Low-cost sensors and machine learning enable real-time motion analysis, making **biomechanics more accessible** for sports, rehabilitation, and health.

Biomechanics, the science of human movement, holds immense potential to improve our everyday lives.

Access to biomechanical analysis is significantly limited, particularly for youth athletes and everyday individuals.

Motion analysis driven by machine learning offers a novel, affordable solution for biomechanical analysis.

The Problem

Analyzing biomechanics is expensive.

Biomechanics, the study of human movement, is essential for preventing injuries, aiding rehabilitation, enhancing sports performance, and promoting lifelong health. However, **access to biomechanical analysis is limited**, particularly for youth athletes and everyday individuals, where movement patterns can shape long-term physical development.

Current biomechanical systems are costly, often exceeding **$10,000**, while advanced motion capture labs can surpass **$100,000**. These expenses make these systems inaccessible to the people who need them the most. Furthermore, specialized expertise is required to interpret the complex data biomechanical systems produce.

Biomechanical System	Focus	Price Range (CAD)
Xsens MVN	Sports science, rehab, movie/VR	$12,000 to $50,000+
Vicon Motion Systems	General lab-grade optical motion capture	$50,000 to $300,000
Noraxon MyoMotion	Clinical biomechanics (rehab, sports)	$100,000 to $150,000
K-Motion/K-Vest	Baseball, golf and physiotherapy	$10,000 to $15,000+
KinaTrax	**Markerless motion capture for baseball**	**$50,000 to $300,000+**

__Fig 1.1:__ Current biomechanical systems with their applications and estimated price ranges.

The Solution

Machine learning allows for the use of low-cost sensors while providing valuable insights in real-time.

This project harnesses low-cost wearable inertial measurement units (IMUs) and machine learning to make biomechanical analysis **affordable, accessible and scalable.**

Artificial Intelligence and Machine Learning excel at **recognizing patterns**. Current applications include image classification, object detection, disease detection, speech recognition, translation, and chatbots.

Applied to biomechanics, they can analyze human motion more accurately and consistently than humans. This not only improves analysis quality but also enables the use of lower-cost sensors and minimal equipment without sacrificing reliability.

By focusing on the baseball throwing motion, it showcases a solution with far-reaching potential. There were four reasons why the throwing motion was the most viable candidate:

Motion Complexity

The baseball throw is a complex motion requiring coordination of the hips, torso, shoulder, and elbow. Analyzing this kinetic chain—how energy transfers through the body—offers insights into optimizing movement efficiency.

High Injury Risk

Throwing generates extreme forces, with shoulder rotation speeds reaching over 7,000 degrees per second, akin to a car engine when traveling at 80 km/hour (Fleisig et al., 1995). Poor mechanics are the leading cause in injuries, with more than **45% of youth pitchers reporting arm pain** (Matsuura et al., 2013). Understanding these stresses can reduce strain and prevent harm.

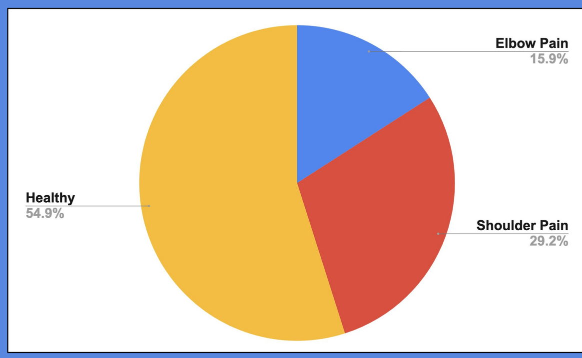

__Fig 2.1:__ Distribution of health status among youth baseball players (Matsuura et al., 2013).

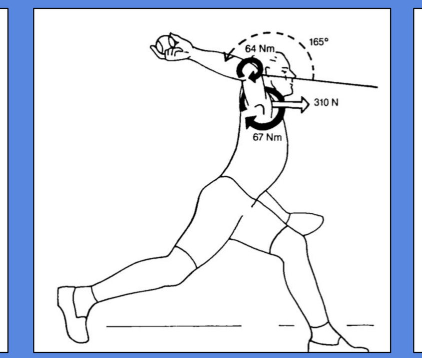

__Fig 2.2:__ Loads are equivalent to holding 60 lbs in this position. (Corocan, 2019)

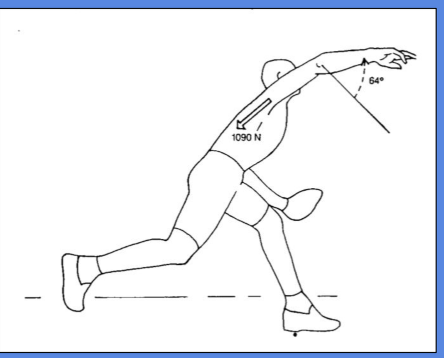

__Fig 2.3:__ The rotator cuff and labrum experience 245 lbs of compressive force. (Corocan, 2019).

Repeatable Motion

The baseball throw is a discrete, well-defined action. Unlike continuous activities like running or walking, it starts and ends cleanly, making it easy to segment and analyze. This repeatability ensures consistent, high-quality data collection across trials and subjects.

Quantifiable

Throwing velocity is simple to measure with a radar gun or high-speed camera and serves as a clear performance metric. This provides a direct label for training machine learning models and a meaningful benchmark to assess biomechanical efficiency.

The development of this system paves the way for widespread biomechanical analysis. It empowers athletes, coaches, and clinicians to optimize performance and prevent injuries across sports, rehabilitation, and daily life.

System Design

Hardware

Two **MPU6050 inertial measurement units (IMUs)**, worn on the **hip** and **upper throwing arm**, capture motion data. This includes information about each sensor's acceleration and angular velocity. An **Arduino Uno R4 WiFi microcontroller** processes and transmits the data in real time using Bluetooth. The devices are connected through the I2C communication protocol.

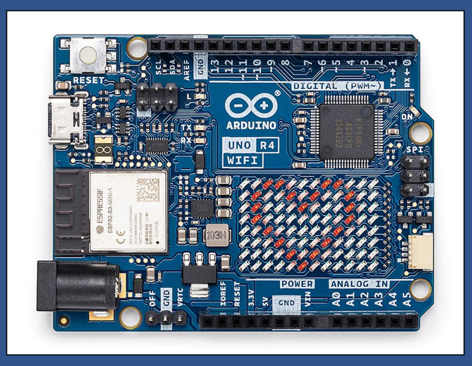

__Fig 3.1:__ Arduino UNO R4 WiFI microcontroller.

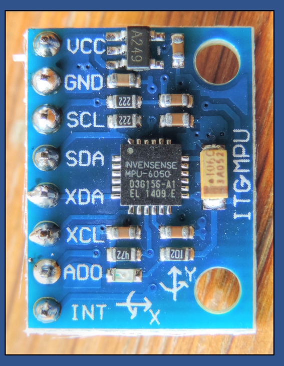

__Fig 3.2:__ MPU6050 IMU.

Firmware

Custom C++ firmware on the Arduino enables seamless communication with the IMUs, ensuring accurate and continuous data collection.

Data Collection Software

A Python script, running on a MacBook, connects wirelessly to the microcontroller via **Bluetooth**. It retrieves motion data and saves it as CSV files for training.

Analysis Software

Using **TensorFlow**, a Bidirectional Long Short-Term Memory (BiLSTM) model with a Temporal Attention layer was trained to predict throwing velocity and uncover biomechanical patterns across diverse movements.

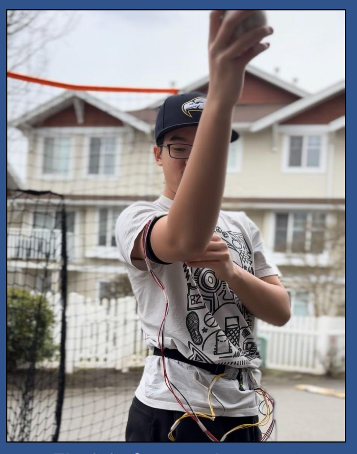

__Fig 3.3:__ Sensor placement.

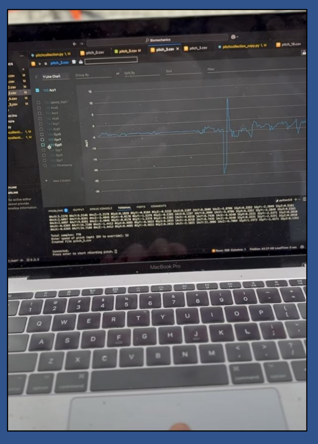

__Fig 3.4:__ Analyzing motion data on a computer.

Methodology

Objective

Demonstrate the ability of machine learning to analyze biomechanics by predicting throwing velocity and generating interpretable visual insights from sensor data.

__Fig 4.1:__ Collecting data.

Data Collection

Twenty youth baseball players ages 10-16 wore two lightweight Inertial Measurement Units (IMUs): one secured **around the hip like a belt**, housing a microcontroller and sensor, and another **strapped to the upper throwing arm**. Data was streamed to a computer for further processing through Bluetooth.

Each player completed about 20 throws, producing over **400 throws and 120,000 data points** (timesteps). A portable radar gun measured throwing velocities for model training.

Data Processing

Accelerometer (m/s²) and gyroscope (°/s) data from the hip and arm IMUs were merged into a unified time-series using a **Complementary Filter**.

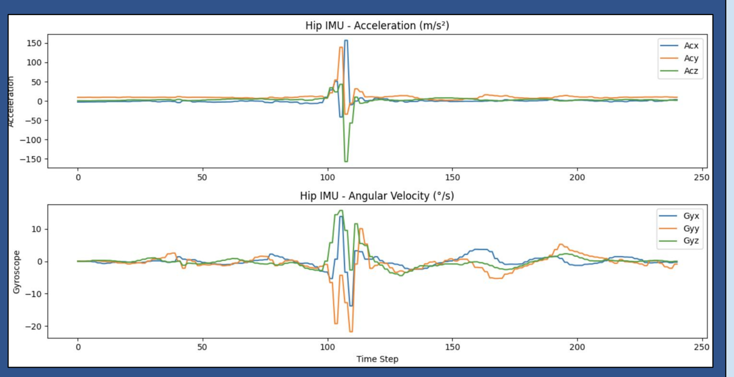

__Fig 4.2__ Raw data from hip IMU.

A Complementary Filter **fuses accelerometer and gyroscope data** by blending their strengths: the gyroscope provides smooth short-term motion, while the accelerometer corrects long-term drift. It offers a simple, efficient way to achieve accurate motion tracking, ideal for real-time, dynamic applications like human movement analysis. The filter was configured with **α = 0.98**, favoring gyroscope data.

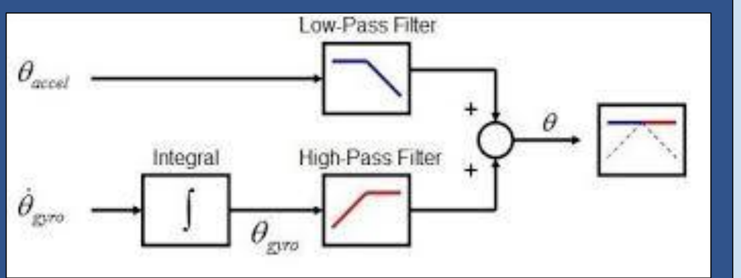

__Fig 4.3:__ Complementary filter (Page et al., 2014)

Normalization standardized the data's scale, ensuring no single feature skewed the model.

Feature engineering was kept minimal to preserve interpretability. Each processed sequence was labeled with radar-measured throwing velocity for supervised learning.

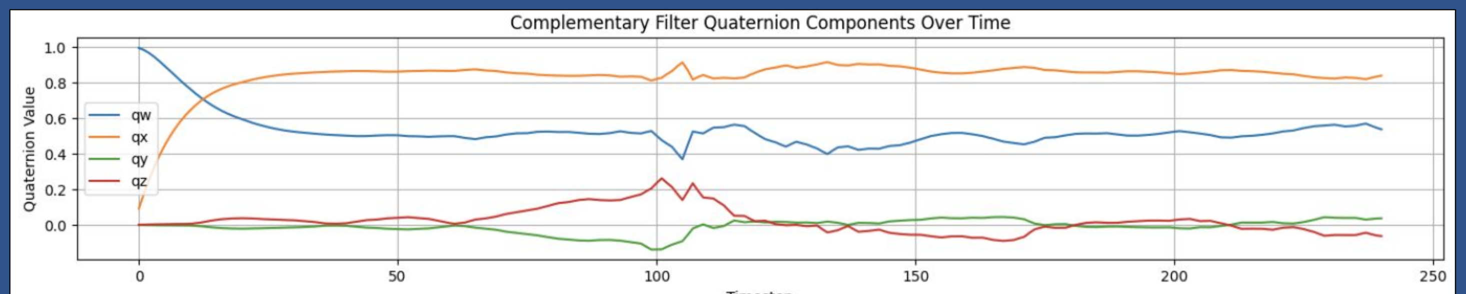

__Fig 4.4:__ Hip IMU data, after sensor fusion using Complementary filter.