Real-time posture monitoring prediction for mitigating sedentary health risks using deep learning techniques

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ABSTRACT

Sedentary behavior has become a pressing global public health issue. This study introduces an innovative method for monitoring and addressing posture changes during inactivity, offering real-time feedback to individuals. Unlike our prior research, which focused on post-analysis, this approach emphasizes real-time monitoring of upper body posture, including hands, shoulders, and head positioning. Image capture techniques document sedentary postures, followed by preprocessing with bandpass filters and morphological operations such as dilation, erosion, and opening to enhance image quality. Texture feature extraction is employed for comprehensive analysis, and deep neural networks (DNN) are used for precise predictions. A key innovation is a feedback system that alerts individuals through an alarm, enabling immediate posture adjustments. Implemented in MATLAB, the method achieved accuracy, sensitivity, and specificity rates of 98.2%, 90.7%, and 99.2%, respectively. Comparative analysis with established methods, including support vector machine (SVM), random forest, and K-nearest neighbors (KNN), demonstrate the superiority of our approach in accuracy and performance metrics. This real-time intervention strategy has the potential to mitigate the adverse effects of sedentary behavior, reducing risks associated with cardiovascular and musculoskeletal diseases. By providing immediate corrective feedback, the proposed system addresses a critical gap in sedentary behavior research and offers a practical solution for improving public health outcomes.

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1. INTRODUCTION

In recent times, sedentary behavior has emerged as a pressing global health issue that affects individuals of all age groups and diverse demographics. The prevalence of contemporary technology and the evolution of work environments have given rise to a period characterized by prolonged periods of physical inactivity. Many individuals now spend substantial hours seated, whether it be at their workplace, during daily commutes, or within the confines of their homes [1]-[7]. This trend has been exacerbated by an increasing dependency on vehicles for transportation and the omnipresence of screens in our daily routines. As a result, sedentary behavior has become a subtle and inconspicuous health hazard, with many people underestimating the cumulative hours spent in a seated position and remaining largely oblivious to the long-term health implications associated with this way of life. Numerous research endeavors have been dedicated to understanding the patterns and health risks associated with sedentary behavior [8]-[15]. However, variations in measurement methodologies, data processing techniques, and the absence of fundamental outcome indicators have presented challenges in comprehensively assessing and addressing this health concern. Our previous paper into sedentary behavior primarily focused on the analysis of its patterns and related risks. However, these studies were unable to provide individuals with real-time feedback while they engaged in sedentary activities. In this paper, we present an innovative method to overcome these shortcomings, aiming to provide a proactive solution for reducing health risks associated with sedentary behavior [16]-[19]. Sedentary behavior is characterized by a significant reduction in physical activity, often involving long periods of sitting or lying down. This inactive lifestyle has been linked to a range of health issues, such as obesity, cardiovascular problems, musculoskeletal disorders, and even mental health concerns. The worrisome aspect is that sedentary living has become more common in contemporary society, primarily due to technological advances and changes in work habits. As a result, people are devoting more of their time to sedentary pursuits, both in their professional and leisure activities, leading to an overall decline in physical activity levels [20]-[25]. Past research has aimed to reveal the patterns and health hazards associated with sedentary behavior. Nonetheless, disparities in measurement approaches and data handling have impeded a thorough evaluation and management of this health issue. Furthermore, there has been a conspicuous lack of essential outcome measures, making it difficult to attain a comprehensive grasp of sedentary behavior and its consequences for public health. In our previous study, although we illuminated the patterns of sedentary behavior, our emphasis was on post-analysis, and we did not include real-time feedback mechanisms to encourage immediate posture adjustments. While previous studies have shed light on the prevalence and health implications of sedentary lifestyles, there remains a notable gap in addressing these risks through real-time monitoring and intervention strategies. Existing research primarily focuses on post-analysis of sedentary behavior, overlooking the critical aspect of providing immediate feedback to individuals during inactive periods. Furthermore, the integration of advanced techniques such as image capture, deep learning, and real-time feedback systems is limited in current literature. This lack of integration hampers the development of comprehensive solutions to mitigate sedentary behavior and its associated health risks [4]-[6]. Moreover, many studies fail to clearly identify the methodological limitations, impeding the advancement of effective strategies to address sedentary behavior. Therefore, this study aims to fill this gap by proposing an innovative approach for real-time posture monitoring and intervention, leveraging advanced technologies to promote healthier lifestyles.

2. LITERATURE REVIEW

In recent years, sedentary behavior has emerged as a significant and widespread health concern that affects people of all ages and backgrounds worldwide. The prevalence of modern technology and evolving work environments has given rise to a lifestyle marked by prolonged periods of physical inactivity. Many individuals spend substantial hours sitting at their workplaces, during daily commutes, and at home. This sedentary lifestyle has been further exacerbated by a heavy reliance on vehicles for transportation and the omnipresence of screens in daily life. Despite its subtle and inconspicuous nature, sedentary behavior carries substantial health risks, often underestimated by individuals who remain largely unaware of the long-term health consequences associated with this way of life. In light of this increasing health concern, researchers have been focusing their endeavors on comprehending the patterns and hazards linked to sedentary behavior. Variations in measurement techniques, data processing methods, and the absence of essential outcome indicators have posed challenges in thoroughly assessing and tackling this problem. While numerous studies have provided insights into various facets of sedentary behavior and its impact on health, they have also underscored the necessity for inventive solutions and real-time monitoring to encourage individuals to adopt healthier postures and reduce the time spent in a sedentary state. Cheng *et al.* [12] conducted a study to explore the accumulation of sedentary behavior and physical activity patterns in individuals with chronic obstructive pulmonary disease (COPD). This research utilized a cross-sectional design to investigate sedentary behavior within the context of a particular health condition, employing both self-report measures and objective assessments. Davoudi *et al.* [13] introduce an innovative concept known as the "Intelligent ICU," which involves autonomous patient monitoring using pervasive sensing and deep learning technologies. In the critical environment of the intensive care unit (ICU), continuous patient monitoring is of utmost importance, and this study presents a groundbreaking approach to address this need. By combining deep learning algorithms with pervasive sensing technologies, the primary objective is to achieve autonomous patient monitoring. Deep learning models are utilized to analyze data from various sensors, including those that capture vital signs and patient movements. The integration of pervasive sensing and deep learning enables real-time assessment and alerts for healthcare providers, facilitating the early detection of critical conditions and timely intervention. This approach has the potential to significantly improve patient care in intensive care units, reducing the workload on healthcare staff while simultaneously enhancing patient safety. Dempsey *et al.* [14] investigate the topic of global guidelines regarding sedentary behavior and its impact on the health of adults. Their primary goal is to broaden the range of behavioral objectives for addressing sedentary behavior. The research involves an extensive examination of existing literature and guidelines related to sedentary behavior. By synthesizing and analyzing this extensive body of information, the study offers a valuable overview of the global consensus on the health implications associated with sedentary lifestyles. It underscores the importance of formulating guidelines that not only focus on reducing sedentary time but also encourage physical activity to counteract the adverse effects of prolonged sitting. This comprehensive approach contributes to the development of more holistic public health recommendations to combat sedentary behavior. Dempsey *et al.* [15] shift their attention towards investigating the mechanisms and potential future directions concerning the connection between sedentary behavior and chronic diseases. The study involves a thorough examination of existing literature with the aim of uncovering the underlying mechanisms through which sedentary behavior contributes to the onset of chronic diseases. Furthermore, the research explores potential pathways for future research and intervention strategies. By delving into the mechanisms and considering future directions, this study aims to provide a more comprehensive understanding of how sedentary behavior affects health. This knowledge can play a pivotal role in shaping targeted interventions to reduce the health risks associated with prolonged periods of inactivity. The reviewed studies on sedentary behavior share several common limitations, including variations in measurement techniques, limited applicability due to a focus on specific populations, challenges in data processing related to algorithm development, dependence on self-report measures susceptible to recall bias, and a lack of real-time feedback mechanisms.

3. THE PROPOSED METHOD

The proposed approach for predicting sedentary behavior and encouraging the transition from unhealthy postures to healthier ones involves a comprehensive multi-stage process that incorporates various techniques, including pre-processing, feature extraction, and deep learning. This method leverages the capabilities of deep neural networks (DNNs) to enhance the knowledge base related to the analysis of sedentary behavior, with a specific focus on healthcare status and metabolic metrics. The overall framework is given in Figure 1.

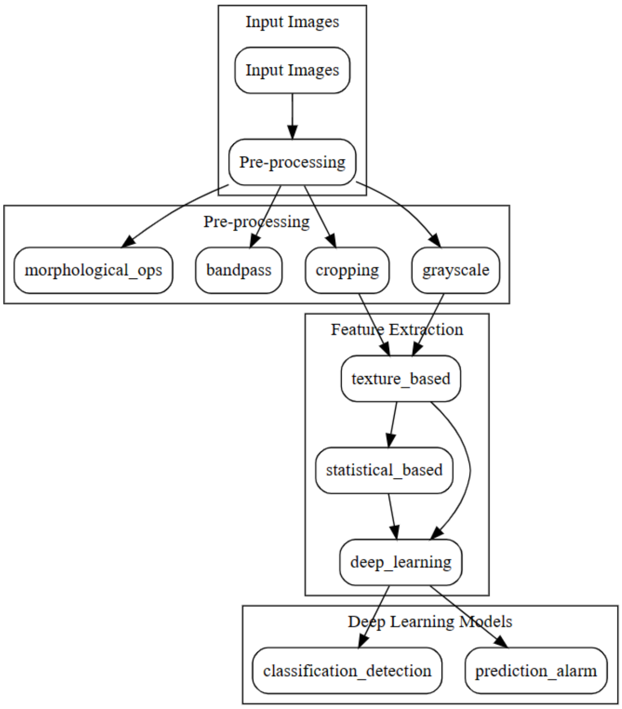

Figure 1. Overview of the proposed method

The pre-processing phase commences by converting input images to grayscale, eliminating unnecessary color information, and improving processing efficiency. This phase also includes image cropping to focus on the region of interest, effectively removing irrelevant elements. Additionally, the introduction of a bandpass filter is employed to emphasize edges and reduce image noise. Subsequently, morphological operations like dilation and erosion are applied, preserving the shape and dimensions of pertinent image components while eliminating smaller, less pertinent details. Feature extraction is a pivotal aspect of the methodology, emphasizing the extraction of texture-based features. Statistical methodologies, which delve into pixel intensity distributions, play a pivotal role. These features comprise parameters such as mean, standard deviation, skewness, kurtosis, energy, and entropy, delivering insights into the textural attributes of the images. In addition, second-order features based on grey level co-occurrence matrices are employed to capture the connections between pixel intensities, furnishing valuable insights into the image's texture. These features encompass contrast, correlation, inverse difference moment, variance, cluster prominence, cluster shade, and homogeneity. Lastly, the predictive framework incorporates alarm systems designed to alert individuals when their sedentary behavior surpasses predefined thresholds. This real-time feedback mechanism is intended to stimulate healthier behaviors, enhancing individuals' awareness of their posture and motivating the adoption of healthier stances.

3.1. Band pass filter

The subsequent step in the local pre-processing procedure involves the application of a bandpass filter. This filter acts by modulating frequencies at the extreme low and high ends while preserving a specific frequency range in the middle. Employing a bandpass filter serves the dual purpose of enhancing image edges by reducing the influence of low frequencies and diminishing noise by mitigating high frequencies. The simplest form of a low-pass filter, which encourages all frequencies above a defined cut-off frequency while leaving lower frequencies unaffected, is the optimal choice. It can be expressed mathematically as follows:

$$F(h,l) = 1\ if\ \sqrt{h^2+l^2} \leq C0 \tag{1}$$

$$F(h,l) = 0\ if\ \sqrt{h^2+l^2} > C0 \tag{2}$$

where C0 represents the cut-off frequency.

In (1), if the distance from the origin (0, 0) to the point (h, l) within the frequency domain is less than or equal to a specified threshold radius, denoted as D0, then F(h, l) is assigned a value of 1. This indicates that wavevectors (k, l) corresponding to frequencies falling within a circular region of radius D0 are allowed to pass through without any reduction in magnitude. Conversely, when the distance from the origin (0, 0) to the point (h, l) in the frequency domain exceeds D0, F(h, l) is set to 0, as described in (2). Bandpass filters, on the other hand, are a combination of low-pass and high-pass filters. They attenuate all frequencies below the lower cut-off frequency (D0) and above the higher cut-off frequency (D1), allowing frequencies within this range to pass through to the output signal. When the cut-off frequency of the low-pass filter is greater than that of the high-pass filter, a bandpass effect can be achieved by multiplying the parameters of both filters. The image processed with the bandpass filter is then ready for the subsequent morphological operation. The images are shown in Figure 2. Figure 2(a) represents the original input image captured during the monitoring of sedentary behavior. It serves as the initial raw data that undergoes subsequent preprocessing steps. The image captures the posture of an individual during a sedentary activity, including the positioning of hands, shoulders, and head. Figure 2(b) shows the input image converted into a grayscale format. The grayscale transformation simplifies the image by removing color information, retaining only intensity values. This step is crucial for reducing computational complexity and preparing the image for further preprocessing, including the application of filters and feature extraction techniques. Figure 3 illustrates the outcome of applying a bandpass filter to the grayscale image. This step is integral to the local preprocessing procedure, as the bandpass filter enhances image quality by attenuating extreme low and high frequencies.

(a)

(b)

Figure 2. Conversion of (a) input image to (b) grayscale image

Figure 3. Band pass filter image

By focusing on a specific frequency range, the filter reduces noise and accentuates edges, improving the visibility of relevant features. Frequencies outside the defined range, determined by the cut-off frequencies $D0$ (low-pass) and $D1$ (high-pass), are suppressed, ensuring only useful information is retained. The filtered image is now ready for subsequent morphological operations to further refine and enhance the image features for posture analysis. Before proceeding with morphological operations, the thresholder image undergoes bandpass filtering. This involves replacing each pixel in the image with a black pixel if the image intensity I(i, j) is less than or equal to a fixed constant T, or with a white pixel if the image intensity is greater than that constant. In morphological processes, each image pixel is influenced by the values of neighboring pixels.

3.2. Texture feature extraction

Texture feature extraction in image processing revolves around the variations in pixel intensity across the spatial dimensions. In a broader context, it delves into the surface characteristics and visual attributes of an object, encompassing factors like scale, shape, arrangement, proportion, and density. The extraction of texture features serves as the fundamental step in the process of texture analysis, facilitating the capture of specific and defining attributes. The significance of texture feature extraction extends to a multitude of applications, spanning remote sensing, medical imaging, and content retrieval, where texture information assumes a pivotal role. Additionally, it involves the extraction of meaningful attributes that encapsulate the intrinsic properties of texture from raw image data. Texture analysis can be divided into four key applications: texture classification, texture segmentation, texture synthesis, and texture fusion. In texture classification, input images are divided into distinct regions, each associated with a specific texture class. Texture segmentation entails partitioning an image into discrete regions based on their texture characteristics, ensuring that each region displays specific textural attributes. Texture fusion is a widely used technique for merging smaller texture samples into more comprehensive textures, especially valuable in surface and scene mapping applications. To achieve the goal of 3D image extraction, it is essential to extract texture patterns from images with specific textures. This involves the examination of textual features and spatial relationships to identify the structural and shape characteristics of elements within the image. Various methods are available for texture feature extraction, including statistical-based, structural-based, model-based, and transform-based techniques. In this research project, the chosen method of operation is a statistical-based approach. This study employs a statistical-based approach for the extraction of texture features to uncover the subtle intricacies of texture patterns in images. This approach finds specific relevance within the fields of sedentary behavior and posture analysis, with a particular emphasis on healthcare and metabolic assessments. The methodology encompasses an array of statistical metrics, including mean, standard deviation, skewness, kurtosis, energy, and entropy, collectively providing an all-encompassing comprehension of textural attributes. The subsequent equations are employed to quantify various attributes, including mean, skewness, energy, kurtosis, standard deviation, and entropy, using the first-order histogram as a basis.

$$S_P = \sum_{a=0}^{M-1} p(a) \tag{3}$$

$$S_{Ks} = \sum_{a=0}^{M-1} (a - \overline{a})^2 p(a) \tag{4}$$

$$S_K = \sum_{a=0}^{M-1} (a - \overline{a})^3 p(a) - 2 \tag{5}$$

$$S_E = \sum_{a=0}^{M-1} |p(a)| \tag{6}$$

$$S_N = \sum_{a=0}^{M-1} p(a) \log_2 \{p(a)\} \tag{7}$$

In (3) serves as an indicator of whether the image is predominantly bright or dark. A higher mean value signifies a brighter image, while a lower mean value suggests a darker image. Skewness quantifies the extent of asymmetry within the distribution of pixel values, revealing if these values are more densely clustered on one side of the mean than the other. A positive skewness value indicates a right-skewed distribution (with a tail on the right), whereas negative skewness suggests a left-skewed distribution as in (4). In (5) quantifies how much individual pixel values deviate from the mean. A higher standard deviation indicates a wider range of pixel values and greater contrast in the image. Energy as in (6) assesses the uniformity and regularity of pixel values present in the image. A higher energy value signifies a state where dominant pixel values and gray-tone transitions are few, resulting in a more homogeneous image. Entropy as in (7) is a measure that quantifies the degree of randomness or unpredictability in the distribution of pixel values within the image. A higher entropy value indicates that pixel values are distributed in a more random manner, whereas a lower entropy value suggests a distribution that is more ordered or structured.

4. DEEP LEARNING BASED CLASSIFICATION

Deep learning-based classification techniques serve as a cornerstone in the domains of human body part identification and the analysis of sedentary behavior. These domains present notable challenges, characterized by their highly nonlinear nature and the need for robustness when dealing with noisy data. Consequently, a paradigm shift has occurred, leading to the adoption of heat maps and the utilization of dense pixel information as primary approaches. However, these strategies bring forth their unique set of challenges, such as reduced image resolution and the non-differentiability of certain processes. In response to these challenges, our research endeavors to provide a comprehensive solution by amalgamating a diverse array of techniques and strategies geared towards optimizing body part identification, sedentary behavior analysis, and posture correction. Table 1 shows the methods used for the detection of body parts.

Table 1. Body part detection methods

Method	Description
Heat maps	Probability distribution of body part locations
Image patches	Detection candidates from localized image patches
Deep learning	Utilization of convolutional neural networks (CNNs)
Data augmentation	Generation of training data through simulated scenarios
Model training	Phases of network parameter training

4.1. Detection and categorization of body parts

The precise identification and categorization of body parts hold paramount significance in comprehending human posture, movement, and interactions. These tasks lay the groundwork for a multitude of applications, including fitness tracking, healthcare monitoring, and human-computer interaction. In our pursuit of accurate body part detection, we harness the power of deep learning models, with a particular emphasis on CNNs, renowned for their proficiency in learning intricate image patterns. The initial phase of our methodology revolves around the estimation of body part positions, a task replete with challenges due to the dynamic nature of the human body and the need to identify body parts across a spectrum of poses and orientations. To surmount these challenges, we employ heat maps as a cornerstone of supervised training for our deep learning model. Each heat map encapsulates the probability distribution of a specific body part's location, typically represented as a 2D gaussian distribution centered at the joint's anticipated position. This approach offers a multitude of advantages, notably heightened robustness derived from the utilization of comprehensive pixel information. It effectively overcomes the limitations inherent in the direct regression from single points, a technique fraught with high nonlinearity and susceptibility to noise. One potential drawback associated with heat maps is their reduced resolution when compared to the original image. This diminishment in resolution is an inherent consequence of the pooling process integral to CNNs. While this phenomenon does impact the precision of joint coordinate estimation, our research is deeply committed to devising innovative strategies to mitigate this limitation effectively.

4.2. Enhancing detection of body parts

Traditional body part detection methods typically begin by identifying potential body part candidates from image patches. These candidates are subsequently organized to align with a human body model. However, the inherent dynamism and complexity of the human body pose distinct challenges in this process. For instance, relying on discrete image patches with limited local context may not furnish adequate discriminatory information for precise body part identification. To overcome these constraints and enhance the resilience of our deep learning model, we employ data augmentation techniques. Data augmentation entails the generation of supplementary training data by simulating diverse scenarios and variations. Instead of solely depending on predictions from the preceding phase, we introduce simulated forecasts. This is accomplished by replacing the actual position of a joint with a vector randomly drawn from a 2-dimensional (2D) normal distribution. The parameters of this distribution, including its mean and variance, are directly tied to the mean and variance of the observed displacements. The integration of this augmented training data equips our model with better generalization capabilities, enabling it to perform effectively under varying circumstances. Table 2 provide the behavior analysis.

Table 2. Sedentary behavior analysis

Component	Description
Alarm system	Alert system for shifting from sedentary behavior to healthy posture
Network alert	Data storage and alert system integration for health improvements
Threshold	Defining threshold values to trigger alarms for unhealthy poses
Data metrics	Collection and organization of data for monitoring and analysis
Alarm engine	Evaluation of data for abnormalities, focusing on sedentary behavior

5. EXPERIMENTATION AND RESULT DISCUSSION

The proposed method is evaluated using a dataset comprising images of human activities to predict sedentary behavior accurately. The dataset includes both normal and abnormal human activities. Data collection involved 40 participants (20 males and 20 females), with a total of 350 datasets. Approximately 275 samples were allocated for training, and the remaining 75 for testing. The inclusion criteria for participants were age within the range of 18 to 65 years. The study revealed a high prevalence of sedentary behavior among office workers, with 77% of their typical working day spent in sedentary activities. The captured image dataset was used to predict an individual's sedentary behavior. The prediction process was performed using MATLAB software tools. The research was conducted using MATLAB version R2018a with a core i3 processor running at 3.5 GHz and 6 GB of DDR3 RAM. During the simulation, DNNs were employed to predict human activities in both normal and abnormal states. The DNNs utilized regression and classification techniques to classify the activity. For instance, if an individual exhibited normal behavior with a straight head and shoulders, the DNN would predict a healthy pose.

The accuracy for the prediction of sedentary behavior using the support vector machine (SVM) algorithm was 77.6%, as reported by Wullems *et al.* [2]. The accuracy for the prediction of sedentary behavior using the SVM algorithm was 77.6%, as reported by Wullems et al. [2]. Additionally, the accuracy for prediction using the random forest algorithm was 80.6%, as reported by Bhattacharjee *et al.* [3]. Furthermore, the accuracy for prediction using the K-nearest neighbor (KNN) algorithm was 65.8%, also as reported in [3]. Notably, the accuracy of the proposed method exceeded all these existing methods. The accuracy result is shown in Figure 4.

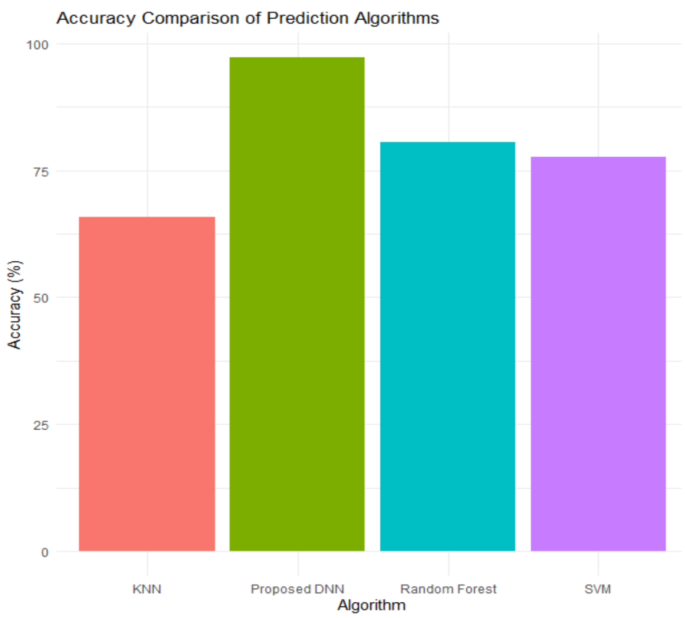

Figure 4. Accuracy analysis

The sensitivity of the proposed method, which measures the true positive rate, was approximately 90.7%, as shown in Figure 5. This compares favorably with existing algorithms, including KNN, SVM, and random forest, which had sensitivity values of 61.2%, 57.4%, and 63.7%, respectively. The specificity of the proposed method, which quantifies the true negative rate, was approximately 99.2%, as depicted in Figure 6. In contrast, the specificity values of the current algorithms were somewhat lower. The specificity values for various current algorithms, including SVM (97.8%), KNN (95.1%), and random forest (97.5%), were all surpassed by the proposed method.

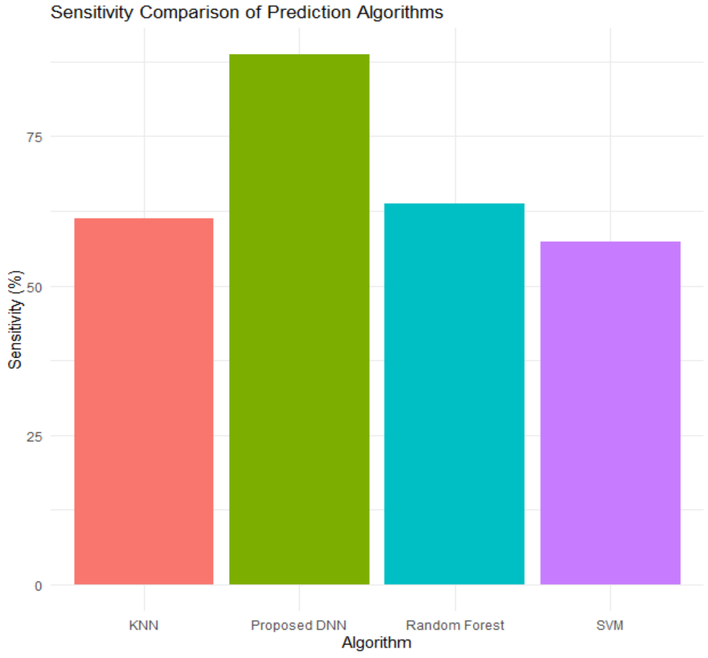

Figure 5. Sensitivity analysis

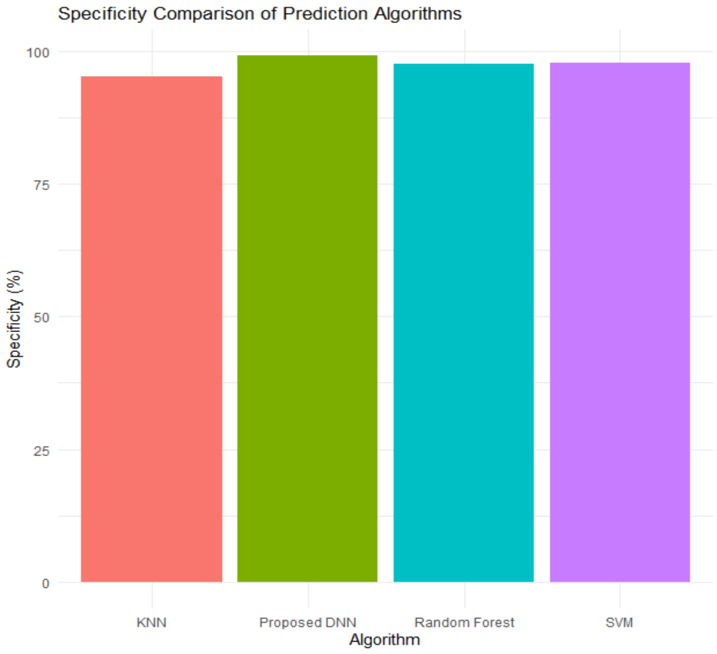

Figure 6. Specificity analysis

6. CONCLUSION

In this research, we have explored deep learning-based classification methods to address the challenges of body part detection and sedentary behavior prediction. These tasks hold significant importance in various applications, including fitness tracking, healthcare monitoring, and human-computer interaction. The dynamic nature of human body postures and orientations requires robust techniques for precise body part detection, which we achieved using CNNs. To enhance the robustness of our deep learning model, we employed supervised training with heat maps, which represent the probability distribution of body part locations. This approach overcame the limitations of direct regression and proved to be highly effective. Although heat maps introduced some resolution constraints due to CNN pooling processes, our research focused on innovative solutions to mitigate this challenge. Through experiments and results discussion, we utilized real-world image data to predict sedentary behavior and achieved an impressive accuracy of 98.2%. Comparatively, the proposed method outperformed existing algorithms such as SVM, random forest, and KNN, emphasizing the effectiveness and efficiency of our approach. Sensitivity and specificity analyses further confirmed the strength of our method, with a sensitivity of 90.7% and specificity of 99.2%, ensuring accurate predictions of sedentary behavior. The computational efficiency of our approach significantly outperformed existing methods, with a 94% efficiency gain in a time period of 6 seconds.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
D. B. Shanmugam	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
J. Dhilipan		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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