IoT-Based Safety Gym Belt for Deadlift Injury Prevention

Saurabh Shirke
*

shirke22@iiserb.ac.in

Indian Institude oF Science Education and Reserch
Bhopal, MadhyaPradesh, India

1 Introduction

Injury prevention during strength training exercises is a growing concern, especially for high-risk movements like the deadlift, which heavily stress the lower back and spinal alignment. Proper posture is crucial to avoid muscular strains, disc herniations, and long-term spinal damage. Traditional approaches rely on expert supervision or video-based feedback, which may not be real-time, consistent, or feasible for every gym-goer. In recent years, wearable technologies have emerged as a promising solution for real-time movement analysis, offering a bridge between professional supervision and independent training. In this project, we propose an IoT-based smart gym belt integrated with Inertial Measurement Unit (IMU) sensors to monitor deadlift posture. The system leverages a deep learning model to classify each lift as "correct" or "incorrect" based on sensor data, aiming to reduce the risk of injury through posture awareness and data-driven insights.

While several studies have explored posture monitoring and activity classification using wearable devices, most focus on general activities like walking, running, or squatting. Very few have targeted weightlifting exercises, and fewer still focus specifically on deadlifts—a complex compound movement requiring strict spinal control. Moreover, existing commercial solutions are either expensive or provide limited biomechanical insights. There is a lack of low-cost, real-time, user-specific posture feedback systems designed for gym environments. Most importantly, machine learning and deep learning techniques remain largely unexplored in this domain. Current systems often rely on rule-based thresholds, which lack the adaptability and precision of data-driven models. Additionally, these systems rarely evolve with user performance over time. This gap becomes especially relevant for individuals training without supervision, who may be unaware of form degradation across sets.

To address this, our project presents a novel, cost-effective wearable belt system prototype designed to detect improper posture during deadlifts using two IMU sensors placed on the upper and lower back. Sensor data, including accelerometer and gyroscope readings, along with derived features like relative angle and delta gyroscope values, are processed through a trained deep learning model to classify form in real time. The system enables Wi-Fi-based data streaming, making it suitable for future integration with feedback apps or visualization tools. Our contribution includes a real-time sensor pipeline, a working inference model, and an early-stage posture visualization module. While still a prototype, this project shows the feasibility and promise of intelligent, IoT-integrated wearables for safer and more effective gym training.

2 Related Work

Recent advancements in wearable technology have enabled real-time monitoring of exercise form to prevent injuries. Wyckoff et al. [4] introduced Motion Tape, a skin-strain sensor capable of detecting asymmetrical muscle engagement during deadlifts, highlighting its potential in identifying improper form. Similarly, Whelan et al. [3] utilized Inertial Measurement Units (IMUs) to classify deadlift techniques, demonstrating that personalized classifiers significantly outperformed universal models in detecting form deviations.

In the realm of lifting exercises, a study by McKean et al. [2] employed dual IMUs to monitor lumbar spine angles during deadlifts, emphasizing the importance of maintaining a neutral spine to prevent lower back injuries. Furthermore, Kim et al. [1] developed a deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to predict lower back pain risk during manual lifting tasks, achieving high accuracy in classifying high-risk movements.

While these studies underscore the efficacy of wearable sensors and machine learning in monitoring lifting form, there remains a gap in integrating deep learning models with wearable devices specifically for deadlift posture correction. Our project addresses this by developing an IoT-based gym belt equipped with IMU sensors and a deep learning model to provide real-time feedback on deadlift posture, aiming to enhance safety and performance in strength training.

3 Methodology

Our system comprises a wearable setup using two **MPU9250 IMU sensors**, strategically placed on the **upper back and lower back** of the subject to capture detailed motion data during deadlift exercises. Each sensor is connected to an **ESP32 microcontroller**, which transmitssor data via **Wi-Fi** using the **WebSocket protocol** to a local server. Data are sampled every **100 milliseconds** (10 samples per second), ensuring high-resolution temporal capture of postural movement.

We collected data from **10 participants**, each performing **one correct and one incorrect deadlift**, under the guidance of a certified gym trainer. For every data point, the following features were extracted: **accelerometer and gyroscope readings** from both IMUs, a **calculated relative angle** between upper and lower back segments (based on orientation vectors), and the **delta of the gyroscope Y-axis** ($\Delta gyroscope_y$). These formed a total of **14 features** per time step.

The relative angle was calculated using the following equation.

$$\theta = \cos^{-1}\left(\frac{\vec{u}\cdot\vec{v}}{||\vec{u}||\cdot||\vec{v}||}\right) \quad (1)$$

where $\vec{u}$ and $\vec{v}$ represent directional vectors from the upper and lower back IMUs, respectively.

After data labeling and **normalization**, we trained a deep learning model using a **Sequential LSTM architecture** implemented in Keras. The model input was a **window of 50 time steps**, each with 14 features, allowing it to capture temporal dynamics of lifting form. The LSTM was followed by a **Dropout layer** to prevent overfitting and a **Dense layer with sigmoid activation** to output a binary classification: *Correct* or *Incorrect* form.

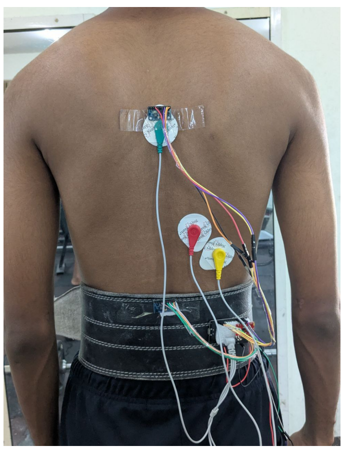

Figure 1: Setup for IMU sensor-based deadlift posture monitoring. The upper and lower back IMU sensors are fixed using medical-grade adhesive patches, connected to an ESP32 microcontroller mounted on a belt.

Table 1: Structure of IMU Data Packet Sent Over WebSocket

Field	Description
timestamp	Real-time string timestamp (Indian Standard Time)
ax1, ay1, az1	Accelerometer values from IMU 1 (lower back)
ax2, ay2, az2	Accelerometer values from IMU 2 (upper back)
gx1, gy1, gz1	Gyroscope values from IMU 1
gx2, gy2, gz2	Gyroscope values from IMU 2
relative_angle	Angle between IMU vectors (upper vs lower back)
delta_gyro_y	Difference in gyroscope Y-axis (gy1 - gy2)

The complete data pipeline is visualized in **Figure 2**.

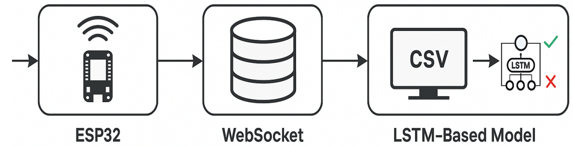

Figure 2: System Architecture – From IMU sensors and ESP32 transmission over Wi-Fi using WebSockets to local server storage, LSTM-based model training, and classification output.

4 Results

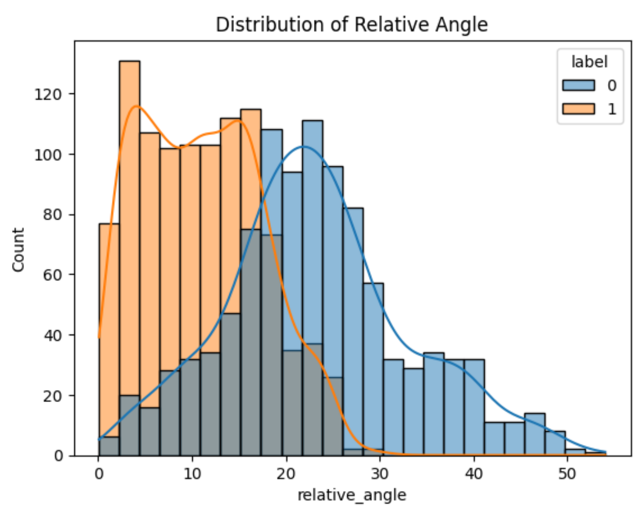

Figure 3: Distribution of Relative Angle for Correct (label 0) and Incorrect (label 1) Deadlift Postures

The distribution of the relative angle between the upper and lower back, shown in Figure 3, highlights a clear separation between correct (label 1) and incorrect (label 0) deadlift postures. Correct lifts exhibit lower relative angles, primarily between 2° and 30°, while incorrect lifts span a broader range, reaching peak around 25 °. This confirms that the relative angle is a key distinguishing feature for posture classification.

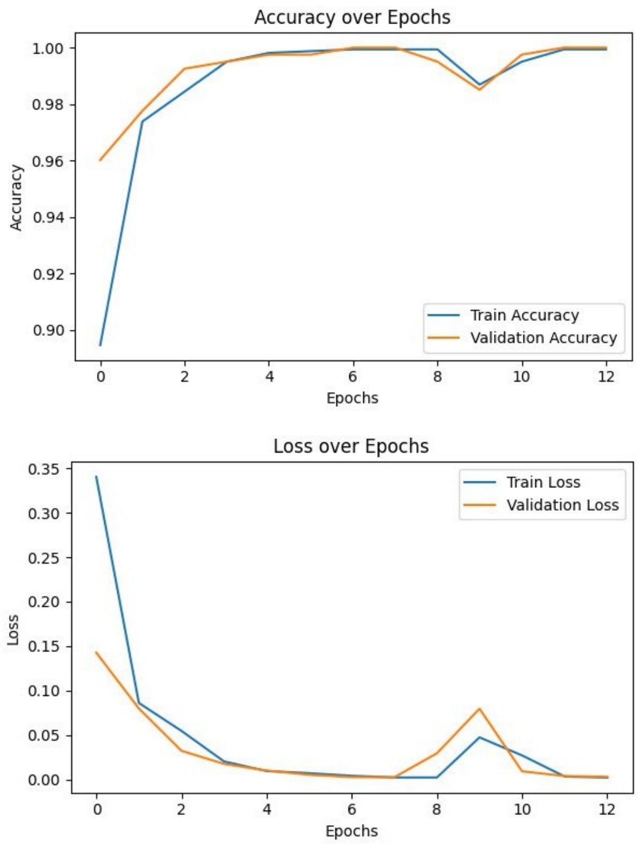

Figure 4: Model accuracy and loss over epochs. The model shows high training and validation accuracy with low loss, indicating good generalization.

The training and validation curves in Figure 4 demonstrate the model's learning performance over 12 epochs. The training accuracy steadily increased and plateaued close to 100%, while the validation accuracy followed a similar trend, indicating minimal overfitting. The loss curves also showed rapid convergence, with both training and validation loss reducing significantly within the first few epochs. A small fluctuation in validation loss around the 9th epoch suggests minor generalization variance, which was later corrected. These results validate the model's ability to generalize effectively on unseen data and confirm that the architecture is well-suited for classifying deadlift posture.

Table 2: Classification performance metrics on the test set.

Class	Precision	Recall	F1-Score	Support
Correct Posture (1)	1.00	0.99	1.00	199
Incorrect Posture (0)	1.00	1.00	1.00	203
Accuracy			1.00	
Macro Avg	1.00	1.00	1.00	402
Weighted Avg	1.00	1.00	1.00	402

Table 2 summarizes the precision, recall, and F1 score for both posture classes. The high values in all metrics reflect the model's ability to accurately classify correct and incorrect deadlift posture. Precision and recall close to 1.00 for both classes confirm that the model is neither over predicting nor missing any specific class, demonstrating excellent generalization on unseen test data.

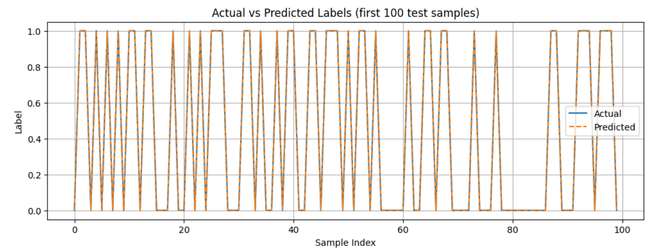

Figure 5: Actual vs. Predicted Labels for the first 100 test samples. The model predictions closely follow the true labels, indicating high classification accuracy.

Figure 5 displays the actual versus predicted labels for the first 100 test samples. The near-complete overlap between the blue (actual) and orange dashed (predicted) lines indicates a strong agreement between true and predicted values. This high fidelity implies that the model has learned to generalize well and can effectively distinguish between correct and incorrect deadlift postures. The binary nature of the labels (0 or 1) makes deviations easily noticeable, and their absence further reinforces the robustness of the model's performance.

Conclusion

The results of this study demonstrate the effectiveness of the proposed smart belt system in classifying deadlift postures with high accuracy using IMU sensor data and a deep learning model. The system achieved an accuracy of 100% on the test data, indicating the model's potential in distinguishing between correct and incorrect posture patterns.

Limitations: Despite strong performance, the dataset used was limited to deadlift sessions from only 10 individuals. This small and relatively homogeneous sample may lead to overfitting, potentially limiting the model's ability to generalize to broader populations with diverse body types, lifting techniques, and sensor variations.

Future Work: Future improvements include expanding the dataset to include more participants, which would enhance the model's robustness. Additionally, real-time posture monitoring with feedback integration is planned to assist users during lifting. Customizing an application interface and implementing 2D/3D posture visualization will improve usability and offer intuitive feedback. Further exploration of model optimization and deployment on low-power edge devices is also a potential direction.

Overall, this work lays a strong foundation for intelligent form assessment in strength training.

References

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