A low-power embedded system for fire monitoring and detection using a multilayer perceptron



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Introduction



Motivation

Existing systems



without any memory or power constraints



continuous power supply



complex algorithm with increasing memory requirements



cannot be implemented on embedded systems

Outline

- Related work
- Background information
- Initial approach
- Optimizations
 - Software optimizations
 - Hardware optimizations
- Results
 - Power consumption
 - Performance of MLP model
 - Memory Requirements
- Summary
- Future work

Related Work

- Common approach
 - 3 or 4 environmental sensors or Image
 - ANN, CNN, Fuzzy Logic, if-then rules
- Implementation platform
 - Arduino Uno, MSP430, Beaglebone, Raspberry Pi
- Drawbacks
 - not suitable for limited-memory embedded systems
 - information on the power consumption was not available





Background information (1/2)

Hardware

STM32L496 MCU



Low-power platform based on ARM Cortex-M4 32-bit RISC

BME680



Temperature and Humidity

CCS811



Total Volatile Organic Compounds (TVOC) & equivalent Carbon Dioxide (eCO_2)

Background information (2/2)

Software

- Multilayer perceptron (MLP)
 - 5 input values (temperature, humidity, eCO_2 , TVOC, MLP previous output)
 - 2 Hidden layer, 1 Dropout
 - 1 output (binary value)



Initial Approach



Software Optimizations (1/3)

Chain of MLP models

 $OutMPL_t = MLP(OutMLP_{t-1}, T_t, H_t, (C0_2)_t, TVOC_t), t \ge 1$



Software Optimizations (2/3)

Chain of MLP models



Software Optimizations (3/3)

Loop unrolling

- minimizes the cost of loop overhead
- increases the code efficiency

Quantization

- reduces the number of bits converting the floating point values to fixed-point integers
- increases the operations between weights
- a value of 8 bits for quantization was used

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$$q_{uint8} = \frac{r_{float32}}{s_{float32}} + z_{uint}$$

Hardware Optimizations (1/2)

Hardware interrupts

- reduce power consumption
- the eCO_2 concentration is used as a threshold
- the selected threshold was $1100 \mbox{ppm}$
- a frequency of 4MHz was chosen



Hardware Optimizations (2/2)

Memory accesses

- the Flash memory interface of STM32L496 includes a 256B data cache
- data lines can be stored in the cache in order to accelerate code execution
- the output of MLP for each timestep was stored in the cache
- has no effect on the performance of the algorithm



Flow Diagram



Evaluation Metrics

- k-fold cross-validation technique, with k = 10
 - avoid over-fit
 - finding the best fit model
- The Area Under The Curve (AUC) Receiver Operating Characteristics (ROC) curve



Results - Performance of MLP model (1/2)

- 4500 data points from the temperature, humidity, eCO_2 and TVOC sensors
- A standardization method was applied, shifting the distribution of each attribute to have a mean of 0 and a standard deviation of 1

Metrics	Value
Accuracy	97.05%
F1 score	97%
Sensitivity	97.1%
Specificity	96.5%

Results - Performance of MLP model (2/2)

A comparison of the two model variation, with 32 and 8 bits representation, using 4 timesteps

- AUC metric 0.99 for 32 bits
- AUC metric 0.97 for 8 bits



Results – Power Consumption

- In active mode the MCU and the two environmental sensors are switched on
- In sleep mode the MCU and BME680 are in sleep mode, while the CCS811 is in Pulse Heating Mode with measurements every 10 sec
- Using a 5100mAh off-the shelf battery the system can operate for over 37 days

Mode	MCU	CCS811	BME680	MLP model	Total Power Consumption
Active	2.3 mW	51.52 mW	6.93 mW	0.043 mW	60.8 mW
Sleep	0.045 mW	15.18 mW	0.003 mW	-	15.2 mW

Results – Memory Requirements

- The execution of the MLP has a computational complexity of 1.8K multiply-accumulate operations for each input
- The memory requirements of the proposed system depend on three factors:
 - the input data from the sensors with value 16 bytes
 - the weights of the MLP model combining with
 - the intermediate results between the hidden layers with total size 25.65 kB



Summary

- A low-power embedded system for fire monitoring and detection using an interrupt-based algorithm with a machine learning model
- A remarkable accuracy close to 97%
- An ultra-low-power consumption
- A model size that requires only 4.9% of the 1Mb Flash memory

Future Work

- It will be interesting to integrate an image sensor on a low-power embedded processor
- The use of a more complex machine learning algorithm, such as CNN for image processing
- The design and implementation of a new eCO_2 sensor with lower power consumption



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Thank you

for your time and attention



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