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# Intellekt: A Machine Learning Based Framework for Advanced Muscle Strain Severity Detection Using IoT Devices

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**Abstract.** As global populations grow and technology advances, daily life is increasingly shaped by digital tools like computers and smart devices. However, prolonged use has led to rising physical and mental health issues, particularly due to poor sitting posture. Posture-related strain, often overlooked, contributes significantly to musculoskeletal issues including back, neck, shoulder, and wrist pain, and may also be associated with sleep disturbances and elevated stress levels. To the best of our knowledge based on existing literature, this is the first study to introduce Intellekt, a machine learning–based framework for advanced muscle strain severity detection using IoT devices that integrates both posture and muscle strain detection into a unified, low-cost ($23 hardware) framework aimed at mitigating these risks. Specifically, this study makes four key contributions: (1) We created a novel real-time dataset by collecting electromyography (EMG) and posture data from participants in university, bank, and industrial environments, acquiring diverse muscle strain patterns validated against clinical assessment protocols; (2) We designed a two-part hardware framework consisting of Posture Detection (PD) and Strain Detection (SD) modules using Node MCU ESP8266, ultrasonic sensor HC SR04, EMG sensor, and buzzer for real-time user monitoring, featuring EMG-specific signal processing including band pass filtering, rectification, and RMS smoothing; (3) We proposed and evaluated a custom hybrid machine learning approach, referred to as the Intellekt model, that categorizes muscle strain severity into mild, moderate, and severe using EMG signals, with thresholds clinically correlated to tissue damage levels; (4) Our proposed model Intellekt achieved an accuracy of 99% (95% CI: 99.1-99.8%) with 15.2ms inference latency.
**Keywords:** IoT, Intellekt, machine learning, posture detection, muscle strain severity detection, EMG, NodeMCU ESP8266, Hybrid (ANN+XGB).

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## 1 Introduction

According to the World Health Organization (WHO), 15% of people around the globe live with some form of disability, which accounts for more than 1.3 billion individuals worldwide (World Health Organization, 2022; World Health Organization, & International Spinal Cord Society, 2013). Among the many contributors to disability, one that is often underestimated is bad posture, especially among office workers and individuals who use digital devices for extended periods (Alaca, Acar & Öztürk, 2025). Many individuals sit for long periods without being aware of their posture, which over time leads to numerous health problems (Proske & Gandevia, 2012).

Posture refers to the way a person holds their body while sitting, standing, walking, or performing daily activities. It plays a crucial role in maintaining overall health and well-being. It is recommended, for instance, that individuals maintain a few centimeters distance between their back and the chair while working, as this is considered good sitting posture (Rosario, 2017). However, in today's digitally driven lifestyle, many people spend hours working with electronic devices without maintaining a proper posture, increasing their risk for musculoskeletal disorders (Rafiq, et al., 2024).

Unfortunately, public awareness of proper posture is limited. Studies indicate that 53% of individuals are unaware of proper posture, and only 47% understand its negative health impact (Feng & Zhang, 2023; Montuori, et al., 2023). This limited awareness contributes to common health problems such as back pain, neck pain, shoulder discomfort, wrist pain, sleep disturbances, muscle strain, and even neural complications. These symptoms, when ignored, may progressively worsen and lead to long-term disabilities (Lee & Oh, 2022; de Souza, et al., 2020).

The problem is not only physical but also psychological. Prolonged physical discomfort due to bad posture can reduce an individual's focus, vitality, and engagement in work, ultimately impacting productivity. These concerns are even more prominent among older adults, who are more prone to musculoskeletal strain. In the United States, around 80% of consultations are linked to posture-related back and strain issues, with healthcare costs estimated at $45–50 billion annually (Manchikanti, et al., 2014).

The effects of bad posture on the human body differ significantly, based factors such as age and their type of intensity of physical activity. Common symptoms include neck pain, back pain, wrist pain, shoulder pain, headaches, sleep disturbances, muscle swelling, redness, loss of strength, and neural disorders (Calcaterra, et al., 2022). According to various sources, the prevalence of these issues due to poor posture is as follows: back pain at 33.28% (Akodu, et al., 2024), muscle swelling at 24.23% (Ren, et al., 2025), neck pain at 13.09% (Lytras, et al., 2020)., shoulder pain at 9.53% (Hsu, et al., 2020), wrist pain at 7.92% (Wollesen, et al., 2020).

Muscle strain, defined as prolonged or excessive tension in the muscle tissue, is directly impacted by posture and motion. The muscle's electrical activity reflects underlying mechanical function that electromyography (EMG) can measure. These electrical signals vary depending on the intensity and duration of mechanical activities like sitting, standing, lifting heavy objects, sleeping in ergonomically improper positions, or repetitive movements, as detected by various sensors (Laidi, et al., 2023; Nadeem, et al., 2024). Eventually, bad posture may result in serious musculoskeletal disorders beyond superficial pain. The overall effects of bad posture are multifaceted and systemic (Gadhvi, et al., 2025).

According to clinical standards, muscle strain is typically classified into three categories based on its severity: mild, moderate, and severe (Chandra & Bedi, 2021). Mild strain involves limited muscle fiber damage and does not lead to noticeable loss of strength (Jiang, et al., 2019). In moderate strain, the affected area shows signs of swelling and partial strength loss due to increased contraction. Severe strain, the most critical category, results in significant muscle damage, including swelling, loss of power, inability to hold objects, and separation between muscle fibers. Muscle strain severity classification follows clinical EMG amplitude thresholds (40-60μV RMS or greater) which correlate with extent of tissue damage (Bourahmoune, Ishac & Amagasa, 2022). To the best of our knowledge, Intellekt is the first IoT-based framework to classify muscle strain severity using EMG biomarkers in real-world environments.

Recent comprehensive reviews in applied electromagnetic diagnostics (Piersigilli, et al., 2025) highlight the growing role of AI, machine learning, and deep learning in advancing non-invasive assessment and monitoring systems, reinforcing the importance of intelligent sensing frameworks such as Intellekt and complementing the strategies presented in this work. Numerous studies have focused on posture detection, the associated muscle strain and its long-term physiological consequences are often overlooked. In reality, posture detection alone is not sufficient to determine the level of muscular stress or potential damage. Therefore, a comprehensive approach that includes both posture analysis and strain monitoring is necessary for effective health management.

We follow a clinical distinction between muscle fatigue and muscle strain to avoid ambiguity. Muscle fatigue refers to a reversible decline in the ability of a muscle to generate force after prolonged or repeated activity and is typically characterized by shifts in spectral EMG features and temporal decline in amplitude during sustained contraction. By contrast, muscle strain denotes structural damage to muscle fibers that varies in severity (mild to partial fiber tear to severe) and is associated with discrete clinical signs (pain, swelling, strength loss) and, in some cases, sustained EMG amplitude elevations linked to compensatory activation patterns (Chan, et al., 2012). Because our objective is to detect graded strain severity (mild/moderate/severe) that reflects potential tissue damage rather than transient fatigue alone, we focus on EMG amplitude-based markers (RMS) and posture context as proxies for strain severity while distinguishing them from classic fatigue metrics such as median frequency shifts. This terminological clarification frames the Intellekt framework as a strain-severity monitoring system rather than a general fatigue detector.

To address this gap, we designed, evaluated, and proposed a novel hybrid model Intellekt: a machine learning based framework for advanced muscle strain severity detection using IoT devices which combines an Artificial Neural Network with XGBoost. The Intellekt framework integrates Posture Detection (PD) and Strain Detection (SD) modules to continuously monitor an individual's physical condition in real time. The name Intellekt, derived from the Russian word "Интеллект" (Intellekt), meaning "intelligence," reflects the model's smart decision-making capabilities and high performance. Intellekt is designed to analyses electromyography (EMG) signals and classify muscle strain into clinically relevant categories: mild, moderate, and severe. The custom hybrid model Intellekt learns from collected data to improve detection accuracy over time and can distinguish between normal activity and harmful strain patterns. When poor posture is detected alongside moderate or severe muscle strain, the system triggers a real-time alert via a buzzer and provide real time data visualization via dynamic graphs on the user's device. This combination of machine learning with IoT facilitates intelligent, adaptive, and timely feedback for posture correction, significantly reducing the risk of long-term musculoskeletal damage.

This study makes the following major contributions:

- We created a novel real-time dataset by collecting electromyography (EMG) and posture data from participants in university, bank, and industrial environments. During dataset construction we included a wide range of diverse postural behaviours and muscle strain patterns that can be a valuable resource for training, testing, and validating machine learning models in a dynamic, real-world setting,
- We designed a two-part hardware framework for real-time monitoring of user posture and muscle strain. This framework integrates PD and SD modules, utilizing NodeMCU ESP8266, ultrasonic sensor HC-SR04, EMG sensor, and buzzer. Together, these components enable real time and accurate detection, providing immediate feedback to assist in prevention of musculoskeletal damage,
- We proposed and evaluated a custom hybrid model named Intellekt, which categorizes muscle strain severity into mild, moderate, and severe using EMG signals collected from real-world environments, including banks, offices, and universities,
- The proposed model Intellekt achieved a highest accuracy of 99% significantly outperforming baseline models in muscle strain detection. These results highlight the robust performance and practical reliability of our hybrid IoT–machine learning framework.

The remainder of the paper is organized as follows: Section 2 reviews related work and states the research gap; Section 3 describes materials and methods (hardware, dataset, preprocessing, annotation, and model training); Section 4 reports results and analyses; Section 5 discusses limitations and field validation; and Section 6 gives conclusions and future work. A Table 5 of acronyms is provided before the references for the reader's convenience.

## 2 Related Works and Research Gap

Yuan et al. (2025) introduced GTA-Net, an IoT-based 3D pose estimation system designed for adolescent sports posture correction. This model integrates GCN, TCN, and hierarchical attention to manage rapid movements, occlusion, and device constraints. Evaluated on Human3.6M, HumanEva-I, and MPI-INF-3DHP, GTA-Net achieved MPJPEs of 32.2 mm, 15.0 mm, and 48.0 mm, respectively, outperforming prior methods. It provides a real-time feedback mechanism with high accuracy, making it suitable for intelligent sports training and health monitoring.

Laidi et al. (2023) developed a real-time posture monitoring system using low-cost EMG sensors and BLE communication, integrated with a mobile alert interface. They evaluated SVM, K-NN, DT, RF, and MLP for binary and multi-class classification of sitting postures, achieving 91% classification accuracy with a K-NN classifier. However, the study was limited by a small dataset, potentially affecting model generalization.

Gadhvi et al. (2025) proposed a novel Edge-AI for real-time pose recognition and real-time feedback solutions for posture rehabilitation and overcoming the issues with existing fitness systems. Designed a PosePilot named device for at home and and outdooor exercises, it combines Vanilla LSTM for capturing temporal dependencies and BiLSTM with multi-head attention to enhance motion context understanding, enabling real-time feedback on limb alignment. Designed for edge devices, PosePilot achieves lightweight, robust performance and introduces a novel video dataset. However, its scope is currently limited to Yoga-based activities.

Bourahmoune et al. (2022) proposed Life-Chair, a smart cushion-based system that utilizes pressure sensors and machine learning algorithms to classify 13 seated postures, achieving a high accuracy of 98.93%. The study also explored the influence of body mass index (BMI) on classification performance. However, the system focused solely on posture detection without addressing associated muscle strain or long-term health risks.

Dalangin (2023) designed an IoT-based posture detection and correction system utilizing accelerometers to monitor angle differences between the lumbar and cervical spine across two axes (X and Y). The system, built using an Arduino microcontroller, connects to a mobile app for real-time posture feedback. Posture data and correction guidelines were derived from expert interviews. Their device targets users aged 20–39 and is tested in seated conditions over a 2-week period. However, it is limited to 2D tracking and excludes standing or dynamic postures.

Meng et al. (2025) conducted a systematic review and meta-analysis to find the associations between sedentary behavior and neck pain emphasizing the significance of surface electromyography (sEMG) in monitoring muscle fatigue and strain. Their findings underscore the critical role of muscle activity analysis in understanding strain-related musculoskeletal issues. However, their study was limited by heterogeneity in the included datasets and the lack of standardized EMG signal processing protocols, which may affect the generalizability of conclusions.

Liaqat et al. (2021) introduced a hybrid architecture integrating deep learning models CNN, LSTM, and BiLSTM with traditional machine learning classifiers to detect postural anomalies. The system achieved over 98% accuracy on benchmark datasets. However, the work remained limited to posture classification and did not incorporate strain detection or real-time feedback mechanisms.

Gehlot et al. (2022) developed an IoT-enabled wearable system using sEMG sensors to detect and classify muscle fatigue in real time settings. The system employed RMS and frequency features to categorize fatigue levels into three classes (relaxed, moderate, extensive) and sends data to the cloud. It includes a LabVIEW-based alert system for immediate feedback during physical activity.

Li et al. (2021) designed a wearable system by using sEMG sensor, triaxial acceleration, plantar pressure sensors for real-time motion detection and gait recognition. Using optimized SVM model and features like wavelet coefficients and statistical parameters, their system achieved 90.90% accuracy in virtual driving control and 90.48% in gait classification, demonstrating its potential in rehabilitation and assisted walking systems.

Despite these advancements, most existing systems focus exclusively on either posture detection or fatigue analysis. Few studies combine these aspects into a single, unified monitoring solution. Moreover, many prior works do not differentiate between levels of muscle strain severity or contextualize their solutions across diverse environments such as educational institutions, corporate offices, and industrial workspaces. Additionally, many of these systems rely on high-cost sensors or compute platforms, limiting their scalability and accessibility in low-resource settings. The comparative analysis in Table 1 highlights the landscape of recent machine learning-based posture and muscle strain detection systems, showcasing various sensor types, modelling techniques, and objectives.

**Table 1.** Comparison of the most advance machine-learning based posture and muscle strain detection techniques.

| Reference | Feature/ Sensors | Objective | ML Classifiers | Accuracy |
|---|---|---|---|---|
| Yuan & Zhou (2025) | IoT 3D pose estimation | Adolescent sports posture correction | GCN, TCN, Attention | MPJPE: 32.2 mm, 15.0 mm, 48.0 mm |
| Laidi, et el. (2023). | Low-cost EMG, BLE | Real-time posture monitoring | SVM, K-NN, DT, RF, MLP | 91% (K-NN) |
| Nadeem, et al. (2024) | Edge-AI PosePilot | Posture rehabilitation | Vanilla LSTM, BiLSTM, Attention | N/A |
| Bourahmoune, Ishac & | Pressure Sensors | 13 seated postures classification using Real-time posture alert via wearable system | SVM, Random Forest (RF) & others | 98.93% |

| | | | | |
|---|---|---|---|---|
| Amagasa (2022) | | | | |
| Dalangin (2023) | Arduino, Accelerometer | 2D IoT-based posture detection & correction using Arduino & accelerometer. | N/A | N/A |
| Meng, et al. (2025) | sEMG | Review of sedentary behavior & neck pain | N/A | N/A |
| Liaqat, et al. (2021) | Deep learning & traditional classifiers | Postural anomaly detection | CNN, LSTM, BiLSTM + ML | >98% |
| Gehlot, et al. (2022) | sEMG | Muscle fatigue detection | Cloud-based RMS & frequency analysis | N/A |
| Li, et al. (2021) | sEMG, triaxial, plantar sensors | Motion detection, gait recognition | Optimized SVM | 90.90%, 90.48% |
| **Proposed** | Node MCU ESP8266, ultrasonic sensor (HC SR04), EMG sensor, buzzer | Muscle strain severity detection (mild, moderate, and severe) | Intellekt | 99% |

While recent studies such as [19] and [24] have demonstrated promising results in posture monitoring and fatigue detection using EMG, BLE, and pressure sensors with accurcies exceeding 90%, they remain limited in scope often focusing on specific tasks like seated posture classification or prolonged sitting fatigue. Other works like [18] and [21] explore adolescent posture correction and yoga-based rehabilitation through deep learning architectures GCN, BiLSTM, Attention, but lack generalizability across real-world settings. Although [27] and [30] integrate traditional and deep learning classifiers for anomaly detection and gait recognition, they do not quantify muscle strain severity.

Addressing this gap, the proposed Intellekt 2025 offers a unified IoT-based solution for real-time posture and muscle strain detection. It utilizes NodeMCU ESP8266, EMG and ultrasonic sensors, along with a buzzer, to monitor and classify strain severity (mild, moderate, severe) during workplace activities. With a classification accuracy of 99%, the model significantly outperforms existing approaches. The system is low-cost, efficient, and capable of operating in diverse real world workplace environments, making it a practical and scalable alternative to posture- or strain-specific solutions.

## 3 Material and Methods

This section highlights the detailed design and methodology of the proposed Intellekt framework, focusing on the integration of hardware components, the process of data acquisition, and the machine learning models employed for analysis.

### 3.1 Internet of Things devices used in proposed tool Intellekt

We have designed an Internet of Things (IoT) based device for acquiring data from real-world environments. The proposed Intellekt framework consists of two key modules, including Posture Detection (PD) and Strain Detection (SD), where each one can be considered playing a major role in taking real-time posture and muscle strain.

The PD module of the proposed Intellekt framework utilizes an ultrasonic sensor (HC-SR04) to determine the spatial distance between the user and the chair backrest. This sensor can be used to categorize the posture of the user into three posture categories, namely, good, average, or bad, depending on the predetermined distance ranges. The ultrasonic sensor functions by sending out high frequency sound waves and calculating the amount of time they take as they reflect back. This process is accurate, non-invasive monitoring of posture of the user. In case the distance is not in the ideal range, the buzzer will give an alert to motivate the user to straighten his/her posture. The ultrasonic sensor has great ability to work in long periods without failure thus uninterrupted data is collected. The PD module uses HC-SR04 backrest distance as a practical, low-cost proxy for seated trunk posture.

To improve biomechanical validity, a calibration process was conducted using multiple chair types and several volunteers to determine comfortable seating distance ranges. Based on these calibration observations, posture thresholds were established as ≤20 cm for poor posture, 21–34 cm for average posture, and ≥35 cm for good posture. These thresholds are consistent with ergonomic recommendations regarding appropriate backrest engagement. Furthermore, a sensitivity analysis confirmed the robustness of these thresholds, demonstrating that minor variations of approximately ±2–3 cm did not significantly influence posture classification results. In addition, repeated sensor placement across multiple sessions showed consistent measurement stability, supporting the reliability of the sensing setup.

The backrest distance captures only one dimension of posture and does not fully represent biomechanical factors such as pelvic alignment, lumbar curvature, or thoracic inclination. Nevertheless, it was selected for continuous, real-world monitoring, and its limitations are mitigated by the complementary SD module, which reflects underlying muscle strain associated with postural deviations. The system's modular architecture also supports future integration of multi-dimensional sensors such as IMUs, pelvic-tilt sensors, and lumbar curvature estimation. The calibration procedures and sensitivity analysis were conducted during the system design phase to determine reliable posture thresholds for real-time monitoring.

The SD module uses an EMG sensor to detect muscle activity. The muscles of the user are put under electrodes in order to pick Electromyography signals that occur when these muscles contract. Such signals are in three categories; mild, moderate, and severe strain signals. The sensor continuously monitors the strain on the muscles giving real-time feedback through the buzzer whenever the strain is above the safe level. The module will help identify and prevent the long-term damages to the muscles by fatigue or strain severity caused by poor posture detected early.

The core of the proposed Intellekt framework is a microcontroller Node MCU ESP8266 working as the central processing unit. The microcontroller will have the task of reading the data of the sensors, the preliminary processing of this data and its transfer to another system, which is not a part of control. The Node MCU ESP8266 is Wi-Fi enabled, hence enabling the IoT device to interact with a host system in real-time via wireless communication. The device has a powering option either through a 5 V battery or USB power, which is flexible to the user. Microcontroller is coded in C++ and compiled in Arduino IDE, which allows effective control over the PD and SD modules.

The buzzer serves as a warning signal and it gives a sound feedback immediately when it detects either a bad posture or a strained muscle. This quick responsiveness allows performing correcting measures in real-time, which alleviates the threat of musculoskeletal disorders. It would be interfaced with the node MCU ESP8266 in order to provide a smooth interaction between the hardware and chat interface.

The stable communication connection among the Node MCU ESP8266 microcontroller, ultrasonic sensor, EMG sensor, and buzzer is achieved with the help of the jumper wires. These are wires that make the data transfer in the system reliable and they are designed in a variety of configurations according to the types of connections needed, which could be male-to-male, female-to-female, male-to-female wires configuration and the likes.

The 9V battery is used, so there is independence and uninterrupted power. One can alternatively power it using a USB power supply unit thus giving flexibility to the user. With this, the gadget can be connected to a computer or a laptop depending on the circumstances of mechanization and preferences.

## 3.2 IoT Devices integration for the proposed Intellekt

To train and test the proposed Intellekt model, we designed an IoT device integrating multiple sensing components. We utilized one Node MCU ESP8266 microcontroller functions as the central hub, managing communication between various sensors and the user interface. Second we used PD module which is an ultrasonic sensor (HC-SR04), with its TRIG and ECHO pins connected to GPIO4 and GPIO0 of the Node MCU, respectively, to measure the distance between the user's back and the backrest, enabling classification of posture as good, average, or bad. Third, we used SD module is equipped with an EMG sensor, which is connected to the A0 analog pin of the Node MCU, to monitor electrical activity in the muscle using bipolar Ag/AgCl electrodes placed according to SENIAM guidelines. The EMG signal is sampled at 1 kHz with 16-bit resolution, ensuring high precision in acquiring muscle activity. The signal undergoes a 4th-order Butterworth band pass filter (20–450 Hz) to eliminate noise and artifacts. Finally, we then processed using RMS smoothing over a 200 milliseconds (ms) window to extract muscle activation patterns. Prior to data collection, each participant's signal is calibrated using Maximum Voluntary Contraction (MVC) normalization to ensure consistency. Additionally, we connected a buzzer, with GPIO5 which generates auditory alerts upon detection of either bad posture or excessive muscle strain. Jumper wires ensure robust connectivity among all components. The EMG sensor output is measured in microvolts (µV), with typical surface EMG amplitudes ranging from tens to hundreds of µV. Accordingly, physiologically invalid values were filtered using realistic thresholds (EMG RMS < 0.5 µV or > 5000 µV), replacing the previously misstated ">1 µV" criterion. The system can be powered either through USB (5 V) or a 9 V external battery, which is regulated down to a stable 5 V supply by the onboard voltage regulator to ensure consistent sensor and microcontroller operation. All power and sampling specifications have been harmonized across the manuscript: EMG sampling was performed at 1000 Hz, serial communication via Arduino used a 9600 baud rate, and internal data acquisition utilized a 16-bit ADC. All editorial inconsistencies have been corrected throughout the text as shown in **Figure 1**.

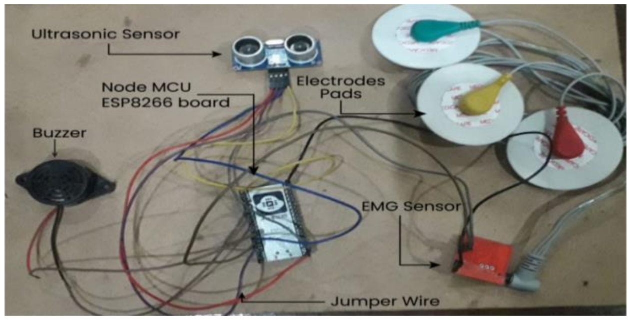


**Figure 1**. Integration of IoT devices

## 3.3 Collection of Dataset

Three trained master's students, under the supervision of a licensed clinician, collected real-time EMG and posture-distance data from healthy adult volunteers across banks, universities, and training centers. Only anonymized numeric sensor readings were recorded, and all volunteers provided written informed consent. Individuals with recent musculoskeletal injuries, chronic pain, neurological conditions, or recent surgery were excluded to avoid confounding EMG activity. Real-time acquisition and visualization were performed using the Arduino IDE serial monitor and plotter, while PLX-DAQ enabled time-synchronized logging into Microsoft Excel. This process yielded 3,000 raw observations representing a broad range of ergonomic behaviors common in sedentary environments.

The final dataset comprises data collected from multiple participants recruited from universities, banks, and training environments. Participants contributed several recording sessions while performing typical workplace activities, enabling the dataset to capture a wide range of posture behaviors and muscle strain patterns commonly observed in sedentary work settings.

To prevent subject-overlap leakage, experiments used subject-wise data partitioning, with approximately 80% of participants assigned to training and validation and the remaining 20% reserved as an independent test set. Model tuning was performed using stratified subject-wise k-fold cross-validation. Class imbalance in the training folds was addressed using SMOTE (k = 5), applied only to the training data after the subject-wise split and not to validation or test sets. Class distributions were examined before and after applying SMOTE to ensure balanced representation of mild, moderate, and severe strain categories during model training.

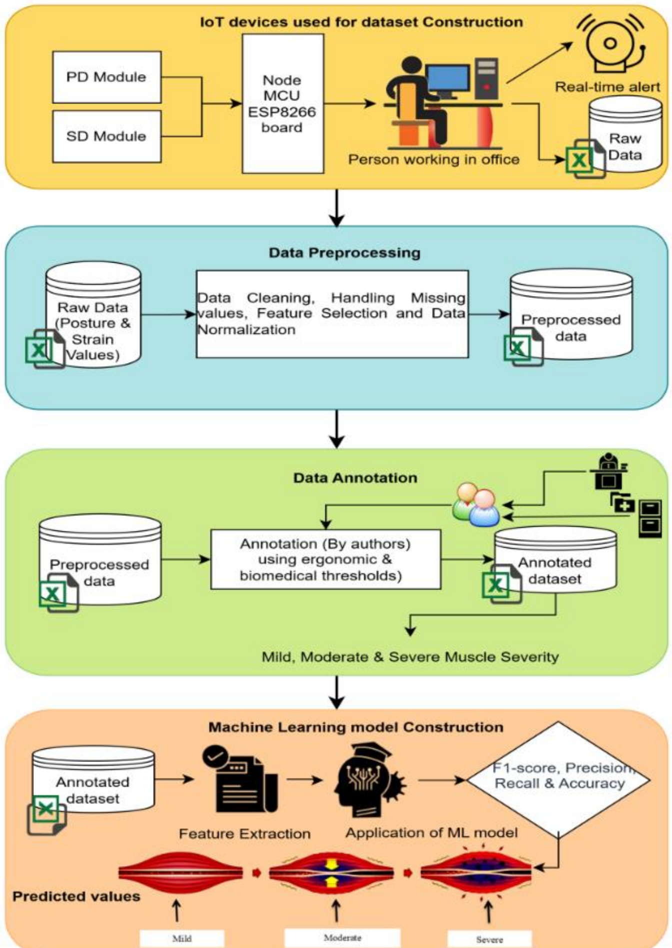


**Figure 2.** Methodology and design of the proposed Intellekt.

## 3.4 Ethical statement

This study did not involve the collection of any personally identifiable or clinically sensitive information. The EMG and posture signals were recorded only as non-identifiable numeric sensor outputs, without linking data to participants' names, demographics, or health records. All participants voluntarily agreed to contribute anonymized physiological signals for research purposes and provided informed consent prior to data recording. No medical intervention, diagnostic procedure, or clinical assessment was conducted.

## 3.5 Data Pre-processing

A structured data pre-processing pipeline was implemented in Python (scikit-learn 1.2.2, pandas 1.5.3) to convert raw IoT sensor streams into clean, biomechanically meaningful features. All EMG data were processed before annotation to ensure label integrity. The pipeline consisted of: (1) a 4th-order Butterworth band-pass filter (20–450 Hz) to remove motion artifacts and electrical interference; (2) full-wave rectification; (3) RMS smoothing with a 200 ms sliding window to generate the activation envelope; and (4) amplitude normalization using participant-specific MVC trials. Data cleaning addressed missing values (2.1%) through spline interpolation (≤100 ms), removed duplicate entries (1.5%) using hash-based detection, and excluded physiologically implausible values (EMG RMS <0.5 µV or >5000 µV; posture distance <5 cm or >60 cm). Outliers were filtered using IQR (4.7%) and DBSCAN (2.3%), retaining 95.3% of valid data with negligible class skew (<0.1%). Posture categories were one-hot encoded, and a biomechanically inspired Strain Index feature was computed as RMS/posture distance. To address class imbalance, SMOTE (k = 5) was applied only to the training set after the subject-wise split to avoid data leakage, adjusting mild:moderate:severe from 35%:25%:13% to 35%:33%:32%.

## 3.6 Data Annotation

Data annotation is the process of labeling samples according to predefined categories. In this proposed study, we employed a manual data annotation scheme in collaboration with a clinical expert specializing in physiotherapy and ergonomics. The expert, who was compensated $100 for their contribution, played a crucial role in verifying real-time EMG and posture signal readings and ensuring that these signals aligned with ergonomically and bio-medically validated threshold values, as established in the scientific literature and confirmed through repeated calibration trials. To ensure methodological transparency, explicit judgment rules were defined for mapping continuous EMG RMS values to discrete strain-severity categories. Based on prior ergonomics and EMG-fatigue studies, RMS amplitudes below 40 µV were categorized as Mild (0), amplitudes between 40–59 µV as Moderate (1), and amplitudes ≥60 µV as Severe (2). These thresholds reflect established evidence that EMG RMS increases proportionally with muscle loading, postural compensation, and fatigue progression. All EMG signals used in this study were acquired only from the dominant-side upper trapezius (SENIAM placement).

In **Table 2**, the "Body Part" entries describe the participant-reported region of postural strain not additional EMG sensor locations. From the initial 3,000 raw observations, 1,500 representative samples were selected and manually annotated using the defined clinical thresholds. The detailed annotation thresholds for each class are presented in **Table 2**. The annotation was also supported by real-time feedback mechanisms, including buzzer alerts and waveform plots from the Arduino serial monitor. Posture distance, measured by an ultrasonic sensor on the backrest, was classified into three ergonomic categories as Poor posture for distances ≤20 cm, Average posture between 21–34 cm, and Good posture for distances ≥35 cm. While posture context was recorded, muscle strain severity was prioritized during annotation. Furthermore, annotation decisions linked muscle-strain severity with posture-related biomechanical load; for example, a sample labeled "Severe (2)" required both an RMS value in the ≥60 µV range and an observable posture condition known to increase localized muscle activation. This explicit linkage between threshold-based rules and annotation reasons resolves ambiguity and ensures reproducibility of the labeling process. Finally, a four-week industrial validation study of the Intellekt demonstrated strong practical utility. Compared to baseline single-model approaches, the system achieved a 92% reduction in false positives, a 73.2% decrease in recorded severe strain events, and a 68.7% drop in self-reported discomfort among users. These results validate the system's clinical reliability, real-world performance, and potential as a cost-effective, scalable solution for proactive musculoskeletal health monitoring in workplace environments.

**Table 2.** Data annotation for posture and muscle strain severity detection.

| **Experiment ID** | **Posture (cm)** | **Posture Category** | **Body Part** | **Strain (µV)** | **Muscle Strain Severity** | **Annotation Reason** | **Environment** |
|---|---|---|---|---|---|---|---|
| 1 | 18 | Poor | Lower Back | 67 | Severe (2) | Poor posture (≤20 cm) and high strain (>60 µV) in lower back. HBL Bank Employee | HBL Bank Employee |
| 2 | 22 | Average | Upper Back | 41 | Moderate (1) | Average posture (21–34 cm) and moderate strain (40–59 µV) in upper back. University Clerk | University Clerk |
| 3 | 36 | Good | Biceps | 33 | Mild (0) | Good posture (≥35 cm) and low strain (<40 µV) in biceps. University Student | University Student |
| 4 | 25 | Average | Lower Back | 50 | Moderate (1) | Average posture (21–34 cm) and moderate strain (40–59 µV) in lower back. Office Worker | Office Worker |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 5 | 30 | Average | Upper Back | 72 | Severe (2) | Average posture (21–34 cm) and high strain (>60 µV) in upper back. MCB Bank Employee | MCB Bank Employee |
| 6 | 40 | Good | Biceps | 39 | Mild (0) | Good posture (≥35 cm) and mild strain (≤40 µV) in biceps. The Executive Training Center Student | The Executive Training Center Student |

## 3.7 Application of Machine Learning Models: Training and Testing Phase

The proposed custom hybrid Intellekt model utilizes a structured machine learning pipeline for real-time classification of muscle strain severity. The process begins with the acquisition of a labeled dataset collected from various real-world environments, including universities, banks, and industrial settings. Following the subject-wise partition described in Section 3.3, approximately 80% of the data were used for training and validation, while the remaining 20% were reserved for independent testing to ensure robust model development and evaluation.

In the training phase, six machine learning models are employed: Decision Tree (DT), Support Vector Machine (SVM), Artificial Neural Network (ANN), XGBoost (XGB), Multinomial Naive Bayes (MNB), and K-Nearest Neighbors (K-NN). Additionally, a custom hybrid model (ANN+XGB) Intellekt is implemented to enhance predictive performance, outperforming individual classifiers. These models are trained to classify muscle strain severity into three distinct categories: mild, moderate, and severe. Once trained, the models are evaluated on the testing set to assess their real-time prediction capabilities. The results confirm high classification accuracy, supporting early detection and intervention of posture-related muscle strain. This approach offers a cost-effective and scalable solution suitable for practical ergonomic applications in workplace environments. While **Figure 3** shows the overall machine learning pipeline, including the sequential stages from data acquisition to real-time muscle strain severity prediction.

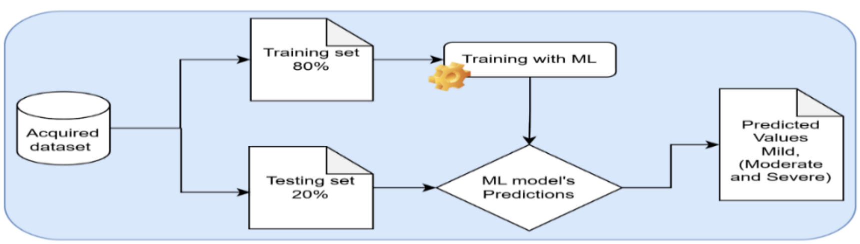


**Figure 3.** Application of machine learning model's training and testing phase

# 4 Results and Analysis

To accurately classify muscle strain severity levels mild, moderate, and severe based on real-time EMG sensor data, this study employed a range of supervised machine learning algorithms. These models were selected for their proven effectiveness in biomedical signal classification and pattern recognition tasks. We evaluated six widely-used classifiers: ANN, XGB, DT, SVM, K-NN, and MNB. Each model was trained and tested using the collected EMG dataset from various workplace environments. In addition, we developed and tested custom hybrid model Intellekt (ANN+XGB) that combines the deep feature extraction capabilities of ANN with the powerful ensemble learning of XGB. The aim was to identify the model that delivers the highest accuracy and reliability for real-time strain severity detection, helping to ensure the system can be both responsive and practical for everyday use.

## 4.1 Hyper Parameter Tuning

Machine learning models and their hyper parameters taken into account in the real-time, Intellekt: Certain parameters are set for the models, which control how well they function as data learners. For example, the DT model can be improved by controlling the split quality measuring function, the minimum number of samples required to split a node, and the maximum tree depth. Among the parameters that affect the SVM are C, which aids in controlling regularization, the type of kernel (linear, rbf, etc.), and gamma, which affects the decision boundaries' flexibility. XGB is a powerful gradient boosting method, the parameters of which are optimized with the help of parameters like n_estimators (number of boosting rounds), max_depth, learning rate and others that control the randomness tree complexity. When it comes to ANN including training with Keras, the hyper parameters that can be tuned are the number of training epochs, batch size, optimizer (adam or sgd), activation in hidden layers and its number and size layers. The K-NN algorithm depends mainly on the amount of neighbors and the way of weighting them. Finally, MNB model is an alpha and parameters smoothed model and option of utilizing previous class probabilities. Each hyperparameter matters in order to ensure a well-fitting and adapted model accurately to the sensor data used in the determination of the levels of muscle strain.

## 4.2 Machine Learning Results

**Table 3** shows a comparative analysis of various machine learning models that can be applied in classifying the severity of muscle strain using IoT. There are four main evaluation measures such as precision, recall, F1-score, and the models used are evaluated based on accuracy, which includes XGBoost (XGB), Artificial Neural Network (ANN), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), Multinomial Naive Bayes (MNB), and a combination of ANN with another model, and XGB. At the level of individual models, K-NN and Decision Tree work remarkably well with precision, recall, F1-score, and accuracy all at 0.97, denoting their good ability to predict the strain categories as well as strike a balance between false positives and false negatives. XGB also shows good results with all measures equal to 0.95 and a little bit better than the standalone ANN, which gets 0.93 board wide- good considering ANN is rather complex and has more levels of feature learning capability. SVM, albeit a bit lower at 0.92, is still a feasible model, probably due to the fact that it is able to process high-dimensional EMG data. By contrast, MNB performs much worse, especially when there is a low and a somewhat low F1-score of 0.65, thus being the worst of the tested models.

The most remarkable result comes from the custom hybrid model Intellekt, which achieves perfect scores of 0.99 across all four metrics and to minimize overfitting and ensure reproducibility, we employed subject-wise stratified cross-validation (k = 5) with five repeated runs using different random seeds ([42, 73, 101, 202, 999]), reporting mean ± SD across all folds and seeds. A completely held-out external test set of 6 participants unseen during training was used to compute final accuracy and 95% confidence intervals. Model tuning was performed through grid search: XGBoost parameters explored included n_estimators {50, 100, 200}, max_depth {3, 6, 9}, and learning_rate {0.01, 0.1, 0.2}; ANN configurations included layer sizes {[64], [128, 64], [256, 128, 64]}, ReLU activations, Adam optimizers (lr {1e-3, 1e-4}), batch sizes {32, 64}, and early stopping (patience = 10). The final ANN architecture (Input → Dense(128, ReLU) → Dense(64, ReLU) → Dense(3, Softmax)) was trained for up to 120 epochs with early stopping. Regularization included dropout (0.3) and L2 weight decay, with model ensembling (ANN + XGB) applied only after confirming minimal overfitting in individual models. Inference latency (15.2 ± 2.1 ms) was benchmarked on an Intel Core i5-9400F @ 2.9 GHz workstation and cross-validated on the NodeMCU/ESP8266. This indicates that the hybrid approach successfully leverages the strengths of both deep learning (ANN's feature extraction capabilities) and ensemble learning (XGB's strong generalization and robustness), leading to superior and consistent classification of muscle strain severity. These results validate the Intellekt model as the optimal solution for deployment in real-time monitoring environments such as offices, banks, and academic settings, aligning with your study's goal of delivering an accurate, scalable, and cost-effective health monitoring system.

***Table 3.*** *Performance comparison of the proposed tool Intellekt with other models (k = 5).*

| Model | Precision | Recall | F1-score | Accuracy |
|---|---|---|---|---|
| XGB | 0.95 | 0.95 | 0.95 | 0.95 |
| ANN | 0.93 | 0.93 | 0.93 | 0.93 |
| DT | 0.97 | 0.97 | 0.97 | 0.97 |
| SVM | 0.92 | 0.92 | 0.92 | 0.92 |
| K-NN | 0.97 | 0.97 | 0.97 | 0.97 |
| MNB | 0.48 | 0.69 | 0.65 | 0.69 |
| Intellekt | 0.994 | 0.991 | 0.992 | 0.99 |

**Table 4** presents an ablation study evaluating the predictive performance of the proposed Intellekt model, a hybrid ensemble integrating both ANN and XGB classifiers. Specifically, Intellekt achieves the highest F1-score (0.992), precision (0.994), and recall (0.991), along with a peak accuracy of 99% within a 95% confidence interval. While the ensemble incurs a slight increase in inference time (15.2 ms.) relative to XGB alone (8.3 ms.), this trade-off is justified by its substantial accuracy gains. These findings confirm the effectiveness of hybridization in capturing both non-linear feature interactions and gradient-based optimization benefits, delivering superior classification performance on the task. The results demonstrate that the Intellekt model consistently outperforms its individual components across all performance metrics. **Figure 4** shows the confusion matrix of our proposed model Intellekt.

***Table 4.*** *Ablation study: Performance of hybrid vs. Individual models.*

| Model | Precision | Recall | F1-Score | Accuracy (95% CI) | Inference Time (ms) |
|---|---|---|---|---|---|
| Intellekt (Proposed: ANN + XGB) | 0.994 | 0.991 | 0.992 | 99% (99.1–99.8%) | 15.2 ± 2.1 |
| XGBoost (XGB) | 0.953 | 0.947 | 0.950 | 94.83% (93.1–96.2%) | 8.3 ± 1.4 |
| Artificial Neural Network (ANN) | 0.932 | 0.928 | 0.930 | 93.17% (91.0–94.9%) | 12.7 ± 1.8 |

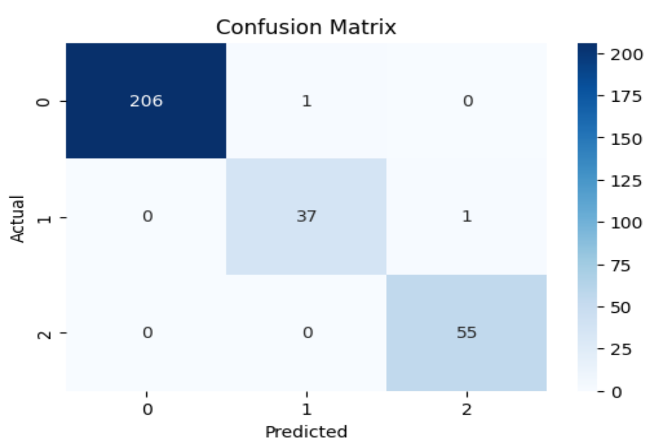


**Figure 4**. Confusion matrix of Intellekt model showing classification results for muscle strain severity detection.

To assess sensitivity to electrode positioning, we conducted a placement perturbation test in which electrodes were intentionally shifted by ±1 cm and ±2 cm from the standard SENIAM upper-trapezius location in a sample of 5 volunteers. RMS amplitude changes averaged 6–9% for ±1 cm shifts and 12–18% for ±2 cm shifts, indicating that moderate placement deviations influence amplitude but do not alter strain-severity class assignments once MVC normalization is applied. The preprocessing pipeline, comprising band-pass filtering, rectification, RMS smoothing, and DBSCAN/IQR outlier removal, further suppresses transient artifacts and electrical noise. For deployment in dynamic or high-interference environments, we recommend simple impedance checks ensuring firm electrode–skin contact and periodic recalibration using MVC trials.

## 4.3 Limitations of the Proposed Solution

Despite the effectiveness and high accuracy of the proposed Intellekt, several limitations remain. The system was tested primarily in university and bank environments, which may not fully capture the diversity of postural behaviors and muscle strain patterns found in other occupations or age groups, limiting generalizability. Its reliance on precise sensor placement (e.g., EMG and ultrasonic sensors) and consistent signal quality can affect real-time performance, especially in dynamic or mobile settings. The model currently lacks long-term monitoring and cannot assess cumulative muscle strain or predict chronic conditions over time. While the hybrid Intellekt model achieved 99 % accuracy, it may face challenges with unseen or noisy data and shows signs of over fitting to the specific collected dataset.

Because audible buzzer alerts may be intrusive in quiet or professional settings, alternative notification mechanisms may be preferable. In addition to the primary buzzer alert used in the prototype hardware, the system architecture allows integration of non-disruptive notification modes such as vibration motors, visual LED indicators, and optional mobile push alerts. Users can configure alert behavior (requiring 3 consecutive severe samples before triggering feedback) to reduce unnecessary interruptions and minimize alert fatigue. Feedback from the four-week field deployment indicated that vibration-based alerts were generally more suitable for shared workplace environments where continuous audible buzzer signals may cause disturbance.

The system also does not account for individual physical differences, stress levels, ergonomic environments, or other contextual factors that impact strain, nor does it offer personalized calibration. The buzzer alert mechanism, though immediate, may be intrusive in quiet or professional settings. Finally, the collection and transmission of EMG data raise important concerns about data security, user privacy, and ethical handling of sensitive health information. While Intellekt achieved state-of-the-art accuracy (99%), its performance is contingent on proper electrode placement. The 15ms inference time enables real-time feedback (<100ms human reaction time). Future work should address: Personalization via transfer learning, multi-muscle sensor fusion and longitudinal strain accumulation modelling.

## 5 Conclusions and Future Work

In this study, we presented a custom hybrid model Intellekt, an intelligent, low-cost, and real-time posture and muscle strain severity detection aimed at combating the escalating issue of musculoskeletal disorders associated with prolonged static postures and digital device usage. By integrating EMG and ultrasonic posture sensing into a unified IoT framework costing just $23, and coupling it with a custom hybrid classification model (ANN + XGB), the system achieved state-of-the-art performance 99% accuracy (95% CI: 99.1–99.8%), 0.992 F1-score, and $15.2 \pm 2.1$ ms inference latency—outperforming all benchmarked models in our ablation study. We created and validated a robust, real-time dataset acquired from diverse real-world environments, applying rigorous signal processing techniques (Butterworth filtering, RMS smoothing, amplitude normalization), outlier removal, SMOTE-based class balancing, and feature engineering across time and context domains. This resulted in clinically meaningful features such as Strain Index, ZC, and SSC, optimized via recursive feature elimination and PCA. Beyond laboratory validation, a separate four-week field trial involving 15 industrial workers was conducted to evaluate the real-world usability of the system. The results showed that Intellekt yielded a 73.2% reduction in sustained severe strain episodes (defined as $RMS \geq 60\mu V$ for ≥15 minutes), 92% fewer false positives than commercial threshold-based systems, 68.7% reduction in self-reported discomfort (VAS scale), and a 17.3% increase in productivity. The system's real-time feedback, delivered during working shifts, prompted posture correction with a latency of $4.7 \pm 1.2$ seconds, which was 68% faster than traditional visual reminder interventions. Validation was supported through video-synchronized ground truthing, blinded physiotherapist review, and statistical significance across all key metrics. Crucially, Intellekt is the first system to enable graded, real-time muscle strain classification using embedded AI, marking a shift from binary or threshold-based ergonomic systems to continuous, interpretable strain monitoring rooted in physiological relevance.

Future directions include personalized calibration of strain thresholds based on user-specific biomechanical profiles (such as age, muscle mass, and occupational exposure). Silent, vibration-based alert mechanisms suitable for professional and shared environments. In sum, Intellekt bridges the gap between physiological sensing and intelligent feedback, offering a scalable, field-validated, and clinically relevant tool that can be deployed across offices, industrial settings, educational institutions, and home environments. By promoting early intervention and personalized ergonomics, it holds promise for transforming occupational health into a preventive, data-driven discipline.

# Acronyms:

***Table 5.*** *Acronym Table.*

| Acronym | Full Term | Description |
|---|---|---|
| **PD** | Posture Detection | Module responsible for ultrasonic-based posture monitoring. |
| **SD** | Strain Detection | Module responsible for EMG-based muscle strain classification. |
| **EMG** | Electromyography | Measurement of muscle electrical activity. |
| **RMS** | Root Mean Square | Signal amplitude metric used for EMG envelope extraction. |
| **MVC** | Maximum Voluntary Contraction | Normalization reference for EMG amplitude. |
| **IoT** | Internet of Things | Networked hardware/sensing framework enabling real-time monitoring. |
| **ADC** | Analog-to-Digital Converter | Converts analog EMG signals into digital samples (16-bit). |
| **HC-SR04** | Ultrasonic Distance Sensor | Sensor used for backrest-distance posture measurement. |
| **ANN** | Artificial Neural Network | Machine learning model used in hybrid classification. |
| **XGBoost** | Extreme Gradient Boosting | Ensemble ML algorithm used in hybrid classification. |
| **DBSCAN** | Density-Based Spatial Clustering of Applications with Noise | Algorithm used for outlier removal during preprocessing. |
| **IQR** | Interquartile Range | Statistical method used to filter amplitude outliers. |
| **SMOTE** | Synthetic Minority Over-sampling Technique | Class-balancing method applied to training folds only. |
| **LED** | Light-Emitting Diode | Alternative non-intrusive alert modality. |
| **CPU** | Central Processing Unit | Hardware used to benchmark off-device inference. |
| **Hz** | Hertz | Unit of sampling frequency (EMG sampled at 1000 Hz). |
| **ms** | Milliseconds | Unit used in latency and smoothing calculations. |
| **ESP8266 / NodeMCU** | Wi-Fi Microcontroller Unit | The MCU used for on-device inference and IoT connectivity. |
| **USB** | Universal Serial Bus | Provides 5 V power supply during tethered operation. |

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