higher computational effort, because local maxima in the sensor stream must be detected reliably and multiple buffer iterations are necessary. However it can be noticed that the extraction of features from a 16 secod windows is still completed within 40.88ms (33ms+7.88ms) .

TABLE II. FEATURES EXTRACTION PERFORMNACE

Features	window size [s]	execution time [ms]	memory usage of sensor data [kB]
ecgRampl-mean	4	1.93	4
ecgR-mean	8	3.91	8
ecgR-min *ecgR-max* *ecgR-median*	16	7.88	16
ecgP-max, , *ecgQ-max* *ecgQ-min*	4	8	
	8	17	
	16	33	

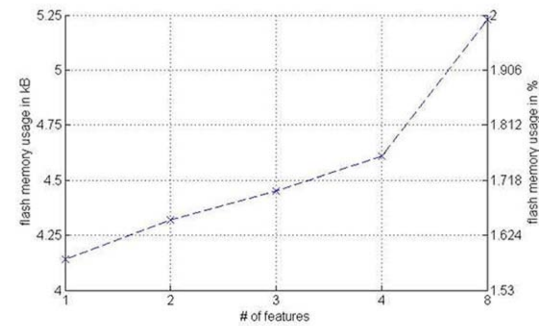

Fig. 8. Memory used Vs number of features

ANN Performance: Fig. 8 shows the flash memory usage of the ANN algorithm for eight features which guarantees 100% accuracy, as presented in the previous section. The figure takes into account that the FANN library takes 26% of the internal flash memory on MSP432 (see also Fig. 9). To check the scalability of the ANN we implemented in the MSP432 a bigger ANN that has been designed to have eight inputs, five outputs (classes), 100 neurons and 10 hidden layers. Such an ANN can be used to detect a large number of classes detected depending on the applicaton scenario. It can been seen that also such an ANN fits the internal memory. Note that there is an additional 1Mbits FRAM that can be used to further expand the network Finally we evaluated the execution time of a bigger ANN to show the future potential of the deep-learning in a low-power device. It can be seen in Fig. 10 that also with such a large network the execution time is in the range of ms. We measured an average power consumption of 8.64mW during the acquistion of sensor data and 7.874mW during the feature extraction and classification.

Fig. 9 shows the execution time and energy spent by the system for a single classification. It can be noticed that the dominant part of the energy consumption is due to the data acquisition as expected. The total energy is 138.24mJ + 0.321mJ to perform per each classification. Performing a classification (including 16second of data acquistion) every 10 minutes (so 540 due to the quiescint current in idle mode) the average power consumption is only 1.295J (350µA from the 3.7V Li-Ion battery). Thus, with a 600mAh battery is possible to achieve two months of lifetime from a single battery.

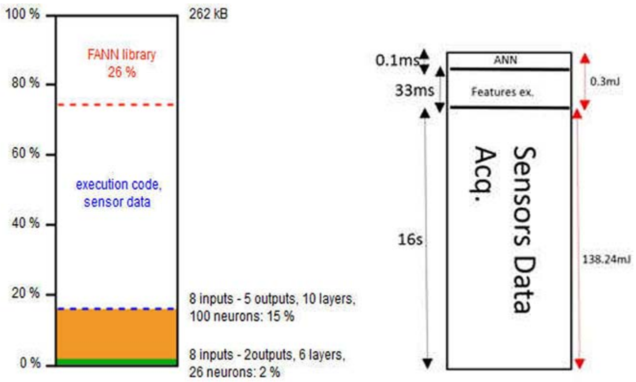

Fig. 9. On left: Internal flash memory usage during the on-board implmentation. On right: Execution time and energy consumption.

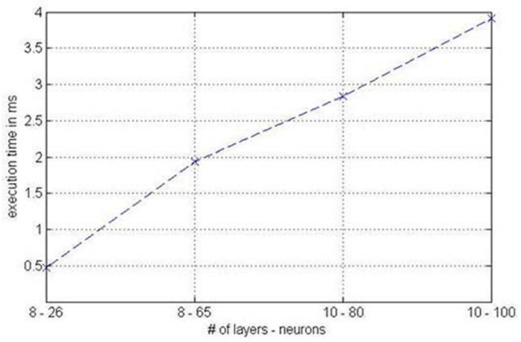

Fig. 10. Execution time of different network structures in terms of numbers of hidden layer and neurons.

VI. Conclusions

Artificial neural networks for wearable devices can greatly improve detection and data analyses. A novel low-power wearable device with multiple sensors and optimized ANN for Cortex M4F has been proposed. We demonstrate that ANNs can be implemented in such a low-power system, and the combination with the low-power design and power management, which can switch off the unused peripherals allowing the device to achieve lifetimes expressed in terms of months, while maintaining a high detection accuracy. Experimental results indicate the performance of the algorithm in terms of accuracy, execution time and memory usage in an emotion detection application. Moreover, evaluation on the bigger ANN are presented to target future application scenarios.

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