Embedded Deep Learning- 18848

Virtual Boxing Trainer

Final Project Report

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Abstract:

The Virtual Boxing Trainer project aims to revolutionize boxing training by integrating wearable technology with intelligent data analysis. Using Arduino Nano BLE 33 boards equipped with inertial measurement units (IMUs), this system records, classifies, and analyzes boxing moves, delivering an interactive and engaging training experience for users. Designed for fitness enthusiasts, professional boxers, coaches, and gyms, the trainer provides a real-time prediction of punch types, enabling users to instantly identify and assess their movements. It also gives real-time feedback on performance metrics such as the number of punches thrown in each punch category (Punch, Hook, Upper, and Block) and the punch power. Additionally, it classifies users into skill levels (beginner, intermediate, or advanced) based on the total punches they have thrown. The trainer evaluates punch power of users, categorizing it as low, moderate, or high, by capturing and analyzing the real-time punch power of each punch. A user interface (UI) has been developed to enhance the usability and accessibility of the system. The UI allows users to view their real-time prediction punch types, training performance metrics including the punch count of each punch category, and power categorization, in an intuitive and visually engaging manner.

Block Diagram:



The block diagram outlines the workflow of the **Virtual Boxing Trainer** system, which is structured into four main components. First, the **Data Acquisition** module uses an Arduino Nano BLE 33 board with IMUs placed on the wrist to sense motion and acceleration data during punches. The collected raw data, which achieved high accuracy without preprocessing, is passed directly to the **Inference - Punch Classifier** module. While we experimented with applying Fast Fourier Transform (FFT) to improve classification accuracy, it increased the inference time significantly, leading us to stick to raw data for real-time predictions. The **Inference - Punch Classifier**, developed using Edge Impulse, processes the data to classify punches into four categories—Punch, Hook, Upper, and Block—while also predicting the punch power in real time. Finally, the **Performance Metrics** module estimates and visualizes key performance indicators, including punch count for each category and punch power, categorized as low, moderate, or high. This streamlined workflow ensures efficient, accurate classification and real-time feedback, enhancing the user's boxing training experience.

Dataset Collection and Cleaning:

The data collection process was a critical component of the **Virtual Boxing Trainer** project, ensuring that the model was robust and representative of real-world scenarios. As a team of three, we contributed equally to collecting data, with each member recording **50 samples per class**. Given the four punch categories—**Punch, Hook, Upper, and Block**—this totaled to **600 samples** (150 samples per class). To further improve model robustness and introduce variability, we added **150 samples each** for the "Idle" and "Other" classes. These additional classes helped the model differentiate between meaningful punches and non-punch motions. While collecting the dataset, we ensured sufficient variation in punching styles, such as differences

in motion speed and angles, to reflect the diverse techniques of different users. This was essential for the model to generalize effectively across varied punching patterns. In Edge Impulse, the data was initially sampled for **3 seconds**, and the signal waveform was then cropped to **1 second** to capture the most significant portion of the motion data. Below image shows waveforms of different punch types.



Feature Extraction:

For feature extraction, we carried out two experiments. In the first experiment, we extracted raw features from the data without any preprocessing. In the second experiment, we applied spectral analysis using an FFT length of 16 with overlapping FFT frames. The results of the spectral analysis, shown below, include the spectral power in log scale, processed features, and on-device performance metrics.



Classifier Architecture:

For the task of classifying four punch types, we implemented a feedforward neural network consisting of multiple dense and dropout layers, as shown in the architecture below. This model is well-suited for motion classification, efficiently handling 600 input features from raw data and 78 features when using spectral analysis. The dense layers progressively learn hierarchical, non-linear patterns in the data, enabling the network to identify key motion characteristics that distinguish each punch type. The dropout layers, with a rate of 0.1, mitigate overfitting by randomly disabling neurons during training, enhancing the model's generalization to unseen data. The output layer contains 6 neurons, tailored for multi-class classification, including the 4 punch types, "idle," and "other" categories. This design strikes a balance between complexity and regularization, ensuring the model effectively captures and classifies motion data with reliable performance.

Input layer (600 features)
Dense layer (60 neurons)
Dropout (rate 0.1)
Dense layer (40 neurons)
Dropout (rate 0.1)
Dense layer (20 neurons)
Dense layer (10 neurons)
Add an extra layer
Output layer (6 classes)

Confusion matrix and overall accuracy metrics:

The images below display the confusion matrices and overall accuracy metrics for two models: the one trained using raw data (left) and the one trained using spectral analysis (right). While the model trained with spectral analysis achieved higher accuracy, the model using raw data outperformed it in terms of deployment latency (6ms vs. 24ms, including feature extraction) and overall accuracy when deployed. As a result, we opted to deploy the model trained on raw data.





Proposed methodology for punch power estimation :

To estimate the power of a punch, we used mass of the fist and the accelerometer readings. We assumed that the fist makes up about 5% of the total body mass. Using the user's input weight, we calculate the mass of the fist accordingly.

Next, we measure the acceleration of the fist during the punch using accelerometer readings. We compute the magnitude of the acceleration vector as follows:

$$|a| = \sqrt{ax^2 + ay^2 + az^2}$$

Initially, we estimated the punch impact (power) by multiplying the fist mass by this acceleration magnitude.

However, we found that less forceful movements and quick movements produced similar values. To better distinguish between light and strong punches, we decided to square the initial power value. This increased the difference between light and strong punches, making it easier to classify punches more accurately.

After that, we applied thresholds to categorize the punch into one of three groups: low, medium, or high power.

Deployment Method:

The **Virtual Boxing Trainer** is a real-time interactive system designed to monitor and evaluate boxing performance through an intuitive graphical user interface (UI). Built using **Python's Tkinter** for the interface and integrated with **Arduino** for real-time data collection, the trainer classifies punch types, calculates punch power, and provides detailed performance feedback.

Key Features:

- 1. Modes of Operation:
 - **Freestyle Mode** Tracks punches for a fixed **60-second duration**.
 - **Trainer Mode** Monitors punches until predefined thresholds for punch types (Punch, Hook, Upper, Block) are achieved.

2. Real-time Tracking:

• Punch types and punch power categories (Low, Medium, or High) are dynamically updated in the UI once per second using averaged real-time data collected from the Arduino.

3. End-of-Session Summary:

- Provides a detailed overview of the training session, including:
 - **Punch Counts**: Total counts for Punch, Hook, Upper, and Block.
 - **Power Breakdown**: Categorizes punches into Low Power, Moderate Power, or High Power.
 - Skill Level: Classifies users as Advanced, Intermediate, or Amateur Boxers based on predefined thresholds.
 - **Punch Power Statement**: Highlights whether the user's punches predominantly exhibit **Low**, **Moderate**, or **High Power**.

The Virtual Boxing Trainer seamlessly combines real-time punch detection, punch power analysis, and user performance evaluation into a visually appealing and interactive platform. It serves as an effective training tool for athletes, enabling performance tracking and encouraging improvement in boxing techniques.

User-Interface of the Virtual Boxing Trainer:

Free Style Mode:



Trainer Mode:



Significant Challenges and Lessons Learned:

Throughout the development of the Virtual Boxing Trainer, several challenges emerged that provided valuable learning opportunities. One significant challenge was ensuring accurate punch classification in real time, as the variability in users' punching styles introduced inconsistencies in the data. To address this, we experimented with fully connected neural network architectures and fine-tuned hyperparameters to improve the system's ability to differentiate between punch types—Punch, Hook, Upper, and Block. Achieving low-latency feedback (under 6 milliseconds) while maintaining high classification accuracy required balancing model complexity with computational efficiency.

Additionally, collecting a diverse dataset to mitigate biases related to user demographics—such as body size, strength, and punching technique—was critical for building a fair and robust model. Designing an intuitive user interface further emphasized the importance of user-centered design, ensuring that performance metrics, including punch count and punch power, were clearly visualized for the end user. These experiences underscored the importance of iterative experimentation, model optimization, and usability considerations in developing practical and effective real-world applications.

Video Drive Link

<u>https://drive.google.com/file/d/1eWbcctMRWaTiQYxFFvqnHHgcvaeEyIEN/v</u> iew?usp=sharing