NeckWatcher: A Real-time Monitoring Tool for the Assessment of the Neck Posture

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ABSTRACT

Persistant poor posture can lead to the development of neck pain. Many different solutions have been proposed to aid in neck posture control, but most of them require additional devices. In this study, we present NeckWatcher, a tool that builds on MediaPipe Pose and utilizes an integrated webcam to monitor a person's neck posture in real-time. It is designed to be user-friendly and realized as a stand-alone solution. Our first results suggest that NeckWatcher can be a useful tool for improving the sitting posture and, by that, reducing the risk of developing neck pain.

CCS CONCEPTS

• **Applied computing** → Health care information systems.

KEYWORDS

pose estimation, machine learning, posture detection, neck pain

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1 INTRODUCTION

Ergonomic problems, such as poor posture when sitting at a computer, put more weight on the neck and cause many symptoms [3]. Studies have shown that increasing the neck flexion angle due to a low screen position results in greater muscle activity to maintain the head's position, which is a risk factor for neck pain [4], temporomandibular disorders, degraded sleep quality, and headaches [3]. Additional physical risk factors for musculoskeletal disorders are, for instance, comparatively static bending positions, invariable muscle activity, repetitive arm movements, and poor recovery [4]. Approximately 40–50% of individuals who spend 3–5 hours per day in front of a computer experience musculoskeletal symptoms and diseases [2]. Compared to other professions, office workers have the highest annual prevalence for neck-shoulder pain (40–70%) and lower back pain (35–40%). Resulting medical conditions increase the risk of long-term sick leaves by 75% and reduce the productivity due to work-related musculoskeletal disorders [4].

To our knowledge, a significant challenge in coping with these issues technologically is the lack of effective solutions that can work only with the peripherals currently in use (e.g., laptops). This need motivated us to develop NeckWatcher, a real-time vision-based tool that builds on a single webcam and notifies users when sitting in a unhealthy posture for an extended period of time. We present here preliminary findings of using this tool in an experimental setting.

2 RELATED WORKS

Kumar and Elias [5] summarize that neck posture monitoring is carried out mainly in one of the following ways: vision-based, sensor-based, infrared-based, or radar-based. Severin [8], for instance, examined a wearable head posture recognition system based on three *Inertial Measurement Units* (IMU). They considered a cervical angle above 30° as a threshold to diagnose a dangerous posture. Their system was able to distinguish between good and bad postures. Lawanont et al. [6] developed a system that monitors the neck angle of the user based on a combination of smartphone IMU sensors and image recognition technology. They similarly defined an angle of 30° as an unhealthy neck angle and examined the precision of their system for different angle settings. Arda et al. [1], a further example, used a smartphone's IMU and its integrated camera to determine the neck angle of users in a supine position. They also used angles above 30° to define unhealthy neck postures and tested their system with one participant. They concluded that their system was suitable for detecting neck angles in supine position. Estrada

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and Vea [2] studied models that recognize proper or improper sitting postures. They used accelerometer readings from some human spinal points through smartphone IMUs and by using a webcam which detected the upper body points' location and distances. They applied various machine learning algorithms such as *k*-nearest-neighbours, support vector machine, neural network, and decision trees. Their system was tested with 60 participants and achieved up to 95.35% accuracy for classifying head and shoulder postures. Finally, Mallare et al. [7] used computer vision to determine the sitting posture. Their study was built on silhouette recognition algorithms using edge detection algorithms. To be effective, however, the room needed to be brightly lit, the walls painted white and the existing chairs covered in white fabric. In addition, all 42 participants had to wear black clothes. A seated posture assessment was performed using a k-fold cross-validation and a support vector machine. The algorithm achieved an accuracy of 61.90%.

3 METHOD AND RESULTS

In contrast to related research, we aim at tracking neck postures in real-time using a single webcam. To this end, we created an experimental setup consisting of a table, a laptop with an integrated webcam, a side camera, a wall poster with sketched angles (0–60°), and a wooden pointer attached to a hairband to easily indicate the ground truth (see Figure 1). Five participants (2 males, 3 females) were recruited for the experiment and data were collected via the aforesaid webcam. The laptop's position was adjusted according to a person's sitting height. We collected data for healthy (0–30°) and unhealthy (30–60°) postures in two distinct sessions (each lasting 30 seconds): in each session, participants had to slowly tilt their head back and forth within the predefined range. While participants were able to examine their movement on the laptop's screen, one researcher supervised the procedure in addition. For each participant, we repeated both sessions with a slight rotation of the laptop to create more variance in the data. Overall, 56 videos were recorded with a duration of about 30 seconds each.

Figure 1: The experimental setup in our laboratory.

MediaPipe Pose was utilized to extract landmarks from the videos. A *landmark* represents a three-dimensional coordinate on a human body. We concentrated on landmarks of the shoulders, the mouth, the brows, the eyes, and the nose. Overall, the resulting feature vector contained 27 dimensions and the corresponding label (i.e., healthy or unhealthy), while the data set ultimately consisted of 78,871 entries. We trained a fully-connected neural network with 9 hidden layers and 1 output layer (i.e., sigmoid activation function). The sigmoid function outputs a value between *0* and *1*, where a value smaller than *0.5* was considered as a healthy posture and otherwise unhealthy. Binary cross-entropy function was applied as loss function. The resulting network was trained for 25 epochs. The model was tested with a test set consisting of 15,774 entries (20%) that were randomly removed before training. The model achieved an average accuracy of 84.40%, an F_1 score of 79%, a precision of 99%, and a recall of 66%. The low value of recall suggests that there was a notable number of false negatives, meaning that the model was more likely to misclassify unhealthy postures as healthy.

Our research has limitations. Some participants, for instance, were positioned too close to the webcam, so that some landmarks belonging to the face (e.g., the eyes) could not be recognized correctly. Another problem is that users did not always strictly stop their movement at 30°, resulting in ambiguous data around this threshold. More data is also needed to ensure that our model can be generalized to other situations. Furthermore, the test set contained at least some data from each participant hence the test data was not completely unknown to the trained model. It should also be noted that data were collected in a controlled environment – i.e., NeckWatcher's effectiveness in real life warrants further investigations.

4 CONCLUSION

In this research, we introduced NeckWatcher, a solution that evaluates a person's neck posture based on the head's tilt angle. We used a single webcam in our experiment and MediaPipe Pose to extract features. Using a fully-connected neural network, we were able to reasonably detect healthy and unhealthy neck postures. In the future, we plan to incorporate more subjects in our research and to test our approach with other postures.

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