Magic Wand using Arduino Nano 33 BLE Sense

Machine Learning

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Introduction

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Introduction

- **The Synergy of Machine Learning and IoT**
  - IoT has revolutionized industries like healthcare, agriculture, and smart cities Hamdan, Ayyash und Almajali, 2020.
  - Many IoT applications demand real-time data processing, unsuitable for traditional cloud computing Shi u. a., 2016.
- **Emergence of TinyML**
  - Enables low-latency, low-power, and efficient model inference on edge devices Sakr u. a., 2020.
  - Operates on compact devices (e.g., RTOS-based microcontrollers) with long battery life Anh und Tan, 2009-09 Abadade u. a., 2023.

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Introduction

- **Arduino and Its Evolution**
  - Initially a prototyping tool, now supports IoT, wearables, and embedded systems Kushner, 2011.
  - Arduino Nano 33 BLE Sense: A 3.3V board featuring embedded sensors like accelerometers for motion detection Arduino, 2021.
- **Objective of the Study**
  - Develop a **Magic Wand"** using Arduino Nano 33 BLE Sense.
  - Program the board to recognize predefined gestures (e.g., wing, ring, slope).

Project Overview

Hardware: Arduino Nano 33 BLE Sense

- **Embedded Sensors:** Three-axis accelerometer for precise motion detection **Arduino**; **2021**.
- **Compact and Energy-efficient Design:** Ideal for portable and edge-based applications.
- **Integration with ML Frameworks:** Supports TensorFlow Lite for deploying optimized models.

Project Objective

- Develop a **Magic Wand** for real-time gesture recognition.
- Recognize predefined gestures such as wing, ring, and slope.
- Integrate lightweight ML models with Arduino Nano 33 BLE Sense for efficient, low-latency inference.

Project Overview

Output

- **Screen Visualization:** Displays real-time gesture recognition results on a terminal.

Enhanced Execution and Future Enhancements

- **Gesture Precision:** Optimized ML models to minimize false readings and ensure accuracy.
- **Edge Intelligence:** Leverage TinyML for efficient and low-latency performance on edge devices.
- **Future Enhancements:**
  - Expand gesture recognition capabilities.
  - Further optimize performance and power efficiency.

Model Implementation and Futuristic Functions

TensorFlow Lite (TFLite)

- Framework for deploying machine learning models on resource-constrained devices.
- Facilitates model optimization using techniques which are quantization and pruning.
- Enables real-time gesture recognition through efficient edge inference.

TensorFlow Lite Micro (TFLite Micro)

- Tailored for microcontrollers, including Arduino Nano 33 BLE Sense.
- Executes quantized models within the device's memory and computational limitations.
- Seamless integration with existing Arduino libraries for gesture-based applications.

Model Training Process

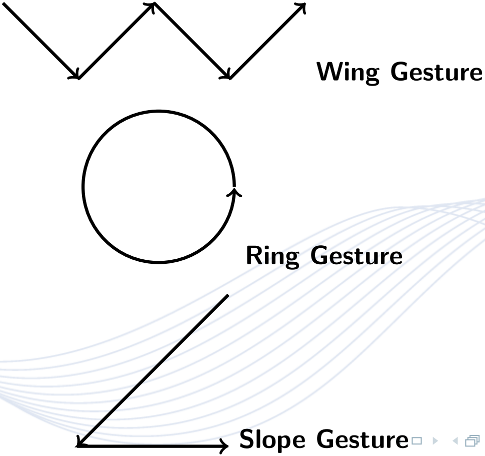
- **Data Collection:** Gather accelerometer data for gestures like "wing, ring,änd ßlope."
- **Preprocessing:** Normalize and augment data to enhance model performance.
- **Training and Optimization:**
  - Utilize CNNs for feature extraction and classification.
  - Apply quantization and pruning to reduce memory footprint.

Futuristic Enhancements

- Use Remotexy to operate the Magic Wand for its dynamic movements.
- Enchance the model by showing digital output on Arduino using Pico4ML and Pico2.
- Explore advanced optimization techniques, such as knowledge distillation, to enhance efficiency.

Gesture Types

Dataset Collection and labeling of data for three trained movements: wing (W), ring (O), and slope (/).The following figures show the direction of motion and shape for each gesture. [Warden und Situnayake, 2020]



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Challenges

Challenge 1

Resource Constraints

- The limited memory and computational power of the Arduino Nano 33 BLE Sense required optimization techniques to adapt machine learning models for deployment. [Arduino, 2021].
- High-performance deep learning models designed for GPUs or clusters are incompatible with microcontroller units (MCUs), demanding significant model simplifications.

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Challenges 2

Gesture Recognition Complexity

- Developing a robust ML model to recognize predefined gestures (wing, ring, slope).
- Accurately distinguishing untrained or ünknown" gestures.
- Avoiding false positives caused by overlapping or extended gestures, which could mislead the accelerometer readings.

Challenges 3

Model Optimization

- Ensuring real-time performance while keeping model size and computational complexity low – a critical balance for edge devices.
- Employing techniques like quantization and pruning to minimize resource usage without degrading accuracy.

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Challenges 4

Framework Adaptation

- Leveraging tools like TensorFlow Lite and TinyML frameworks, which are not fully optimized for intricate applications.
- Tailoring frameworks to meet project-specific requirements.

Solutions

Solution 1: Optimization Techniques for MCUs

- Use **model quantization** to convert 32-bit floating point models into 8-bit integer models[Arduino, 2021].
- Implement **pruning techniques** to remove insignificant model weights.
- Leverage **TinyML frameworks**, such as TensorFlow Lite for Microcontrollers.

Solution 2: Enhanced Data Collection and Model Training

- Gather a diverse and high-quality dataset covering predefined and random gestures[**shi:2016**].
- Incorporate **data augmentation** to simulate real-world noise and variations.
- Use **1-D Convolutional Neural Networks (CNNs)** for effective feature extraction.

Solution 3: Balancing Accuracy and Efficiency

- Optimize the neural network architecture by reducing layers or parameters[**shi:2016**].
- Apply **transfer learning** to adapt pre-trained models and reduce training time.
- Utilize profiling tools for performance benchmarking and fine-tuning.

Solution 4: Customizing Frameworks

- Extend TensorFlow Lite for Microcontrollers with project-specific optimizations[Warden und Situnayake, 2020].
- Use **hardware-specific libraries** like the Arduino TensorFlow Lite library.
- Implement modular testing for incremental verification.

Display Results

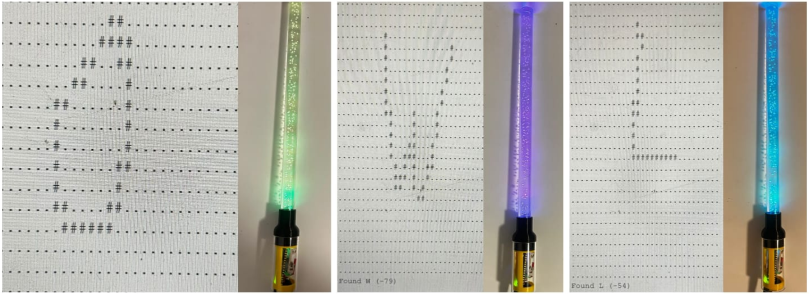

Abbildung: Magic Wand Results

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Results

Technical Achievements

- Deployed a gesture-recognition system on the Arduino Nano 33 BLE Sense[Arduino, 2015].
- Used Convolutional Neural Networks (CNNs) for feature extraction and classification.
- Optimized model size and computational efficiency through quantization and pruning.
- Achieved real-time gesture recognition on edge devices.

Future Improvements

- **Model Optimization:** Explore advanced pruning and quantization techniques[Shi u. a., 2016].
- **System Robustness:** Enhance error handling for sensor data inconsistencies.
- **Scalability:** Recognize more gestures and integrate with additional applications.
- **User Experience:** Refine gesture output and response mechanisms.

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Thanks a lot

for your attention