COMPARISON OF MACHINE LEARNING MODELS FOR WORKOUT ANALYSIS

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Abstract— **The integration of machine learning in fitness tracking has significantly enhanced workout recognition, particularly with the use of wearable devices. However, existing models often demand high computational resources, making them unsuitable for real-time processing on resource-constrained devices. This study addresses this limitation by developing a lightweight residual convolutional neural network (ResCNN) for efficient gym workout classification. The dataset comprises 50 sessions of 11 gym workouts collected from 10 participants using inertial measurement unit (IMU) sensors. Data preprocessing steps, including segmentation, normalization, feature extraction, and augmentation, were applied to enhance model performance. The proposed model is evaluated on microcontrollers such as ARM Cortex-M4, Cortex-M7, and GAP8 to assess its real-time feasibility in terms of accuracy, execution time, and energy consumption. Results indicate that the developed model effectively balances accuracy and computational efficiency, making it a viable solution for on-device workout recognition.**

Keywords:
Machine Learning, Fitness Tracking, Workout Recognition, Wearable Devices, Inertial Measurement Unit (IMU), Lightweight Neural Networks, Real-time Processing, Data Preprocessing, Resource-Constrained Devices, Convolutional Neural Networks (CNNs).

I. INTRODUCTION

The application of machine learning (ML) in fitness tracking has significantly advanced workout recognition, performance monitoring, and personalized training. Wearable devices integrated with ML algorithms enable real-time physical activity monitoring, providing valuable insights into workout routines. However, despite these advancements, existing models often suffer from limitations such as high computational demand, poor generalization, and inefficient real-time processing. This paper focuses on identifying and analyzing the key research gaps in automatic gym workout recognition using wearable resource-constrained devices, paving the way for future improvements in this domain.

II. LITERATURE SURVEY

Automatic recognition of gym workouts has been explored extensively, particularly using sensor-based and video-based methodologies. Inertial measurement unit (IMU) sensors and accelerometers are commonly used to collect motion data for exercise classification.

Um et al. proposed a convolutional neural network (CNN)-based approach for classifying 50 gym exercises using a forearm-worn sensor, achieving an accuracy of 92.1% [1]. While this study demonstrated the capability of deep learning in activity recognition, the reliance on high-computation CNN architectures limits its feasibility for real-time applications on embedded devices.

Pasula and Saha introduced a video-based deep learning framework using X3D and SlowFast models for exercise classification and muscle group activation prediction [2]. This method enhanced exercise classification accuracy but was highly dependent on video data, requiring extensive computational resources that make real-time deployment on wearable devices impractical.

Hybrid models combining sensor data with video-based analysis have also been explored, improving classification accuracy. However, these methods remain constrained by the need for significant processing power, hindering their usability in real-world fitness applications.

III. RESEARCH GAPS INDENTIFIED

Despite progress in ML-driven workout recognition, several critical challenges persist, necessitating further research. The key research gaps identified in this domain are:

1. *High Computational Demand:* Many state-of-the-art models, particularly CNN-based architectures, require extensive processing power, making them unsuitable for real-time execution on embedded wearable devices.
2. *Limited Adaptability to Real-World Scenarios:* Existing models struggle to generalize across diverse user profiles due to variations in sensor placement, individual movement patterns, and exercise execution styles.
3. *Dependency on Large and Labelled Datasets*: Most current methods rely on extensive manually labeled datasets, which are often difficult to obtain and may not cover all possible workout variations.
4. *High Latency in Inference*: The execution time of deep learning models is often too high for real-time applications, reducing their effectiveness for instant feedback systems in fitness tracking.
5. *Energy Constraints for Wearable Devices:* Many ML-based solutions are not optimized for low-power consumption, posing a significant challenge for battery-powered wearable devices.
6. *Lack of Personalized Adaptation:* Most models are designed for generic exercise recognition and fail to adapt to individual user differences, impacting overall accuracy and user experience.

IV. RESEARCH OBJECTIVES

1. *Developing Lightweight ML Models for Real-Time Workout Recognition*
   Addressing the challenge of high computational demand, this research aims to develop an efficient, lightweight neural network architecture. The proposed model will be optimized for embedded systems, ensuring minimal latency and power consumption while maintaining high classification accuracy. Techniques such as model pruning and quantization will be explored to achieve this balance.
2. *Improving Generalization Across Different Users and Sensor Placements*
   To mitigate the limited adaptability of existing models, this study will investigate domain adaptation techniques. The objective is to develop a model capable of generalizing across diverse users by incorporating data augmentation strategies and transfer learning. This will enhance robustness against variations in sensor placement and individual exercise execution styles.
3. *Reducing Dependency on Large Labeled Datasets Through Semi-Supervised Learning*
   Considering the challenges associated with acquiring large-scale labeled datasets, this research will explore semi-supervised and self-supervised learning techniques. These approaches will leverage unlabeled data to enhance model training efficiency, reducing reliance on extensive manual labeling efforts while maintaining recognition accuracy.
4. *Optimizing Model Efficiency for Real-Time Inference on Embedded Systems*
   To address the issue of high latency in inference, this study will focus on implementing knowledge distillation and hardware-aware optimizations. The objective is to reduce execution time while ensuring that the model remains accurate and reliable for real-time workout recognition in fitness applications.
5. *Minimizing Energy Consumption for Prolonged Wearable Device Usage*
   The research will explore low-power computing techniques, including hardware acceleration and edge AI optimizations. The goal is to ensure that the developed model operates efficiently on battery-powered wearable devices without significant power drainage, thereby increasing device longevity.
6. *Incorporating Personalized Adaptation Mechanisms for Individual Users*
   To enhance user-specific workout recognition, this study will integrate reinforcement learning and online learning techniques. This will allow the system to dynamically adjust to individual movement patterns and execution styles, improving long-term accuracy and user experience.

V. DATA DESCRIPTION

The dataset used in this study consists of 50 recorded sessions of 11 distinct gym exercises performed by 10 participants. The data is collected using wearable IMU sensors positioned on the participants' bodies, capturing accelerometer and gyroscope readings at a sampling rate of 20 Hz. The dataset includes exercises such as squats, bench presses, and deadlifts, with labeled annotations indicating exercise type and repetition count.

Dataset Availability:

The dataset used in this study is publicly accessible and can be obtained from the following repository:
https://arxiv.org/abs/2301.05748

VI. DATA PREPROCESSING METHODOLOGY

1. *Feature Reduction for Lower Computational Demand:* Using dimensionality reduction techniques like Principal Component Analysis (PCA) to retain only the most informative features, thereby reducing model complexity and processing time.
2. *Domain Adaptation for Generalization:* Implementing transfer learning and synthetic data generation to enhance model adaptability to different users and sensor placements.
3. *Data Augmentation for Limited Labeled Data:* Applying transformations such as time-warping, jittering, and signal permutation to artificially increase the dataset size, improving model robustness.
4. *Real-Time Data Streaming for Low-Latency Inference:* Optimizing data pipelines to preprocess and feed data in small batches, ensuring efficient real-time inference.
5. *Power-Efficient Preprocessing for Wearable Devices:* Implementing edge-computing-friendly preprocessing techniques that require minimal computational resources.
6. *Personalized Learning Implementation:* Using online learning strategies to allow real-time model updates based on user feedback, ensuring adaptive and user-specific workout recognition.

VII. CONCLUSION

This study systematically identifies and addresses key research gaps in automatic gym workout recognition on wearable resource-constrained devices. By focusing on efficient model architectures, generalization techniques, and energy optimization strategies, this research contributes to the development of real-time, low-power fitness tracking solutions. Future work will involve refining the proposed models and expanding their adaptability across broader fitness activities.

VIII. REFERENCES

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