Artificial intelligence model for continuous, in-home, posture and health monitoring including user feedback and predictions of clinical assessment.

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## Introduction

According to (Gill et al., 2023) in 2020 alone, musculoskeletal disorders (MSDs) had been ranked 2nd as the leading non-fatal disability which has been affecting more than a billion people worldwide. In Finland, MSD had taken the spotlight as being the leading cause of temporal disability within the nation, through which a lot of resources allocated towards the health services (Martimo, 2010). It might be misconceived that only the elderly are the only ones that suffer from this condition. However, a report by (European Agency for Safety and Health at Work., 2021) has concluded that quite a number of individuals across different age groups are currently suffering from it. It was reported that MSDs can often originate during the childhood stage mainly due to adoption of abnormal postures and low physical activities, which subsequently lead to long-term chronic pain, discomfort, and physical limitations. Traditional examination and treatment procedures most often consist of regular clinical visits and are currently viewed as being inconvenient and costly. According to (Bevan, 2015), MSDs have said to have cost the EU over 2% of its gross domestic product (GDP), which is estimated to be over €240bn each year. There is no doubt that this is a steadily growing concern that needs to be properly addressed.

Currently, a majority of office work requires one to be in a seated position for an extended period of time, which is said to have adverse effects to one’s health. According to (Arora and Khatri, 2022) and (Putsa et al., 2022), prolong sitting is one of the leading causes of MSDs among office workers. It is therefore recommended that the users should go for small walk breaks after every few hours.

Furthermore, with the rapid advancement in data sensor technology and Artificial Intelligence in this present age, there should be new and commercialized solutions out there in the market for continuous posture and health monitoring. There is no doubt that these types of systems have the potential of contributing towards the idea of personalized healthcare and improving the quality of life, especially for individuals that are suffering from MSDs.

With that in mind, various research studies have investigated the development of posture monitoring systems which are aimed at detecting bad sitting postures to help the end user in maintaining the right sitting posture at every given time. These types of systems are named as “smart sensing chairs” which goes all the way back to a research study done by (Tan et al., 2001) which fitted a chair with a pressure distribution sensor in order to classify a user’s sitting postures which was just first of many. Furthermore, with a lot of research papers being published in this field, this literature review aims to evaluate related studies and identify research gaps that can pave the way for further investigation into this study. By exploring existing studies, it is possible to gain a better understanding of the current state on the implementation of a smart sensing chair for posture classification and health monitoring.

## Literature Review

### Existing Sitting Posture Monitoring Systems

As previously stated, the development of a sitting posture monitoring system is not an entirely new concept, rather it is an area that has been explored by multiple researchers in the past until this present day. To conduct this literature review, 30 relevant research papers were carefully selected and examined as seen in Table 1. have been published focusing on the of the use of unobtrusive means for the classification of different sitting positions. Systematically examining these papers would surely some shed light on the most common machine learning algorithms and sensors being used to be able to classify various sitting postures.

### Sensor Technology

Upon in-depth evaluation of the research papers, it was seen that there are different variations of sensor technology being used in the classification of different sitting postures. Overall, it was concluded that Force Sensing Resistors (FSRs) and Load Cells were 2 of the most widely used sensors of choice in the classification of different sitting postures.

#### Flex Sensors

* What are flex sensors?
* What are they made from?
* Other use-cases

#### Load Cells

#### Other types of sensors

* Web cameras
* RFID
* Sensors Combinations

### Different Sitting postures

### Smart Wheelchair Systems

### User Feedback System

### Machine Learning Algorithm

### Machine Learning

### Research Gaps

### Future/Proposed Plans

### Commercialization

## Conclusions

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## Appendixes

Tables 1 – Sitting Posture Monitoring Research Papers

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Reference** | **Sensors** | **Number of Postures** | **Classification Method** | **Classification Accuracy** | **Test Subjects** | **Limitations** | **User Feedback System** | **Is Realtime** |
| (Pereira and Plácido Da Silva, 2023) | Load Cell - Posture Conductive Nappa - ECG | 5 | K-NN | 98.50% | 10 | Not used in a real-life setting | |  |
| (Ahmad et al., 2021) | Screen Printed Pressure units (16 Array) | 4 | LightGBM | 99.03% | 32 | Not used in a real life setting | |  |
| (Huang et al., 2017) | 52 by 44 Piezo-Resistive Sensor Array | 8 | ANN | 92.20% |  | No accuracy |  |  |
| (Martínez-Estrada et al., 2023) | 10 Presence textile capacitive sensor (embroidered) | 8 |  |  | 5 |  |  |  |
| (Matuska et al., 2020) | 6 Flexible Force Sensors | 9 | Average Standard deviation with 3 Threshold values to determine good/bad postures (Non AI) |  | 12 |  |  |  |
| (Aminosharieh Najafi et al., 2022) | 8 Force Sensing Resistors | 8 | EMNM | 92.68% | 40 |  |  |  |
| (Kundaliya et al., 2022) | A502 Force Sensor & Flex Sensor | 5 |  |  |  | No accuracy |  |  |
| (Ran et al., 2021) | Pressure Array (IMMM00014, I-MOTION | 7 | 5 Layer Artificial Intelligence | 97.07% | 100 |  |  |  |
| (Roh et al., 2018) | 4 Load Cells | 6 | SVM using RBF kernel | 97.94% | 24 | No accuracy |  |  |
| (Kim et al., 2018) | Textile Pressure Sensors (Conductive Ni-Ti alloy fiber) | 7 |  |  |  | No accuracy |  |  |
| (Feng et al., 2019) | RFID tags | 3 | RF | 99.27% | 14 | Small number of postures | |  |
| (Hu et al., 2020) | 6 Flexible Force Sensors | 7 | 2 Layer ANN | 97.43% | 11 |  |  |  |
| (Jeong and Park, 2021) | 6 Pressure Sensors & 6 Infrared Reflective Distance Sensors | 11 | K-NN | 92% | 36 |  |  |  |
| Martins et al. 2013 | 8 | ANN | 93.40% | 30 |  |  |  | |
| (Mutlu et al., 2007) | 10 | SimpleLogistic | 87% | 46 |  |  |  | |
| (Ma et al., 2017) | 5 | Decision Tree (J48) | 99.47% | 12 |  |  |  | |
| (Zemp et al., 2016) | 16 Force Sensor | 7 | Random Forest | 81% - 98% | 41 |  |  |  |
| (Tsai et al., 2023) | 13 pressure sensors (FSR-406) | 10 | SVM (Linear) | 99.10% | 20 |  |  |  |
| (Kim et al., 2018) | 8x8 Pressure Sensor | 5 | CNN | 95.30% | 10 |  |  |  |
| (Luna-Perejón et al., 2021) | 6 Force Sensitive Resistors (FSR) | 7 | ANN | 81.00% | 12 | Low accuracy |  |  |
| (Cai et al., 2021) | 3x3 Flexible Array Pressure Sensor | 6 | SOM (ISOM-SPR) | 95.67% | 40 | Few Test Samples | Mobile App |  |
| (Fan et al., 2022) | 44 × 52 Pressure Sensor Array | 5 | CNN | 99.82% | 8 | \_ Few Test Samples \_ Lack of detection of spine curvatures | N/A | YES |
| (Chen, 2019) | Astra3D Sensor |  | CNN | 90% |  | Privacy issue with Camera Can't work in bad lighting Lack of proper user feedback system for posture correction | PC Screen (Correct/Wrong) | YES |
| (Ma et al., 2020) | Pressure array | 5 | Decision Tree | 89% |  |  |  |  |
| (Fard et al., 2013) | 64 Pressure Sensors Array (40x50) cm2 | 4 |  |  | 5 | Limited number of subjects | N/A | NO |
| (Ren et al., 2019) | 6 Square-Type force Sensing Resistors |  | ANN |  |  |  | RGB LED | YES |
| (Wang et al., 2021) | 2 Pressure Sensors Array (FSR) | 15 | SNN (LSM) | 88.52% | 19 | Lack of focus on the User feedback aspects Not used in real-life setting to prove it's usefulness | Desktop App | YES |
| (Xu et al., 2013) | Electrical Textile | 7 | Naive Bayes Network | 85.90% | 14 | The mobile just visualizes the sitting pressure distribution, however the value of this is not really seen to the end user's persepective. No sort of recommendation system. | Mobile App | Yes |
| (R et al., 2023) | Web Camera | 6 | RCNN & CNN | 92.50% |  | No good user feedback/recommendation system | N/A | YES |
| (Fu and Macleod, 2014) | 8 Force Sensing Resistors (FSR) FSR 406 |  | HMM Decision Tree |  |  | Lacks Proper testing  There's a need to implement a feedback system | N/A | YES |