THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

DEPARTMENT OF ELECTRONIC & COMPUTER ENGINEERING

Hardware Implementation of Neuromorphic Circuits

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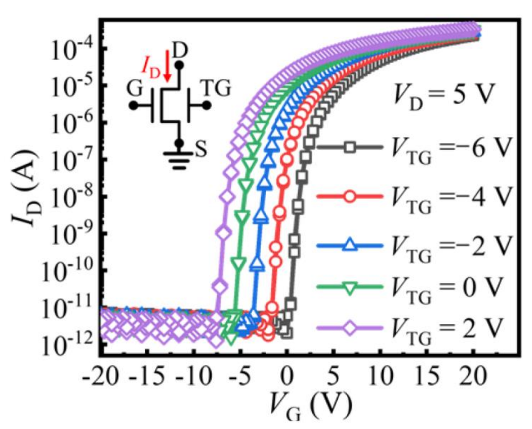
Overview

To realize "smart" sensors that can collect data and process it in real time with AI, relying on the cloud is not viable due to the latency introduced by the internet connection. So, it is desirable to integrate a computational unit with the sensor.

Neuromorphic circuits:

A recent proposal is to implement the structure of an artificial neural network (ANN) in hardware using an array of dual-gate thin-film transistors (DG-TFTs). The secondary gate allows to modulate the threshold seen by the primary gate, effectively shifting the I-V curve, as shown in the diagram:



DG-TFT circuit symbol and I-V characteristic

This way it is possible to implement variable weights, needed for ANN nodes. The design looks to be scalable, requiring low power and is compatible with CMOS, but its limitations are not yet well understood.

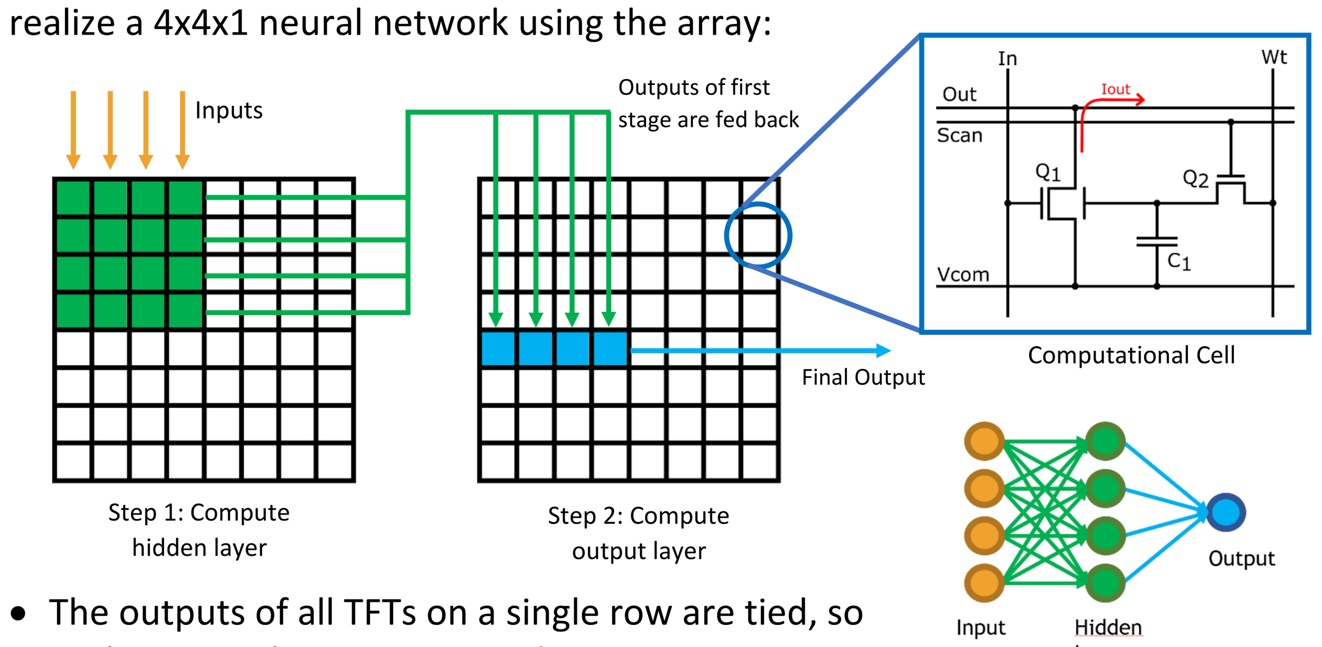
In this project, experiments will be conducted to explore the capabilities of this ANN design and show it can be used in practical applications, specifically to realize a *smart gas sensor*.

Objectives

- To write a flexible driver for the ANN that supports different network structures and training algorithms.
- To train the ANN with gas sensor data to achieve:
  ❖Gas classification ❖Concentration Extraction ❖Both
- To compare the performance of the different training algorithms and strategies in terms of accuracy.

Methodology

The hardware ANN is an 8x8 array of computational cells, each containing a DG-TFT (Q_1). The weights of the ANN are stored in capacitors (C_1) connected to the top (secondary) gate of the TFT. The following diagrams show how to realize a 4x4x1 neural network using the array:



Structure of 4x4x1 Neural Network (with corresponding colors)

- The outputs of all TFTs on a single row are tied, so each row implements one node.
- The ANN interfaces with an STM32 microcontroller via a PCB driver board containing amplifiers and multiplexers.

Training of the ANN:

The ANN is designed to implement simple feed-forward networks and was trained using *gradient descent*. The following strategies were considered:

- Use of learning rate scheduling.
- Different neural network structures.
- Encoding gas type into voltage levels to classify with one output node.

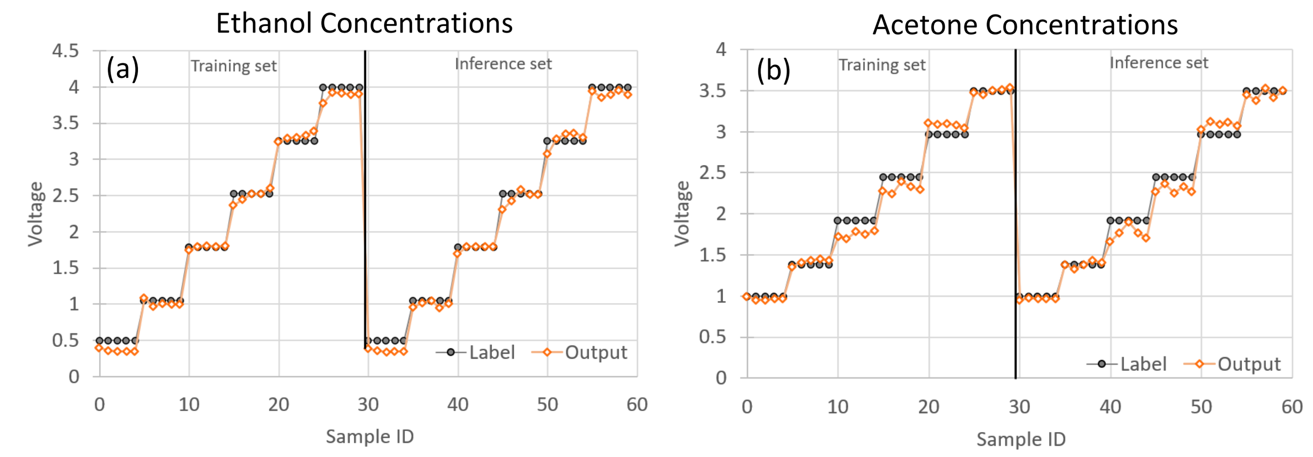
The data comes from a gas sensor with 4 outputs. It was experimented with different pre-processing methods to improve the accuracy of the results:

❖4D-to-2D PCA ❖Adding bias ❖ Using input ratios ❖ Removing inputs

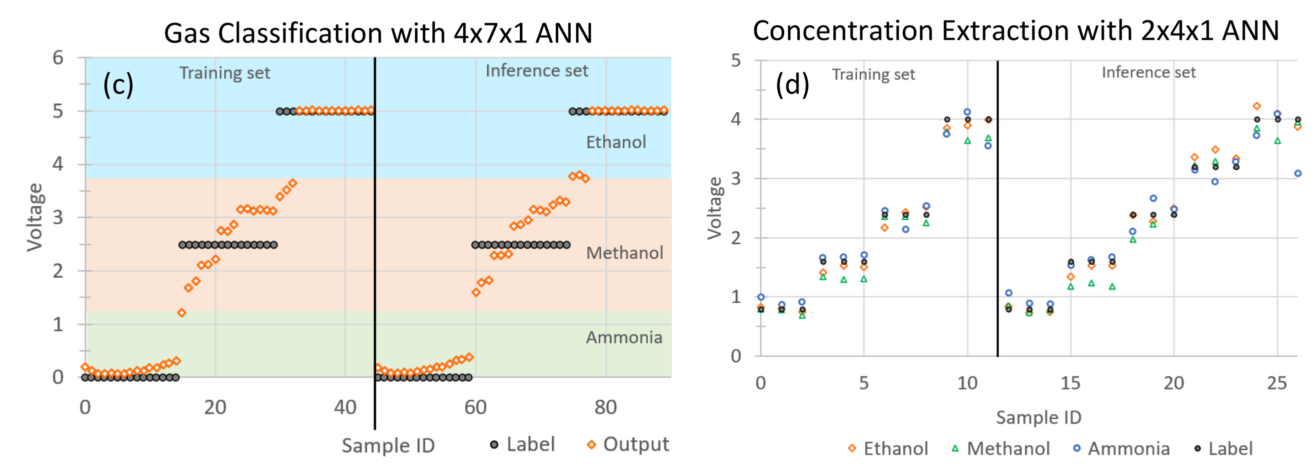
Finally, the trained models can be cascaded to extract both the classification and the concentration for the same sample. First, the type of gas is identified and then the appropriate concentration model for that gas can be used.

Results

It was possible to obtain high-quality models for *concentration inference* using a 4x4x1 ANN and training it on 30 raw sensor samples with the learning rate scheduling:



It was also possible to achieve *gas classification* by training a 4x7x1 ANN on 45 samples of 3 gases without pre-processing (Fig. (c)):



12 samples from each type were used to train models for concentration extraction (Fig. (d)). Each sample was added a suitable species-dependent bias and 2 of the sensor inputs could be removed. These 4 models were used to construct the 2-stage cascaded ANN successfully.

Conclusion

A user-friendly driver was developed, which can support many ANN structures with minimal code modifications. The hardware ANN has shown it can be trained to implement gas classification and concentration inference with high accuracy. Minimal pre-processing was needed, so these methods can potentially be used in a smart sensor application.