

ELECOMP CAPSTONE DESIGN PROGRAM

FALL 2023 SEMESTER

Homework #10

DUE: November 19th, between 8-9pm; via Google doc attachment.

Each Team will compile a word doc, with the information below, for approval by your Technical Directors, for the Symposium Handouts. You **MUST** use the Template provided at the end of this section, and also attach the 4 Figures:

- Project Motivation (~150 words)
 - Anticipated Best Outcome (ABO) (~100 words)
 - Implications for Company & Economic Impact (~100 words)
 - ***Total of 350 words, for these 3 sections (+, or – 10-word flexibility in each section)***
 - Technical Accomplishments to-date (300 words; +/- 20 words)
 - Remaining Technical Challenges for Anticipated Best Outcome (300 words; +/- 20 words)
- (The total should be about 600 words, for these 2 sections)***

For the last 2 items, use bullet format, with a few words title in bold, followed by a few lines of explanation. See the example in the template provided at the end.

Label the doc as: “Team Name: Symposium Doc: Fall 2023”

We also need 4 diagrams/pictures/etc, ***in color***, for inclusion in the Symposium Poster. Label them as **Fig. 1** through **Fig. 4**, and refer to them in the last 2 items, in the word doc, in **bold**. Each figure must have a brief caption and should be below the figure. Low resolution figures can be included in this doc. (see example template below)

Go to this link for another example of the information required in the Symposium Doc:

<https://web.uri.edu/elecomp-capstone/files/ELECOMP-Symposium-Sample-Pages.pdf>

(When compiling the Symposium Poster, you must use **high resolution** figures. More details at this Link:

<https://web.uri.edu/elecomp-capstone/files/High-Resolution-Images-Guide.pdf>

Acumentrics FaultLine: Symposium Doc: Fall 2022

Project Motivation

All electronic devices require energy to operate – which can be derived from a voltage and current value. In these electronics, power consumption changes over time; appliances consume a varying amount of power depending on their intended usage. By analyzing power consumption, a system can uniquely identify specific device characteristics. Through learning this “power signature”, a system could identify abnormal device behavior and notify users to prevent catastrophic failure.

Due to the deployment of Acumentrics’ systems in secure environments, data collection will not occur in the field. Therefore, most cases of failure analysis occur upon the return of the system to the company, usually after system failure. Similar to earthquake prediction - accomplished by analyzing characteristics at notable fault lines - the goal of the project is to be proactive instead of reactive. By leveraging machine learning, we hope to be able to predict electromechanical failures.

Anticipated Best Outcome (ABO)

The ABO is a functional prototype capable of modeling a single connected device and detecting abnormalities in behavior. The system must be non-intrusive and rely solely on the power signature of the connected device. Should our team accomplish the ABO for one device, the ideal outcome would be a prototype that can perform the above action for multiple devices connected on the same line, with unique identification of each device based on its signature.

Implications of ABO for Company and Economic Impact

As Acumentrics’ products are built to last in normally inoperable environments, integrity is an absolute requirement. As the company extends its knowledge of power systems to autonomous power, the need for data analytics and understanding continues to grow. To have a deeper understanding of electrical devices and their power signatures, Acumentrics can not only improve its own products but also improve the longevity of devices connected to those products. Therefore, the economic impact is too large to accurately measure. For existing customers, the project would allow Acumentrics to better understand its devices’ points of failure and continue to improve the longevity of those devices.

Technical Accomplishments to-date:

Appliance Selection: A fan was selected as a target appliance due to its low-cost, easily induced electromechanical faults, and complex power load. Since the appliance has both real and complex power components, the unique power signature of the device will be more identifiable. Additionally, fault modes were identified to be inducible via both environmental factors and electrical power failures.

Integrated Circuit (IC) Selection: After thorough research, the analog ADE7880 IC and corresponding evaluation board was selected for its functionality, compatibility, and accuracy. With advanced power analysis features and single/poly-phase data acquisition, the chip was an ideal choice for its high precision energy monitoring calculations that are necessary to determine unique power signatures.

Prototype Assembly: A functional prototype was designed, encompassing the evaluation board, current sense transformers and 3.3V power supply (**Fig. 1**), allowing us to sense the power data from the fan. The system is stored in an encasement with three connection receptacles: USB Type-B for computer connections, NEMA 5-15R single wall outlet input for the fan, and a C13 power socket that will feed electricity to the system from the wall (**Fig. 2**).

Machine Learning (ML) Model Selection: A Recurrent Neural Network (RNN) was selected for our application to enable effective training on the power data. RNNs are capable of learning relationships within temporal data; given an input data series, the model is capable of learning the effect of previous entries on the currently processed value. For power data, the underlying characteristics of the signature can be understood by an RNN.

ML Training Setup Formation: A script was developed to train an RNN using TensorFlow. The process includes splitting the dataset (i.e. training, validation, and test), training the model on data windows from the training/validation datasets, and evaluating the model accuracy on the test dataset. As input, a user can define the batch size, number of epochs, and data window size.

Remaining Technical Challenges for Best Anticipated Outcome:

Data Collection: Using the ADE7880 LabView software, the power data from the microcontroller can be visualized. However, access to the underlying power data is limited. Thus, a method for the collection and storage of the power data must be implemented to train the ML model.

ML Model Accuracy Improvement: As with any ML application, the main focus of the model development is on improving its accuracy. For the given application, there are a variety of methods that can be utilized to enhance the accuracy of the ML model. These methods include model hyperparameter tweaking, generation of additional feature vectors, and varying the model layer structure.

Inference System Design: A system needs to be designed to enable efficient model inference (**Fig. 3**). The system must be capable of measuring power data, feeding the data to the ML model, and informing the user of the end result. As such, the planned implementation involves using a Raspberry Pi to both facilitate the IC communication and handle on-chip model processing (**Fig. 4**). Additionally, the Raspberry Pi will notify users of the model prediction via LEDs and cellular messages.

SPI Communication Implementation: Due to the lack of a pre-built library for the ADE7880, a library will be implemented that utilizes built-in SPI functions to communicate with the IC. Although the IC manufacturer provides adequate documentation of the protocol, the technical complexity of the implementation is difficult to assess.

ML Model Export: To utilize an ML model on a microprocessor, the model will need to be exported from TensorFlow to TensorFlow Lite and deployed onto the microprocessor. This process poses a variety of technical challenges, including ML model conversion, ML model deployment, and microprocessor software development.

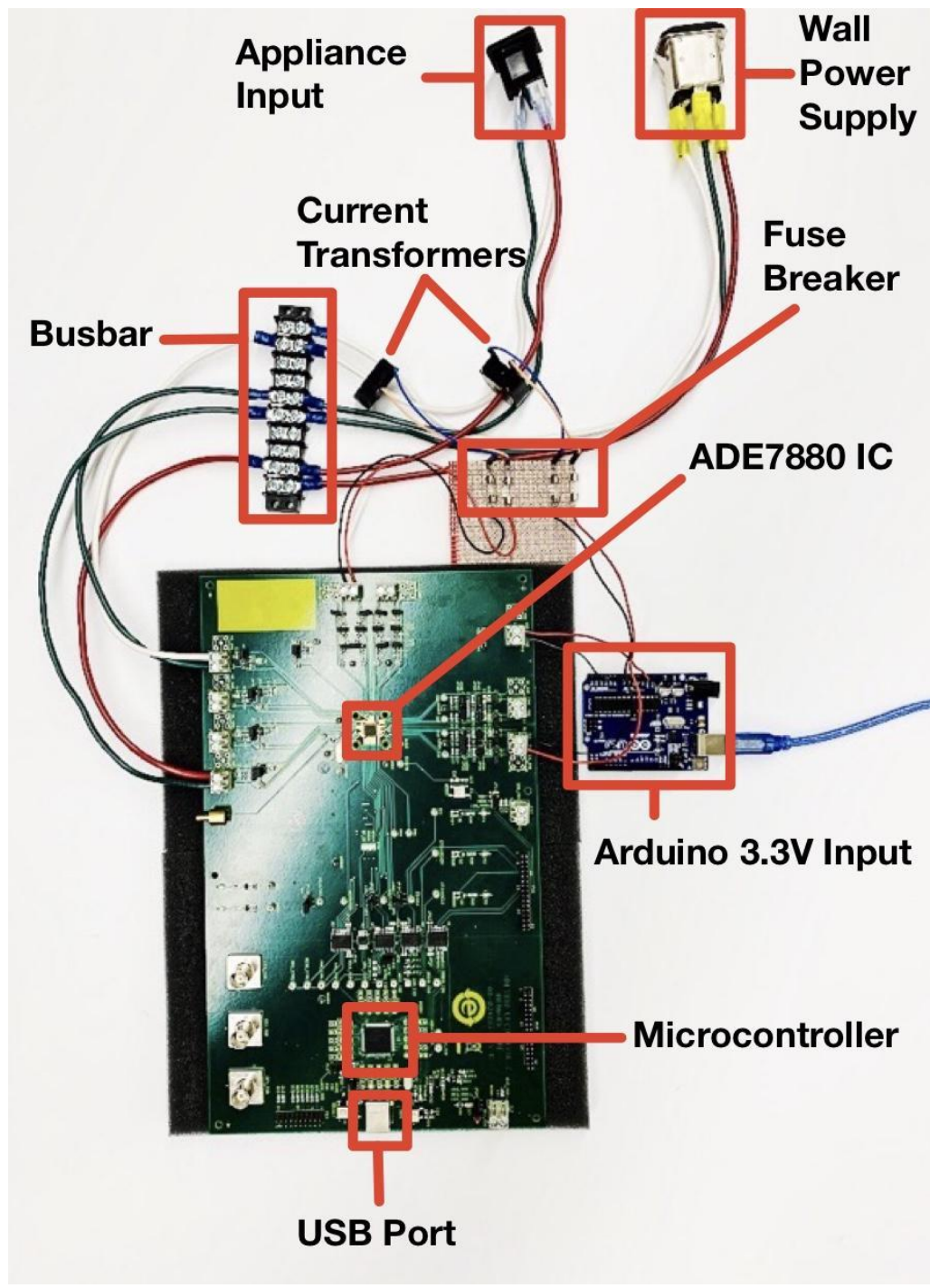


Fig. 1: The functional prototype assembly

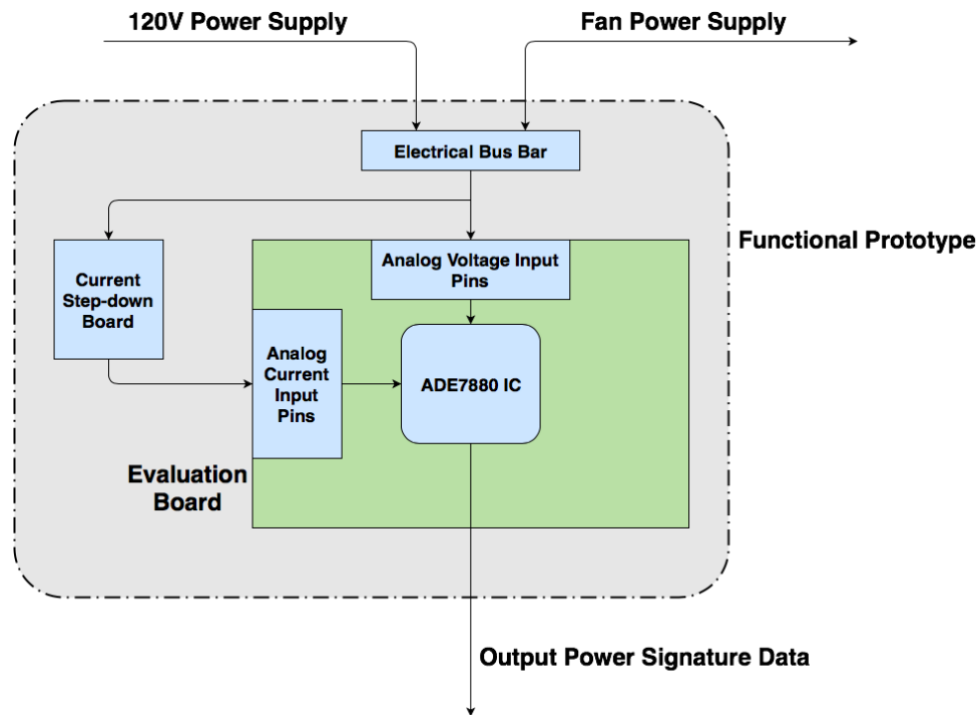


Fig. 2: The functional block diagram

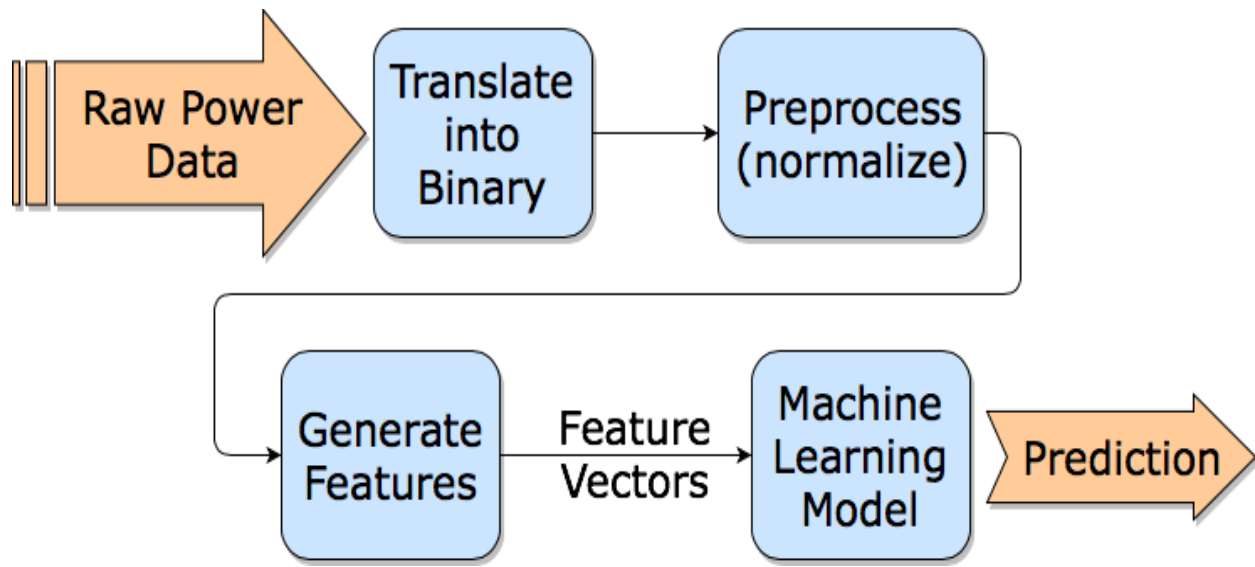


Fig. 3: Machine Learning inference process

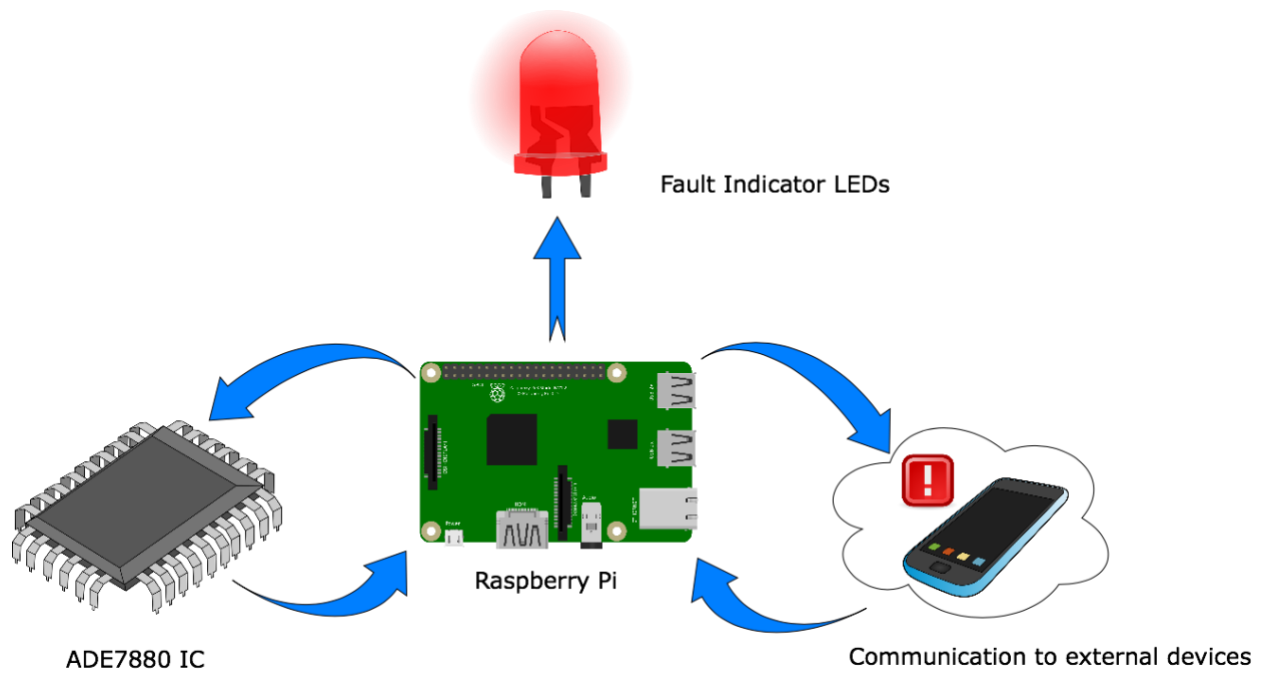


Fig. 4: Communication flowchart for the Machine Learning inference system