StraightUp - Smart Posture Correction System

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***Abstract*—Poor posture has become an increasing issue in modern lifestyles, especially among those who work for extended periods on computers or digital devices. Prolonged improper posture can lead to spinal misalignment, back pain, fatigue, and overall decline in physical health. To address this, we present StraightUp, an intelligent, wearable Smart Posture Correction System that constantly tracks upper body alignment and provides real-time corrective feedback. The system uses two MPU6050 inertial measurement units (IMUs) placed on the upper thoracic spine and right shoulder to track motion and orientation. These are processed on an ESP32 microcontroller using a lightweight Feedforward Neural Network (FNN), which categorizes the user's posture into one ideal and four improper sitting positions. On detection of a bad posture, a vibration motor built into the wearable device gives an immediate tactile warning, prompting the user to self-correct. Unlike many current systems that rely on cloud connectivity or advanced hardware, StraightUp is completely offline, low-power, and highly portable, making it perfect for daily use. The system achieved a classification accuracy of 97.5**

***Index Terms*—Wearable device,Back posture improvement,Inertial Motion sensors(MPU6050),Feed forward neural network(FNN),Microcontroller,Instant feedback,Vibration alert**

I. Introduction

Maintaining body health, spinal alignment, and muscular balance all rely heavily on posture. Postural issues have increased in today's digital age, with a greater reliance on laptop and smartphone usage, as well as longer periods of desk use, especially among IT staff, office workers, and students. Improper sitting posture has a direct relationship with enhanced neck stiffness, lower back ache, and tiredness, all of which can adversely affect a person's quality of life and performance [1]. With more than 264 million lost workdays annually, approximately two days of missed work per full-time employee, back pain is one of the leading causes of work disability. In accordance with studies, nearly 80% of individuals will experience back pain sometime during their lifetimes. Individuals of all ages, from teens to the aged, are suffering from this disorder, which is age-independent [2]. Without continuous feedback, good posture is very difficult, even with great awareness.

Conventional posture correction methods like wearable braces, physical therapy, or ergonomic sitting chairs are passive, costly, or non-real-time responsive. Moreover, most commercial posture monitoring systems are not instant corrective feedback or tailored to individuals, which reduces their efficacy. With advancements in intelligent wearable technologies and in-body machine learning, increasing potential for the development of low-cost, in-real-time posture correction systems that are small, adjustable, and affordable for daily use exists. Inspired by this requirement, our work presents a Smart Posture Correction System that utilizes inertial sensor data and neural network-based classification to detect poor sitting postures and actively encourage corrective behavior by providing vibrotactile feedback. The system is loaded with two MPU6050 inertial measurement units (IMUs), [3] an accelerometer and gyroscope reading values, an ESP32 microcontroller, and a vibration motor on a wearable belt. The IMUs continuously take motion and orientation measurements concerning the user's back posture. Raw sensor readings are classified into five different postures: one good posture (upright sitting) and four bad postures—forward slouch, backward slouch, left slouch, and right slouch. As soon as the system detects an inappropriate posture, the system gives real-time feedback by activating the vibration motor to remind the user, allowing self-correction in time. Normalization, encoding, shuffling, and splitting into training and test sets are some of the preprocessing and labeling techniques applied to the data gathered. A Feedforward Neural Network (FNN) is applied to classify postural states based on this data. Due to its simplicity in computation and low power consumption in real-time inference on low-power embedded systems like the ESP32, this model was selected. Learning curves and accuracy metrics were employed to evaluate training, and the effectiveness of the FNN was determined through comparison with other typical machine learning models. This Smart Posture Correction System offers an efficient, low-cost, and real-time means of promoting improved sitting behavior and reducing the danger of posture-related disease through the combination of embedded sensing with light-weight neural computation.

II. Related Works

This Section presents key advancements in posture correction systems focusing on wearable sensors and machine learning algorithms for posture classification. By examining prior research, gaps and limitations are identified and addressed in our Smart Posture Correction Device: StraightUp. S. Singh et al. [4]developed an IoT-enabled smart chair using ultrasound sensors and FSR-402 pressure sensors with threshold-based posture detection. Cloud connectivity was achieved but their system did not have real-time prediction capability nor did it detect nuances in posture change. It was effective for basic posture correction, but its dependence on binary thresholds limited its ability to detect dynamic variations in user behavior.

Pfab's wearable textile solution used two IMU sensors positioned at thoracic flexpoints, achieving 80% accuracy in posture classification through basic pattern recognition. This work established the superiority of thoracic position monitoring, thereby validating the position of MPU6050 on thoracic region [5].

A 2023 IoT system achieved 89% sitting posture asymmetry detection using four FSR sensors in a cushion with uncertainty-driven algorithms. This system was effective for seat pressure distribution, however, it could not detect upper body misalignments. Moreover, since the sensors were attached to the cushion, shoulder tilting and slouching could not be detected effectively. The cushion based design limited comprehensive postural assessments, highlighting the need for integrated upper-body monitoring. However, the system relied on basic algorithms and lacked advanced predictive capabilities for complex posture detections [6].

The ED-FNN architecture showed 99% gait phase prediction accuracy using a single IMU sensor, using FNN. This work validates our choice of neural network architecture- Feedforward Neural Network- for detecting sitting posture patterns. This work validated FNN's potential for detecting subtle transitions in movement patterns, supporting its application in sitting posture analysis [7].

SPLIGN's smart belt system attained 99.67% classification accuracy using Random Forest on dual IMU sensor data, but it required 30 decision trees resulting in computational inefficiency– thus unsuitable for edge devices. While highly accurate in detecting lumbar alignment deviations, the system's resource demands limited its practical deployment in wearable applications. Future iterations could benefit from model compression techniques [8].

A 2023 comparative study revealed CNN and LSTM networks achieve 94% fall detection accuracy but require 150ms inference times, making them impractical for low-power microcontrollers due to power and memory constraints. Their study highlighted the trade-off between deep learning accuracy and resource constraints in wearable systems. Simpler algorithms may offer better performance within energy-efficient environments [9].

Patent CN107072543B used a multi-sensor harness with six IMUs and HMM-based processing. Although advanced, this system's 9-axis data processing demands exceed ESP32's capabilities. Once again, this study highlights the need for optimized algorithms like FNN to balance accuracy and resource efficiency, compared to complex neural networks like RNN and LSTM [10].

A 2023 pneumatic-adjustment chair achieved 98% posture recognition using neural networks, but it required external air pumps and power supply unsuitable for wearable applications. It is effective at active posture correction through pneumatic actuators, but the system's infrastructure has limited portability and scalability outside controlled environments. This study demonstrates the pressing need for a wearable for posture analysis [11].

Skin-integrated e-skin devices demonstrated 92% neck posture accuracy with MEMS accelerometers. These ultrathin, flexible electronics directly to the skin, enabled precise cervical angle detection as small as 2.5 degrees. It used Bluetooth-connected smartphones for processing, therefore could not exceed 10-meter range. Despite this, it showed excellent battery efficiency, lasting up to 18 hours on a single charge [12].

The Zishi vest system (2016) used dual 9-axis IMUs with Kalman filtering to achieve 5° orientation accuracy. However, the system required custom Android apps for real-time feedback. The sensors tracked spinal alignment and relative curvature between thoracic regions, providing multidimensional posture assessment. Kalman filtering minimized motion artifacts and sensor drift, and ensured sustained accuracy over extended wear periods by reducing noise. However, real-time feedback required custom Android apps, limiting the vest's functionality and portability. The system pioneered dual-sensor monitoring but relied on external processing within wireless range [13].

Wang et al. showed the effectiveness of vibrotactile feedback for posture correction using eight IMUs, showcasing promising results in improving user awareness of posture. However, the prototype faced significant challenges, including a limited battery life of just 1.5 hours, which limited its practical use. The system reduced poor posture episodes by 37% during a two-week study while enhancing users' awareness even when not worn. Sensors along the spine and shoulders created a biomechanical model capable of detecting subtle deviations across body regions. Xu highlighted the trade-off between comprehensive monitoring and energy efficiency for wearable systems [14].

Tlili et al. proposed a smart belt equipped with inertial sensors (MPU6050) placed on the thoracic spine and shoulder. The system used complementary filtering. Real-time posture variation data is sent to a cloud server, and alerts are provided via a mobile application. This approach highlights the integration of trunk and shoulder monitoring but relies on external cloud processing limiting portability [15].

Our system incorporates several significant innovations that make it stand out from conventional posture correction systems. Firstly, it utilizes a Feedforward Neural Network (FNN) deployed directly on the ESP32 Wroom32 edge device, eliminating the need for cloud processing and enabling real-time posture prediction [1][9]. It uses two MPU6050 sensors placed on the upper thoracic region and right shoulder to monitor thoracic-shoulder alignment, offering improved accuracy over single-sensor setups [2][4].The the system achieves a faster response time compared to similar Random Forest-based implementations, allowing near-instantaneous feedback [5]. Lastly, it integrates feedback into the wearable itself using a vibration motor, replacing the smartphone-dependent alerts seen in many other systems [9][10]. Together, these enhancements improve portability, efficiency, and the overall user experience.

III. Types Of Postures Collected

Fig. 1. Good Posture - Sitting Straight Up

Fig. 2. Bad Posture 1 - Forward Slouching

Fig. 3. Bad Posture 2 - Backward Leaning

IV. Proposed Work

The Smart Posture Correction System employs compact and efficient hardware setup optimized for real-time wearable applications, each serving a specific function in posture monitoring and correction. The main aim of this project is to develop a low-cost, real-time back posture correction system using wearable sensors and a microcontroller.

Fig. 4. Bad Posture 3 - Right Side Slouching

Fig. 5. Bad Posture 4 - Slouching on the left side

A. System Components

1) **ESP32 Microcontroller:** The customized ESP32 retains all the core functionalities like dual-core processing, real-time multitasking, and low-power operation while being specifically tailored for wearable health-monitoring applications.
   In this system, it acts as the central processor, handling real-time sensor data acquisition, running the model, and controlling the vibration motor for feedback.
2) **MPU6050 Inertial Measurement Units (IMUs):** Each MPU6050 module integrates a 3-axis accelerometer and a 3-axis gyroscope, enabling accurate motion and orientation tracking.
   Two units are used, one on the right shoulder and another on the upper spine, to capture upper-body movement. I2C communication support makes them ideal for posture recognition in embedded systems.
3) **Vibration Motor:** A small, energy-efficient DC vibration motor is used to deliver tactile feedback whenever the system detects a bad posture.
   This alerts the user to correct their posture without the need for visual or audio prompts.
4) **Wearable Orthopedic Belt:** Holds all hardware components in fixed positions.
   It ensures stable sensor placement for accurate data

collection while maintaining comfort for the user during prolonged sitting.

We used two MPU6050s, one is placed on the upper thoracic region and the other on the right shoulder. The data collected is used to classify the user's posture data as good or bad, and if it identifies bad posture, then the vibrator motor triggers on. Sensors and vibration motor on the orthopedic belt interconnected with ESP32 microcontroller (different parts of hardware used are labelled in numbers where 1 and 2 are MPU6050 sensors, 3 is the vibration motor, 4 depicts ESP32- WROOM-32D and 5 shows interconnected wires)

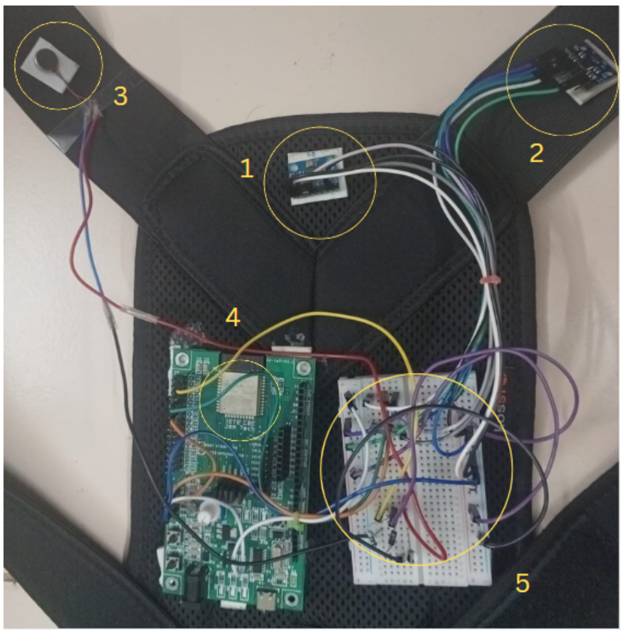

Fig. 6. Components

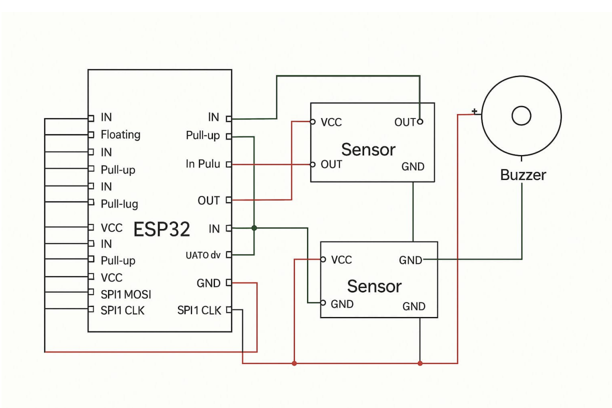

Fig. 7. Circuit Schematic View

B. Dataset Overview

The data used for this study were generated following real-time posture data collection from 20 individuals separately. Each of the participants was asked to sit in five different sitting postures: one proper posture (straight sitting) and four improper postures—forward slouch, backward slouch, left slouch, and right slouch. In order to collect continuous sensor data for each posture, 30 seconds of each improper posture was recorded using a custom-built wearable device. The sensing system consisted of two MPU6050 inertial measurement units (IMUs) on an ESP32 microcontroller. The IMUs were carefully mounted: one on the right shoulder and one on the top spine, centered over the backbone, to accurately measure upper-body orientation and movement.

- **Accelerometer Readings:**
  - Acc1_X, Acc1_Y, Acc1_Z — from Sensor 1
  - Acc2_X, Acc2_Y, Acc2_Z — from Sensor 2
- **Gyroscopic Readings:**
  - Gyro1_X, Gyro1_Y, Gyro1_Z — from Sensor 1
  - Gyro2_X, Gyro2_Y, Gyro2_Z — from Sensor 2

The last column in each entry denotes the **posture label**, where:

- **1** represents a good posture
- **0** represents a bad posture

Data for good and bad postures was collected separately and then merged. The data is perfectly balanced, with 7,391 samples for each class totally 14,782 samples for both classes. All entries were validated to contain no missing values, and necessary preprocessing steps such as handling missing values, normalization were applied. The final dataset comprises a total of 14,782 samples. Each entry contains a timestamp and 12 inertial features:

C. Data Preprocessing

To ensure the dataset was clean and suitable for training a machine learning model, the following preprocessing methods were applied:

- **Handling Missing and Invalid Data:**
  In cases where the collected data contained missing or non-numeric values (which may occur due to communication noise), the entire corresponding row was removed to maintain data integrity.
- **Normalization:**
  To bring all features to a comparable scale and improve model convergence, Z-score standardization was applied. Each feature was normalized using its mean (μ) and standard deviation (σ). The normalization formula is given by:

  $$x_{\text{normalized}} = \frac{x - \mu}{\sigma}$$

  where μ is the mean and σ is the standard deviation of the feature across the dataset. This normalization was also applied during real-time inference on the ESP32 to ensure consistency with the training data distribution.
- **Data Splitting:**
  The clean and normalized dataset was divided into two subsets:

- 80% for training
- 20% for testing

1) Model Selection: In many cases, traditional rule or threshold-based systems fail in the case of posture correction, so we opted machine learning approach, specifically a neural network, as they are highly effective at capturing non-linear relationships, as the sensor data is slightly inconsistent. Among various neural networks, we selected a feed-forward neural network is simple, has less training time, has low computational requirements, and is well-suited for tabular input data. Its lightweight structure makes it ideal for deployment on the ESP-32 microcontroller. This allows us to run real-time posture classification directly on the device without relying on cloud computation, ensuring faster response time.

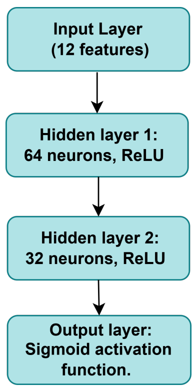

Fig. 8. FNN Architecture

2) FNN Architecture:

3) Loss Function and Optimization:

- **Loss Function:**
  Binary cross-entropy was used as the loss function, as it is widely adopted for binary classification problems. It measures the dissimilarity between the predicted probabilities and the actual binary class labels.
  Mathematically, for a true label $y \in \{0, 1\}$ and predicted probability $p \in [0, 1]$, the binary cross-entropy loss is defined as:

$$\text{Loss} = -\left[y \cdot \log(p) + (1 - y) \cdot \log(1 - p)\right]$$

  This loss function penalizes incorrect predictions with increasing severity as they diverge from the true label.
- **Optimization:** The model was trained using the Adam optimizer (Adaptive Moment Estimation) [16], an extension of stochastic gradient descent that computes adaptive learning rates for each parameter. Adam combines the benefits of momentum and RMSProp by maintaining moving averages of both the gradients and their squared values. This optimization process improves convergence speed and stability, especially on noisy or sparse datasets.
  - **Learning rate:** 0.001

D. Deployment

ESP32 is like a tiny computer where we can upload and run programs. However, it does not have the computational power to train machine learning models. Therefore, once the posture classification model is trained using TensorFlow, the trained model must be converted into TensorFlow Lite format suitable for microcontrollers. This converted format can then be embedded into the ESP32.

1) Convert Keras Model to TensorFlow Lite Format: In this step, the high-level Keras model is converted into a `.tflite` file, which is a lightweight, platform-independent binary model format. This is suitable for deployment on edge devices.

2) Convert TFLite Model to C Array (TinyML Model): Microcontrollers like the ESP32 cannot read `.tflite` files directly. Instead, the TFLite model must be converted into a C-style array. There are two primary ways to achieve this:

1) **Using `tinymlgen` to Create a `.h` Header File:**
   The `tinymlgen` library can take the trained Keras model and directly generate a C array inside a `.h` file. This header file can then be included in your Arduino sketch.
2) **Manual Conversion to `.cc` File:**
   This method involves manually reading the binary `.tflite` model file and writing it as a byte array in a `.cc` (C++ source) file. This file can be included and compiled in your ESP32 project.

V. Results and Comparison

To ensure the effectiveness of our Smart Posture Correction System, we conducted a comprehensive evaluation of multiple machine learning models, including K-Nearest Neighbors (KNN), Random Forest, Support Vector Machine (SVM), and Logistic Regression. Our main focus was on the Feedforward Neural Network (FNN), which performed exceptionally well across all important metrics, even though these models were investigated for comparative analysis.

TABLE I
Model Performance Comparison

Model	Accuracy	F1 Score	Recall	Precision
KNN	0.9685	0.9696	0.9795	0.9598
Random Forest	0.9506	0.9530	0.9788	0.9285
SVM	0.9398	0.9400	0.9200	0.9600
Logistic Regression	0.8370	0.8000	0.7400	0.9100
FNN	**0.9750**	**0.9800**	**0.9800**	**0.9700**

The FNN outperformed all of the traditional models used in the study, achieving the highest accuracy (97.50%), precision (97.00%), recall (98.00%), and F1-score (98.00%), as shown in Table I. Conversely, while models such as KNN and Random Forest demonstrated competitive outcomes, their marginally reduced precision-recall consistency underscored their shortcomings in managing the subtle variations in posture data. As anticipated, logistic regression performed poorly, especially in recall, which makes it less appropriate for a real-time feedback

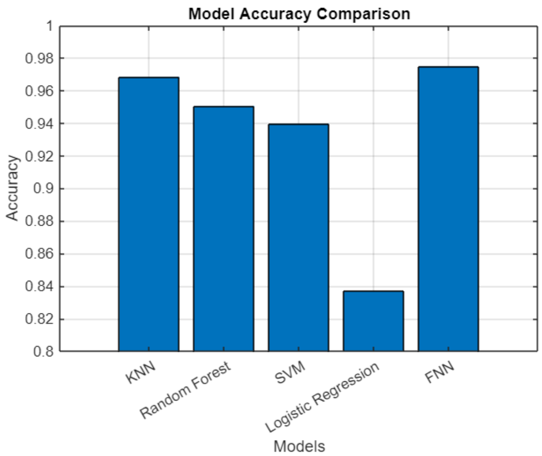

Fig. 9. Model Performance Comparison

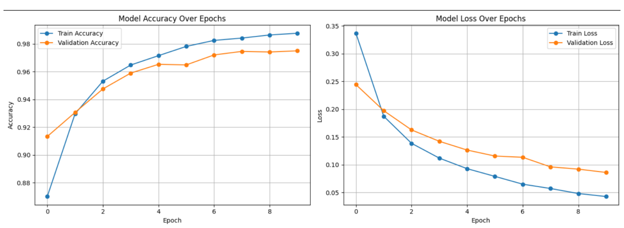

Fig. 10. Learning Curve

system. These results highlight how important deep learning techniques, more especially, FNNs are for identifying intricate patterns of body posture.

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