DNN design for posture ID using magnetometer sensor data on Arduino Nano33

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Overview

In our attempt to incorporate existing work, we maintained the same structure as prior with the modification of the sensor data considering the values of Magnetometer for the training of our model. Converting to TensorFlow lite will require a new model but has the same architecture with an additional feature for our analysis.

In the collection of sensor data, I wanted to be able to train a model with a significantly larger data set than when I had completed the operational collection for Project 02. As a result, I decided it was crucial to expedite the sensor reading process by developing a collection program for sensor data that collected data at a higher frequency than prior. Below you can see how the code for each differentiated, as I hoped to enhance the abilities of my sensor reading abilities by increasing the readings per second and expediting the baud rate. Although there would be duplications of data per second, I saw it as an opportunity to make it easier to collect larger amount of data with smaller step sizes, allowing for the ability to collect batch samples of code for each posture & record them in the Serial Monitor.

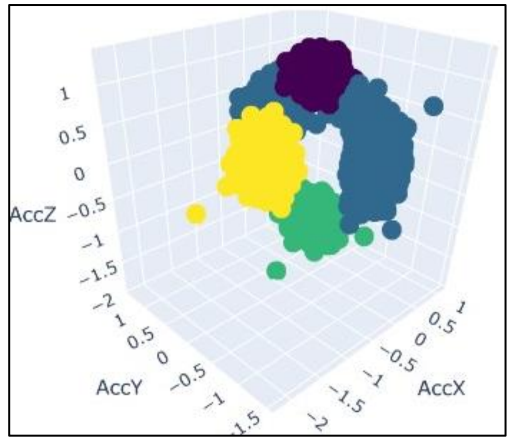
This data was recorded through the Serial Monitor and then saved into a .csv file through this script written in Python deployed for collection.

```python
import serial
import csv

# Open a serial connection to the Arduino
serial_port = 'COM6'  # Replace with the appropriate serial port
baud_rate = 115200
ser = serial.Serial(serial_port, baud_rate)

# Create and open a CSV file for writing
csv_file = open('sensor_data.csv', 'w', newline='')
csv_writer = csv.writer(csv_file)

# Write the header row to the CSV file
csv_writer.writerow(["AccX", "AccY", "AccZ", "GyroX", "GyroY", "GyroZ"])

try:
    while True:
        # Read a line of data from the Arduino
        data = ser.readline().decode().strip()

        # Split the data into individual values
        values = data.split(",")

        # Extract numeric values (skip labels)
        numeric_values = [float(val.split(":")[1]) for val in values if ":" in val]

        # Ensure that the received data contains the expected number of values
        if len(numeric_values) == 6:
            # Write the data to the CSV file
            csv_writer.writerow(numeric_values)

except KeyboardInterrupt:
    pass

# Close the CSV file and the serial connection
csv_file.close()
ser.close()
```

Data was then parsed and put into classifications.

The motivation behind my development was to create large batch files of posture data for each position to capture the discreet differences in positioning that may exist in lying face up, down, on your side, or sitting. My motivation for this project was to create a higher-level machine learning model with a large amount of data that could be reliability for sampling in the event of a future parsing/optimization of data for implementation in an embedded system. As such, it required a lot of initial data to accomplish high-level deduction now so whatever smaller model is developed from it would have a reliability dataset to rely on. My higher-level design goes through a DNN model, a dense neural network due to the sampling method resembling batches rather than sequential data. This enabled me the ability to render the data with a merged file with the states (postures) being classified numerically. 1: Supine, 2: Side, 3: Prone, 4: Prone, 5: Unknown.

Initially, I saw the possibility of using CNN to provide the ability to classify data on a 3D space, so I can use a more dimensional portrayal of the data for interpretation. This would enable me the ability to use the axis to develop the interpretation of data. Unfortunately, the use of CNN would require some material I was unfamiliar with & unable to render past a few layering pools. I chose to use a DNN architecture for the development of a functional neural network instead, which allows for the interpretation of data on a 1D vector. It runs through activation functions to model the complex relationships of the data. The SoftMax activation function is recommended for taking an output layer in a multi-class classification deciding on which is the most likely to be the data point's class.

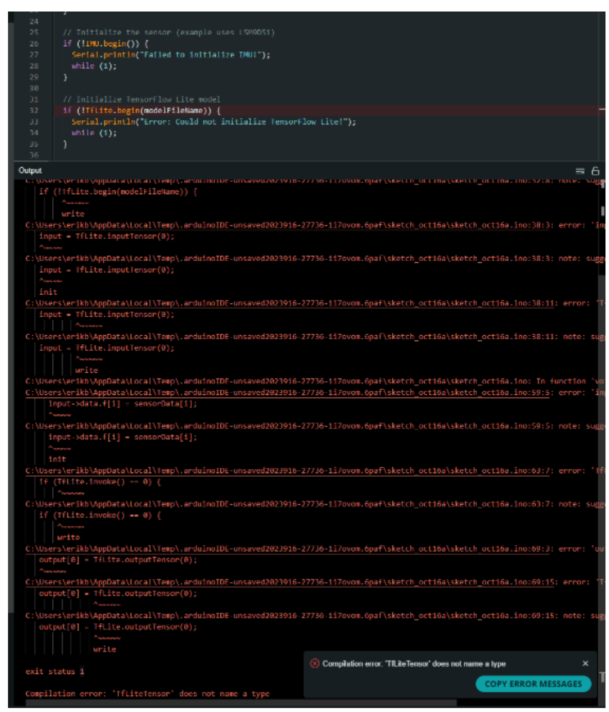


Upon collecting the data in batches for each posture, I merged the files with class identification at the beginning in the first column, 1 for supine, 2 for side, 3 for prone, 4 for sitting, 5 for unknown. Using Python, I split the data set into 60% training data, 20% validation data, and 20% test data for development of the model. Prior to splitting the data, I added noise to the files to introduce some larger variation that would not have occurred in the simulated environment as it would in a real-life sensor on someone's chest.

Function Description

After developing the model from our DNN (with no activation function) with a new dataset including data from all three sensors (Accel,Gyro,Mag). Using these for indication of the system's ability. I created a simple inclusion of all these for a model trained in Colab on Google's coding suite. As a result, I have been able to render a file model.tflite that could be deployed on an Arduino Nano33 BLE Sense board. Once I pulled in the github repository from Arduino_TensorflowLite, I attempted to deploy onto the Arduino platform. Unfortunately, the model was unable to render an understanding of the function of tf type due to the lack of ability to solve the error message:

```python
import tensorflow as tf

# Convert the model to TensorFlow Lite
converter = tf.lite.TFLiteConverter.from_keras_model(model_no_activation)
tflite_model = converter.convert()

# Save the TensorFlow Lite model to a file
with open("model.tflite", "wb") as f:
    f.write(tflite_model)
```



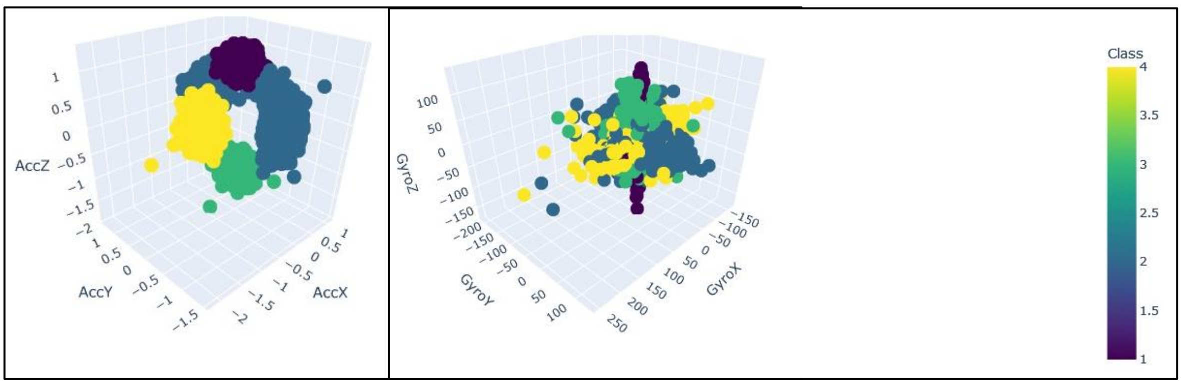
Deliverables

Rendering models into a new format required the modification of the existing DNN structure from Project 3 to classify a new sensor's data. In addition to that, we need to be able to input into the computer system which sensor we wish to read from. The prototype was a Nano33 BLE Sense Board with an adapted model in TensorFlow lite that can read live data from the accelerometer, gyroscope, or magnetometer.

Deliverables:

- New Sensor Data for Magnetometer for each class (1,2,3,4,5)
- Modified Dense neural network for the evaluation of data by evaluated variables/sensors with an interactive interface.

Experiment



In addition to the data provided for the development of the previous Project, where we saw a lot of nonlinearities in these clustering, we are intaking magnetometer data now for training& modeling a predictive model that takes in data from one of the three models exclusively. Although it is more well defined now across three different sensors, there is an extensive data collection that creates a lot of data without much space in Arduino TensorFlow Lite model. This results in some planning of the data across the y, x plane & the z axis so as to make the sensor able to detect the posture irrespective of the orientation of the Arduino board across an individual's chest or proximity to other magnetic objects (for the magnetometer specifically).

Identical collection methodology to Project 03 sensor data:

"The experiment was simulated in each position for batch data collection. I always began at supine (1) and then moved into the corresponding posture then started collecting data. This methodology coupled with 20 data points per second enabled a great return on data. A lot of data can lead to overfitting though, so I looked or methods to counter it for my non activation function DNN, which could work due to a large data set informing the options available. Pruning of the data on the edges of each use case and moving the sensor along a centerline while maintaining the position (such as supine) but orienting myself across the entire plane to make sure that all supine scenarios was a standardized methodology for training it to data that is regardless of the position of the USB orientation of the sensor. For the unknown category, I moved it around in large accelerative stages around the air, to create a dataset that when batched together would show no relational consistency & would output unknown. In a similar way, I had some cases that had large errors for certain data points in my array that ended up with wrong predictions, such as the one above from my test dataset."

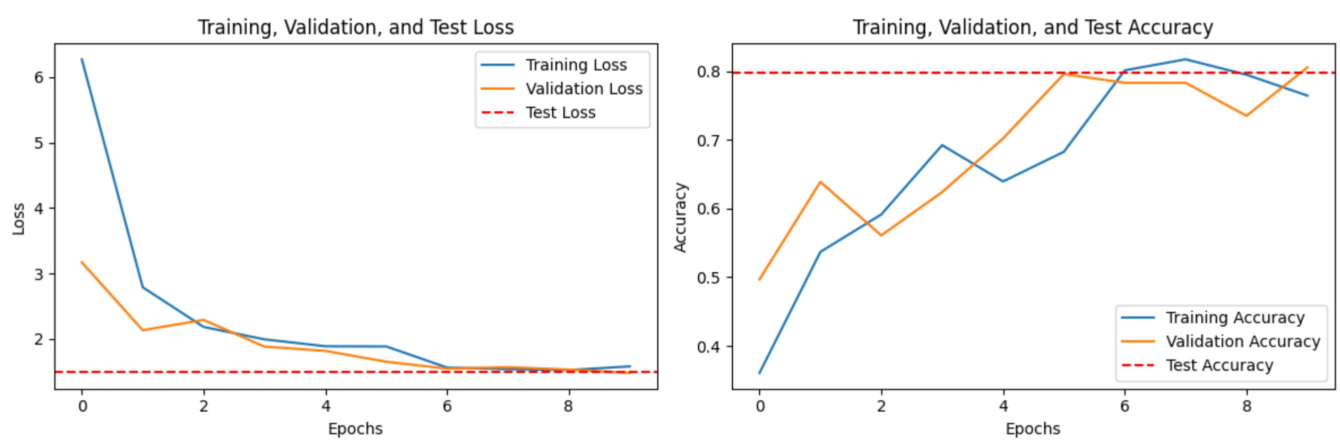
Algorithm/Architecture Development

My DNN architecture comprises an input layer with 6 nodes, representing the sensor data features (AccX, AccY, AccZ, GyroX, GyroY, GyroZ, MagX,MagY,MagZ). This is interpreted through class identification, which is developed through incorporated two hidden layers, the first with 64 nodes and the second with 128 nodes, utilizing a DNN with no activastion based on experimental comparisons on how they interpret the same training dataset. In the inclusion of new data & more data, removing the activation function will help increase simplicity for adaptation in a TensorFlow Lite model.

The output layer consists of 5 nodes, one for each classification class, employing the SoftMax activation function for converting raw model outputs into class probabilities, this was employed from documentation that had a similar structure which was used as a reference (1).

Using references & documentation, I employed the same Adam optimizer for training, which changes the learning rate during training so there is mitigation of overfitting with large datasets. In multi-class classification, an ML reference shared that **'sparse_categorical_crossentropy'** provided a way to minimize loss, this was maintained in our model, although it is unsure what quantitative effect this had once transferred into a tensorflow lite model. Regularization in the form of L2 regularization with a lambda value of 0.01 is applied to the weights of the dense layers to mitigate overfitting. The training process utilizes a batch built from a merged data excel that congregates all data for development of the training, validation, and testing of the model.

The results are show below:



Key Components:

- **Activation Functions:** The choice of activation function (e.g., Sigmoid, Tanh, ReLU) affects the model's capacity to capture complex patterns in the data.
- **Optimizer (Adam):** The optimizer algorithm (e.g., Adam) is responsible for updating the model's weights during training.
- **Loss Function (Sparse Categorical Cross-Entropy):** The loss function quantifies the difference between the predicted class probabilities and the true class labels.

- **Regularization (L2 Regularization):** L2 regularization is applied to the model's weights to prevent overfitting. It adds a penalty term to the loss function based on the magnitude of weights.
- **Validation Data:** Using a validation dataset helps monitor the model's performance and early stopping to prevent overfitting.
- **Batch Size:** Batch size determines how many data samples are processed together before updating the model's weights (set at 1000).
- **Epochs:** The number of epochs controls how many times the entire training dataset is used during training.

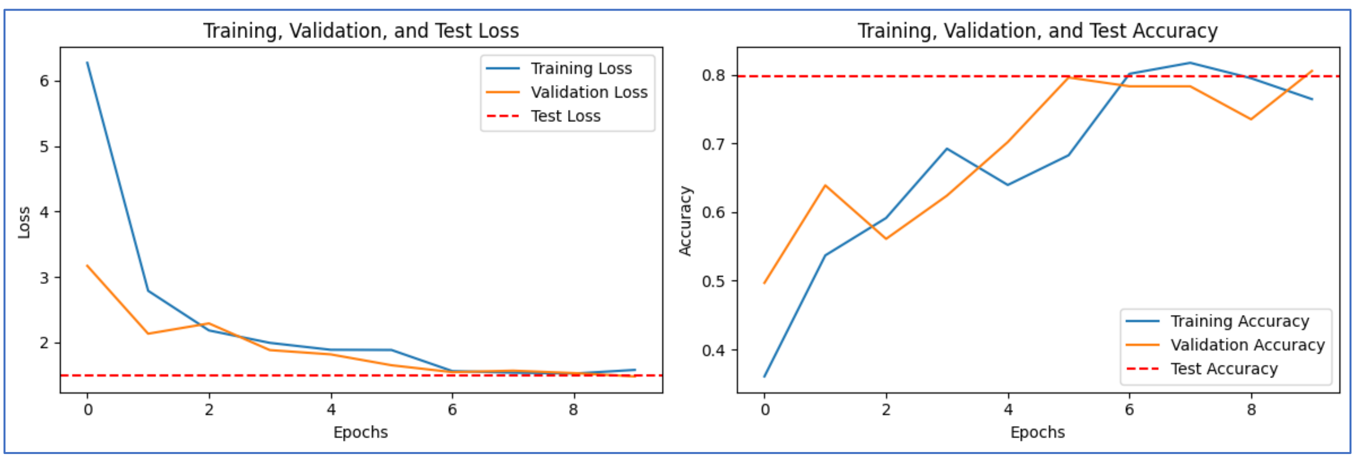
My approach for communication with the base-station was the wired connection to a laptop that would alternate between read sensors with the input of Letters A G or M for the indication of which sensor to read from.

1	Prediction using accelerometer
2	Prediction using gyroscope
3	Prediction using magnetometer

Results

The validation process teaches so much about how the code uses activation functions and neural networks to help modify and cover the development of weights and functions for decision making.

The performance for each section can be seen below, and as you can see variability exists at each section and stage on how it performed in its development:



Discussion

Unfortunately, due to issues in the import of the tensorflow library, I was unable to render predictive inferences in real time. However, test data from my model shows an 85% accuracy. Upon converting it to the lite format but being unable to deploy on the Nano33 BLE Sense board, I knew I could improve it through an alternative method of impelmention. In the future, I will look into the library to see what undefined issues I have with my tensor & what I can improve to get over this hurdle. An alternative approach can also be reducing my data for a much more simpler model, which can reduce the errors encountered so real time prediction will be accurate and capable.

References

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