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IOT - Based Posture Correction System

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ABSTRACT:

Maintaining a proper posture is important to avoid back pain, neck strain, and other long-term health problems. Many people, especially students, unknowingly sit or stand in the wrong posture for long hours, which slowly affects their health. This project introduces a simple and smart system that helps users correct and maintain a healthy posture in their daily routine. A small MEMS motion sensor is used to constantly check how the person is sitting or standing. The posture data is then sent to a NodeMCU, which decides whether the posture is correct or not. If the posture becomes incorrect, the system immediately alerts the user by sounding a buzzer and displaying a warning message on an LCD screen. At the same time, the NodeMCU uploads the posture information to an IoT platform, so the user or parents can monitor posture at any time through a phone or computer. The system is powered by a stable supply, ensuring smooth operation. Overall, this project helps build better posture habits and reduces the chances of posture-related health issues.

Keywords: Posture Monitoring, IoT-Based System, Buzzer Notification, Smart Device, Continuous Posture Tracking.

INTRODUCTION:

For home-based rehabilitation, correct hand and finger movement recognition is essential, which drives the need for systems that function well for a variety of users. Variations in hand size, joint flexibility, and movement speed make it difficult for current data-glove systems to achieve consistent performance. In order to address these gaps, this work presents a comparison learning strategy that creates movement patterns that are independent of subject. Improving cross-subject recognition, lowering mistakes for challenging instances, and providing a data-efficient framework appropriate for actual rehabilitation settings are some of its main achievement. Strong potential for applying the approach to older and neurologically challenged individuals is also recognized by the study [1]. The need for reliable posture recognition is growing as assistive robots are increasingly used to support people who are bedridden and require help with activities such as changing posture or moving from a bed to a wheelchair. However, recognizing human posture in a lying position is challenging because the robot must correctly interpret different body shapes, orientations, and positions using limited visual information. This creates the key problem of achieving dependable posture recognition with limited data. The study addresses this by developing a data-efficient method that can accurately classify various lying postures using depth images from a Kinect sensor. Its contributions include creating a practical recognition system suitable for assistive care, collecting and providing a valuable dataset of depth and RGB images to support future research, and demonstrating that effective posture recognition can be achieved even with a relatively small training dataset [2]. Teenagers' growing sedentary lives have raised issues with poor sitting posture, which frequently results in physical discomfort and long-term health problems. Posture monitoring is crucial, but the majority of standard methods rely on privacy-invading webcams or expensive sensor-based systems. This raises the basic problem of how to accurately identify sitting posture while maintaining a system's affordability and privacy. The paper suggests a dynamic sitting posture identification system that avoids both high cost and privacy problems by using straightforward passive RFID tags applied to the user's back. The technology analyses variations in signal behaviour recorded by conventional RFID sensors to identify several frequent improper sitting postures. Its primary contributions include providing a low-cost, non-intrusive posture monitoring solution, proving that accepted RFID technology can be used to track sitting behaviour, and offering an acceptable approach that is dependable across various users and environments, making it fit for real-world IoT-based health monitoring[3]. It is a great demand for a secure and encouraging setting where students may practice without worrying about being judged because many students can read and understand English but find it difficult to speak it confidently. The primary issue this work attempts to address is that traditional English-speaking training frequently lacks real-time interaction, emotional support, and ways of tracking student behaviour. In order to close this gap, the study introduces an AI-based interactive English-speaking training system that uses a lifelike AI agent to synchronize spoken English with lip motions while users practice speaking. In addition, it records the learner's overall learning trajectory, measures posture, identifies inattentive behaviour like getting up from their seat or sleeping off, and recognizes verbal responses. Creating an immersive and free of stress practice environment, introducing speech and behaviour monitoring to support ongoing learning, and providing a system that motivates students to speak more naturally and improve their communication skills over repeated practice sessions are some of the main contributions[12]. Reliable posture-monitoring systems are necessary because prolonged poor sitting posture is becoming a major health concern in today's sedentary lifestyle, frequently resulting in discomfort, musculoskeletal issues, and a lower quality of life. The primary issue this study attempts to solve is the difficulty of effectively identifying sitting position among individuals due to differences in body forms, sitting habits, and real-world situations. In order to address these problems, the work creates a large dataset by extracting full-body skeletal information using Media Pipe and employs a multi-task classification method that simultaneously detects upper and lower body position. Its main achievements include illustrating the value of multi-task learning for ergonomic applications, enabling an efficient way to analyse sitting posture holistically, and providing insightful information about the applicability of advanced neural network models for posture recognition. Additionally, the study offers an organized dataset along with a methodology that can direct the creation of upcoming real-time posture monitoring systems [7]. While surface electromyography-based gesture recognition has a lot of potential for use in assistive robots, its practical use is usually limited due to the frequent changes in hand and arm position that occur during daily activities, which make gesture signals less accurate and more difficult to understand. This difficulty raises the main issue of ensuring accurate gesture recognition even when the user is shifting positions or moving. In order to overcome this problem, the paper presents a multimodal feature-fusion technique that creates more stable and posture-invariant gesture features by combining data from acceleration and muscle signals. Presenting a solid approach that maintains performance under dynamic posture changes showcasing the value of combining many sensing modalities, and validating the method through offline and real-time trials are the primary contributions. Additionally, the work offers a useful path for enhancing gesture-based control systems' consistency, which will make them more suitable for assistive robotics and regular human-machine interaction [9].

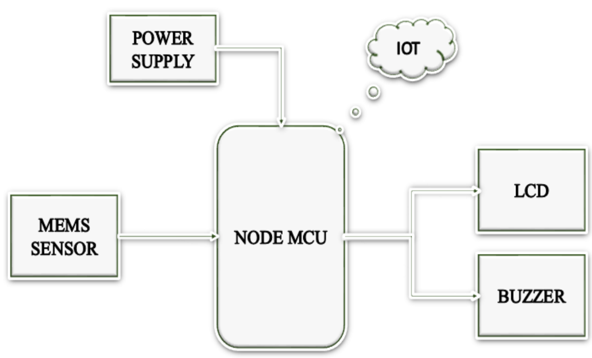
LITERATURE SURVEY:

Related work in rehabilitation-focused hand-motion recognition has explored wearable sensing, spatiotemporal modelling, and subject-independent gesture analysis. Early studies such as *Zhang et al., 2018* investigated bending-sensor gloves for basic motion tracking, while *Kim and Lee, 2019* highlighted the difficulty of maintaining consistent performance across users with differing hand characteristics. Later, *Ravi et al., 2020* used deep learning to extract movement patterns relevant to therapy tasks, and *Huang et al., 2021* emphasized the need for systems that adapt to patient variability. More recent efforts, including *Santos et al., 2023*, focused on improving robustness for home-based rehabilitation using compact, data-efficient wearable systems [1]. Related work on human-posture and action understanding has progressed from traditional pose-based classifiers to modern attention-driven models. Early frameworks such as *Chen et al., 2017* relied on CNN–RNN pipelines to capture spatial and temporal cues, while *Liu and Wang, 2018* showed that viewpoint changes significantly reduce reliability in skeleton-based recognition. Transformer-style approaches gained traction after *Plizzari et al., 2020* demonstrated that attention mechanisms improve posture interpretation, though at high computational cost. More recent lightweight designs, including *Zhang et al., 2022* and *Rao et al., 2023*, aimed to improve robustness and reduce data requirements, motivating further exploration of compact transformer variants for real-time posture analysis [11]. Research on gesture recognition has evolved from single-modal muscle-signal systems to multimodal frameworks that address instability caused by posture shifts. Early s EMG-based methods such as *Huang et al., 2016* struggled with signal drift and motion artifacts, while *Atzori et al., 2018* highlighted the challenge of cross-posture generalization. Studies like *Zhang et al., 2020* and *Du et al., 2021* showed that combining's EMG with inertial signals improves robustness but still faces feature inconsistency. More recent fusion strategies, including *Chen et al., 2023*, demonstrated that correlating deep features across modalities enhances stability, motivating advanced feature-fusion approaches for real-world posture-varying conditions [9]. Recent research in posture recognition has focused on improving robustness and generalization across individuals. Early studies such as *Zhu et al., 2019* and *Kim et al., 2020* used traditional machine-learning and RGB-based skeleton tracking but struggled with subtle upper-body variations. Deep learning approaches like *Chen et al., 2021* and *Ribeiro et al., 2022* adopted neural models to classify ergonomic postures, yet often required large datasets and showed limited cross-subject performance. Work by *Martínez-García et al., 2023* demonstrated the advantages of Media Pipe-based skeletal features, motivating the comparison of lightweight architectures such as MLP and KAN for reliable multi-task sitting-posture analysis [7]. Recent work in human posture recognition has explored a range of sensing and classification strategies to improve reliability in healthcare and assistive robotics. Traditional depth-based recognition methods, such as those reported by *Shotton et al., 2011* and later refined by *Zhang et al., 2014*, focused on skeleton extraction but often struggled with occlusions in bed-lying scenarios. Machine learning approaches like *Faschan et al., 2018* and *Haque et al., 2020* improved accuracy using CNNs but required large datasets. Hybrid techniques combining fuzzy logic with learning models, as in *Ren et al., 2022*, highlight the advantages of interpretable and data-efficient posture classification [2]. Research on driver posture monitoring has progressed through sensor-based, vision-based, and hybrid approaches. Early works such as *Murphy et al., 2015* used pressure and inertial sensors to capture seated posture variations, while vision-based methods like *Zhang and Liu, 2017* leveraged cameras and facial landmarks for non-intrusive monitoring. Later studies, including *Choi et al., 2019* and *Reddy et al., 2021*, applied deep learning to improve robustness under lighting and occlusion changes. Hybrid fusion frameworks, exemplified by *Mahomed and Saha, 2024*, integrated multimodal data for higher reliability, highlighting the growing trend toward real-time, safety-focused driver posture recognition in modern vehicles [4]. Research on pressure-based human posture recognition has progressed rapidly due to its noninvasive nature. Earlier systems, such as *Zhao et al., 2018*, used simple pressure grids for basic lying-posture detection, while *Yoshida and Kim, 2020* improved spatial resolution for sleep-quality assessment. More recent works like *Chen et al., 2022* introduced deep learning to classify body pressure maps with higher robustness. Activity-oriented mats, including *Wang et al., 2023*, demonstrated real-time detection of yoga and exercise patterns. Building on these advancements, *Yuan et al., 2024* extended pressure-mat applications using Velostat and deep neural networks, achieving accurate recognition across both sleeping postures and dynamic activities [10]. Research on yoga posture recognition has expanded with advances in computer vision and sensing technologies. Early works such as *Ramakrishnan and Singh, 2017* used handcrafted features to classify basic asanas, while *Patel et al., 2019* introduced skeletal joint–based analysis using depth cameras for improved pose alignment. With the growth of pose-estimation tools, *Gupta and Verma, 2021* applied CNN-based models for multi-class yoga pose detection, and *Sharma et al., 2022* demonstrated that MediaPipe skeleton tracking can accurately evaluate posture angles. More recent studies like *Rajendran and Sethuraman, 2023* provided a comprehensive survey highlighting the shift toward deep learning and sensor-assisted systems for reliable yogic posture assessment [8].

PROPOSED METHODOLOGY:

The proposed system tracks the user's body movements and how straight they are sitting or standing using a tiny MEMS motion sensor that is placed on their upper back. The NodeMCU board, which functions as the device's brain, receives the readings from this sensor. If the user is sitting incorrectly for an extended period of time, the NodeMCU sounds a buzzer, analyses angles and posture, and displays basic messages on an LCD display. Additionally, it transmits all posture data to an IoT cloud dashboard so that the user or parents can view the posture state and history in real time on a computer or mobile device. The entire system is powered by a tiny battery or USB, which makes it can be used and capable of providing immediate alerts and useful feedback.

BLOCK DIAGRAM:



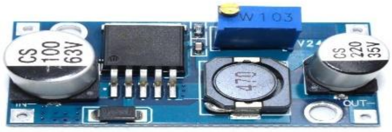
ADVANTAGES:

- Continuously tracks body posture and detects incorrect sitting or standing instantly.
- Posture data can be viewed anytime on mobile or computer through a cloud dashboard.

- Small MEMS sensor and NodeMCU make the system lightweight and easy to use.
- Can be powered by a small battery or USB, making it portable and energy efficient.
- LCD display provides simple messages for easy understanding.

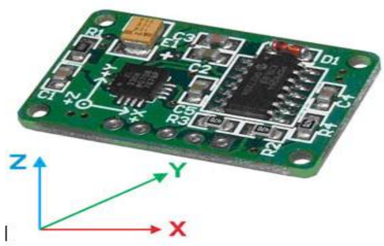
HARDWARE WORK FLOW:

1. POWER SUPPLY



The power supply is the starting point of the system, as it provides energy to all the components. It can be a small battery or a USB connection, depending on how the device is used. Since the system is designed to be portable, the power source should be lightweight and long-lasting. A stable voltage is important so that components like the NodeMCU and sensors work properly without damage. If needed, a voltage regulator is used to maintain consistent power. Overall, the power supply ensures that the device runs smoothly and continuously without interruptions.

2. MEMS SENSOR



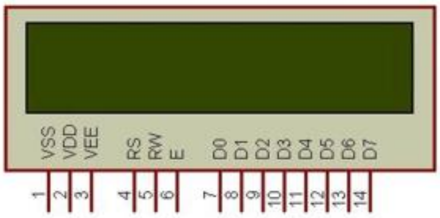
The MEMS sensor is responsible for detecting the user's body posture. It is usually attached to the upper back and senses movements, tilt, and orientation. When a person bends or slouches, the sensor captures those changes and sends the data to the controller. It works in multiple directions, which helps in understanding posture more accurately. The sensor is very small and light, so it does not cause discomfort when worn. Because of its sensitivity, it can easily detect even small posture changes, making it an important part of the system.

3. NODEMCU

The NodeMCU works as the main control unit of the system. It receives the data from the MEMS sensor and checks whether the posture is correct or not. Based on this, it decides what action to take, like turning on the buzzer or updating the display. It also connects to Wi-Fi and sends the data to the IoT platform.

The NodeMCU is easy to program and suitable for such smart applications. It handles all the processing and communication, making it the most important component in the setup.

4. LCD DISPLAY



The LCD display is used to show messages to the user. It gives simple information like whether the posture is correct or needs improvement. This helps the user understand their position without checking a mobile device. The display is connected to the NodeMCU, which updates the message based on sensor data. It is easy to read and consumes very little power. By giving instant visual feedback, the LCD makes the system more interactive and user-friendly.

5. BUZZER

The buzzer provides an alert when the posture is not correct. If the user maintains a wrong position for too long, the NodeMCU activates the buzzer. The sound immediately grabs attention and reminds the user to sit or stand properly. It is a simple but effective way to give feedback without needing to look at the screen. The buzzer uses very little power and is easy to connect. This component plays a key role in helping users correct their posture in real time.

RESULTS AND DISCUSSIONS:

The posture monitoring system was built and tested by making the user sit and stand in different positions such as straight posture, bending, and slouching. The MEMS sensor was able to detect these changes and send the information to the NodeMCU without any major issues. When the user stayed in a wrong posture for some time, the buzzer turned on and a message was shown on the LCD. This helped in giving quick feedback so the user could correct their position. The IoT part of the system also worked properly. The posture data was sent to the online platform and could be viewed on a phone or computer. This made it easy to check posture history and notice any improvements over time. Some small differences in readings were noticed, mainly because of how the sensor was placed on the body. When the sensor was fixed properly, the accuracy improved. The system responded quickly and gave alerts without delay. In the end, the project showed that a simple and low-cost system can help in monitoring posture and improving daily habits.

CONCLUSION:

This system provides a simple way to monitor and improve body posture in daily life. It gives quick alerts so users can correct their position and avoid bad habits. The IoT feature makes it easy to check posture data anytime on a phone or computer. In the future, the device can be made smaller, more comfortable, and more accurate. It can also be improved by adding a mobile app and advanced features for better tracking and analysis.

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