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WEARABLE-BASED KINEMATIC ANALYSIS OF CRICKET BOWLING

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Abstract: This work presents a low-cost wearable sensor system for real-time kinematic analysis of cricket bowling. The system integrates MPU6050 IMU sensors placed on the wrist, elbow, and spine, along with a MAX30100 heart-rate sensor and DHT11 temperature—humidity sensor. Data is captured through an ESP8266 NodeMCU and transmitted to a cloud platform for processing. Machine learning algorithms classify bowling phases and detect technique deviations, while a synchronized 30-FPS camera provides visual verification. A web dashboard displays real-time biomechanics, physiological status, and automated performance reports. The system provides an affordable alternative to high-end motion-capture solutions, supporting injury prevention and performance improvement.

Keywords: Data Visualization, Kinematic Analysis, Machine Learning, Wearable Inertial Sensors, Cloud Storage.

I. INTRODUCTION

Cricket fast bowling involves complex biomechanical movements that, when repeated incorrectly, can lead to spine, shoulder, and elbow injuries. Traditional coaching mainly depends on manual observation and video analysis, which lack precision and real-time insights. High-end motion capture systems exist but are costly and unsuitable for field use.

Wearable sensors and machine learning now enable accessible, portable biomechanical analysis. IMUs can capture acceleration, angular velocity, and orientation, providing accurate measurements of bowling phases and joint mechanics. This project develops a multi-sensor wearable system capable of capturing bowling motion, classifying actions using machine learning, and displaying analytics through a cloud dashboard.

This project focuses on the **development and implementation of a low-cost wearable sensor system** that can accurately capture the bowling motion, classify the different phases of the bowling action, and assist in identifying improper techniques that may contribute to injury risks. By leveraging **machine learning algorithms**, the proposed system is capable of recognizing and classifying the different motion patterns of a bowler, thereby providing actionable feedback to coaches and athletes.

The **core of the system** lies in the fusion of hardware and intelligent software. The hardware component includes sensors such as the **MPU6050** (accelerometer + gyroscope) mounted on the bowler's wrist, elbow, and spine to record real-time motion data. A heart rate sensor (MAX30100) and temperature and humidity sensor (DHT11) can be integrated to monitor physiological responses during bowling. These readings are transmitted through the **ESP8266 NodeMCU**, which connects to the cloud for data visualization and storage. The software component, implemented in **Python and Arduino IDE**, processes and filters the data, applies **machine learning models** such as Decision Tree, K-Nearest Neighbour (KNN), and Artificial Neural Networks (ANN) to classify motion patterns, and presents insights through an interactive dashboard.

For instance, in bowling, the sequence from the **run-up**, **delivery stride**, **release**, and **follow-through** involve complex interactions among the trunk, shoulder, elbow, and wrist. Each phase contributes to the outcome of the delivery, including ball speed, line, and swing. Even minor inconsistencies in the sequence can affect accuracy and potentially lead to injury. Wearable inertial sensors can quantify parameters such as joint angular velocity, arm rotation, and back flexion, thereby enabling **objective performance evaluation**.



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II. METHODOLOGY

This methodology consit of:

- Multi-Sensor Data Collection
- Centralized Processing Using ESP8266 NodeMCU
- Wireless Data Transmission to Server
- Camera Feed for Visual Motion Capture
- Machine Learning–Based Analysis
- Generation of Analysed Output
- Real-Time Web Dashboard Visualization
- Video Output with ML Overlay

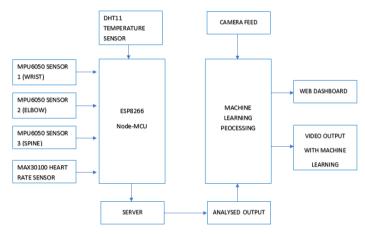


Fig 1 Block diagram of Wearable-Based Kinematic analysis of Cricket Bowling

- The system begins by collecting real-time physiological and biomechanical data using three MPU6050 IMU sensors placed on the wrist, elbow, and spine, along with a MAX30100 heart-rate sensor and a DHT11 temperature sensor.
- All sensor modules interface with the ESP8266 NodeMCU, which gathers, preprocesses, and wirelessly transmits the combined data to a cloud server for storage and analysis.
- The ML system extracts features such as body alignment, arm trajectory, release angle, follow-through, and
 posture consistency, combining them with sensor data to detect deviations and potentially risky movement
 patterns.
- The analyzed results are displayed on a web dashboard showing graphs, trends, and performance summaries, while ML-enhanced video output overlays skeleton markers and motion insights directly onto the recorded footage.
- Using combined sensor and ML insights, an intelligent chatbot or feedback module provides personalized suggestions on technique correction, posture improvement, timing adjustments, and workload management, enhancing training effectiveness.

2.1 CIRCUIT DIAGRAM

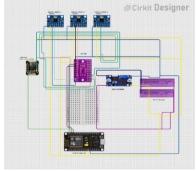


Fig 2.2 Circuit Diagram



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Representation February F

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The circuit diagram represents the complete hardware setup of the wearable-based cricket bowling analysis system. At the center of the design, the ESP8266 NodeMCU acts as the main microcontroller, receiving data from multiple sensors through the I2C communication lines (SDA and SCL). Three MPU6050 IMU sensors are connected at the top, each capturing motion data from different body parts (wrist, elbow, spine). All IMU modules share common SDA, SCL, VCC, and GND lines, enabling synchronized kinematic data collection.

A MAX30100 heart-rate sensor is placed on the left side and is also connected via I2C to measure heart rate and blood oxygen levels during bowling. On the right side, a DHT11 or environmental sensor monitors temperature and humidity, ensuring the system accounts for physical stress and external conditions. A voltage booster module steps up the 3.7V Li-Po battery power to a stable 5V required by the NodeMCU and sensors.

All connections are arranged using a breadboard and jumper wires for prototyping. The circuit ensures continuous power flow, real-time data acquisition, and reliable wireless transmission to the cloud for further machine-learning analysis and performance visualization

III. IMPLEMENTATIONS

3.1 SYSTEM ARCHITECTURE

The system integrates three MPU6050 IMUs (wrist, elbow, spine), a MAX30100 heart-rate sensor, and a DHT11 environmental sensor, all connected to an ESP8266 NodeMCU via I²C communication. A 30-FPS HD webcam records the bowler's motion for synchronization with wearable data.

3.2 SENSOR PLACEMENT & WEARABLE DESIGN

Sensors are mounted using lightweight neoprene straps on:

- Wrist: measures arm rotation, angular velocity.
- **Elbow:** detects elbow extension angle and forearm acceleration.
- **Spine:** captures trunk flexion, lateral tilt, and rotational stability.

A compact controller unit houses the ESP8266, battery, and regulator mounted on the lower back for unrestricted motion.

3.3 DATA ACQUISITION

- 1. IMU sampling frequency: 100 Hz
- 2. Heart-rate update rate: 2 Hz
- 3. Camera: 30 FPS synchronized with timestamps
- 4. Wireless data streaming to Google Sheets via NodeMCU Wi-Fi

3.4 MACHINE LEARNING PIPELINE

- 1. Feature Extraction: max accel, angular velocity, wrist/elbow/spine angles, RMS values
- 2. Models Used: Decision Tree, KNN, ANN
- 3. Classification Tasks:
 - Bowling phase recognition (Approach, Backswing, Forward Swing, Release, Follow-Through)
 - Delivery type detection (Fast, Swing, Off-Spin, Leg-Spin, Bouncer, Yorker)
- 4. Accuracy Obtained:
 - Decision Tree: **94%**
 - KNN: 89%ANN: 87%

3.5 VIDEO GESTURE RECOGNITION

Using MediaPipe Pose, joint landmarks are extracted frame-by-frame to classify movements such as:

- Approach stance
- Backswing
- Forward swing
- Ball release
- Follow-through

The system overlays skeleton joints and angles on each frame for visual analysis.

3.6 DASHBOARD & CLOUD INTEGRATION

Using MediaPipe Pose, joint landmarks are extracted frame-by-frame to classify movements such as:



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- Approach stance
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- Ball release
- Follow-through

The system overlays skeleton joints and angles on each frame for visual analysis.

IV. RESULTS

4.1 REAL-TIME DASHBOARD OUTPUT

The system provides ball-by-ball selection and analysis, allowing each delivery to be uniquely recorded and evaluated. It continuously monitors bowling speed, displaying real-time updates such as the last measured speed, for example, 57.2 km/h. Using machine-learning—based motion interpretation, the system performs delivery classification, identifying styles like fast bowling, swing, or off-spin. Additionally, it offers smart feedback on joint angles, helping bowlers maintain correct wrist, elbow, and spine alignment to reduce injury risk and improve performance. The setup also includes comprehensive environment and vitals monitoring, capturing surrounding conditions and the bowler's physiological indicators. All of this is supported by real-time IMU readings from sensors placed on the wrist, elbow, and spine, ensuring accurate tracking of biomechanical movements throughout each delivery.



Dashboard contains:

Ball-by-ball selection

Bowling speed (last speed: 57.2 km/h)

Delivery classification (Fast, Swing, Off-Spin, etc.)

Smart feedback on joint angles Environment & vitals monitoring

Real-time IMU readings for wrist, elbow, and spine

4.2 POSE-RECOGNITION BASED BOWLING PHASE DETECTION

Using MediaPipe, the system detects each bowling phase with confidence scores:

1. Approach Stance - 0.80 Confidence

Image shows straight body alignment and initial setup.



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2. Backswing Motion – 0.90 Confidence

Elbow rises, arm rotates backward, indicating start of energy loading.

3. Forward Swing – 0.90 Confidence

Accelerated motion forward, shoulder rotation increases.

4. Ball Release – 0.80 Confidence

Wrist extension + forward trunk flexion captured clearly.

5. Follow-Through – 0.70 Confidence

Body relaxes, arm decelerates.







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4.3 WEARABLE PROTOTYPE TESTING



- Working prototype with LEDs
- Full strap-based wearable system
- Back-mounted controller
- Clean wiring for IMU and power lines

V. CONCLUSION

The proposed wearable-based system provides an efficient, portable, and affordable method for analysing cricket bowling biomechanics. By integrating IMU sensors, physiological monitoring, machine learning, and synchronized video analysis, it offers scientific insights traditionally available only through expensive lab-based systems. The system improves coaching precision, supports injury prevention, and enhances performance evaluation.

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