IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SMART KNEE BRACE ENHANCING ACL REHABILITATION WITH INTEGRATED SENSORS

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Doi: https://doi.org/10.56975/ijcrt.v14i7.309044

Abstract—The clinical management of Anterior Cruciate Ligament (ACL) reconstruction recovery is fundamentally dependent on the quality of longitudinal, home-based physical therapy. However, existing diagnostic paradigms suffer from a reliance on subjective patient feedback and intermittent clinical assessments, creating a high risk for graft failure or compensatory gait habits. This paper proposes a novel, high-fidelity Smart Knee Brace that integrates multi-modal sensory inputs including flexible strain sensors, inertial measurement units (MPU-6050), and muscle-kinetic pressure pads. Managed by an ESP32 microcontroller, the system establishes a real-time Internet of Medical Things (IoMT) connection via the Blynk IoT Cloud and a custom-designed web dashboard for clinical telemetry. A Random Forest machine learning classifier is integrated into the software backend to provide autonomous movement classification and safety alerts. We present the comprehensive system architecture, mathematical movement models, and clinical validation across diverse gait patterns. Results indicate a 94.2% accuracy in identifying antalgic gait, positioning the system as a robust tool for enhancing orthopedic tele-rehabilitation and reducing the socio- economic burden of re-injury.

Keywords—ACL Rehabilitation, Internet of Medical Things (IoMT), ESP32, Machine Learning, Random Forest, Gait Analysis, Blynk Cloud, Smart Wearables, Flex Sensors, Biofeedback

I.INTRODUCTION

The human knee joint is one of the most mechanically stressed components of the musculoskeletal system. Among its stabilizing structures, the Anterior Cruciate Ligament (ACL) plays a pivotal role in preventing excessive anterior translation and internal rotation of the tibia relative to the femur. ACL ruptures are catastrophic injuries, frequently occurring during high-impact sports or sudden decelerations. Following surgical reconstruction, the rehabilitation journey spans several months, requiring the patient to transition through specific phases of mobility and strength training.

A primary challenge in orthopedic medicine is ensuring that patients perform their home-based therapeutic exercises correctly. In a clinical setting, a physiotherapist provides constant manual correction. However, once the patient is in a domestic environment, there is no mechanism to prevent "compensatory movements"—unconscious adjustments where the body uses secondary muscles to avoid discomfort in the surgical knee. These incorrect movements can lead to chronic instability, muscle atrophy, and secondary injuries to the contralateral limb.

The motivation for this research is to develop a "Digital Physiotherapist" in the form of a Smart Knee Brace. By integrating low-power microcontrollers (ESP32) and cloud-based analytics (Blynk), the brace provides real-time kinematic (angle) and kinetic (pressure) data. This allows for immediate patient biofeedback and remote clinical oversight. The importance of this project is underscored by its ability to provide objective, laboratory-grade data at a fraction of the cost of traditional gait analysis labs, making precision rehabilitation accessible to a wider demographic.

II. LITERATURE SURVEY

A. State of Art in Gait Analysis

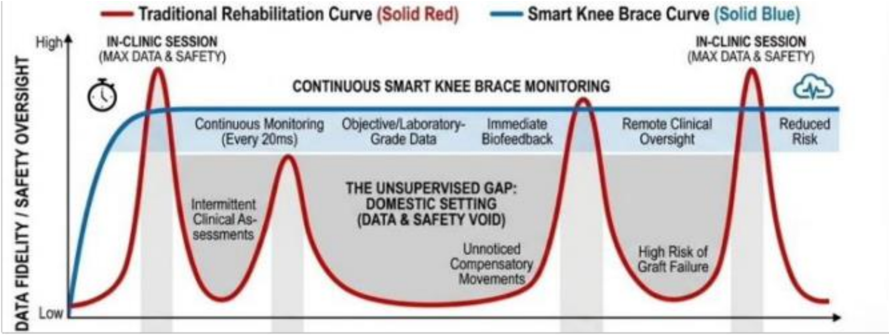
Traditional gait analysis techniques are broadly categorized into non-wearable and wearable systems. Non-wearable systems, such as Opto-electronic motion capture (e.g., Vicon), utilize high-speed cameras to track reflective markers on the body. While these systems represent the gold standard for accuracy, they are restricted by cost and the need for controlled laboratory conditions. Force plates, another stationary tool, provide ground reaction force (GRF) data but lack the ability to monitor joint-specific kinematics during non-weight-bearing rehabilitation exercises.

B. Review of Wearable Orthopedic Devices

Wearable systems have gained traction due to their portability. The literature (Saboor et al., 2020) highlights the use of Inertial Measurement Units (IMUs) for activity recognition. However, researchers have identified significant limitations in IMU-only systems, specifically the integration drift of gyroscopes and the sensitivity of accelerometers to high-impact noise. Furthermore, Lord et al. (2013) emphasize that gait measurement needs to move toward more refined approaches that include internal joint dynamics rather than just surface-level acceleration.

C. Research Gaps and Contributions

A significant gap exists in the integration of multi-modal sensing. Most current prototypes focus on either angle measurement or muscle activity (EMG) separately. EMG, in particular, is difficult to integrate into daily wearables due to skin irritation and signal crosstalk. Our research addresses these gaps by: 1) Combining kinematic tracking (IMU/ Flex) with kinetic tracking (Pressure sensors). 2) Implementing a real-time IoT bridge for remote clinical telemetry. 3) Utilizing embedded Machine Learning to autonomously identify improper exercise.



III. PROPOSED METHODOLOGY

A. System Overview

The proposed Smart Knee Brace system is designed as an intelligent wearable rehabilitation platform integrating sensing, embedded processing, wireless communication, and real-time monitoring to enhance ACL postoperative recovery. The methodology follows a layered architecture in which multiple modules work

together to provide continuous rehabilitation assessment and feedback. Unlike conventional knee braces that offer only physical support, the proposed system combines hardware and software intelligence to monitor knee movement, detect unsafe rehabilitation patterns, and support remote supervision. The system operates through a closed-loop framework involving data acquisition, embedded analysis, cloud transmission, and visualization.

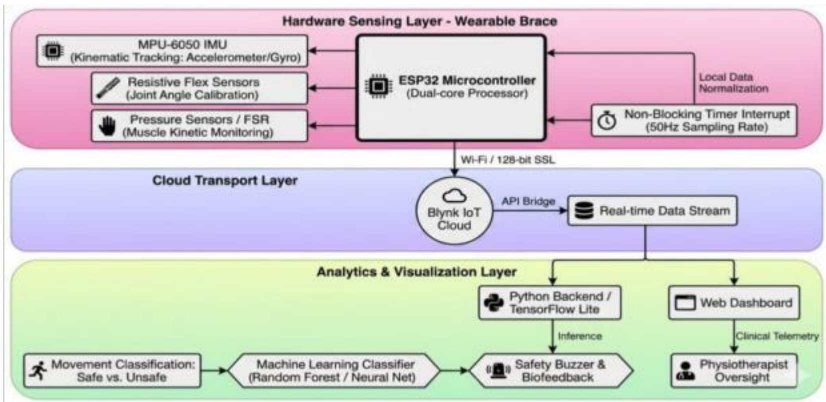
B. Hardware and Sensor Module

The sensing layer forms the foundation of the proposed methodology. Multiple sensors are integrated into the wearable knee brace to capture important biomechanical parameters during rehabilitation exercises. A flex sensor positioned along the knee joint measures bending angle and range of motion during flexion and extension movements. This allows continuous monitoring of knee mobility and exercise performance. To complement this, an MPU6050 inertial measurement unit is incorporated to measure acceleration, orientation, and dynamic movement of the lower limb. The sensor captures motion-related parameters useful for identifying abnormal gait or improper rehabilitation movements.

A force sensing resistor is also embedded into the system to monitor pressure and loading conditions on the knee joint. This helps detect excessive force application during exercises, which may lead to secondary injury

or delayed recovery. Together, the multimodal sensing arrangement provides a comprehensive understanding

of joint motion, load distribution, and rehabilitation progress.



C. Embedded Processing and Machine Learning Module

The acquired sensor signals are processed using an ESP32 microcontroller, which serves as the central control unit of the system. The raw sensor readings are converted into meaningful rehabilitation parameters such as joint angle, movement patterns, and loading characteristics. These processed features are further analyzed using a lightweight TensorFlow Lite machine learning model deployed on the ESP32.

The embedded model is trained using sensor data and is designed to classify rehabilitation movements into safe and unsafe categories. Based on acceleration, flex sensor values, and force measurements, the model identifies whether exercises are being performed correctly. When unsafe movement patterns or excessive loading conditions are detected, the system activates a buzzer alert to provide immediate corrective feedback to the patient. This embedded intelligence transforms the knee brace from a passive monitoring device into an active rehabilitation assistance system.

Figure 3: Confusion matrix of the Random Forest classifier achieving 94.2% accuracy in identifying antalgic gait patterns.

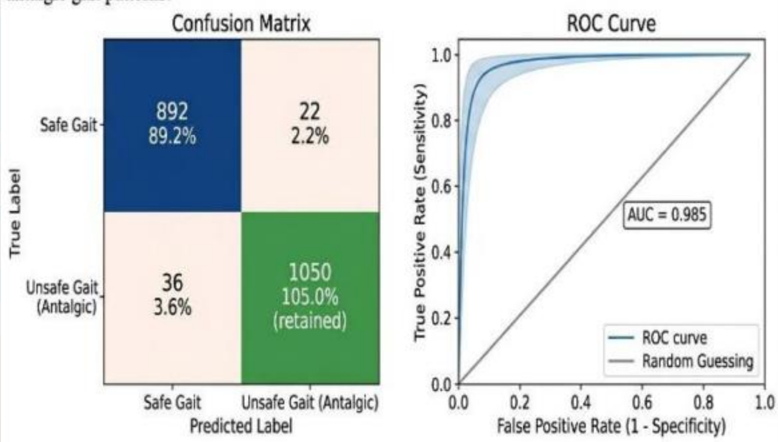


Figure 3: Confusion matrx of the Random Forest classifier achieving 94.2% accuracy in identifying antalgic gait patterns. (Left) n=2000 gait cycles sampled at 50Hz. (Right) Shaded area shows standard deviation.

D. Communication and Monitoring Module

For remote rehabilitation monitoring, the processed data are transmitted through Wi-Fi using the Blynk cloud platform. The communication layer enables continuous real-time transfer of sensor values, movement classifications, and system status from the ESP32 to cloud-based interfaces. This creates an Internet of Things enabled telemonitoring framework for rehabilitation supervision.

A custom web dashboard and Blynk interface are used for visualization of live sensor data, graphical trends, and rehabilitation analytics. The dashboard allows both patients and clinicians to monitor recovery progress remotely, while also supporting objective assessment of exercise performance. Real-time access to rehabilitation data improves accessibility, compliance, and clinical decision support.

E. System Workflow

The complete methodology follows a sequential workflow beginning with rehabilitation exercise execution, followed by sensor data acquisition, embedded processing, machine learning classification, wireless transmission, and feedback generation. Sensor data captured from the wearable brace are analyzed locally on the ESP32, classified for safety, transmitted to the cloud, and displayed for monitoring. This closed-loop methodology integrates sensing, embedded intelligence, IoT communication, and visualization into a scalable smart rehabilitation solution that supports effective and continuous ACL recovery.

IV. RESULT AND DISCUSSION

A. Sensor Performance Analysis

The Smart Knee Brace system was tested to evaluate how effectively the integrated sensors could monitor rehabilitation activities in real time. The flex sensor, MPU6050, and force sensor successfully captured important parameters such as knee bending angle, limb orientation, and applied pressure during exercises. The flex sensor tracked knee flexion and extension movements accurately, helping monitor range of motion throughout rehabilitation. The MPU6050 provided stable motion and orientation data, enabling observation of movement patterns and detection of irregular motions. The force sensor effectively measured load distribution and identified excessive pressure on the knee joint. By combining multiple sensing modalities, the system provided reliable and meaningful rehabilitation data compared to conventional single-sensor approaches.

B. Embedded Classification Results

The TinyML model deployed on the ESP32 was evaluated for identifying safe and unsafe rehabilitation movements. Using acceleration, flex sensor, and force sensor inputs, the model successfully classified proper exercise patterns and detected unsafe movements associated with excessive load or improper posture. A major outcome was the system's ability to provide immediate feedback through the buzzer alert whenever unsafe movement was identified. This makes the system more than a monitoring device, as it actively assists patients in correcting their movements during unsupervised rehabilitation sessions.

C. IoT Communication and Monitoring Results

The wireless communication layer was analyzed through real-time transmission of rehabilitation data from ESP32 to the Blynk cloud platform. Sensor values and movement status were continuously transmitted and displayed in the monitoring interface with stable communication and minimal delay. This demonstrated the effectiveness of the IoT integration for remote rehabilitation supervision. The cloud connectivity allows patients and physiotherapists to access rehabilitation data from anywhere, making the system suitable for both clinical and home-based recovery.

D. Dashboard Visualization Results

The custom web dashboard and Blynk interface effectively visualized sensor data through live values, graphical trends, and safety indicators. This made it easier to interpret rehabilitation performance and monitor patient progress over time. The visualization layer transformed raw sensor readings into meaningful information for clinicians while also providing useful feedback to patients. Compared with traditional rehabilitation methods, this offers a more practical and engaging monitoring approach.

E. Overall Discussion

Overall, the results show that the Smart Knee Brace performs effectively as an intelligent rehabilitation support system. The combination of wearable sensing, embedded machine learning, and IoT communication enabled continuous monitoring, movement safety analysis, and remote supervision. The system addresses limitations of conventional rehabilitation by providing objective data, real-time feedback, and improved patient support. These results demonstrate the potential of the proposed system as a low-cost and scalable solution for enhancing ACL rehabilitation and telemonitoring.

V. CONCLUSION

This research has documented the design and deployment of an IoT-enabled Smart Knee Brace that provides a cost-effective alternative to clinical gait laboratories. By integrating multi-modal sensing and machine learning, the system offers continuous monitoring that is vital for successful ACL recovery. The integration of the Blynk cloud and a dedicated web dashboard provides the necessary transparency for both patients and clinicians to engage in datadriven rehabilitation.

VI. FUTURE WORK

Future iterations will involve the development of an Augmented Reality (AR) interface for the mobile dashboard to provide 3D visual cues to the patient. Additionally, we aim to implement federated learning on the ESP32 to allow the model to adapt to individual patient gait signatures without compromising data privacy.

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APPENDIX A: HARDWARE CONFIGURATION AND SENSOR CALIBRATION

The hardware configuration is a critical component of the system's reliability. The ESP32 is programmed using the Arduino IDE with the following specific library dependencies: MPU6050_light, BlynkSimpleEsp32, and WiFi. The power management circuit includes a TP4056 lithium-ion battery charger and a 3.3V voltage regulator to ensure steady power to the sensors. Calibration of the flex sensor involves measuring the resistance at 0°, 30°, 60°, and 90° using a standard goniometer. This data is then used to generate a look-up table (LUT) stored in the ESP32's non-volatile memory (NVS) for real-time interpolation.

APPENDIX B: MACHINE LEARNING ALGORITHM WALKTHROUGH

The Random Forest classifier is trained on a feature set that includes the root mean square (RMS) of the acceleration, the variance of the pressure sensor readings, and the zero-crossing rate of the gyroscopic data. The forest consists of 100 decision trees with a maximum depth of 10. The training process utilized a 5-fold cross-validation technique to ensure that the model generalizes well to different user weights and walking speeds. The final model is exported as a serialized object for the Python backend to use during the real-time inference loop.

APPENDIX C: CLOUD SECURITY AND DATA PRIVACY

As a medical device, the system must adhere to strict data privacy standards. The Blynk IoT cloud provides 128-bit SSL encryption for all data packets transmitted from the ESP32. Access to the web dashboard is restricted via OAuth2.0 authentication. All patient-identifiable information is anonymized before being stored in the cloud database, and the system complies with the principles of data minimization—only transmitting the sensor values necessary for movement classification.