LITERATURE REVIEW

Problem statement: Real-time Posture Monitoring and Correction System Using Laptop Camera for Enhanced Ergonomic Health

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Table of Contents

Body Posture Detection Using Computer Vision

Methodology used: The methodology used in the paper for body posture detection involves the integration of OpenCV and OpenPose MobileNet Technology. OpenCV serves as a powerful framework for real-time computer vision, providing essential functions for image processing and analysis. The OpenPose framework is employed to detect keypoints on the human body, which represent major joints and body parts. By utilizing MobileNet, a lightweight deep learning model, the system efficiently processes these key points while maintaining accuracy, making it suitable for mobile and embedded applications.

The implementation begins with capturing video frames or images, which are then analyzed to extract keypoint locations. The spatial relationships between these keypoints are assessed to determine the overall body posture, allowing for the classification of various postures such as standing, sitting, or walking. This approach not only enhances human-computer interaction but also has significant applications in fields like surveillance, healthcare, and entertainment. However, the paper acknowledges challenges related to real-time performance and the need for further research to improve the accuracy and reliability of the posture detection system.

Pros:

1. **Robustness:** The discussed approach is noted to be reliable and robust in recognizing human body postures from video and image content.
2. **Wide Applications:** The methodology has significant applications in various fields such as surveillance, healthcare, and entertainment, enhancing human-computer interaction.
3. **Advancements in Technology:** The use of OpenPose MobileNet Technology allows for efficient processing and recognition of body postures, contributing to the ongoing development in the field of computer vision.

Cons:

1. **Real-Time Performance Issues:** The paper mentions that there are still challenges to be addressed regarding real-time conditions and performance, indicating that the current model may not be fully optimized for immediate application.
2. **Limitations in Recognition Accuracy:** The effectiveness of the posture detection may vary based on environmental factors and the complexity of human movements, which can affect recognition rates.
3. **Need for Further Research:** The paper acknowledges that many issues remain unresolved, suggesting that further advancements and refinements are necessary to achieve a perfect model for body posture detection

Sitting Posture Recognition Based on OpenPose

Methodology used: The methodology employed in this study involves the development of a sitting posture recognition system that utilizes OpenPose for feature extraction and a convolutional neural network (CNN) for classification. Initially, video data is captured from classroom monitors, which provides a real-time view of students' sitting postures. OpenPose, an open-source library developed by Carnegie Mellon University, is then used to extract key posture features by identifying 18 body joints and the connections between them. These extracted features are organized into datasets that represent both correct and incorrect sitting postures, which serve as the training set for the CNN.

Once the datasets are prepared, the Keras deep learning framework is utilized to construct and train the CNN. The model undergoes training over 100 epochs, during which it learns to differentiate between various sitting postures based on the features extracted by OpenPose. The trained model is subsequently tested on separate validation datasets to evaluate its accuracy and effectiveness in recognizing sitting postures in real-time. The results demonstrate that the system can accurately identify students' sitting postures, providing a practical solution for promoting better sitting habits and addressing health concerns related to poor posture among adolescents.

Pros:

1. **High Accuracy:** The system achieved an accuracy of up to 90% on both the test and verification sets after training for 100 epochs, indicating effective posture recognition capabilities.
2. **Real-time Monitoring:** The use of video monitoring allows for continuous assessment of students' sitting postures, enabling timely feedback and correction.
3. **Non-invasive:** Unlike sensor-based methods, this approach does not require additional hardware, making it more accessible and easier to implement in classroom settings.

Cons:

1. **Dependence on Video Quality:** The effectiveness of the system may be influenced by the quality of the video feed, including lighting conditions and camera angles, which can affect posture detection accuracy.
2. **Limited to Visible Postures:** The system may struggle to recognize postures that are partially obscured or not fully visible to the camera, potentially leading to misclassification.
3. **Training Data Requirements:** The need for a substantial dataset to train the CNN effectively may pose challenges in terms of data collection and processing

Computer Vision-Based Human Body Posture Correction System:

The paper presents a methodology to detect and correct poor sitting postures using computer vision and deep learning techniques. Here's an overview of the methodology, along with its pros and cons:

Methodology:

System Architecture and Hardware Design:

- ➔ Utilizes Raspberry Pi 4B and Raspberry Pi Camera Module V2.
- ➔ OpenCV for visual processing and YOLOv8 for object recognition and keypoint detection.
- ➔ Incorporates an SVM classifier for posture judgment.
- ➔ Provides real-time feedback through alarms and voice prompts.

Program and Algorithm Design:

- ★ Key-point Detection and Localization:
  - ○ YOLOv8n model used for detecting key points (eyes, nose, ears, shoulders).
  - ○ CSPDarknet53 for feature extraction.
  - ○ PAN (Path Aggregation Network) structure for feature fusion.
- ★ Pose Analysis and Classification:
  - ○ Calculation of distances between key points (e.g., ears to shoulders).
  - ○ Features f1f1f1 and f2f2f2 derived from these distances to determine posture.
  - ○ SVM classifier used to classify posture as "good" or "bad".
- ★ Error Threshold Analysis:
  - ○ Considers physiological differences, environmental factors, and minor postural adjustments to set error thresholds.
- ★ Support Vector Machine (SVM) Classification:
  - ○ Gaussian kernel used for SVM to handle non-linearity and high-dimensional pattern recognition.
  - ○ Grid search method to optimize penalty parameter CCC and kernel parameter σ2\sigma^2σ2.

Pros:

1. **High Accuracy:** The system achieves an average recognition rate of 95%, indicating reliable posture detection.
2. **Real-time Performance:** The system provides immediate feedback to the user, helping to correct posture promptly.
3. **Compact and Portable:** The hardware setup is compact, supporting both Windows and Linux operating systems.
4. **Practical Implementation:** Successfully deployed on Raspberry Pi, demonstrating good practicality and stability.
5. **Versatile Design:** Can detect various postures and remind users to correct poor posture or take breaks from prolonged sitting.

Cons:

1. Hardware Limitations: Using Raspberry Pi might limit processing power, which could affect performance in more complex or resource-intensive tasks.
2. Environmental Dependence: Accuracy might vary depending on environmental conditions such as lighting, camera angle, and user distance from the camera.
3. Physiological Variability: Individual differences in body structure might affect the system's ability to uniformly detect and correct posture across different users.
4. Error Threshold Sensitivity: Setting appropriate error thresholds is challenging due to the variability in user posture and environment, potentially leading to false positives or negatives.
5. Limited Scalability: The system is designed for individual use and might need significant modifications for larger-scale applications or different settings.

Overall, the paper demonstrates a robust approach to posture correction using computer vision and machine learning, with practical implementation and real-time feedback capabilities. However, certain limitations related to hardware, environmental conditions, and individual physiological differences need to be addressed for broader applicability.

A Deep-Learning Based Posture Detection System for Preventing Telework-Related Musculoskeletal Disorders:

This paper proposes a system to detect and correct poor posture in teleworkers. The system utilizes a convolutional neural network (CNN) to process video in real-time, detecting the posture of the neck, shoulders, and arms, and providing recommendations to improve posture.

Key Components:

- ★ **Hardware Setup:**
  - The system includes a camera (such as a webcam) positioned to capture the user from head to arms.
  - The video from the camera is processed using an embedded system that runs the CNN for posture detection.
- ★ **Software Setup:**
  - The neural network used is a pose estimation model called TRT_Pose, designed to run on NVIDIA devices (e.g., NVIDIA Jetson family).
  - The neural network is pre-trained using the MSCOCO dataset, which includes diverse images of people.
- ★ **Posture Detection and Recommendations:**
  - The system estimates the position of key joints (neck, shoulders, arms) and calculates angles to assess posture.
  - Recommendations are provided based on ergonomic guidelines to maintain correct posture and avoid musculoskeletal issues.
  - The system runs in real-time, providing feedback at up to 25 frames per second with low power consumption.
- ★ **Evaluation:**
  - Various NVIDIA hardware platforms are evaluated for their performance in terms of execution time, power consumption, and efficiency.

The study compares the hardware platforms to determine the most effective one for real-time posture detection.

Pros

1. **Real-Time Processing:** The system processes video in real-time, providing immediate feedback to users to correct their posture.
2. **Low Power Consumption:**The specialized hardware used in the system ensures low power consumption, making it suitable for continuous use.
3. **High Accuracy:** The system achieves over 80% accuracy in detecting posture, making it reliable for practical use.
4. **Embedded System Integration:** The use of embedded systems (like NVIDIA Jetson) allows for a compact and efficient solution that can be integrated into various environments, such as on top of computer screens.
5. **Comprehensive Evaluation:** The study thoroughly evaluates different hardware options, ensuring the system's effectiveness and efficiency.

Cons

1. **Hardware Dependency:** The system relies on specific hardware (NVIDIA devices), which may limit its accessibility and increase costs for some users.
2. **Pre-Trained Model Limitations:** While the pre-trained model on the MSCOCO dataset is diverse, it may still have limitations in accurately detecting posture in all real-world scenarios or with all body types and clothing styles.
3. **Initial Setup Complexity:** Setting up the system may require technical knowledge, particularly in configuring and integrating the embedded systems and neural networks.
4. **Limited Scope of Detection:** The system focuses on the neck, shoulders, and arms, which means it may not detect poor posture involving other body parts like the lower back or legs.

Overall, the methodology presented in this paper demonstrates a practical and effective approach to addressing telework-related musculoskeletal disorders through real-time posture detection and correction. However, its dependency on specific hardware and potential limitations in detection scope should be considered when evaluating its overall utility and applicability.

Ergonomic risk assessment based on computer vision and machine learning

Methodology Used:

- ★ **RULA Assessment:**
  - RULA (Rapid Upper Limb Assessment) is a tool designed to provide a grand score representing the postural load on a worker's musculoskeletal system based on joint angles of different body parts. The score is derived from a hierarchical combination of individual body part scores, which are then integrated into intermediate scores summarizing upper limb and overall body stress. Finally, these are combined into a single grand score indicating the need for ergonomic intervention.
- ★ **Pose Estimation using OpenPose:**
  - The OpenPose CNN architecture is employed for human pose estimation. OpenPose detects and tracks key points on the human body from video inputs, which are then used to compute joint angles necessary for RULA scoring.
- ★ **Data Collection and Experimental Setup:**
  - Synthetic and real-world datasets are used to evaluate the proposed method. The synthetic dataset involves a 3D model performing regulated movements, captured from various viewpoints. Real-world data comprises videos of actual working scenarios.
- ★ **Validation Methods:**
  - The method is validated using several approaches:
    - Self-Occlusion Tests: A simulated 3D model is used to assess the impact of occlusions on joint detection accuracy.
    - Controlled Image Sequences: Real and synthetic datasets are compared to evaluate joint angle accuracy.
    - Expert Comparison: RULA scores computed by the method are compared with those given by experienced ergonomists using Cohen’s kappa to measure agreement.

Pros:

1. **Robustness:** The proposed method shows resilience to common visual challenges such as uneven lighting, occlusions, and varying camera angles, which often hinder traditional observational assessments.
2. **Automation:** It automates the process of ergonomic risk assessment, reducing reliance on subjective expert judgment and potential human errors.
3. **Cost-Effectiveness:** Utilizing low-cost, off-the-shelf RGB cameras and open-source CNN architectures makes the solution affordable and easily replicable.
4. **Flexibility:** The methodology can be adapted for various real-world conditions and different ergonomic assessment needs beyond just RULA, such as REBA (Rapid Entire Body Assessment) and MRULA (Modified RULA for computer workers).

Cons:

1. **Dependence on Technology:** The accuracy of the CV-based assessment relies heavily on the performance of the OpenPose algorithm and quality of video input.
2. **Complexity of Real-World Conditions:** Despite advancements, challenges like extreme occlusions and highly variable lighting conditions can still affect the precision of joint detection and pose estimation.
3. **Limited Scope:** Currently, the methodology may be limited to assessing single workers and may face difficulties with multiple workers or highly dynamic environments.

Light-Weight Seated Posture Guidance System with Machine Learning and Computer Vision

Methodology Used:

★ **Pose Estimation via BlazePose:** The BlazePose model is employed to extract 33 different body key points from each frame captured by a webcam or smartphone camera. BlazePose is chosen for its real-time inference capabilities and high accuracy on mobile devices.

★ **Data Collection:** Videos of eleven participants (nine males and two females, aged 19 to 46) were recorded in various postures. The data was collected under IRB Protocol #2016-0693. Participants were recorded in both good and bad postures from multiple angles, and the videos were then sliced into frames for analysis.

★ **Normalization of Keypoint Coordinates:** To account for variations in camera angles and positions, the key points were normalized by translation and scale. This involves finding the midpoint between the left and right hips and adjusting the coordinates to remove translational variations. The maximum distance from the pose center is used to normalize the scale of the pose.

★ **Posture Classification:** The normalized keypoints are fed into a machine learning model to classify the posture as good or bad. Two models were trained: one using all keypoints and another using only upper body key points for cases where the lower body is occluded. The system continuously classifies frames and issues a notification if ten consecutive frames show bad posture.

Pros

1. Accessibility: The system can be implemented on any device with a webcam or smartphone camera, making it highly accessible and cost-effective.
2. Real-time Performance: Utilizing the BlazePose model ensures that the system can operate in real-time, providing immediate feedback to users.
3. High Accuracy: The posture classification model achieves 98% accuracy, ensuring reliable monitoring and feedback.
4. No Additional Hardware Required: Unlike other posture correction systems that require expensive trackers or sensors, this system relies solely on existing devices.

Cons

1. Camera Placement Sensitivity: Although the machine learning model is trained to handle various angles, the accuracy can still be affected by improper camera placement.

2. Occlusion Handling: While the system has a model for upper body keypoints, significant occlusions can still impact the accuracy of posture classification.
3. Limited Participant Diversity: The study involved a relatively small and homogeneous sample size, which may limit the generalizability of the results.
4. Potential Privacy Concerns: Continuous video monitoring may raise privacy concerns among users, especially in home environments.

Advanced interdisciplinary approaches for bad posture detection using computer vision and IoT

Methodology:

The paper proposes two distinct methodologies for bad posture detection:

1. Computer Vision Approach using MediaPipe:

★ **Data Acquisition:** A webcam captures real-time video of the user.
★ **Pose Estimation:** Google's MediaPipe library processes the video feed to identify and track key body landmarks (e.g., shoulders, elbows, hips, knees).
★ **Posture Analysis:** Algorithms analyze the spatial relationships between the identified landmarks, calculating angles and distances to determine deviations from a predefined neutral posture.
★ **Feedback:** The system provides real-time feedback to the user, typically through visual cues on the screen (e.g., highlighting misaligned body parts) or auditory alerts.

2. IoT Approach using Flex Sensors:

★ **Data Acquisition:** Flex sensors, strategically placed on the user's body (e.g., back, shoulders), measure the degree of bending or curvature.
★ **Data Transmission:** The sensors transmit the bending data wirelessly to a central processing unit (e.g., an Arduino microcontroller).
★ **Posture Analysis:** The central unit analyzes the sensor data, comparing it to pre-established thresholds for good posture.
★ **Feedback:** The system provides feedback to the user, typically through a buzzer or visual display, when poor posture is detected.

Pros:

1. **Real-time Monitoring & Feedback:** Both approaches provide immediate feedback, allowing users to make real-time adjustments to their posture. This immediacy is crucial for promoting awareness and encouraging proactive correction.
2. **Personalized Feedback (Potential):** The paper suggests the possibility of customizing the system based on individual body parameters and posture habits. This personalized approach could lead to more accurate detection and targeted feedback.
3. **Versatility and Scalability:** The proposed system can be adapted for various environments, including offices, healthcare facilities, and educational institutions. Its scalability allows for potential integration into existing systems or development of standalone applications.
4. **Interdisciplinary Approach:** The paper highlights the integration of knowledge from biomechanics, human-computer interaction, and health sciences. This interdisciplinary approach contributes to a more holistic understanding of posture and its impact on overall well-being.

Cons:

1. **Limited Accuracy (Especially with Computer Vision):** The accuracy of the computer vision approach is susceptible to environmental factors like lighting conditions, clothing, and background clutter. The accuracy of the flex sensor approach can be limited by sensor placement and calibration.
2. **Cost:** Implementing the system, particularly the computer vision approach, may involve significant costs, including hardware (webcams, sensors), software licenses, and potentially cloud computing resources.
3. **Privacy Concerns (Computer Vision):** The use of a webcam for posture monitoring raises privacy concerns, especially regarding the storage and potential misuse of video data. Addressing these concerns requires robust privacy protocols and user consent.
4. **Complexity (IoT Approach):** The IoT approach, involving sensor integration and data transmission, might be complex to set up and maintain, requiring technical expertise.

In Summary:

The paper presents two innovative approaches for bad posture detection, leveraging both computer vision and IoT technologies. While promising in their real-time monitoring and feedback capabilities, the proposed methodologies face challenges related to accuracy, cost, privacy, and complexity. Further research and development are necessary to refine these approaches and address the identified limitations before widespread adoption can be expected.

Automated Postural Ergonomic Risk Assessment Using Vision-based Posture Classification

Methodology:

This paper proposes a novel vision-based method for automated posture classification and ergonomic risk assessment. The key innovation lies in leveraging virtual images for training the classification algorithm, eliminating the need for extensive real-world image datasets. The methodology can be broken down into the following steps:

- ★ **Virtual Image Generation:** Diverse virtual human models are used to generate images of various postures relevant to the target tasks and occupations. This allows for creating a large and varied training dataset without the logistical challenges of capturing real-world images.
- ★ **Feature Extraction from Silhouettes:** Body silhouettes are extracted from both the virtual training images and the real-world images captured during assessment. This step reduces the impact of variations in lighting, clothing color, and individual physical attributes.
- ★ **Classification Algorithm Training:** Machine learning classification algorithms are trained using the features extracted from the virtual image silhouettes. The paper doesn't explicitly specify the algorithm used, but suggests the use of standard classifiers suitable for image recognition tasks.
- ★ **Real-world Posture Classification:** The trained algorithm analyzes the features extracted from real-world image silhouettes to classify the observed postures into predefined categories based on ergonomic risk levels.
- ★ **Ergonomic Risk Assessment:** Based on the classified postures, the system automatically assesses the ergonomic risk associated with the observed tasks and provides feedback, potentially in real time.

Pros:

1. **Reduced Data Collection Effort:** The use of virtual images significantly reduces the time and effort required to create a comprehensive training dataset for posture classification.
2. **Robustness to Variations:** Silhouette-based feature extraction makes the system less susceptible to variations in lighting, clothing, and individual appearances.
3. **Automation and Real-time Potential:** The proposed method enables automated and potentially real-time ergonomic risk assessment, facilitating timely interventions and preventive measures.

4. **Broad Applicability:** While focusing on construction, the methodology can be adapted for ergonomic risk assessment in various other industries and occupations.

Cons:

1. **Generalizability of Virtual Models:** The effectiveness of the approach hinges on the realism and representativeness of the virtual human models used for training. Discrepancies between virtual and real-world postures could impact accuracy.
2. **Computational Demands:** Real-time performance may be computationally demanding, requiring sufficient processing power for image processing, feature extraction, and classification.
3. **Limited Validation:** The paper presents results from laboratory-based tests, but further validation in real-world construction settings is needed to assess the practical performance and robustness of the system.
4. **Lack of Specificity on Algorithm and Features:** The paper doesn't provide details about the specific classification algorithm used or the precise features extracted from the silhouettes, making it difficult to fully evaluate the technical aspects of the methodology.

Conclusion:

The proposed vision-based method presents a promising approach for automating postural ergonomic risk assessment. Its use of virtual training images addresses a key bottleneck in the development of such systems. However, further research and development are needed to validate its performance in real-world scenarios and address limitations related to the generalizability of virtual models and computational demands.

This paper contributes to the growing body of research exploring computer vision techniques for improving workplace safety and ergonomics. The potential for real-time feedback and automated risk assessment could significantly impact efforts to prevent WMSDs and promote healthier working environments.

A Scene Recognition and Semantic Analysis Approach to Unhealthy Sitting Posture Detection during Screen-Reading

Methodology:

This paper introduces a novel approach to detecting unhealthy sitting postures during screen-reading by incorporating scene recognition and semantic analysis. The methodology leverages a Microsoft Kinect sensor and a deep learning model, Faster R-CNN, to achieve a more comprehensive understanding of the context and improve posture detection accuracy. The key steps involved are:

- ★ **Skeletal Data Acquisition:** A Microsoft Kinect sensor captures the skeletal data of the user, providing information about the position and orientation of key body joints.
- ★ **Scene Recognition with Faster R-CNN:** A deep learning model, Faster R-CNN, is employed to detect and classify objects within the scene. This allows the system to understand the context of the user's activity, specifically focusing on screen-reading scenarios.
- ★ **Semantic Analysis with Gaussian-Mixture Behavioral Clustering:** The system performs semantic analysis by clustering the identified objects based on their spatial relationships and functionalities. This helps in understanding the user's interaction with the environment.
- ★ **Feature Fusion:** The skeletal features extracted from the Kinect data are combined with the semantic features derived from scene recognition and analysis. This fusion creates a richer representation of the user's posture and context.
- ★ **Unhealthy Posture Classification:** A classification model, which is not explicitly specified in the paper, is used to analyze the fused features and classify the sitting posture as healthy or unhealthy. The paper focuses on detecting various types of unhealthy postures, including those often missed by traditional methods that rely solely on skeletal data.

Pros:

1. **Contextual Awareness:** Incorporating scene recognition and semantic analysis allows the system to understand the context of the user's activity, leading to more accurate posture detection.

2. **Improved Accuracy in Complex Environments:** By considering the surrounding objects and their relationships, the system can avoid misclassifications that might occur in cluttered or dynamic environments.
3. **Detection of Diverse Unhealthy Postures:** The method can detect a wider range of unhealthy postures compared to traditional approaches that solely rely on skeletal data.
4. **Potential for Medical Assistance:** The system has potential applications in healthcare and treatment, providing valuable insights for medical professionals and assisting in ergonomic interventions.

Cons:

1. **Computational Complexity:** The use of deep learning models for scene recognition and semantic analysis can be computationally expensive, potentially limiting real-time performance or requiring powerful hardware.
2. **Dependence on Kinect Sensor:** The system relies on the availability and accuracy of a Kinect sensor, which may not be readily available in all settings.
3. **Limited Generalizability:** While effective for screen-reading scenarios, the system's performance may need to be evaluated for other activities and environments.
4. **Lack of Specificity on Classification Model:** The paper doesn't explicitly mention the classification model used for final posture classification, making it difficult to fully assess the technical details of this crucial step.

Conclusion:

The proposed methodology offers a promising advancement in unhealthy sitting posture detection by leveraging the power of deep learning and contextual awareness. Its ability to accurately detect diverse unhealthy postures in complex environments makes it a valuable tool for promoting ergonomic health and well-being. However, further research is needed to address the computational demands and explore its generalizability to different activities and settings.

This paper contributes to the growing body of research exploring the use of computer vision and artificial intelligence for human behavior analysis and health monitoring. The integration of scene understanding into posture detection opens up new possibilities for developing intelligent systems that can provide personalized feedback and interventions for improved ergonomic practices.

This detailed literature review provides a comprehensive analysis of the paper's methodology, strengths, limitations, and contributions to the field. It offers valuable insights for researchers and practitioners interested in applying computer vision and AI techniques for posture analysis and ergonomic interventions.

Sitting Posture Recognition Using a Spiking Neural Network

Methodology:

This paper proposes a novel approach for sitting posture recognition using a spiking neural network (SNN) based on a liquid state machine (LSM) and a logistic regression (LR) classifier. The system utilizes a custom-designed pressure-sensing smart chair to collect data and provide feedback to the user. The methodology can be broken down into the following key steps:

★ **Data Acquisition:** A smart chair equipped with two arrays of pressure sensors (one for the seat pan and one for the backrest) captures pressure distribution data for various sitting postures.
★ **Data Encoding:** The pressure matrix data, which is inherently spatial, is encoded into a time-varying spike sequence suitable for processing by the SNN. A custom algorithm maps the pressure values to a cosine-ranked 0/1 matrix with adjustable sparsity.
★ **Liquid State Machine Processing:** The encoded spike sequence is fed into the LSM, which acts as a dynamic reservoir, transforming the input into a complex spatiotemporal representation. The LSM consists of interconnected excitatory and inhibitory neurons with recurrent connections.
★ **Readout and Classification:** The output of the LSM, representing the liquid state, is passed to a logistic regression classifier. The LR classifier is trained to recognize different sitting postures based on the unique patterns generated by the LSM.
★ **Posture Recognition and Feedback:** The system classifies the current sitting posture based on the output of the LR classifier. If an unhealthy posture is detected, the smart chair provides feedback to the user, guiding them towards a more ergonomic posture.

Pros:

1. **Biologically Inspired Processing:** The use of SNNs, inspired by the workings of the biological brain, offers potential advantages in terms of efficiency, robustness, and the ability to process temporal information.
2. **Dynamic Posture Recognition:** The LSM's ability to capture dynamic patterns makes the system suitable for recognizing postures that involve movement and transitions.
3. **Personalized Feedback:** The smart chair system provides personalized feedback to the user, promoting awareness and encouraging corrective actions for improved posture.
4. **High Accuracy:** The reported accuracy of 88.52% demonstrates the effectiveness of the proposed approach for recognizing a diverse set of sitting postures.

Cons:

1. **Computational Complexity:** SNNs, especially those with complex architectures like LSMs, can be computationally demanding, potentially requiring specialized hardware for real-time processing.
2. **Data Encoding Challenges:** The effectiveness of the system relies on the chosen encoding method. Finding an optimal encoding scheme that preserves relevant information while maintaining computational efficiency can be challenging.
3. **Limited Generalizability:** The system's performance may be affected by variations in individual body shapes, sizes, and seating habits. Further validation with a larger and more diverse dataset is needed to assess its generalizability.
4. **Dependence on Custom Hardware:** The system requires a custom-designed smart chair with integrated pressure sensors, limiting its immediate applicability to broader contexts.

Comparison with Existing Literature:

This paper distinguishes itself from previous work by its innovative use of SNNs for posture recognition. Most existing approaches rely on traditional machine learning techniques, such as support vector machines (SVMs) or artificial neural networks (ANNs), which may not be as well-suited for processing temporal data. The use of an LSM-based SNN allows the system to capture the dynamic aspects of sitting postures, potentially leading to more accurate and robust recognition.

Conclusion:

The proposed SNN-based approach for sitting posture recognition offers a promising avenue for developing intelligent systems that can promote ergonomic well-being. The combination of a pressure-sensing smart chair and a biologically inspired processing model provides a unique solution for real-time posture monitoring and personalized feedback. However, further research and development are needed to address the computational demands, explore different encoding strategies, and assess the system's generalizability to diverse populations and settings.

This paper contributes to the growing body of research exploring the application of SNNs in human-computer interaction and health monitoring. The potential for developing energy-efficient and robust posture recognition systems based on SNNs holds significant promise for future advancements in ergonomic design and personalized healthcare technologies.

This detailed literature review provides a comprehensive analysis of the paper's methodology, strengths, limitations, and contributions to the field. It offers valuable insights for researchers and practitioners interested in exploring the use of SNNs for posture analysis and ergonomic interventions.

Contributions

1. **Poornisha**
   - ➢ Body Posture Detection Using Computer Vision
   - ➢ Sitting Posture Recognition Based on OpenPose
2. **Mohammed Tawfiq**
   - ➢ Computer Vision-Based Human Body Posture Correction System
   - ➢ A Deep-Learning Based Posture Detection System for Preventing Telework-Related Musculoskeletal Disorders
3. **Deepika**
   - ➢ Ergonomic risk assessment based on computer vision and machine learning
   - ➢ Light-Weight Seated Posture Guidance System with Machine Learning and Computer Vision
4. **Vishwadharani**
   - ➢ Advanced interdisciplinary approaches for bad posture detection using computer vision and IoT
   - ➢ Automated Postural Ergonomic Risk Assessment Using Vision-based Posture Classification
5. **Aravinthan**
   - ➢ A Scene Recognition and Semantic Analysis Approach to Unhealthy Sitting Posture Detection during Screen-Reading
   - ➢ Sitting Posture Recognition Using a Spiking Neural Network