Methodology

Machine Learning Model

A supervised learning regression model was trained to predict throwing velocity from the processed IMU data. **Two** key machine learning techniques were employed:

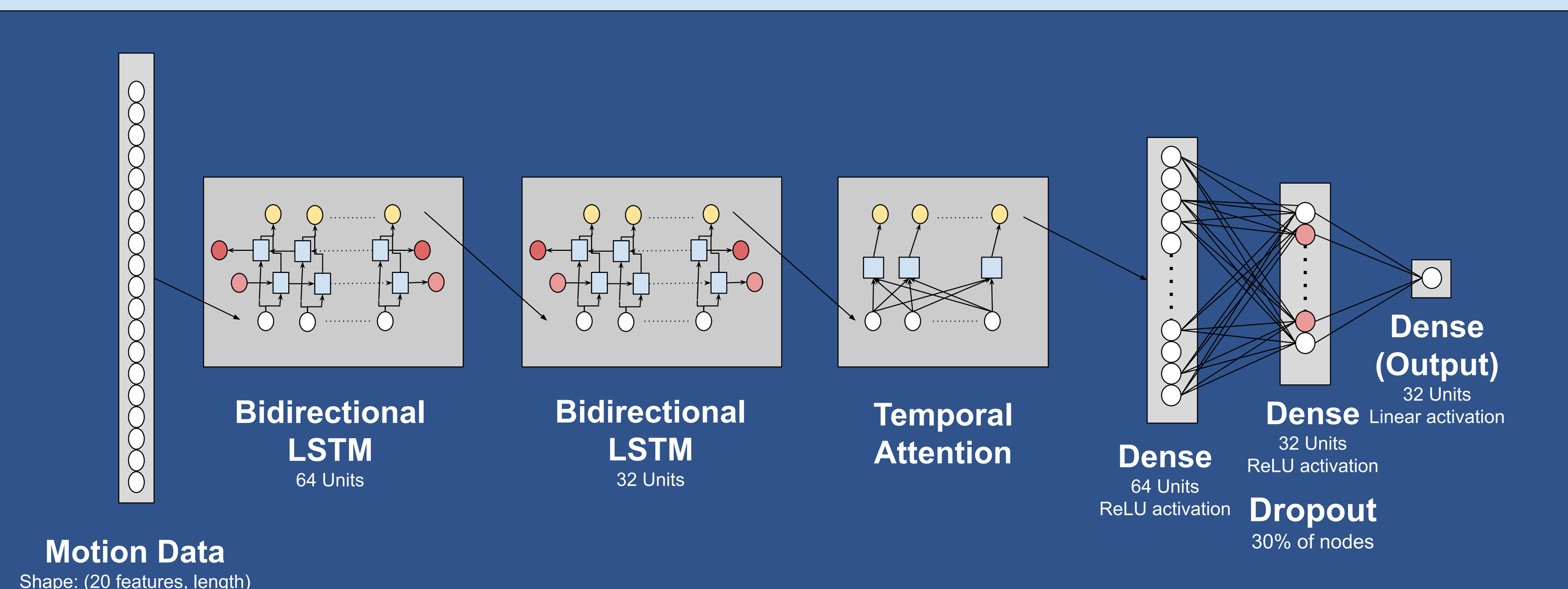


Fig 5.1: Machine Learning model parameters.

Bidirectional Long Short-Term Memory

A Bidirectional Long Short-Term Memory (BiLSTM) model, ideal for time-series analysis, was trained to capture the kinetic chain dynamics during throwing.

Recurrent Neural Networks (RNNs) are designed to process sequential data by propagating information through time steps, capturing temporal dependencies essential for modeling dynamic movements. However, standard (vanilla) RNNs suffer from the **vanishing gradient problem**, which hampers their ability to learn long-range patterns. This is problematic, especially in complex motions like throwing.

Long Short-Term Memory (LSTM) networks address this limitation by introducing a persistent memory cell and gated mechanisms that regulate information flow. This enables LSTMs to retain important information across longer sequences, making them well-suited for modeling biomechanical time-series data such as IMU outputs.

To further enhance temporal understanding, the **Bidirectional LSTM (BiLSTM)** architecture was chosen. BiLSTMs extend traditional LSTMs by processing the motion sequence in both forward and backward directions. This is particularly advantageous in biomechanics, where **early movements such as hip rotation drive and influence later actions like shoulder rotation and ball release**. By learning from both past and future context, BiLSTMs offer a more complete view of the kinetic chain, which is a concept well-established in sports science (Fleisig et al., 1995).

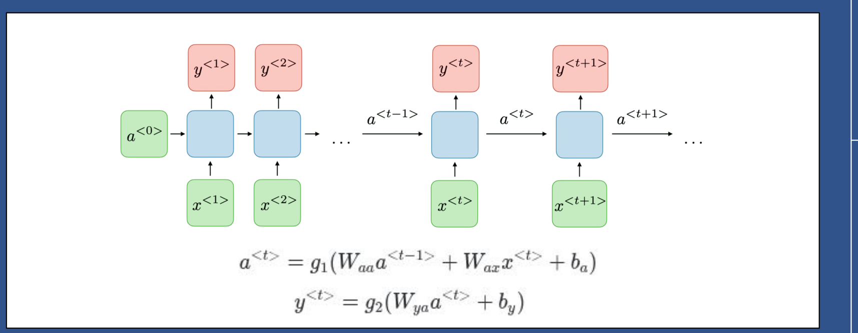


Fig 5.2: Visualized RNN (Stanford CS320).

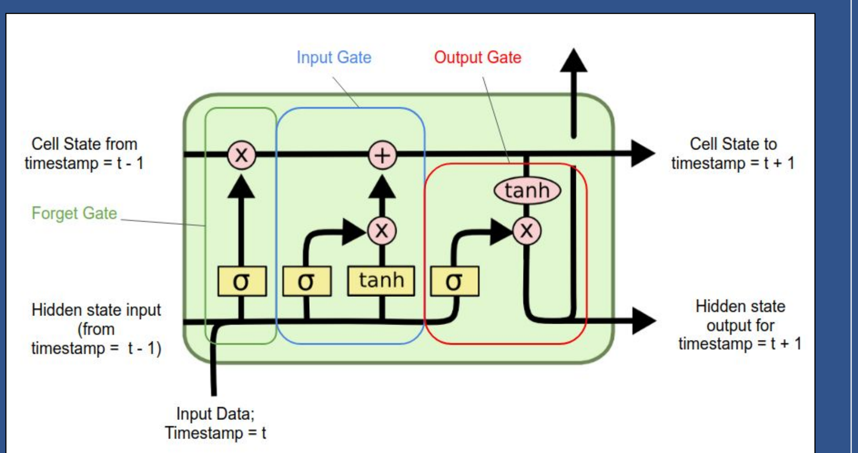


Fig 5.3: Visualization of the LSTM cell.

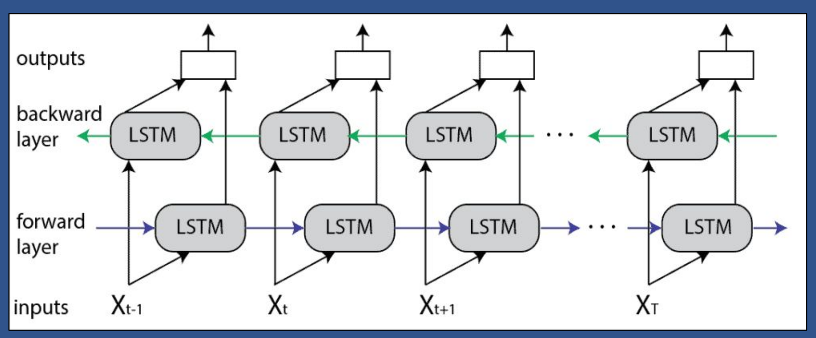


Fig 5.4: Bidirectional LSTM (BiLSTM).

Temporal Attention

A **Temporal Attention layer** prioritized critical motion phases, revealing key biomechanical patterns. This allowed the model to **weigh different parts of the motion sequence dynamically**, focusing on the most important moments in the throwing motion.

Not all parts of a motion sequence are equally important. In a baseball throw, for example, phases like arm acceleration, shoulder rotation, and ball release have a far greater impact on pitch velocity than preparatory steps or the follow-through.

A Temporal Attention mechanism allows the model to dynamically assign weights to each time step in the sequence, **highlighting the most critical moments** while **downplaying less relevant ones**. It works by first computing a relevance score for each time step based on the BiLSTM's hidden outputs. These scores are then normalized using a softmax function, producing attention weights that reflect the importance of each frame in the motion. The model then creates a weighted combination of the hidden states—emphasizing key biomechanical events such as peak hip rotation or shoulder torque.

This not only **improves prediction accuracy** but also **enhances interpretability**, allowing for an understanding of which parts of the motion the model considered most influential.

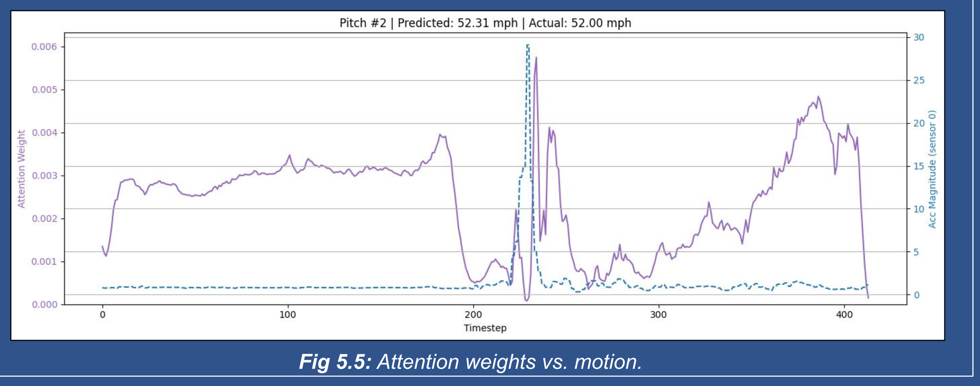


Fig 5.5: Attention weights vs. motion.

Results

MAE of 1.08 mph demonstrates the ability of machine learning to find biomechanical patterns.

Accuracy

The final model achieves a **Mean Absolute Error (MAE) of 1.08 mph**, demonstrating strong accuracy in predicting throwing velocity. This is within the typical error range of **handheld radar guns** and far better than what experienced coaches estimate visually. Considering the model uses motion sensor data instead of direct speed measurements, this accuracy is both practical and competitive. It is also low-cost, **totalling $75**. Standard radar guns, on the other hand, range from $400-$3000. Most importantly, this level of performance confirms its ability to detect subtle biomechanical cues within the kinetic chain.

Biomechanical Insights

Attention maps from the model reveal key drivers of throwing performance:

- **High-velocity throws display strong, widespread sensor activations**, particularly in hip gyroscope channels, signaling robust pelvis rotation. This reflects efficient energy transfer through the kinetic chain, where motion starts in the lower body, flows through the torso, and powers the throwing arm. A key indicator is hip-shoulder separation, where hips rotate before shoulders, creating a torque that boosts velocity. The model's focus on early hip movement mirrors this principle, aligning with elite throwing mechanics (Fleisig et al., ASMI).

- **Low-velocity throws display limited, shoulder-focused activations**, suggesting over-reliance on the arm and weak lower-body coordination. This inefficiency may reduce performance and elevate injury risk. These insights validate the system's potential for broad biomechanical analysis in sports, rehabilitation, and beyond.

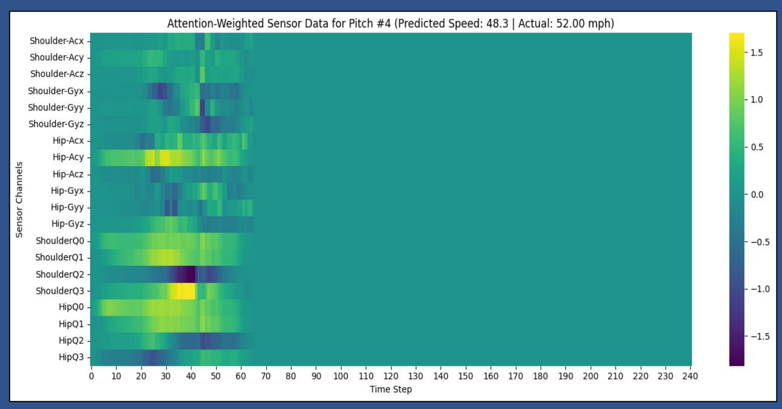


Fig 6.1: Broader activations reflect effective transfer of energy, leading to higher velocity throws.

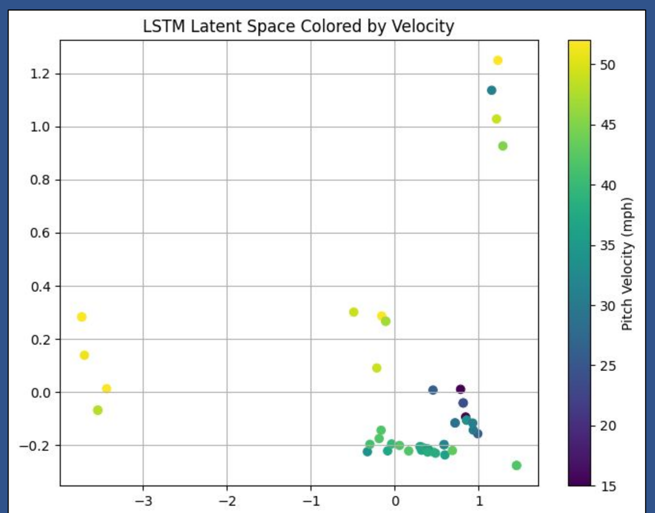


Fig 6.2: Distinct clusters are present, indicating that the model is learning crucial patterns.

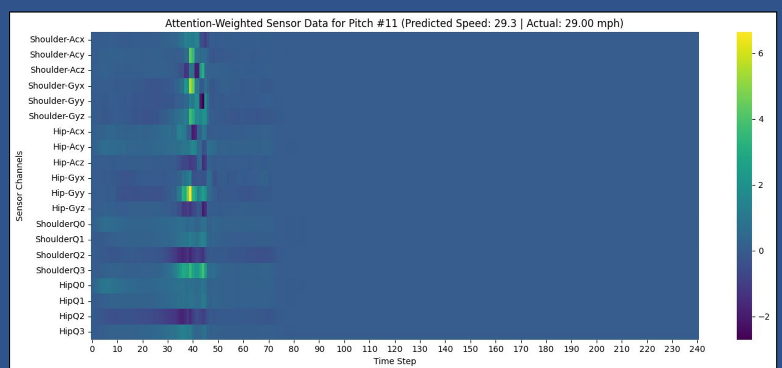


Fig 6.3: Short, narrow activations indicate lack of full-body movement and over-reliance on the arm.

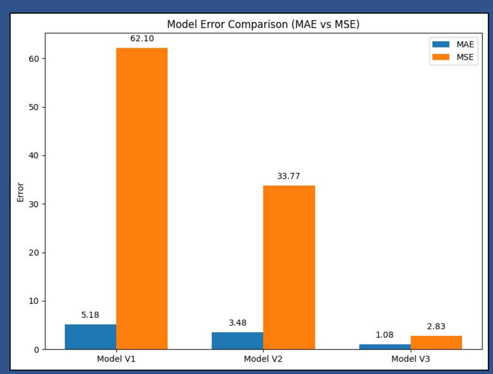


Fig 6.4: Model error comparison on test set.

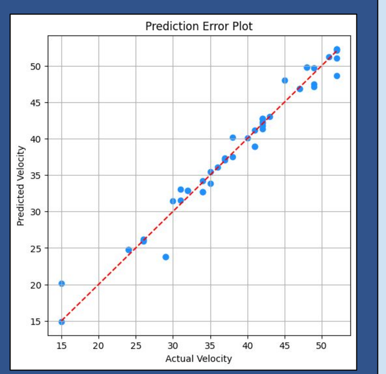


Fig 6.5: Model V3's prediction error on the test set.

Impact

Techniques used can be extended to diverse fields, making everyday life better for billions of people.

Breakthrough Innovation

This system successfully demonstrates how wearable sensors and deep learning can integrate to analyze complex human movements. It pioneers affordable biomechanical analysis with affordable hardware combined with deep learning, yielding **high accuracy**. Unlike existing solutions, such as motion capture labs exceeding $100,000 or other systems priced well above $10,000, which prioritize performance over interpretability, it incorporates novel methods to deliver both high accuracy and clear insights into the kinetic chain. **No other current low-cost solution exists which matches this balance of precision and analyzability.**

Open Source

This work is **open source on GitHub and Colab,** meaning anyone can build off of this work and improve research in the field.

Broad Application

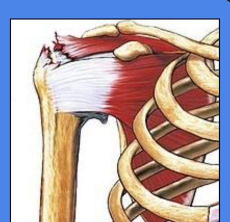
By analyzing complex movements like the baseball throw, this system democratizes advanced motion analysis for youth athletes and extends its techniques to diverse fields. It empowers users with real-time, actionable feedback to optimize performance, prevent injuries, and enhance health.

The first ever low-cost, scalable method for biomechanical analysis using machine learning.

Prosthetics & Assistive Technology
Track limb motion to improve responsiveness in prosthetic systems.

Ergonomics & Workplace Safety
Monitor worker movements to prevent repetitive strain injuries.

Injury Prevention
Detect inefficient movements to reduce joint stress and overuse risk.



Healthcare & Rehabilitation
Provide affordable, real-time feedback to correct motion during therapy exercises.

Future Improvements

Data Diversity and Bias

Expand the dataset with diverse athletes and address **right-handed dominance bias** to improve model accuracy and generalizability across athletic profiles.

Fig 8.1: An example of electromyography (EMG) sensors placed on hand.

Muscle Sensor Integration

Incorporate **electromyography (EMG) sensors** to capture muscle activation patterns, enhancing understanding of biomechanical dynamics in the kinetic chain.

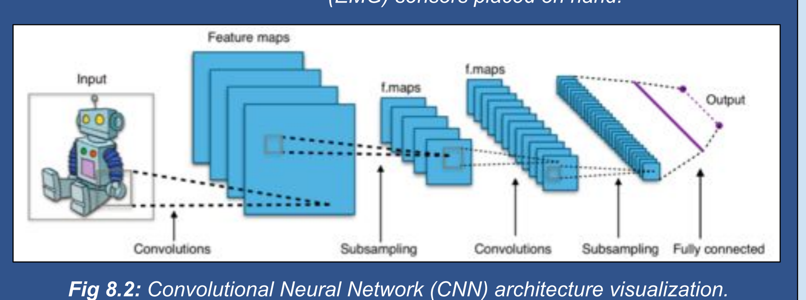


Fig 8.2: Convolutional Neural Network (CNN) architecture visualization.

Computer Vision Analysis

Extend the machine learning pipeline with a **Convolutional Neural Network (CNN)** to analyze motion visualizations and enable AI-driven feedback.

Broader Applications

Adapt the system for use in **rehabilitation, ergonomics, and physiotherapy beyond sports.**

Sources of Error

IMU Drift

Low-cost sensors like the MPU6050 can suffer from **gyroscope drift and high-frequency noise**, especially over longer durations. This can distort acceleration and angular velocity readings.

Limited Sensor Coverage

With only two IMUs (hip and shoulder), important motions at the elbow, wrist, or foot are not captured. Missing these segments can reduce model performance when trying to understand the full kinetic chain.

Attachment Inconsistency

Slight differences in how tightly the sensors are strapped on, or variation in placement between throws or participants, can affect the reliability of the measurements.

Participant Variability

Individual differences in throwing style, strength, and consistency introduce noise into the data. Especially with a small sample size, this can make it harder for the model to generalize.

Thanks and References

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