Spiking Neural Network on an FPGA

ECE 07

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Abstract

Sleep apnea is a potentially deadly affliction causing irregular or halted breathing during periods of sleep that many individuals will unknowingly suffer from in their lifetime. It is usually diagnosed using polysomnography (PSG) testing either in a lab environment, which is costly and accurate, or in-home tests (IHT) where it is cheaper in exchange for underestimating the apnea's severity. Machine learning has the potential to accurately predict sleep apnea severity using the same oxygen saturation levels as a PSG or IHT test. Deep learning has emerged as a vital subfield using a multi-layered architecture vaguely reminiscent of the human brain in its complexity, and it has shown to be incredibly accurate with the expense being increased power, complexity, and time requirements. The gap between PSG tests and IHTs may be reduced with a machine learning model that has the accuracy of the PSG tests and that can be implemented on the resource limited IHT kits. Bridging this gap will contribute to wider test availability while remaining economically feasible. Initially, spiking neural networks (SNN) have been observed to decrease power, computing, and time while being able to process in near real-time. Similarly, FPGAs (field-programmable gate arrays) have shown to further reduce power, computing, and time when such an SNN is programmed onto them. In addition, the FPGA's re-programmability makes it suitable to utilize any onboard SNN model. CPUs and GPUs may be used to generate these models, while the FPGA will house them and make predictions using the trained model's rules.

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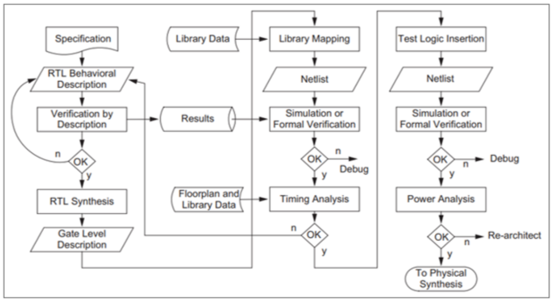
1 Executive Summary

Objective

- Implement a low-cost machine learning model that will be able to predict in near live time whether a sleep apnea episode has occurred.
- Integrate the machine learning model onto an FPGA to further reduce power and computation time.



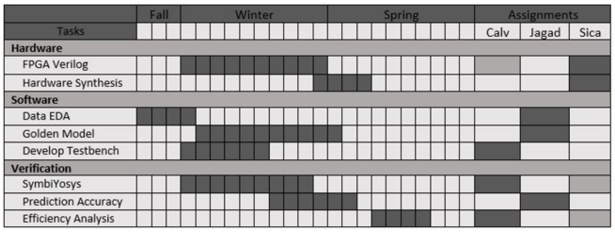
Process flow from Software to Hardware

Approach

- Utilizing sleep apnea data as an input, segment and then encode the data which then can be used to train and test a neural network to classify if an episode has occurred.
    - Primary model is a Spiking Neural Network
- Using the given machine learning model, translate the logic onto an FPGA with various gates

Key Milestones

- Machine Learning Model 2/26/2021
- Verilog Code 2/28/2021



	Fall			Winter										Spring										Assignments		
Tasks																								Calv	Jagad	Sica
Hardware																										
FPGA Verilog				■	■	■	■	■	■	■	■	■	■											▒		■
Hardware Synthesis													■	■	■	■										■
Software																										
Data EDA	■	■	■	■																					■	
Golden Model					■	■	■	■	■	■	■	■	■	■											■	
Develop Testbench				■	■	■	■	■	■															■		
Verification																										
SymbiYosys				■	■	■	■	■	■	■	■	■												■		▒
Prediction Accuracy										■	■	■	■	■	■										■	
Efficiency Analysis																	■	■	■	■				■		▒

2 Introduction

2.1 Motivation

Sleep apnea is a sleeping condition which causes the airway to become blocked at various times throughout the night, which is known as obstructive sleep apnea. If the brain does not send any signals to breathe, it may be central sleep apnea. Regardless of type, it can be very deadly to suffer from sleep apnea as it lowers the oxygen levels of the body which can reduce performance in the short-term, and if left undiagnosed, contribute to a myriad of health issues such as a heart attack, diabetes, cancer as well as a shorter life span [1].

2.2 Problem Statement

Utilizing the data as a potential use case, the team will develop and implement a machine learning model, a spiking neural network, on a processing unit, an FPGA, to improve detection and labeling of oxygen levels and brain signals. Since a technician must be required to view and analyze the data for sleep apnea, this model may eliminate the need for a technician until an episode has occurred or a sensor has been shifted. This frees the technician and allows them to perform other tasks unless the device notifies them, which will only occur if a sleep apnea episode has been detected or there is a need for adjustment. In the case of the sensor being shifted for both a PSG or an in-home test, someone can be notified, and a mark can be indicated for such an event and projections can be produced to reduce impact of data loss. Another contribution will be to reduce the threshold to utilize an in-home test kit as the accuracy will be boosted since extrapolations will be made when taking in data based on previous data acquired from the candidate's preliminary analysis. Such an analysis may include feature data such as age, height, weight, and previous medical history. Utilizing the base model and tuning the meta parameters to an individual, a model can be used in addition to a CPAP (Continuous Positive Airway Pressure) machine to reduce noise pollution and energy usage. This process anticipates bridging the gap between test types using SNNs implementations on FPGAs and producing a use case to further explore the implementation potential applications.

Present implementations utilize deep learning techniques on sleep apnea data to detect if a subject has experienced sleep apnea. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) dominate the deep learning implementation space. However, these methods do not process signals in real-time and do not predict as the events are occurring. A cornerstone for our implementation is to predict in near live time before an episode occurs based on the signals being read in. One of the important features that has been leveraged previously and will be leveraged in this implementation is the oxygen saturation index (SpO_2) which is a measurement of oxygen in the blood. These measurements will be taken from various points of the body [2]. Previous implementations have been on CPUs and GPUs. Another cornerstone is implementing this onto an FPGA. While there have been implementations of FPGAs with sleep apnea in mind, there has been a larger focus on screening and monitoring strictly [3]

2.3 Stakeholders needs

Sleep apnea impacts approximately 936 million people worldwide and more that are left undiagnosed due to the expensive cost for diagnosis. It is shown that sleep apnea impacts all walks of life regardless of gender, age, ethnicity, and location [4]. There have been studies performed in various regions to understand the demographic that experiences sleep apnea. To rank countries by how the many people of the population experience sleep apnea, the apnoea-hypopnoea index (AHI) is used. The AHI is an index that essentially states how many times a subject has experienced a severe reduction in oxygen levels which is known as an apnea episode. The criterion defined for severity is as follows: minimal cases experience five or less episodes an hour, moderate cases experience between 15 and 30 episodes an hour, and severe cases experience more than 30 episodes an hour. Utilizing this knowledge, the top ten countries that have an estimated large population of people with some case of sleep apnea are the USA, France, Germany, Russia, Japan, China, Brazil, Nigeria, Pakistan, and India. China has the largest projected population with mild cases of sleep apnea coming in at 176 million. However, this may be due to the sheer size of the overall population. It is important to note that India also has a population size comparable to China but has projected numbers comparable to the USA. This demonstrates that there does not seem to be any racial bias for sleep apnea. There are significant differences in the number of men and women affected in the Americas and in European countries. These differences are negligible in Asian countries and Australia, which may indicate a bias towards men in some parts of the world [5].

2.4 State of the Art

To diagnose a potential candidate, a polysomnograph (PSG) is taken which is a sleep study to observe the oxygen levels at various points in the body and brain signals. However, this method is expensive, in the US it approximately costs $2,999, and may not create a familiar sleep environment for the candidate which may cause complications in testing that can lead to needing more sleep studies or a misdiagnosis [6]. Another option is to take an in-home kit test; however, this option is only for candidates that may have previous familial history and show a higher proclivity for sleep apnea based on personal health history. The pricing of an in-home test can vary between $300-$600 before insurance and can vary between $0-$50 after insurance [7]. Both solutions are deemed viable, however, a PSG needs a technician or doctor to analyze the data in real-time and to ensure that the patient has not shifted the sensors while asleep. This same problem may be present with an in-home test kit and may additionally result in necessary repeats of the test since it cannot be corrected by an attending technician.

2.5 Approach

Present implementations utilize deep learning techniques on sleep apnea data to detect if a subject has experienced sleep apnea. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) dominate the deep learning implementation space. However, these methods do not process signals in real-time and do not predict as the events are occurring. A cornerstone for our implementation is to predict in near live time before an episode occurs based on the signals being read in. Spiking neural networks (SNNs) will be able to maximize the benefits of deep learning while minimizing power and computation time. One of the important features that has been leveraged previously and will be leveraged in this implementation is the oxygen saturation index (SpO_2) which is a measurement of oxygen in the blood. These measurements will be taken from various points of the body [2]. Additionally, electrocardiogram (ECG) signals of the heart or electroencephalogram (EEG) signals may be used to determine states of sleep apnea. Previous implementations have been on CPUs and GPUs. Another cornerstone is implementing this onto an FPGA. While there have been implementations of FPGAs with sleep apnea, there has been a larger focus on screening and monitoring strictly [3].

3 Materials/Resources

3.1 Hardware

- Xilinx FPGA
- Verilog - Language used to write the hardware for the FPGA
- Xilinx Vivado - Used for programming the FPGA
- CocoTB - Used for formal verification of the hardware subsystems

3.2 Software

- Python - open source programming language with a large community to leverage various libraries

  Pandas - Formally structure the data to process efficiently

  Numpy - Perform matrix manipulations

  SKLEARN - Utilize base libraries for metrics of machine learning models

  Keras & Tensorflow - Build neural network layers and preprocess data

  Seaborn - Effectively visualize features, data points, and metrics

  MNE - Effectively read and analyze signals for processing

  Snntoolbox - Convert developed ANN model into SNN equivalent

4 Results and Analysis

4.1 Artificial Neural Network (ANN)

4.1.1 Concept

ANN is an artificial neural network that is a computational model that mimics biological neural networks. There are many types of ANNs such as CNN, RNN, and SNN. There are 3 major components of an ANN. There is an input layer, hidden layers, and output layer. There are neurons or nodes for each hidden layer that connects between each layer of the neural network. The connections have assigned weights that are developed during training. An activation function drives the signal based on the weighted sum. The primary functions used were rectified linear units (ReLU), hyperbolic tangent (TANH), and Softmax. ReLU is a commonly used function for neural networks because of its simplicity. If the weighted sum of the previous connections is negative, the output is 0. However, if the weighted sum is positive, the output is the positive value. The TANH function takes the weighted sum and outputs a value in the range of -1 to 1. Softmax is a probabilistic version of the argmax activation function. An argmax activation function returns the largest value of the weights.

4.1.2 Detailed Design

The software model was developed and tuned on data available from PhysioNet, a database with electrocardiogram (ECG) signals labeled during expertly identified periods of apnea or no apnea. The PhysioNet apnea database consisted of 70 patients, with one half designated as the learning set and the other half designated as the testing set. Continuous ECG signals are provided for seven to ten continuous hours with a resolution of 100 samples per second [8]. Signals from this database were converted into binary sequences corresponding to points when the ECG signal was greater than an 80% threshold of the maximum amplitude and when the signal was below that threshold. Each patient was aggregated along with the others in the designated data category, either test or train, as a set of binary sequences all labeled as 60-second periods of apnea or no apnea. Periods of time that fell short of the 6,000 datapoints were padded as being below the threshold, and periods of time greater than this time period were truncated.

The ANN was designed to intake each binary sequence as a time series of datapoints, which would be convolved using a one-dimensional convolution layer. Training instances were grouped into batch sizes no greater than 64 at a time, and the model was compiled to train using a sparse categorical cross-entropy and accuracy metric. The decision to use a categorical metric stems from interpreting the classification of each sequence as a binary task where the sequence may be one of two classes. Following batching, the data would be further processed by a normalization layer for each batch and then rectified using a rectified linear unit (ReLU). The remainder of the network consisted of a dense layer of four neurons with weights adjusting according to the training algorithm, and finally an output softmax layer choosing between one of the two possible classifications.

4.1.3 Results

After pre-processing the data and training our model, we leveraged the training data as our testing data. This was an initial litmus test to observe the functionality of the model. The initial accuracy is 0.7955. The confusion matrix is shown in Figure 4.1.3. Other metrics that allow one to analyze the performance of the model are precision and recall. Precision determines what portion of the signals that were determined to be apnea were actually apnea. Recall determines that the signals that were actually apnea episodes were labeled as such. The precision was 0.6327 and the recall was 0.7955.

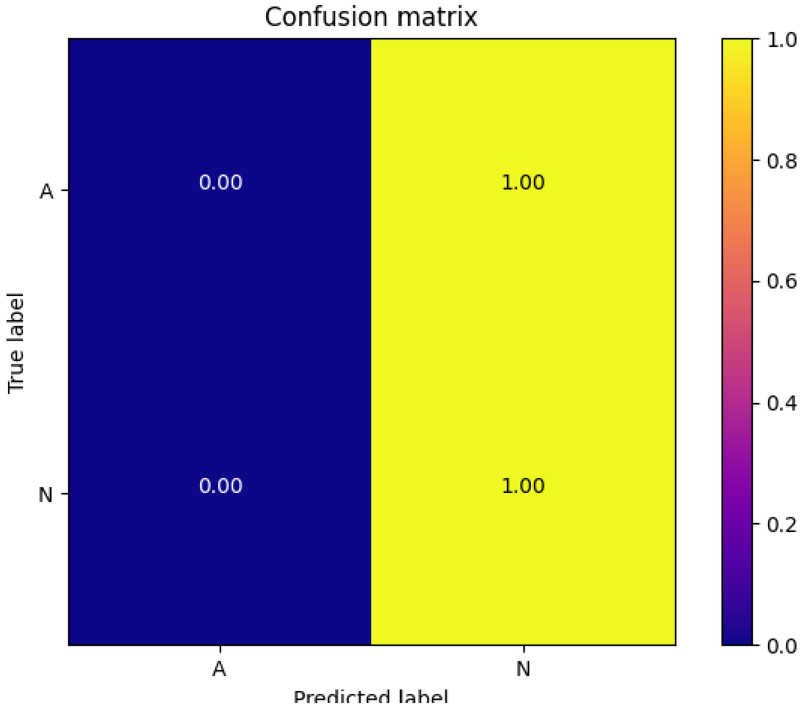


Figure 1: This is a confusion matrix of the initial ANN. It can be observed that the model is currently guessing one answer for all time segments and obtaining a high accuracy.

4.1.4 Analysis

It is evident that the model is simply just labeling each signal an apnea episode and the accuracy is simply the probability of the signal being an apnea episode. This can be attributed to the fact that at the current stage, we are passing in the training label as test labels. Currently, we are developing a pipeline that will transform and split the data in order to increase the sample size for training and testing. We are also analyzing other methods to process signals and saturation levels to extract the most important features and reduce the noise of the signals.

5 Discussion

5.1 Process

Most of the time spent thus far has been upon exploratory data analysis (EDA) as well as model synthesis. Even though most of the EDA has been completed, various modifications in how data is presented to the model has improved performance. Polysomnography signals make up the datasets for training and ideally is what the final device will use to output results. Methods for how such a set of channel waveforms should be presented to the network were explored. The simplest representation was passing a vector of values with respect to time of each signal was initially theorized for an artificial neural network. Prediction of apnea or no apnea was thought of like a natural language processing problem where a character, or in this case a signal value, would come in and the model would predict the next one. Such prediction would then be classified into apnea or not with a simple threshold. This exploration yielded results that were wildly inconsistent and seemed to depend greatly on which test data was applied to the network. A more enlightened approach took advantage of the sinusoidal and periodic nature of some of the signals such as from the echo cardiogram (ECG), which tracks the beating of the heart. By applying a Fourier transforms, or more specifically a short-term Fourier transform (STFT), features were extracted from the frequency domain instead of the time domain. Parameters of the STFT included a variable number of samples per time period that determined how long the STFT would observe the signal for before outputting a frequency analysis. Although an algorithm for determining this optimal window size has not yet been developed a cursory analysis involving hardcoded "magic number" has shown that with a proper window-size, predictions come out consistently, but with a lack of generality as well. Further considerations for how to better optimize the network such that the prediction accuracy is at an acceptable level continue to be explored. This continues at the same time as converting the software model to one that is hardware compatible with the conversion tool. Progress is presently being made on converting simpler networks fitted to the data to be compatible with the FPGA and surrounding programmable architecture.

5.2 Result

Preliminary results have shown promise when implemented with the STFT pre-processed PSG data when fed into the ANN model. Previous implementations were sporadic on predictions and during any training epoch the completion accuracy would either become insanely high or shockingly low. The inconsistencies were mitigated considerably upon first applying the STFT pre-processing step before fitting the network. Training results now feature accuracy scales well above 70% with validation falling within a similar range. Architecture modifications are underway to solve an anomaly in prediction that has developed recently where a dense ANN architecture would output the positive apnea state most of the time. Naturally, this bodes well for predicting a patient who suffers from apnea but does not generalize well to control or borderline cases.

6 Budget Update

The total cost of all materials consists only of the expenses incurred by the hardware design choice. The FPGA provided by Xilinx is the only part that incurs a cost because while there is a licensing fee of $3,500 for Vivado, there is a free webpack or lab version that can be used to program the FPGA. All other technologies used are open-source or publicly licensed databases. However, the focus is shifted onto the implementation of the software leading up to integration onto an FPGA. Therefore, the budget is $0.

7 Project Management Update

Project progress is conducted in a six-month time frame split up into three academic terms as shown in the gantt chart in Table 1. Dark colorings represent portions of time where the task is being worked on with shading under assignments corresponding to the participation of the corresponding team member. The initial month of progress determines familiarity with sleep apnea datasets and obtaining access authorization for proprietary data once familiarity is established. Following the feature selection from available data the software golden model of the SNN is developed as well as the initial architecture layout on the FPGA. Much of the winter season is spent on configuring the model and developing the hardware framework.

Connection between the hardware and software will be facilitated with a software testbench. Following the connection of the hardware and the software, prediction accuracy tests will be conducted to determine how, if at all, the model needs to be tuned. Concluding progress are the final efficiency tests for the FPGA implementing the SNN following the synthesis of the hardware bitstream. The following chart showing the time dedicated to each design goal and the relative participation of each team member to the goal is provided below.

There were delays in the implementation of the model and therefore in the integration of the FPGA. Delays were incurred from change of data type. Parsing and re-designing data pipeline, encoding data, decoding data, and transforming the models. Trial and error of fine-tuning the models through various methodologies was another source of delays.

7.1 Project Budget

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7.2 Success Benchmarks

Performance metrics such as the MSE and LSM error will give accuracy results from the software and hardware implemented model. Efficiency tests run on the hardware give a method of quantifying the total energy cost of the implementation which must remain as low as possible.

References

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Appendices

A Detailed Project Management

Table 1: Gantt chart showing the responsibilities of each team member

	Fall			Winter										Spring										Assignments		
Tasks																								Calv	Jagad	Sica
Hardware																										
FPGA Verilog				■	■	■	■	■	■	■	■	■	■											▨		■
Hardware Synthesis													■	■	■	■										■
Software																										
Data EDA	■	■	■	■																					■	
Golden Model					■	■	■	■	■	■	■	■	■	■											■	
Develop Testbench				■	■	■	■	■	■															■		
Verification																										
SymbiYosys				■	■	■	■	■	■	■	■	■												■		▨
Prediction Accuracy										■	■	■	■	■	■										■	
Efficiency Analysis																	■	■	■	■				■		▨