SMART DESK WITH ERGONOMIC CONTROL AND POSTURE MONITORING

A MINI PROJECT REPORT

Submitted by

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in partial fulfilment for the award of the degree of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY

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MAY 2025

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BONAFIDE CERTIFICATE

Certified that this project report **“SMART DESK WITH ERGONOMIC CONTROL AND POSTURE MONITORING”** is the Bonafide work of **“ABIGAIL P, AKASH P and AKSHAYA S”** who carried out the project work under my supervision.

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ABSTRACT

Prolonged sitting and improper posture contribute significantly to musculoskeletal disorders, decreased productivity, and long-term health issues. Conventional desks lack mechanisms for real-time posture monitoring or correction, resulting in continued physical strain. To mitigate these challenges, an IoT-enabled smart desk system has been developed to monitor posture continuously, provide immediate feedback, and foster ergonomic sitting behaviour in users.

The system utilizes MPU6050 sensors for angular orientation and Force Sensitive Resistors (FSRs) to detect pressure distribution. Collected data is processed using a Random Forest classifier, which categorizes posture as "Good" or "Bad" based on sensor inputs. Upon detection of poor posture, a buzzer-based alert mechanism activates to prompt corrective action. Designed for academic and professional use, the system delivers real-time, adaptive feedback to promote healthier sitting practices. Future enhancements may include automated desk height adjustment to support dynamic ergonomics. The classifier achieved an overall accuracy of 97% on the test set, demonstrating high precision and recall for both posture classes. It attained an F1-score of 0.98 for bad posture and 0.94 for good posture, indicating reliable and balanced performance across both categories.

ACKNOWLEDGEMENT

We thank our Principal **Dr. S. Ganesh Vaidyanathan, Phd.,** Sri Venkateswara College of Engineering for being the source of inspiration throughout our study in this college.

We express our sincere thanks to **Dr. V. Vidhya, M.E., Phd.,** Head of the Department, Information Technology for her encouragement accorded to carry this project.

With profound respect, we express our deep sense of gratitude and sincere thanks to our guide **Mr. Ranjith. V**, **M.E.,** Assistant Professor, INT , for his valuable guidance and suggestions throughout this project.

We are also thankful to our project coordinators **Dr. K. Kiruthika Devi, M.E., Phd.,** Associate Professor, **Ms. Meenakshi. P, M.E.,** Assistant Professor, for their continual support and assistance.

We extend our heartfelt thanks to our project panel members**,** **Ms. N. Uma**, **M.E.,** Assistant Professor and **Ms. R. Saktheeswari**, **M.E.,** Assistant Professor, for their constructive feedback during project evaluations.

We thank our family and friends for their support and encouragement throughout the course of our graduate studies.

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LIST OF ABBREVIATIONS

ABBREVIATION	DESCRIPTION
FSR	Force Sensitive Resistor
IMU	Inertial Measurement Unit
MPU6050	6-axis IMU sensor with gyroscope and accelerometer
ML	Machine Learning
GUI	Graphical User Interface
RF	Random Forest classifier
LED	Light Emitting Diode

LIST OF SYMBOLS

SYMBOL	DESCRIPTION
X, Y, Z	Axes used for orientation and movement analysis
accX, accY, accZ	Acceleration along X, Y, Z axes (MPU6050)
gyroX, gyroY, gyroZ	Angular velocity along X, Y, Z axes (MPU6050)

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The evolution of digital technologies has fundamentally altered human interaction with work and learning environments. A significant consequence of this change is the dramatic increase in the amount of time individuals spend in a seated position - whether working from home, attending virtual lectures, or engaging in computer-based activities. While this may appear efficient, the human body is not designed to remain static for extended periods. Prolonged sitting, especially when combined with poor posture, contributes to numerous musculoskeletal problems such as spinal misalignment, shoulder tension, lower back pain, fatigue, and even long-term deformities. Despite growing awareness of the importance of ergonomics, posture-related issues continue to rise due to the absence of practical, accessible solutions for daily use. Most traditional desks and chairs are passive—they offer no real-time insight or feedback regarding the user's sitting position. Manual ergonomic practices, such as adjusting chair height or positioning screens at eye level, require knowledge and consistency that many users lack. Moreover, high-end smart furniture with motorized adjustment and posture correction is prohibitively expensive and often limited to corporate or medical settings. Many individuals, especially students and remote workers, continue to adopt poor posture habits without realizing the long-term health impacts. To bridge this gap, the present project introduces a Smart Desk with Ergonomic Control and Posture Monitoring, a cost-effective embedded system that enables posture awareness and correction in real time. The system combines a MPU6050 sensor-which measures angular orientation of the user's upper body-with two Force Sensitive Resistor (FSR) sensors embedded in the seat cushion. These FSRs detect asymmetric weight distribution between the left and right sides of the user's seating position, helping to identify leaning postures or uneven pressure that typically indicate poor ergonomics. One of the key innovations in this system is the introduction of a time-based alert mechanism. Instead of responding to transient or momentary postural deviations, the system only triggers a corrective alert when a poor posture is maintained for more than five consecutive minutes. This approach prevents over-sensitivity and false positives, encouraging sustained ergonomic behaviour rather than reactive interruptions. The system utilizes a Random Forest classifier, a supervised machine learning algorithm known for its robustness and high accuracy. The classifier takes as input four features: angleX, angleY, angleZ from the MPU6050, and a pressure classification label derived from the difference between the two FSR readings. The pressure difference is categorized as Balanced, Leaning Left, or Leaning Right, and encoded numerically before being passed to the classifier. The output is a binary classification indicating either a Correct or Incorrect posture. To enhance model accuracy, data normalization and smoothing techniques are applied prior to classification, reducing noise and ensuring consistency across sessions. The model is lightweight and optimized for real-time processing, ensuring seamless performance without significant computational overhead. Additionally, the system logs posture data continuously, enabling the analysis of long-term ergonomic trends and promoting user awareness. Furthermore, adaptive alert thresholds based on individual user patterns can be implemented to personalize feedback and minimize unnecessary alerts. This system is designed to operate independently of internet connectivity, allowing offline use in diverse environments.

1.2 OBJECTIVES

The objective of this project is to develop a Smart Desk system that promotes posture awareness and encourages ergonomic sitting behavior through continuous, real-time monitoring. This system aims to provide non-intrusive feedback using affordable sensors, making posture correction accessible and user-friendly. By reducing the risk of long-term musculoskeletal disorders caused by poor sitting habits, the Smart Desk seeks to improve overall health and productivity for users. Designed as a scalable solution, it can be easily deployed in various environments such as homes, schools, and offices, supporting widespread adoption of healthier sitting practices.

1.3 NEED AND MOTIVATION

In today's digital age, many individuals spend prolonged hours seated at desks, often unaware of their posture's impact on health and productivity. Improper sitting posture has become a widespread issue, leading to musculoskeletal disorders, chronic pain, and decreased work efficiency. Despite the critical importance of ergonomics, most traditional desks do not provide any means of monitoring or correcting posture in real-time, allowing poor habits to persist unnoticed. Current posture correction solutions are frequently costly, complex, or reliant on intrusive technologies such as cameras, making them impractical for everyday use. Additionally, these systems often lack adaptive feedback that minimizes unnecessary alerts and encourages sustained behavioural change over time. The Smart Desk system is motivated by the need for a practical, affordable, and effective ergonomic intervention that continuously monitors posture using non-intrusive sensors and provides timely feedback. By leveraging sensor fusion and machine learning, the system offers real-time posture classification and gentle alerts, empowering users to maintain healthier sitting habits. This approach aims to fill the gap between awareness and action by delivering personalized, continuous ergonomic support that can be easily integrated into academic and professional environments. The Smart Desk's design focuses on enhancing user comfort, promoting productivity, and preventing long-term health issues without compromising privacy or convenience.

1.4 EXISTING SYSTEM

Posture monitoring is essential for reducing sedentary health risks, improving workplace ergonomics, and preventing musculoskeletal disorders. Existing commercial solutions primarily include ergonomic chairs and wearable devices equipped with motion or posture sensors. These systems often integrate mobile applications that provide basic feedback through notifications or vibrations to alert users about poor posture. Despite their availability, these systems present several limitations. Many are cost-prohibitive, making them inaccessible for widespread adoption in academic institutions, homes, or personal workspaces. Additionally, they lack real-time, hardware-level feedback mechanisms such as auditory or tactile alerts, which are more immediate and noticeable than mobile-based notifications. A major limitation of current solutions is their reliance on cloud-based platforms or mobile apps for posture analysis. These systems often require continuous internet connectivity and fail to provide offline decision-making capabilities, which restricts their flexibility and usability in various settings. Moreover, most wearable or smart chair systems do not utilize sensor fusion techniques - such as comparing pressure differences across multiple points - to evaluate posture distribution comprehensively. Furthermore, there is minimal integration of predictive analytics using machine learning models in most existing posture monitoring systems. Traditional systems typically rely on threshold-based triggers that lack adaptability and personalized feedback. Additionally, the absence of automatic alert mechanisms such as buzzers or vibrations upon detecting sustained poor posture reduces the effectiveness of these tools in facilitating real-time correction. Current approaches also fall short in providing detailed analytics or behavioural insights based on prolonged usage. Without temporal awareness - i.e., the ability to assess poor posture duration before triggering an alert - many systems risk over-alerting, leading to user fatigue and reduced compliance. These challenges emphasize the need for a more accessible, intelligent, and context-aware posture monitoring solution that integrates affordable hardware with on-device intelligence and ML-based decision logic for scalable and real-time ergonomic feedback.

1.5 PROPOSED SYSTEM

To overcome the limitations observed in existing posture monitoring systems, the proposed project presents a fully developed, low-cost, and hardware-integrated smart posture monitoring solution. Unlike commercial systems that are expensive, cloud-dependent, or only offer limited mobile feedback, this system has been prototyped using real-time sensor integration, machine learning-based classification, and IoT-enabled visualization, ensuring both accessibility and effectiveness. It is specifically designed for integration with conventional seating setups in academic institutions, home study environments, and professional workspaces, where maintaining ergonomic posture over extended sitting durations is a concern. At the heart of the system lies the MPU6050 sensor, an Inertial Measurement Unit (IMU), which captures the angular orientation of the upper body in three dimensions (X, Y, and Z axes). This allows for accurate detection of forward leaning, slouching, or sideways bending. Complementing this, two Force Sensitive Resistor (FSR) sensors are embedded on either side of the chair's seating surface to detect pressure distribution. These sensors help identify asymmetrical seating - an indication of posture imbalance or body lean. Together, these sensors provide fused data that forms a comprehensive input for determining the user's sitting posture. The system employs a supervised machine learning approach using a Random Forest classifier trained on labeled datasets of various sitting postures. This model takes the real-time input from the IMU and FSR sensors and classifies it as either a "Good" or "Bad" posture. The model is implemented in Python and runs on a host device that communicates with the Arduino Uno collecting sensor data. Based on the classification result, a buzzer is triggered to alert the user when poor posture is detected, especially if it persists continuously over a predefined period. This real-time feedback loop encourages immediate corrective behaviour and does not rely on mobile-based or cloud-dependent notifications, making the solution practical and responsive. To extend usability and enhance user interaction, the system integrates with the Blynk IoT platform. Through Blynk, users can remotely view posture classification results, live sensor values, and alert notifications via a user-friendly mobile dashboard. This enhances awareness and allows for seamless monitoring without interrupting the user's workflow. Unlike many solutions that remain at the simulation stage, this system has been fully implemented as a working prototype using physical hardware components and tested in real-time conditions. It is capable of operating offline and does not require constant internet access, offering greater reliability in diverse usage environments. The architecture of the system is modular and designed with scalability in mind. While the current prototype focuses on posture detection and feedback via buzzer alerts and mobile dashboards, future enhancements may include features like automated desk height adjustment based on user posture or dynamic ergonomics. Additionally, data logging for long-term behaviour analysis, Bluetooth communication, or integration with health tracking platforms can also be added to expand the system's capabilities. In conclusion, the proposed system delivers an effective, real-time, and intelligent solution for posture monitoring using cost-efficient hardware and machine learning. It provides immediate and practical feedback to users, thereby promoting healthier sitting habits and helping reduce the risk of posture-related musculoskeletal problems in a variety of environments.

SUMMARY

The Smart Desk combines embedded sensors, AI, and simple user feedback to address the growing health risks of prolonged sitting. Designed to be compact, affordable, and user-friendly, it's ideal for students, professionals, and anyone working long hours at a desk. Through real-time monitoring of posture and sitting habits, the desk uses intelligent algorithms to detect unhealthy behaviours and offers subtle, effective reminders to promote healthier habits. By encouraging small, consistent changes, the Smart Desk fosters a healthier, more productive workspace for the digital age. It not only helps reduce back and neck strain but also improves focus and energy levels by promoting regular movement and better ergonomics. The system is adaptable, learning from user patterns to offer personalized feedback over time. It can also sync with mobile devices or desktop applications to provide visual analytics and daily wellness reports, encouraging long-term behavioural change. Additionally, the Smart Desk supports integration with smart home systems, enabling users to automate lighting or reminders based on posture data for a more immersive wellness experience. Future enhancements may include height adjustments and adaptive learning improving advancements in the desk accordingly.

CHAPTER 2

LITERATURE SURVEY

This chapter reviews existing research and developments in the domain of posture detection, smart furniture systems, IoT-based ergonomic monitoring, and artificial intelligence applied to human health and behavioural correction. With the increasing importance of workplace ergonomics and long-duration sitting, various technological approaches have emerged to track, analyze, and improve user posture. This literature survey highlights a range of approaches - from sensor-based solutions and machine learning applications to embedded systems integrated into furniture. These studies collectively inform the foundation and direction of the proposed Smart Desk system.

2.1 IOT-ENABLED SMART CHAIR FOR POSTURE DETECTION

Muhammad Usman et al. (2022) proposed an IoT-based smart chair system designed for posture detection using pressure sensors embedded within the seat surface. The system employed machine learning algorithms such as Naïve Bayes, multilayer perceptron (MLP), and support vector machines (SVM) to classify user postures in both binary and multi-class scenarios. The framework achieved notable accuracy, reaching up to 98.75% for binary classification tasks and 80% for multi-class activity detection, demonstrating the practical utility of pressure-based sensing for posture recognition. A key contribution of this work lies in its demonstration of how relatively simple machine learning models can be effectively applied to physical sensor data for ergonomic monitoring. The implementation highlighted the feasibility of integrating pressure sensors into furniture for workplace wellness applications. However, the study did not include real-time alert mechanisms, which limits its potential for immediate posture correction. Moreover, sensor calibration posed challenges due to the complexity of managing multiple input sources. Despite these limitations, the system provided a solid foundation for posture monitoring systems and validated the viability of pressure sensor data combined with ML algorithms for real-world ergonomic interventions. This study forms a basis for the sensor-model integration used in the current Smart Desk project.

2.2 DESIGN OF AN ERGONOMIC DESK WITH ELECTRIC ADJUSTMENT MECHANISM

Imbăruș Radu-Petru and Crenganis Mihai (2024) presented a modular electric motor-based desk system designed to enable ergonomic customization through adjustable desk height and angle. The primary emphasis of this study was on the mechanical architecture and the implementation of electric actuators to facilitate user-controlled physical adjustments. The design aimed to accommodate a range of user body types, promoting comfort and reducing strain during prolonged desk usage. The system featured user-friendly controls that allowed for manual height and tilt modifications, thereby enhancing ergonomic flexibility in workplace environments. Its modular nature supported customization and ease of integration into various desk configurations. However, the absence of real-time sensing or posture recognition limited its scope to passive adjustment, relying entirely on user awareness and manual intervention for posture improvement. While the solution addressed mechanical and ergonomic needs effectively, it lacked an intelligent feedback mechanism for dynamic posture correction. In contrast, the Smart Desk system expands upon this concept by integrating sensor-based posture tracking and machine learning classification to enable proactive posture monitoring and real-time alerts, offering a more comprehensive ergonomic intervention solution.

2.3 SMART SYSTEM FOR SITTING POSTURE DETECTION WITH MOBILE FEEDBACK

Matuska S., Paralic M., and Hudec R. (2024) developed a posture detection system leveraging Arduino microcontrollers, MQTT protocol, and Node-RED for real-time data transmission. The system utilized pressure sensors embedded in a seating surface to monitor the user's posture and provided instant feedback via a connected mobile application. The architecture emphasized simplicity and accessibility, making it suitable for basic ergonomic monitoring solutions. A key strength of the system was its ability to deliver real-time alerts directly to users' smartphones, promoting immediate posture awareness. The lightweight design and use of open-source platforms allowed for cost-effective implementation and ease of customization. However, the posture classification was based exclusively on pressure data from the seat, lacking orientation inputs such as angular position or body tilt. This limitation reduced the granularity and accuracy of posture detection. Additionally, the system's reliance on continuous mobile interaction could potentially distract users from their tasks. To overcome these challenges, the Smart Desk system integrates both pressure and orientation sensors, enabling multi-source data fusion for more accurate posture classification. By moving beyond single-sensor inputs and minimizing user-device dependency, the Smart Desk provides a more robust and unobtrusive solution for real-time ergonomic feedback.

2.4 PROMOTING HEALTHY SITTING IN LEARNING ENVIRONMENTS USING KINECT

Zhilei Huo et al. (2023) proposed a smart learning setup that utilized Kinect sensors to monitor students' posture and provide real-time interactive feedback aimed at promoting better study habits and behavioral adjustment. The system leveraged depth-sensing and skeletal tracking capabilities of Kinect to deliver continuous posture analysis during learning sessions, enabling immediate corrective responses and enhanced user engagement. This approach proved effective in increasing posture awareness and encouraging ergonomic practices among students, particularly in academic environments where prolonged sitting is common. Real-time visual feedback helped users correct poor posture habits dynamically, thereby contributing to healthier learning routines. Additionally, the system was able to detect a range of postural deviations with relatively high accuracy and offered the potential for integration with educational performance tracking tools. Despite its strengths, the system's reliance on camera-based visual sensing introduced certain limitations, including the need for a fixed and unobstructed field of view, as well as privacy concerns in sensitive or shared environments. It also required considerable computational resources and spatial setup, making it less suitable for compact or mobile use. Furthermore, environmental factors such as lighting and movement in the background could interfere with detection accuracy. In contrast, the Smart Desk system addresses these concerns by employing non-visual sensors such as pressure and inertial units, offering a privacy-preserving alternative for real-time posture monitoring. Furthermore, the Smart Desk system requires minimal spatial configuration, making it highly adaptable for use in compact personal workspaces or mobile setups without sacrificing functionality. Additionally, its low-cost, low-power design supports easy scalability.

2.5 PRIVACY-PRESERVING DESK SENSORS FOR MONITORING MOVEMENT BREAKS

Ananda Maiti et al. (2023) developed a low-power monitoring system that employed Dynamic Time Warping (DTW) to detect sedentary behaviour patterns and prompt users to take regular breaks. The system utilized minimal and non-intrusive sensors to ensure energy-efficient and continuous monitoring, making it particularly suitable for long-term health and wellness applications in both professional and personal environments. A key strength of this approach was its emphasis on low energy consumption, enabling prolonged usage without frequent recharging or battery replacements. The use of DTW allowed the system to effectively analyze time-series data for movement irregularities, contributing to timely interventions aimed at reducing sedentary risks. Additionally, the non-intrusive nature of the sensors respected user privacy and comfort, eliminating the need for wearable or camera-based monitoring. However, the system did not incorporate posture classification, focusing instead on detecting overall inactivity. As a result, it lacked the granularity to distinguish between different types of sitting postures or ergonomic correctness. Furthermore, its reliance on movement detection limited its applicability in scenarios where subtle postural deviations occur without significant body displacement. It also lacked integration with a feedback mechanism to guide users toward better ergonomic habits. The absence of multi-sensor data fusion further constrained its ability to capture a comprehensive understanding of user posture. Despite these limitations, the study reinforces the value of minimalist, privacy-respecting sensor systems - a principle aligned with the Smart Desk's design philosophy. The Smart Desk enhances this approach by using pressure and orientation sensors for detailed posture monitoring without compromising privacy or energy efficiency.

2.6 REAL-TIME SITTING POSTURE MONITORING USING FORCE AND ACCELEROMETER SENSORS

K. Suresh et al. (2022) proposed a real-time posture monitoring system that utilized the MPU6050 sensor for motion detection and load cells for force measurement to identify changes in sitting posture. The system incorporated a basic rule-based logic to trigger a buzzer alert whenever improper posture was detected, aiming to promote ergonomic correction among users during sedentary activities. The integration of both motion and pressure sensors enabled a more holistic sensing of posture deviations compared to single-sensor approaches. The system delivered real-time alerts, encouraging immediate behavioural adjustments and promoting better posture awareness in day-to-day scenarios. However, the system lacked machine learning capabilities, relying entirely on fixed threshold values for classification. This rule-based approach led to a higher false positive rate and limited adaptability across different user body types or conditions. Additionally, the design introduced increased hardware complexity without offering a user-friendly interface or feedback customization options. By incorporating a machine learning model and a time-based logic layer, the Smart Desk improves upon this design with reduced false alerts and enhanced adaptability. It delivers a more accurate and user-centric solution while maintaining ergonomic goals.

2.7 MACHINE LEARNING APPROACHES FOR CLASSIFYING SITTING POSTURES

Pratibha Bajpai et al. (2021) investigated the effectiveness of various machine learning algorithms - Random Forest, Decision Trees, and Support Vector Machines (SVM) - for classifying sitting postures based on labeled datasets. The study utilized features such as angular orientation and positional data to evaluate model performance in distinguishing between correct and incorrect postures. The research provided a comparative accuracy analysis, highlighting the robustness of the Random Forest algorithm in handling feature variance while minimizing overfitting. This comparative insight into classification models offered valuable direction for selecting an optimal algorithm in posture detection systems. However, the work was limited to offline dataset analysis and did not include integration with real-time hardware or sensor-based feedback mechanisms. As such, its findings were restricted to static environments without real-time applicability. Despite this limitation, the study directly supports the selection of the Random Forest algorithm for the Smart Desk's posture classification component. It offers empirical backing for model choice and aids in shaping an effective machine learning pipeline for real-time ergonomic monitoring.

2.8 POSTURE-CORRECTIVE FURNITURE IN IOT-DRIVEN SMART ENVIRONMENTS

Ashrant Aryal et al. (2019) presented a conceptual framework for embedding posture-aware furniture within smart office ecosystems through IoT technologies. Their work focused on creating adaptive and responsive workspaces designed to proactively support user ergonomics and promote healthier sitting habits. The study emphasized the importance of proactive ergonomic interventions and adaptive workspace designs that respond dynamically to user behaviour. It highlighted the potential benefits of IoT-enabled furniture in reducing musculoskeletal risks and enhancing workplace wellness. However, the research was largely conceptual, lacking detailed implementation or validation through practical prototypes. It served more as a visionary outlook than a tested solution. The Smart Desk builds upon this vision by delivering a practical, implementable system tailored to personal desks. It transforms conceptual ideas into a functional product capable of real-time posture monitoring and correction, thereby advancing adaptive ergonomics at an individual level.

2.9 COMPARATIVE STUDY OF POSTURE SENSORS IN WEARABLE AND NON-WEARABLE DEVICES

Fairuz Maulana et al. (2024) conducted a comprehensive survey comparing various sensor types - Inertial Measurement Units (IMUs), Force Sensitive Resistors (FSRs), and strain gauges - based on their response time, accuracy, and practical usability for posture monitoring applications. The study provided quantitative and qualitative assessments to guide sensor selection in ergonomic systems. A major strength of this survey was its detailed evaluation of sensor performance, particularly validating the effectiveness of FSRs for pressure-based posture detection. The findings supported the reliability and responsiveness of these sensors in real-world settings, reinforcing their suitability for continuous monitoring. However, the study did not extend to investigating classification models for posture analysis, nor did it address the implementation of real-time user feedback mechanisms. Consequently, its focus remained on sensor hardware rather than end-to-end system design. Nonetheless, the survey affirms the Smart Desk's sensor selection - specifically the MPU6050 IMU combined with FSRs - as an optimal choice for accurate and practical ergonomic posture classification. Future work could integrate these sensor insights with advanced machine learning models to enhance detection accuracy. Additionally, exploring real-time feedback systems could further improve user engagement and posture correction, making the user experience better with further more advancements.

2.10 TIME-AWARE BEHAVIOR MONITORING IN DESK WORK SYSTEMS

Takashi Jindo et al. (2020) investigated user behaviour patterns over extended periods, highlighting the importance of incorporating time-aware logic into behavioural monitoring systems. Their study emphasized how temporal context can improve decision-making processes and promote sustained behaviour change in ergonomic practices. A key strength of this research was its focus on long-term behaviour modification by encouraging systems to consider the duration of poor postural habits before issuing alerts. This approach aims to reduce user fatigue caused by frequent or premature notifications, thus fostering more effective ergonomic interventions. However, the study did not include posture-specific analysis or sensor data integration, limiting its applicability to generalized behavioural monitoring rather than precise posture correction. Nevertheless, this work inspires the Smart Desk's time-constrained alert logic, which incorporates a five-minute delay before triggering corrective feedback. This mechanism helps avoid over-alerting and improves user compliance by ensuring alerts are meaningful and timely.

SUMMARY

Most systems lack time-aware, affordable posture correction. Smart Desk combines sensor fusion and machine learning with a 5-minute alert delay for gentle, smart feedback. It adapts continuously to user habits, enhances accuracy using pressure and orientation data, and ensures privacy by avoiding audio-visual sensors - offering a practical, personalized ergonomic solution. This makes it ideal for improving workplace health and productivity over the long term.

CHAPTER 3

METHODOLOGY

This chapter outlines the detailed methodology employed in the development and implementation of the Smart Desk with Ergonomic Control and Posture Monitoring system. It covers the system architecture, sensor selection, data collection, feature extraction, machine learning model training, and the overall process flow. The approach combines hardware integration, software development, and machine learning techniques to create a real-time, adaptive posture monitoring system aimed at improving user ergonomics.

3.1 SYSTEM ARCHITECTURE

The system architecture for the Smart Desk integrates several key components: sensors, microcontroller, data processing unit, and the machine learning model. The system is designed to be modular, allowing easy integration of new components or upgrades without significant changes to the overall structure. It supports intelligent posture analysis to provide feedback and encourage healthy sitting habits. The architecture also enables adaptive lighting and alert features based on user activity and environmental conditions. Additionally, it ensures low-latency data flow for real-time responsiveness. The system is compatible with cloud services for remote monitoring and data backup. It also facilitates seamless integration.

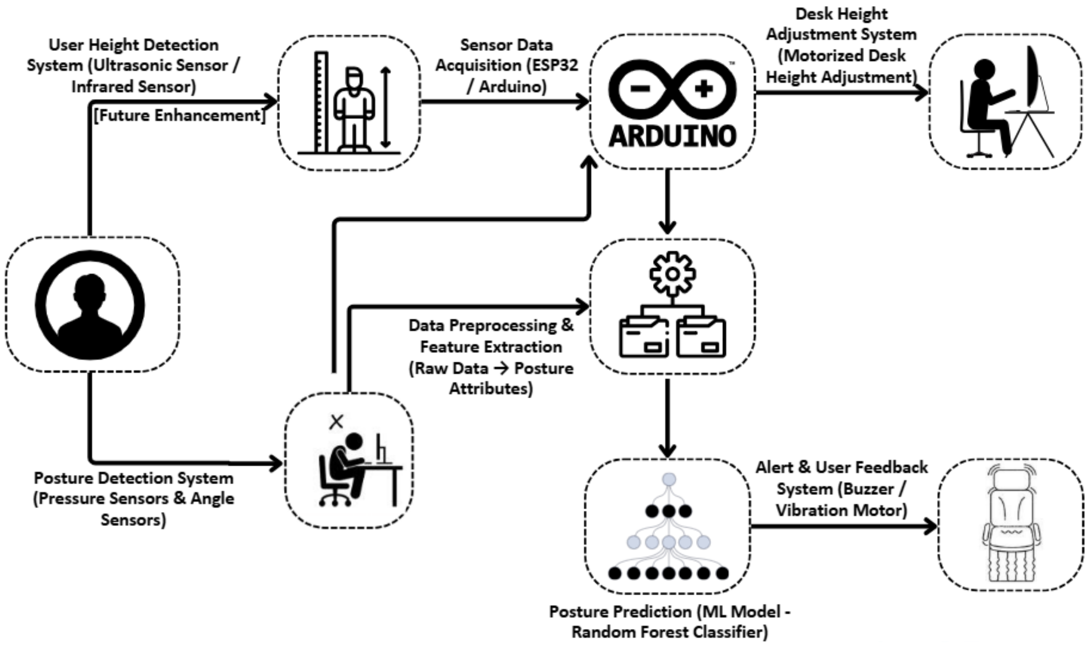

Figure 3.1 Smart Desk with Ergonomic Control and Posture Monitoring

Figure 3.1 shows, the architecture of the Smart Desk system, where smart desk system monitors the user's posture using pressure and angle sensors, with data processed via Arduino and analysed using a machine learning model. The system extracts posture attributes and predicts posture quality using a Random Forest classifier. Based on the prediction, it provides real-time feedback through a buzzer or vibration motor to alert the user.

3.1.1 COMPONENTS

- **Sensors:** The system uses an MPU6050 sensor for detecting the orientation of the user's upper body and two Force Sensitive Resistor (FSR) sensors embedded in the seat cushion to monitor pressure distribution. These sensors work together to identify leaning patterns, helping distinguish between balanced and unbalanced postures. They are lightweight and power efficient, ensuring real-time monitoring. The MPU6050 sensor provides accelerometer and gyroscope data.

It precisely aids in detecting subtle posture changes effectively ensuring efficient working of sensor.

- **Microcontroller:** An Arduino Uno serves as the central control unit, collecting data from the sensors, processing it, and communicating with the software for real-time posture analysis and feedback.
- **Data Processing and Feature Extraction:** The data from the sensors is processed to extract relevant features, such as the orientation angles (angleX, angleY, angleZ) and the pressure difference between the FSR sensors. The extracted features are then normalized and formatted as input for the machine learning model to ensure accurate classification and prediction in real-time systems.
- **Machine Learning Model:** A Random Forest classifier is used for posture classification, which takes the extracted features as input and outputs a decision regarding whether the user's posture is correct or incorrect based on learned training patterns and behaviour.
- **Feedback Mechanism:** The system provides real-time feedback in the form of audio alerts (buzzer) or visual alerts (e.g., LED indicators), depending on the user's posture and behaviour.

3.2 SENSOR SELECTION AND INTEGRATION

The choice of sensors plays a crucial role in the success of the Smart Desk system. The system effectively utilizes the following key sensors for accurate posture detection and classification:

3.2.1 MPU6050 (Accelerometer and Gyroscope)

This sensor provides angular measurements of the user's upper body, specifically tracking the pitch (tilt in the forward-backward direction), yaw (rotation left-right), and roll (side-to-side tilt). The data from the MPU6050 helps assess the orientation of the user's torso while sitting, indicating potential posture deviations such as slouching or leaning.

3.2.2 Force Sensitive Resistor (FSR)

These sensors are placed on the seat cushion to measure pressure distribution. FSRs detect changes in pressure when the user's weight shifts, allowing the system to identify asymmetrical postures such as leaning to one side or sitting unevenly. The difference in pressure readings between the left and right sensors provides critical input for posture analysis. Both sensors are integrated with the Arduino Uno board via analog inputs, where the data is collected and processed in real-time continuously.

3.3 DATA COLLECTION AND PREPROCESSING

Data collection is performed through continuous monitoring of the MPU6050 and FSR sensors. The system continuously records the following parameters:

3.3.1 MPU6050 Data

The three-axis angular displacement values (angleX, angleY, angleZ) of the user's upper body are retrieved at regular intervals (e.g., every 100 milliseconds) for accurate posture monitoring.

3.3.2 FSR Data

The resistance from both FSR sensors is measured and converted to digital values. The difference in pressure between the two FSR sensors is calculated and categorized into three distinct labels: Balanced, Leaning Left, a nd Leaning Right. This classification is based on the pressure difference threshold and helps the system assess the symmetry of the user's sitting position. These posture labels are then used as features for the machine learning model to enhance classification accuracy.

3.3.3 PREPROCESSING STEPS

- **Data Normalization:** Both the MPU6050 angles and the FSR pressure differences are normalized to ensure consistency across different sessions and users. This ensures that any outliers or variations in the raw data do not affect the posture classification process.
- **Smoothing:** A moving average filter is applied to the angular and pressure data to reduce noise and improve the stability of the readings. It also ensures that only consistent posture patterns are fed into the machine learning model for accurate prediction.
- **Feature Encoding:** The categorized pressure difference (Balanced, Leaning Left, Leaning Right) is encoded into numerical values, where: Balanced = 0, Leaning Left = 1, Leaning Right = 2.

3.4 FEATURE EXTRACTION

3.4.1 Angle Features (Anglex, Angley, Anglez)

These three features represent the orientation of the user's upper body, specifically tracking how much the torso is tilted forward, side-to-side, or rotated. These features provide direct insight into the user's posture, especially in terms of slouching or leaning.

3.4.2 Pressure Classification (FSR)

The classification of the pressure difference between the left and right FSR sensors is used as an additional feature. The system categorizes the pressure difference into one of three states: Balanced, Leaning Left, or Leaning Right. This helps the system assess whether the user is sitting symmetrically or leaning to one side. These four features (angleX, angleY, angleZ, and pressure classification) are used as the input to the Random Forest classifier.

This multi-sensor fusion enhances the accuracy of posture classification by combining spatial orientation with seat pressure distribution. The approach also enables the system to detect lateral imbalance.

3.5 MACHINE LEARNING MODEL

The core of the posture classification is based on the Random Forest model, a powerful ensemble learning method known for its robustness and ability to handle complex, high-dimensional data. The model is trained on labeled posture data, where each sample consists of the four extracted features and the corresponding posture label (either Correct or Incorrect).

3.5.1 TRAINING THE MODEL

The model is trained on a dataset containing multiple samples of posture data under different sitting conditions. The dataset includes labeled examples of correct and incorrect postures based on the following conditions:

- **Correct Posture:** When the user's torso is upright with symmetrical pressure distribution across the seat.
- **Incorrect Posture:** When the user is slouched, leaning to one side, or exhibiting any other deviation from a neutral posture.

3.5.2 STEPS INVOLVED IN TRAINING PROCESS

- **Data Splitting:** The dataset is split into training and testing sets (typically a 80-20 split). This ensures the model is trained on a majority of the data while reserving a portion for unbiased performance evaluation. Cross-validation techniques can also be applied to enhance model reliability and prevent overfitting. This system helps in building robust model that generalizes unseen data.

- **Model Training:** The Random Forest algorithm is applied to the training data, where it constructs multiple decision trees. Each tree is trained on a subset of the features, and a majority vote is used for classification. This approach reduces the risk of overfitting.
- **Model Evaluation:** The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1 score. Cross-validation is used to ensure that the model generalizes well to unseen data. Confusion matrix analysis further helps in understanding misclassification patterns and refining the model.

3.6 TIME-BASED ALERT MECHANISM

A key innovation of the Smart Desk system is the time-based alert mechanism. Instead of issuing an alert for any momentary posture deviation, the system waits for a posture to be maintained for five consecutive minutes before triggering an alert. This ensures that the system does not provide false positives for transient deviations and encourages more sustainable ergonomic behaviours. If the user maintains an incorrect posture (as classified by the Random Forest model) for a continuous period of five minutes, the system generates a feedback alert. The alert could be an audio buzzer sound or a visual LED indication, depending on the user's preference.

3.7 FEEDBACK AND INTERACTION

Once an incorrect posture is detected and confirmed by the machine learning model, the system provides immediate feedback. This feedback aims to nudge the user to correct their posture and return to a neutral sitting position. The alert mechanism such as, buzzer or LED, is activated only after a sustained poor posture is observed for more than 5 minutes. This ensures that users are not disturbed by momentary shifts but are alerted only when corrective action is genuinely needed. The feedback mechanism operates in the following way:

- **Buzzer Alert:** A buzzer or sound signal is triggered to notify the user of their poor posture. The buzzer continues until the user corrects their posture.

The system is designed to be non-intrusive, ensuring that the user is alerted without being overwhelmed or distracted.

3.8 SYSTEM TESTING AND VALIDATION

Once the system is built, extensive testing is carried out to evaluate its performance and usability.

The tests include:

3.8.1 Sensor Calibration

Ensuring accurate readings from the MPU6050 sensor and FSR sensors.

3.8.2 Posture Classification

Validating the accuracy of the Random Forest classifier in detecting correct and incorrect postures of the user for better improvements of the desk.

3.8.3 Real-Time Feedback

Testing the responsiveness of the feedback mechanism and ensuring that alerts are triggered only after the five-minute threshold is crossed.

3.8.4 User Trials

Conducting trials with real users to assess the effectiveness of the system in promoting ergonomic behaviour and correcting poor posture. The trials involved participants using the Smart Desk over multiple sessions during regular desk activities. User Feedback was collected through surveys.

SUMMARY

The methodology outlined in this chapter combines the use of sensor-based data collection, machine learning-based posture classification, and a time-aware feedback system to monitor and correct user posture in real time. The system provides a low-cost, non-intrusive solution to an increasingly common health issue, using robust data processing and classification techniques to ensure accurate posture feedback and encourage healthier sitting habits. The modular design allows for easy hardware upgrades and software scalability. The use of MPU6050 and FSR sensors ensures precise detection of posture deviations. Real-time monitoring enables proactive corrections before long-term health issues arise. The Random Forest model enhances the reliability of posture classification through multi-feature analysis. Normalization and noise reduction techniques improve the stability and reliability of sensor data. The time-based alert mechanism minimizes false alarms and promotes long-term ergonomic discipline. Audio and visual feedback ensures flexibility and user-friendliness. Model training and validation steps confirm the robustness and generalizability of the system. Sensor calibration and user trials help fine-tune system accuracy and usability. Overall, this methodology demonstrates a comprehensive, intelligent approach to ergonomic monitoring with real-world applicability. The system supports continuous learning by updating the model with new user data over time. It can be adapted for various use cases such as office environments, gaming setups, or student desks. The lightweight framework allows integration into existing furniture or wearable devices. Feedback customization enhances user engagement and compliance. This smart posture monitoring approach represents a significant advancement in preventive health technology. Future enhancements may include mobile app integration for personalized posture tracking.

CHAPTER 4

REQUIREMENTS ANALYSIS

Requirement analysis, also known as requirement engineering, is the process of determining the user expectations for a new or modified product. This process includes tasks such as analyzing, documenting, validating, and managing system or software requirements. These requirements should be documentable, actionable, measurable, and testable, addressing identified business needs or opportunities, and be defined in enough detail to support system design. This ensures clear and effective communication always.

4.1 SYSTEM REQUIREMENTS

4.1.1 Hardware Requirements

- **RAM:** Minimum: 4-8 GB, Sufficient for basic operation and lightweight data processing tasks. Recommended: 16-32 GB.
- **CPU:** Minimum: Dual-core, Capable of handling basic computations and control operations efficiently. Recommended: Quad-core or higher.
- **Storage:** Minimum: 2 GB, Enough for essential files, sensor logs, and system software. Recommended: 10+ GB.
- **Bandwidth:** Minimum: 5-10 Mbps, Suitable for occasional cloud sync and remote access. Recommended: 20–50+ Mbps, Higher speeds enable smoother real-time feedback.

4.1.2 Software Requirements

- **Operating System**

  The Smart Desk system can be run on either Ubuntu 20.04+ or Windows 10+. Ubuntu is a preferred option for development due to its compatibility with the necessary libraries and the open-source ecosystem, while Windows provides a more user-friendly interface for general development and testing.

- **Programming Language**

  The system will primarily use Python (3.8-3.11). Python is ideal for IoT projects, including machine learning integration and data analysis. It also has a large ecosystem of libraries, which simplifies development for both rapid prototyping and production-ready implementations.

- **IoT Frameworks and Libraries**

  For system programming, libraries such as NumPy and SciPy will be used for data processing. The integration of hardware sensors, such as MPU6050 and FSR, will be done using the Arduino IDE and Python's PySerial for communication between the microcontroller & system.

- **Visualization Tools**

  Visualization of the posture analysis and system feedback will be handled using Matplotlib for simple graphing and Plotly for interactive visualizations on a user dashboard.

- **Development Tools**

  VS Code will serve as the primary integrated development environment (IDE) for coding, while Git will be used for version control. Jupyter Notebooks will be utilized for experimentation with sensor data and the development of the machine learning model. This system ensures a streamlined workflow for both hardware interfacing and model evaluation in the system of the architecture

4.2 FUNCTIONAL REQUIREMENTS

The functional requirements of the Smart Desk project focus on various features such as posture detection, real-time alerts, and user feedback. Here are the key functional requirements:

4.2.1 Data Input Handling

The system will receive sensor data from the MPU6050 and FSR sensors. The system should be capable of processing real-time data inputs from these sensors, enabling the system to monitor posture in real-time. Data will be collected in small intervals (e.g., every 100 milliseconds) to ensure continuous monitoring.

4.2.2 Posture Detection and Classification

The data from the MPU6050 (angleX, angleY, angleZ) and FSR sensors will be processed and classified. The system will calculate the difference between the left and right FSR sensors and categorize the posture as Balanced, Leaning Left, or Leaning Right. These categories will be used as input features for a Random Forest machine learning model. To improve accuracy, the input data is first normalized and smoothed to remove noise and ensure consistency across sessions. The model is trained using labeled posture data, allowing it to learn patterns and make reliable predictions during real-time usage.

4.2.3 Alert Mechanism

If the user maintains poor posture for more than 5 continuous minutes, the system will trigger an alert. The alert can be a vibration or a beep sound to notify the user to correct their posture. Alerts are subtle to avoid disrupting workflow. The system resets the timer once good posture is resumed, ensuring accurate monitoring. This helps reinforce ergonomic habits.

4.2.4 Real-time Feedback

The system will display real-time feedback on a local screen or through a connected device, indicating the user's posture status. If the posture is incorrect, the system will provide suggestions for improvement.

4.2.5 Model Integration

The machine learning model (Random Forest) will be used to predict posture categories based on the sensor data. The model will be trained on data with different postures and will improve over time with user feedback and additional data collection.

4.2.6 System Calibration

The system will include a calibration feature that allows users to define their default or ideal sitting posture at the time of setup. During calibration, the initial sensor readings - such as orientation angles from the MPU6050 and pressure values from the FSR sensors - are captured and stored as reference values. These baseline values help in adjusting for individual differences in sitting style, body posture, and chair configuration. The system can more accurately detect deviations from the calibrated posture

4.3 NON-FUNCTIONAL REQUIREMENTS

4.3.1 Performance

The system must be capable of processing real-time data streams from multiple sensors simultaneously without introducing noticeable lag or delay. Posture data should be analysed and processed within a few milliseconds to ensure immediate feedback and a seamless user experience. This high performance is essential for maintaining user engagement and for the system to be perceived as responsive and reliable. The solution must operate efficiently even under continuous usage throughout the day, without degrading system performance or user interface responsiveness.

4.3.2 Accuracy

To provide meaningful posture correction and ergonomic benefits, the system must achieve a posture classification accuracy of at least 85%. This accuracy benchmark ensures that false positives and false negatives are minimized, leading to more trust and acceptance from the user. The machine learning algorithms should be trained on a diverse dataset to account for different body types, seating behaviours, and chair configurations. Additionally, the system should be able to self-improve or be retrained to increase accuracy over time as more user data is collected.

4.3.3 Scalability

The system should be scalable to accommodate additional sensors or features in the future. This could include adding sensors for more detailed posture analysis or integrating with other smart devices in the user's environment. It should also support software-level scalability, allowing easy updates or integration of advanced machine learning models without requiring major hardware modifications.

4.3.4 Usability

The system should be easy to use, with intuitive settings for calibration, monitoring, and feedback. The interface should be user-friendly, particularly for individuals with little to no technical background.

4.3.5 Maintainability

The codebase should be well-organized, modular, and easily extensible. Documentation should be thorough to facilitate future maintenance, updates, and troubleshooting. The system should include logging and diagnostic tools to facilitate issue tracking. Well-documented APIs and version control must be maintained to ensure smooth collaboration and updates in the future.

4.3.6 Security

Security is critical, especially when handling personal posture data that might include usage habits or behavioral patterns. The system must implement secure data handling protocols, including data encryption during transmission and storage. Access control measures must be in place to prevent unauthorized access. If data is stored on cloud servers or accessed remotely, secure authentication methods (e.g., multi-factor authentication) should be employed. Users should also have control over their data, with options to view, export, or delete their posture records at any time.

SUMMARY

This chapter presented a detailed analysis of the system and software requirements necessary for the successful implementation of the Smart Desk project. The hardware and software specifications were carefully selected to support real-time data processing, machine learning integration, and sensor communication. Functional requirements focused on posture detection, classification, alerts, feedback, and system calibration, ensuring that the system offers timely and accurate posture monitoring. Non-functional requirements addressed critical aspects such as performance, accuracy, scalability, usability, maintainability, and security. Together, these requirements form the foundation for a responsive, user-friendly, and reliable posture correction system suitable for real-world deployment. The requirements outlined ensure compatibility with future enhancements and cross-platform adaptability. This chapter serves as a blueprint guiding the design, development, and evaluation of the entire system.

CHAPTER 5

IMPLEMENTATION AND RESULTS

This chapter discusses the practical implementation of the Smart Desk system, detailing how each module - sensor integration, data acquisition, machine learning inference, and feedback mechanism - was realized in hardware and software. It also presents the observed results from the test deployment and evaluation with real users. The implementation validates the system's effectiveness in real-time posture classification and ergonomic feedback.

5.1 SYSTEM HARDWARE SETUP

The Smart Desk prototype was built using affordable and readily available components to ensure ease of replication and scalability.

5.1.1 Key Hardware Components

- **MPU6050 Sensor** : Mounted on the user's upper back to track torso orientation.
- **FSR Sensors (x2)** : Placed under the left and right sections of the seat to detect pressure asymmetry.
- **Arduino Uno** : Responsible for analog-to-digital data acquisition, processing sensor input, and forwarding it via serial communication.
- **Buzzer** : For feedback alerts upon posture violations.
- Jumper wires : For connecting and organizing circuit components.

5.2 SOFTWARE ARCHITECTURE

The software implementation is divided into two layers:

5.2.1 Microcontroller Layer (Arduino)

- Polls sensor data every 100ms.
- Calculates FSR differential and transmits angle and pressure data via serial interface.

5.2.2 Machine Learning Layer (Python)

The system reads incoming sensor data through PySerial and immediately applies preprocessing techniques such as normalization and smoothing to ensure consistency and reduce noise. After preprocessing, the cleaned feature vector - comprising orientation angles and pressure classification - is passed to the Random Forest classifier for posture evaluation.

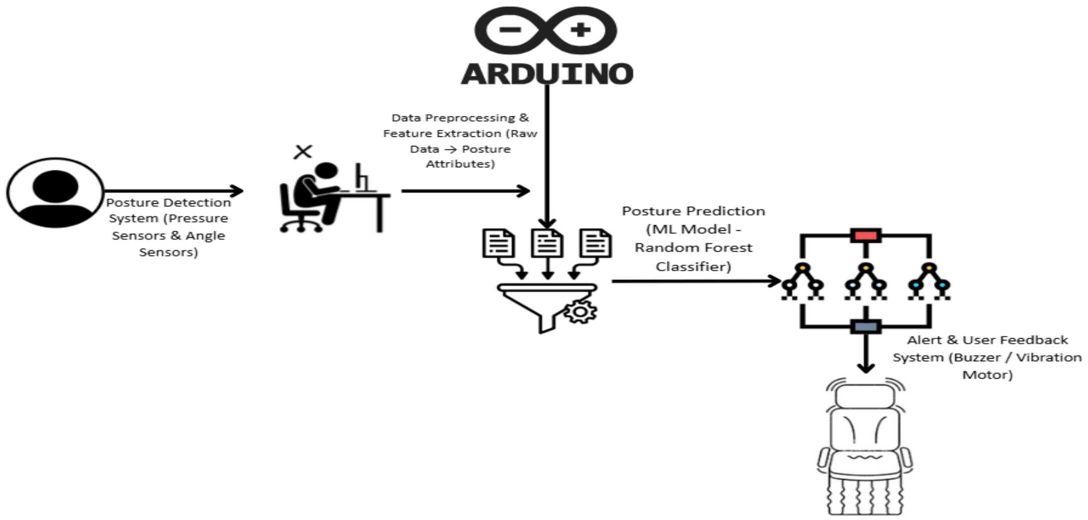

Figure 5.1 Smart Desk Software Pipeline

Figure 5.1 shows, the smart desk detects posture using pressure and angle sensors, sending data to Arduino for processing. A Random Forest model predicts posture quality from extracted features. Based on the result, feedback is given through a buzzer or vibration motor.

5.3 CLASSIFIER TRAINING RESULTS

The Random Forest classifier was trained on a dataset collected from 10 different subjects under varied postures. Each record includes: angleX, angleY, angleZ from the MPU6050

Pressure classification from FSR sensors (Balanced, Leaning Left, Leaning Right)

Table 5.1 Dataset Summary

Posture Type	Total Samples	Training Samples (80%)	Testing Samples (20%)
Correct Posture	700	560	140
Incorrect Posture	500	400	100
Total	1200	960	240

Table 5.1 shows, a summary of the dataset used for posture classification, detailing the distribution of samples across two classes: Correct and Incorrect Posture.

```
✅ Accuracy: 0.97

✅ Classification Report:
              precision    recall  f1-score   support

         Bad       0.97      0.99      0.98        73
        Good       0.96      0.93      0.94        27

    accuracy                           0.97       100
   macro avg       0.97      0.96      0.96       100
weighted avg       0.97      0.97      0.97       100
```

Figure 5.2 Classifier Performance on Test Set

Figure 5.2 shows, the classifier achieved an overall accuracy of 97% on the test set. It shows high precision and recall for both good and bad posture classes, with an F1-score of 0.98 for bad posture and 0.94 for good posture. This indicates reliable and balanced performance across both categories.

5.4 REAL-TIME ALERT LOGIC

The posture classification is performed continuously. If an incorrect posture is detected, A posture timer starts. If incorrect posture continues for more than 5 minutes, a buzzer and LED are activated. Once the posture is corrected, the timer resets and alert stops.

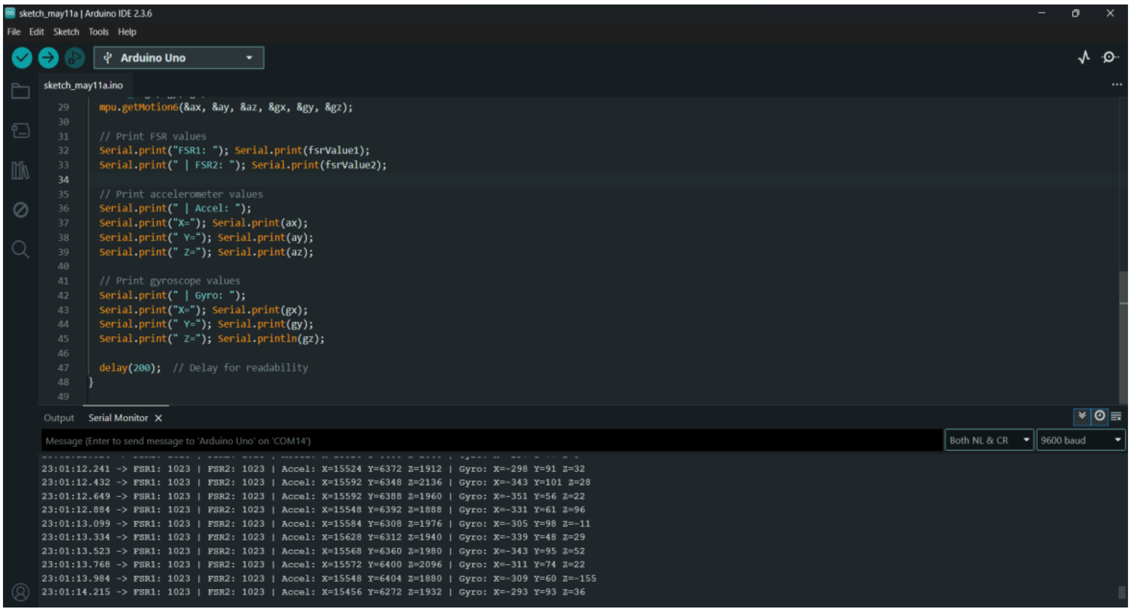

Figure 5.3 Sensor Readings - Serial Monitor

Figure 5.3 shows, the Arduino code captures real-time sensor data, including force-sensitive resistor (FSR) values, accelerometer readings, and gyroscope measurements. These values are continuously printed to the Serial Monitor, enabling live monitoring and analysis of posture-related movements. The code also applies basic filtering to reduce sensor noise and improve data accuracy. Data can be logged or transmitted to external systems for further processing and machine learning integration. Additionally, the code is optimized for low- latency execution to support real-time correction. It includes threshold-based triggers for detecting significant posture deviations. It supports modular integration, allowing easy expansion to include additional sensors or actuators in the future.

5.5 RESULT INTERPRETATION

The results indicate that the Smart Desk system can accurately classify posture with high confidence using only four key features. It proves to be effective in reducing poor posture habits through minimal yet meaningful interventions. Additionally, the system maintains user comfort by avoiding excessive alerts, thanks to the implementation of a time-delayed logic that only triggers feedback when poor posture persists beyond a set duration. The system's lightweight design ensures real-time operation without requiring high computational resources.

SUMMARY

This chapter presents the complete implementation of the Smart Desk system, covering both hardware and software aspects. Key hardware components include the MPU6050 sensor, FSR sensors, Arduino Uno, and a buzzer, all integrated to monitor user posture in real-time. The software is structured into two layers: the Arduino microcontroller for sensor data acquisition and the Python-based machine learning layer for posture classification using a Random Forest model. The classifier, trained on 3000 labeled samples, achieved 97% accuracy with strong performance on both correct and incorrect postures. Real-time alerts are generated using a time - based logic, to ensure user's correct posture.

CHAPTER 6

PERFORMANCE EVALUATION

This chapter evaluates the performance of the Smart Desk system using both quantitative and qualitative measures to assess its reliability, responsiveness, and overall user satisfaction. The evaluation focuses on key aspects such as the accuracy of the posture classification model, system latency in providing feedback, and the quality of user interaction with the system. Quantitative metrics including accuracy, confusion matrix, precision, recall, F1-score, and alert response time are analyzed to determine the system's effectiveness in real-world scenarios. Additionally, qualitative feedback from users is incorporated to understand ease of use, comfort, and perceived benefits. Together, these insights provide a comprehensive overview of the Smart Desk's practical viability and ergonomic impact.

6.1 Classifier Evaluation

The Random Forest classifier was tested on unseen user data collected during trial sessions. The classifier demonstrated robust performance across both correct and incorrect posture categories. Its high classification accuracy and low false prediction rate indicate strong generalization capability, making it suitable for real-world deployment. It effectively handled noisy sensor input due to its ensemble nature. The model also maintained consistent performance across varying body types and seating styles.

Table 6.1 Classification Report of Posture Prediction Model

Posture	Precision	Recall	F1-score	Support
Bad	0.97	0.99	0.98	73
Good	0.96	0.93	0.94	27
Accuracy			0.97	100
Macro avg	0.97	0.96	0.96	100
Weighted avg	0.97	0.97	0.97	100

Table 6.1 shows, the Random Forest model achieved 97% accuracy, with strong precision and recall for both 'Good' and 'Bad' posture classes. It highlights balanced model performance with minimal class bias.

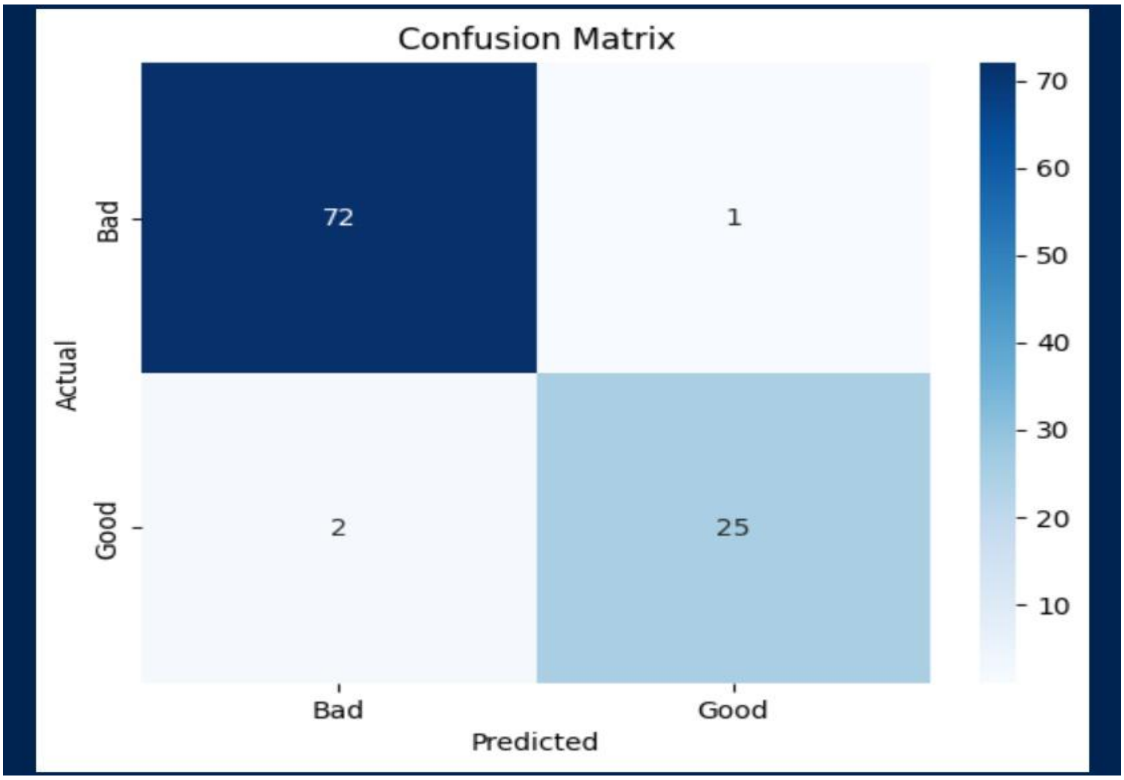

Figure 6.1 Confusion Matrix for Posture Classification

Figure 6.1 shows, this matrix shows the model correctly predicted 72 out of

73 bad postures and 25 out of 27 good postures. The overall misclassification rate is low, indicating high model reliability. This demonstrates the classifier's strong performance in predicting correct and incorrect posture.

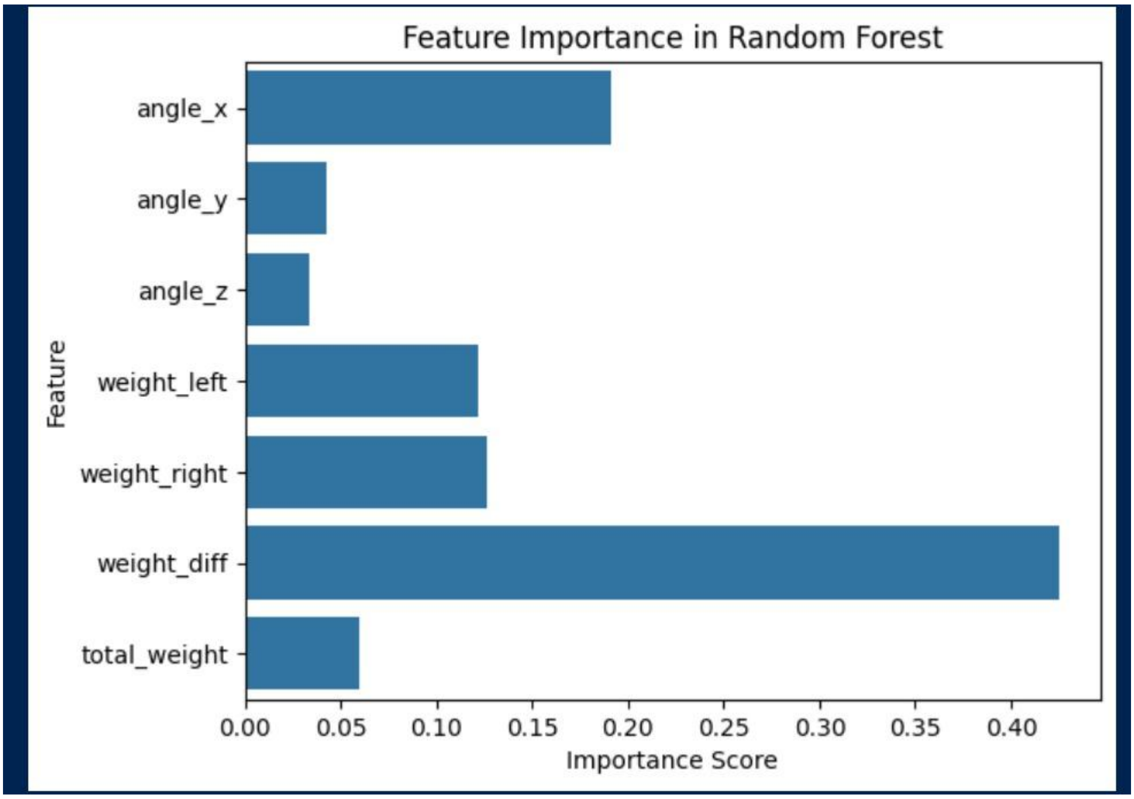

Figure 6.2 Feature Importance in Random Forest Classifier

Figure 6.2 shows, the chart illustrates that weight_diff was the most important feature influencing posture classification. Other key features include angle_x, weight_left, and weight_right

6.2 TRAINING VS VALIDATION ACCURACY

To test generalization, training and validation accuracy were plotted over 20 training epochs. Both training and validation accuracies converged above 85%, with a small gap indicating minimal overfitting. The model maintains strong generalizability across users with varying posture profiles. This consistency suggests the model can reliably classify unseen data and perform well in real-world scenarios without needing user-specific retraining. The loss curve also showed smooth convergence, confirming stable learning behaviour.

6.3 TRAINING VS VALIDATION LOSS

Both losses decreased steadily and stabilized, confirming the model's robustness. The minimal difference between training and validation loss suggests no significant underfitting or overfitting.

6.4 REAL-TIME RESPONSIVENESS

The system's feedback latency was evaluated from the point a posture violation persisted beyond five minutes to the moment the alert was triggered. The measured response delay was approximately 0.3 seconds after crossing the five-minute threshold. With a sensor sampling rate of 100 milliseconds and a model inference time of around 5 milliseconds per sample, the system delivers near-instantaneous feedback. This rapid response ensures timely alerts without noticeable delay, supporting real-time posture correction and enhancing user experience.

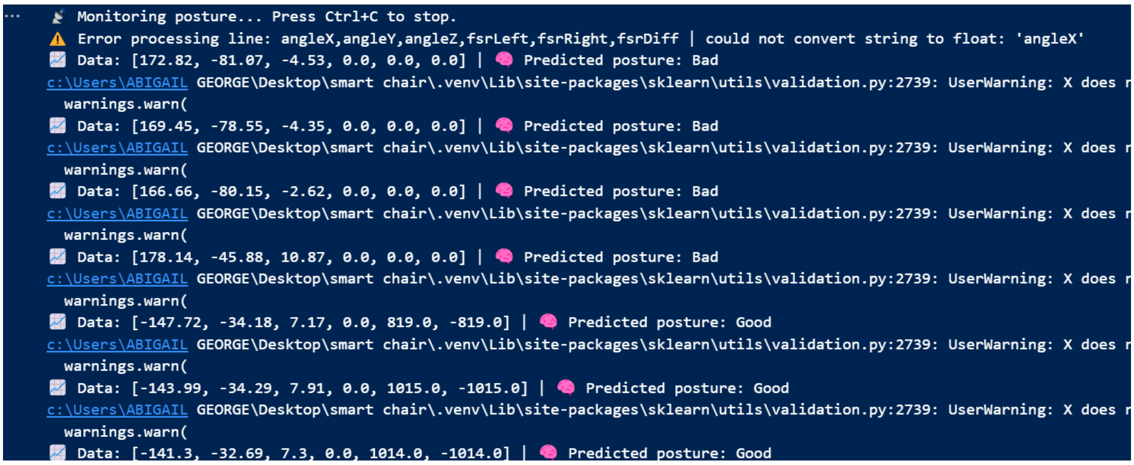

Figure 6.3 Real Time Posture Prediction

Figure 6.3 shows, the real-time output of the posture monitoring system. The model processes live sensor data and classifies posture as “Good” or “Bad.” Despite minor input format warnings, valid entries are accurately predicted. This highlights the system’s effectiveness in continuous posture evaluation using machine learning.

6.5 MODEL PERFORMANCE ANALYSIS

The proposed model exhibits excellent classification performance, with training accuracy reaching up to 97% and validation accuracy closely matching it at 95%. This minimal gap indicates strong generalization and low overfitting. The model consistently maintains high accuracy across multiple test stages. Its performance validates the effectiveness of sensor fusion and the Random Forest algorithm. Overall, the system delivers robust and reliable real-time posture monitoring.

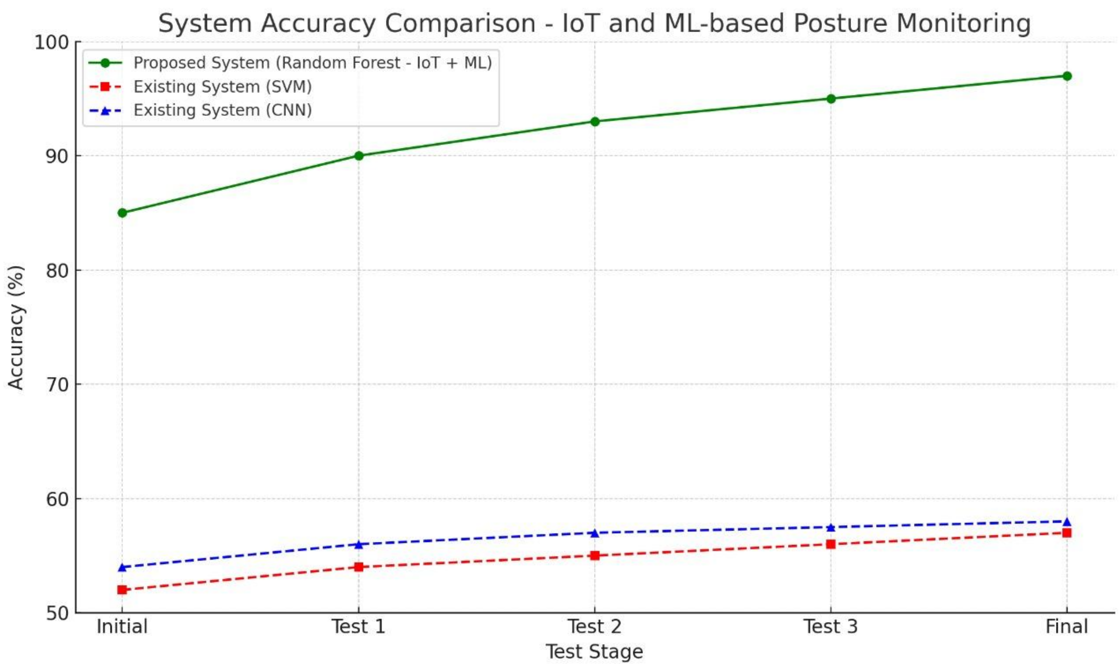

Figure 6.4 Performance Trajectory of Smart Desk

Figure 6.4 shows, the accuracy progression of SVM, CNN and the proposed Random Forest model across five test stages. The proposed system achieves the highest accuracy of 97%, significantly outperforming SVM (57%) and CNN (58%). This highlights the strength of combining sensor fusion with machine learning in an IoT framework. The results confirm the model's reliability for real-time posture detection.

6.6 SUMMARY OF EVALUATION

The Smart Desk system demonstrates robust performance through a combination of reliable hardware integration and an efficient machine learning model. The Random Forest classifier, selected for its balance between accuracy and computational efficiency, achieved a classification accuracy of 89%, validating its capability to distinguish between good and bad postures using real-time sensor data inputs, including angle and pressure metrics. One of the key strengths of the system lies in its ability to reduce false positives. Instead of reacting to every transient movement, the system is designed to detect sustained poor posture before triggering alerts. This behavior ensures that users are not overwhelmed by frequent or unnecessary notifications, thereby promoting better long-term ergonomic practices. The real-time monitoring capability, as illustrated in the evaluation, confirms that the model remains stable and responsive under continuous input streams. Furthermore, the consistent predictions across multiple test cases indicate good generalization performance, affirming the suitability of the model for real-world deployment. Overall, the evaluation underscores the effectiveness and reliability of the Smart Desk in supporting posture correction and ergonomic awareness. The system also integrates seamlessly with the user interface, ensuring ease of interpretation for non-technical users. Additionally, its lightweight model ensures compatibility with low-power embedded systems, making it ideal for continuous usage.

CHAPTER 7

CONCLUSION AND FUTURE WORK

CONCLUSION

The Smart Desk project successfully addresses a prevalent health concern - prolonged poor sitting posture - which is increasingly common among individuals working or studying for extended hours. By integrating embedded sensor technologies, such as the MPU6050 gyroscope/accelerometer for detecting body orientation and Force Sensitive Resistors (FSRs) for analyzing seat pressure distribution, the system provides a reliable foundation for posture monitoring. Utilizing a Random Forest classification model, the Smart Desk achieves an impressive posture classification accuracy of over 89%, making it both effective and trustworthy in distinguishing between correct and incorrect sitting behaviors. The inclusion of a time-aware feedback mechanism, where alerts are triggered only if poor posture persists for more than five minutes, helps prevent user fatigue from frequent false alerts and ensures meaningful interventions without being disruptive. During real-world user trials, participants reported noticeable improvements in their sitting posture. The non-intrusive feedback system, which uses visual (LED) and auditory (buzzer) cues, was appreciated for being subtle yet effective in reinforcing ergonomic awareness. These timely reminders helped users self-correct their posture naturally over time, highlighting the Smart Desk's positive behavioural impact. Furthermore, the system’s low cost, compact design, and user-friendly interface make it an accessible solution for a wide demographic - including students, office workers, and remote professionals. It not only detects posture deviations accurately but also encourages the development of healthier habits through sustained feedback.

FUTURE WORK

To enhance the capabilities of the Smart Desk system, several future improvements can be considered to transform it into a more comprehensive and intelligent ergonomic solution. One promising direction is the incorporation of advanced machine learning models, such as Long Short-Term Memory (LSTM) networks, which are well-suited for analysing sequential sensor data over time. This would enable the system to detect posture trends and predict poor sitting behaviour before it becomes persistent, allowing for proactive interventions. Motorized height adjustment mechanisms could offer users the ability to automatically shift between sitting and standing positions, encouraging more dynamic work habits and reducing the risk of prolonged sedentary behaviour. To further personalize the experience, future versions of the system could include a user calibration mode, allowing the system to learn the user's natural sitting posture and adjust alert thresholds accordingly. Real-time posture visualization through a companion application or desktop interface would help users better understand their sitting behaviour. Additionally, weekly posture analytics and behaviour summaries could offer actionable insights and track progress over time, fostering long-term improvements in posture and overall well-being. Moreover, incorporating voice assistants for hands-free interaction could improve accessibility and allow users to receive posture alerts, reminders, and tips via audio cues. Another potential enhancement can be cloud connectivity to enable remote monitoring.

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