

Exercise Abnormality Detection Using *BlazePose* Skeleton Reconstruction

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Abstract. There still exists a knowledge gap in the field of computer vision in respect of posture prediction and deviation evaluation is an important metric for various medical applications, that require posture abnormality quantization. Our paper proposes a deep heuristic neural network architecture, using *BlazePose* as a backbone, that is capable of reconstructing users skeleton from a real-time monocular video feed, using which we are able to evaluate the subjects performed exercise and measure the deviation from expected values. The proposed heuristics are able to identify and evaluate most of the abnormalities, with the highest indicator of postural issues being the spinal deviation accounting for 95%. Additional evaluation of real-time performance has shown that our method is capable of maintaining 23-ms response times, making it applicable to real-time applications.

Keywords: Exercise analysis · Posture estimation · Skeleton reconstruction · Abnormality detection

1 Introduction

Thanks to advancements of shallow artificial intelligence, mostly in the field of deep artificial neural networks (DANNs), we are able to solve more and more tasks that were previously hard to solve using classical approaches, allowing for fields like computer vision to expand into new frontiers. While the ANNs have been proposed more than half a century ago, only recently we are able to leverage them thanks in large part to parallelized computing systems, such as graphical processing units (GPUs) and tensor processing units (TPUs). Deep-learning based black-box models have shown state-of-the-art performance in a wide variety of real world applications, including medical applications. These can be ranging from driver fatigue detection [9], lung abnormality detection in X-ray imaging [18], detection of heart and blood vessel disease [15,38], diagnosing of

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cancer [40], hypoglycemia [35]. Early detection and evaluation of course of the disease for neurodegenerative disorders like Huntington's [21] and Parkinson's disease [1]. Predicting mortality rates [33] and wide variety of autism spectrum disorders [41]. In addition, machine learning has shown the ability to analyze electroencephalographic signals which can be used for brain-computer interfaces [8] or even developing new drugs and treatments [13] for various ailments.

Various ailments may cause various posture related impairments, these can range starting with Pompe disease [36,39], various neurological disorders [30] and general spinal injuries [20]. Additionally, bad posture onto itself can be a cause of health risks [11,27,31]. Patients abnormal posture analysis, while performing various exercises, may be useful for a physician in order to diagnose and/or evaluate posture-related illnesses, appropriate application of treatment and rehabilitation measures and evaluating their effectiveness. In this paper we propose deep neural network with heuristic analysis for the evaluation of 7 types common exercises as described by field experts: 1) shoulder flexion; 2) shoulder flexion and internal rotation; 3) shoulder flexion and internal rotation, elbow flexion; 4) shoulder extension and internal rotation; 5) shoulder flexion; 6) fool shoulder flexion; 7) shoulder adduction.

The majority of state-of-the-art human posture classification research focuses on the classification of posture without measuring the absolute deviation from the norm. Whereas, the methods that do provide deviation from correct results, generally depend on availability of special depth sensors in order to capture the human skeleton, making the accessibility of such approaches have a higher upfront cost. Instead, our approach uses state-of-the-art *BlazePose* [3] neural network as the backbone for skeleton reconstruction with which, in combination with our devised heuristics analysis, we are able to identify exercise abnormalities in addition to measuring the severity of abnormality ($\Delta\phi$) for the given exercise.

Our paper is organized as follows: firstly in Sect. 2 we present related works. Afterwards in Sect. 3 we present our methods and approach. Followed by results in Sect. 4, and finally Sect. 5 we present our conclusions.

2 Related Work

One of labor-related musculoskeletal ailment risk factors is the improper posture positions adopted by office workers. With one of direct consequences of inadequate posture being back pain, whereas indirectly linked improper posture ailments can range from cardiovascular disease, lumbar disease and even early mortality [5]. Some studies have suggested that body posture is an important predictor of stress [14,28] and mental fatigue [2].

There exist multiple solutions with regard to human posture detection. One of such solutions attempts to detect various course-grained posture operations such as *standing*, *bending*, *sitting* and *crawling* [32]. This solution was able to separate ergonomic from non-ergonomic values, however it does not provide the quantized error as feedback to determine if the posture is improving or deteriorating, in addition it requires a depth sensor in addition to closed-source software, which

both increases underlying cost and reduces the solutions' reliability. Another attempt at predicting subject posture by using 3D motion analysis, allowing to identify such subject actions as *walking* and *falling* [16]. However, it does not provide the ability to differentiate between properly and improperly performed action in addition to being sensitive to lightning conditions. Other solutions attempt to detect the human position in an office environment [12], or to identify inadequate subjects posture using depth sensors such as Kinect [22,25,37]. Whereas structured light depth sensors are more robust against lightning conditions they are generally more noisy and have much higher initial costs, making them less-than ideal in certain applications. Other solutions depend on skeleton evaluation [23,29] which may fail due to occlusion in addition to the solutions becoming obsolete due to the discontinuation of the used depth sensing devices by the manufacturer. Some solutions however, avoid skeleton evaluation altogether, instead using semantically linked hierarchical tree, thus solving for occlusion problem [19] by predicting human posture with as little as 30% of the body visible in addition of having discrete posture prediction sub-states. Other approaches such as pulse-coupled neural networks were capable of recognizing moving human [42] skeleton in a crowded background, while others used 2D image mapped into 3D space to acquire depth information for full skeleton prediction [7]. 3D data obtained from both synthesis of depth from a monocular frame [17] and from depth sensors such as Kinect has other general applications such as gender recognition from body shape [6] or evaluation of physical performance from training exercises [34] (Table 1).

Table 1. Comparison of algorithms capable of human posture classification. Different methods are compared in terms of being applicable to monocular and non-monocular cameras, whether they are able to detect posture abnormalities, quantize the abnormality error and if they are occlusion resistant against other objects in the scene.

Method	Monocular	Detects abnormality	Quantize error	Occlusion resistant
Ray et al. [32]	✗	✓	✗	✗
Hsieh et al. [16]	✓	✓	✗	✗
Kulikajevas et al. [19]	✗	✓	✓	✓
Li et al. [22]	✗	✗	✗	✓
Liu et al. [25]	✗	✓	✗	✓
Wang et al. [37]	✗	✗	✗	✓
Ryselis et al. [34]	✗	✓	✓	✓
Proposed	✓	✓	✓	✓

While the mentioned approaches have shown the capability of classifying subject posture, they tend to lack the ability to quantify the error level that the posture has. In our paper, we propose heuristic approach as an extension to deep neural network posture estimation for the quantification of posture error.

3 Methods

3.1 Pose Estimation Pipeline

With the main focus of our approach is being real-time pose abnormality detection we need fast and robust way of detecting humanoid skeleton. While many approaches exist for humanoid skeletal analysis, we have opted to use *BlazePose* as our backbone, as it has shown to be one of the most-performant solutions using monocular cameras in terms of prediction speed, robustness and stability, this makes it more than suitable for our approach. In order to achieve real-time performance of the *BlazePose* each of its components have been designed to be suitable for real-time applications. This is done by making certain assertions and generalizations about the human body, i.e. that the best indicator for the human torso is the direction of the subjects face. Assertions like these allow for simplification of the pose estimation by using well established face detection networks that are capable of sub-millisecond performance—*BlazeFace* [4]. Additionally, based on the relationship between human torso and human head it is also possible to extrapolate other key body features such as the maximum radius of the human body, this allows for detecting such key features like the bodies center of mass, it's rotation and scale, which are required for the estimation of more complicated poses with very little computing cycle overhead. To estimate the pose a two-stage detector pipeline is used (see Fig. 1), where the detector located the Region-of-Interest (RoI) for the given image that is most likely to contain the subject, while the tracker predicts the joints within the given RoI.

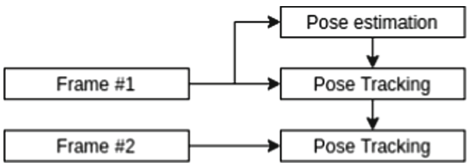

Fig. 1. Pose estimation pipeline. First frame is used to estimate the RoI of the subject that will be tracked, with the subsequent frames using previous frames' prediction to improve the pose tracking.

3.2 Network Architecture

While other methods for humanoid skeleton estimation tend to use computationally expensive heatmap predictions, instead *BlazePose* only uses heat and offset maps for supervised learning stage, the overview of the artificial neural network architecture can be seen in Fig. 2. Firstly, *BlazePose* downsamples a monocular image to 256×256, which is then used as the input for the ANN. A heatmap and an offset loss are used during the supervised training stage is used in order to improve the networks convergence by supervising the coordinate regression layers, however the supervision layers are then stripped from the final network.

This gives our backbone network the real-time performance that is critical for our applications. Unfortunately, the existing solution while fast proved to be too unstable to be used in medical applications. For this reason before applying our heuristics to the estimated skeleton we have added one-dimensional stabilization kernel which uses the last 5 frames in with Gaussian [10] which has greatly improved the estimation stability performance with very little abnormalities due to never frames having the highest weight impact into the final pose estimation.

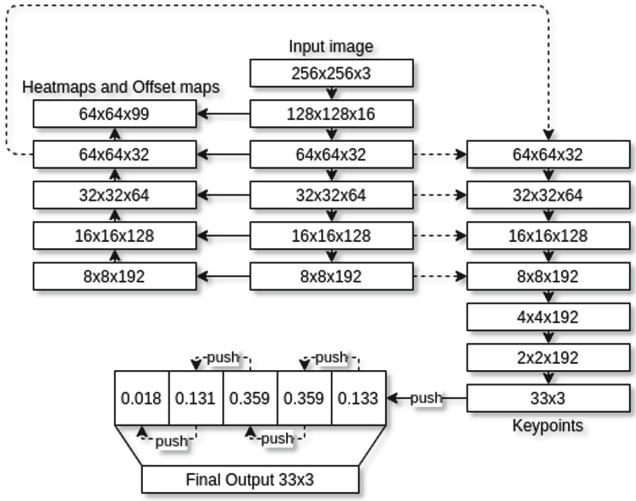

Fig. 2. *BlazePose* network architecture. Given a 256×256 RGB image neural network outputs 33 joint x, y coordinates in addition to probability if the given joint is visible in cases when it parts of the subject may be occluded. The output of *BlazePose* is then sent to stabilization kernel to stabilize the skeleton.

The output joint topology uses expands upon *COCO* [24] skeleton topology, outputting 33 joints (see Fig. 3) for a given input image. Each of the joints containing their x and y coordinates in the image space in addition to the *visibility* probability, the latter is used to predict how likely the given joint is visible in the image, this is useful when the given joint may be occluded or out of frame.

Using transfer learning, we have trained our network using *Stochastic Gradient Descent* (SGD) [26], using learning rate of 5×10^{-3} and momentum of 0.9 for 1000 epochs with the batch size of 16, The network was implemented using Python and Tensorflow to allow for GPU accelerated training.

3.3 Exercise Abnormality Detection

In order to detect abnormalities in subject exercises we use multiple heuristic protocols based on the simplified skeleton posture predicted by the *BlazePose* backbone. We use these heuristics for 7 of our main exercises: 1) raise hand 90°

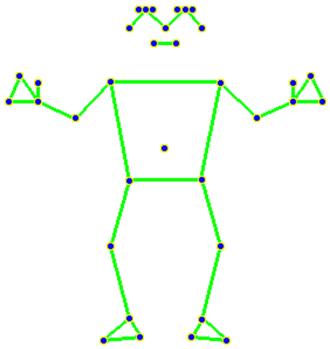

Fig. 3. 33 joints predicted by *BlazePose* skeleton joints

and move it to front (Hand 90° Side to Front); 2) raise the hand and place it on top of the head (Hand to top of Head); 3) raise hand and touch the nose (Hand to Nose); 4) raise the hand and touch lower back (Hand to Back); 5) raise the hand to front 90° (Hand 90° Up Front); 6) raise the hand 180° above the head (Hand 180° Up); 7) raise the hand 90° to the side (Hand 90° Side). Each of the exercises have special heuristics designed in order to evaluate the patients posture abnormality severity, see Fig. 4 for full UML activity diagram of the system. The heuristics we have chosen are based on contracted *BlazePose* skeleton (see Fig. 5). We reduce the 33 joints provided by the *BlazePose* into 17 joints and 2 reference axes. The joints are as follows: J1) right heel; J2) right knee; J3) right hip; J4) left heel; J5) left knee; J6) left hip; J7) spine bottom; J8) right wrist; J9) right elbow; J10) right shoulder; J11) left wrist; J12) left elbow; J13) left shoulder; J14) spine top; J15) right ear; 16); left ear; J17) nose. The 3 references axes: a) horizontal eye line axis; b) vertical spine axis.

Main Heuristics. The three main error heuristics that are shared between all the exercises is spine deviation error $\Delta\phi_{sp}$ (see Eq. 1), head deviation error $\Delta\phi_{h}$ (see Eq. 2) and shoulder deviation error $\Delta\phi_{sh}$ (see Eq. 3). These three main heuristics are used to classify healthy subject from one that suffers from an ailment which induces posture related abnormalities when performing exercises in addition to identification of abnormality severity.

$$\Delta\phi_{sp} = \arccos \frac{J14 - J7}{\|J14 - J7\|} \cdot b \tag{1}$$

$$\Delta\phi_{h} = \arccos \frac{J16 - J15}{\|J16 - J15\|} \cdot a \tag{2}$$

$$\Delta\phi_{sh} = \arccos \frac{J13 - J10}{\|J13 - J10\|} \cdot a \tag{3}$$

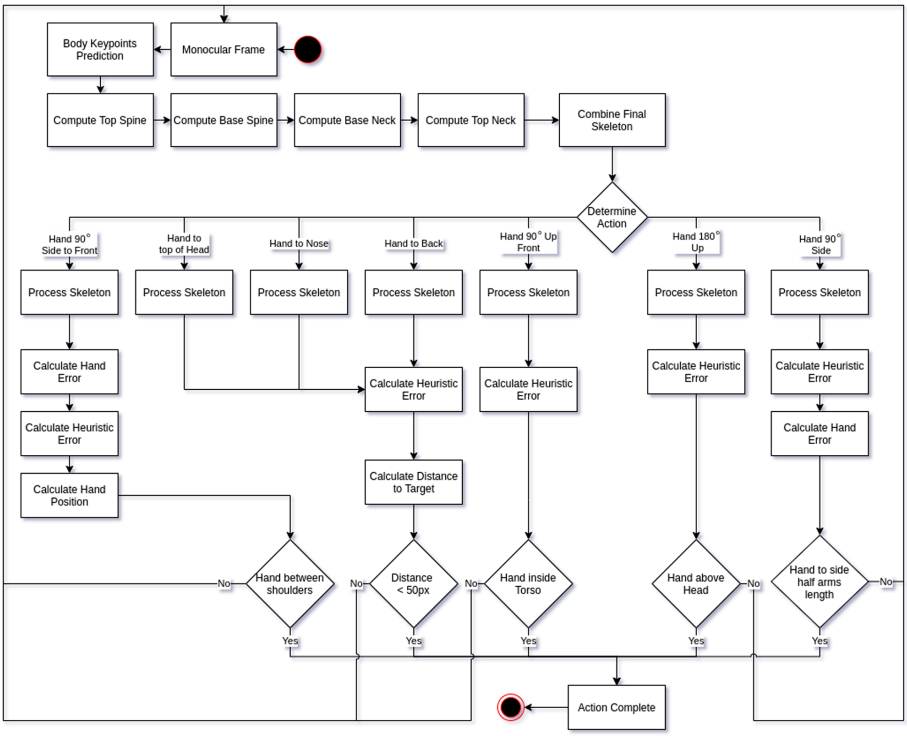

Fig. 4. UML activity diagram denoting our heuristic algorithm used for abnormality detection.

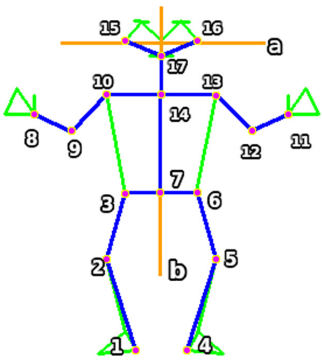

Fig. 5. Green—original *BlazePose* skeleton; blue—contracted skeleton. Additionally, we add world reference axes: a) horizontal eye line axis; b) vertical spine axis. Contracted skeleton along with references axes is used in our heuristic analysis. (Color online figure)

First heuristic $\Delta\phi_{sp} \in [-5°, 5°]$ is used as the main identifier to classify between a properly and improperly completed exercise, when the subjects' spine tilts more than 5° away from the vertical axis b the exercise is considered executed improperly, at this point physician is informed about exercise abnormalities and their severity. The $[-5°, 5°]$ grace range has been defined by experts. Additionally, $\Delta\phi_h$ shows how much the patients head has tilted from the a horizontal axis. As with $\Delta\phi_{sp}$, grace range for $\Delta\phi_h \in [-5°, 5°]$. This heuristic alone generally is unable to show if the person suffers from any ailment and is instead used in conjunction with others to better evaluate the deviation from norm. Finally, $\Delta\phi_{sh} \in [-5°, 5°]$ is used to evaluate the shoulder deviation from horizontal axis a, as with $\Delta\phi_h$] it is generally used for assessing the deviation from the benchmark exercise parameters instead of classification of healthy/unhealthy subjects.

4 Results

To evaluate the deep heuristic artificial neural network we validate it against our collected dataset consisting of 57 videos. To validate our heuristics we evaluate each of the heuristics ($\Delta\phi_{sp}$, $\Delta\phi_h$ and $\Delta\phi_{sh}$) capability to classify the subjects' performed exercise as either normal or abnormal. We have calculated deviation mean and Probability Density Function (PDF) for each of our heuristics. As we can see from Figs. 6 and 7, there is a clear separation of both probability density function indicating that $\Delta\phi_{sp}$ has very little overlap, indicating that patients' spine deviation from the vertical axis is a great indicator of any postural abnormalities that may be affecting the subject. When comparing $\Delta\phi_h$ spread in Figs. 8 and 9 we can see that while a person with a posture abnormality has a larger probability density function when compared to a healthy subject, this heuristic alone is not sufficient to evaluate if the person is healthy. In the same matter $\Delta\phi_{sh}$ has large overlap between sick and healthy subjects (see Figs. 10 and 11) meaning they alone cannot be used for classification. However, in conjunction they allow for finer evaluation of the severity of posture problems when performing the exercises. This assertion is further supported by Shoulder-Spine deviation chart seen in Fig. 12, where we can see that shoulder deviation alone is rarely an indicator of any posture abnormalities on its own accord. In similar matter Head-Spine deviation as seen in Fig. 13 head tilt alone is not good enough standalone indicator that the person is healthy or not. Additionally, we evaluate the deep heuristic neural networks ability to work in real time, the results can be seen in Fig. 14, as we can see that processing a single frame takes around 23 ms, this equates to around 43 frames per second, which is more than enough for real time video analysis. Finally, while our findings have been evaluated by the experts with clinical experience, further validation in a clinical environment is required and should be performed in future work.

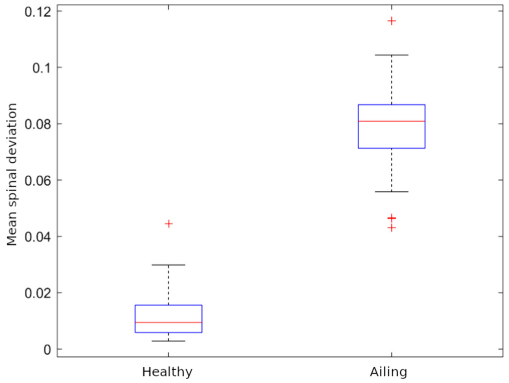

Fig. 6. Overall mean $\Delta\phi_{sp}$ deviation.

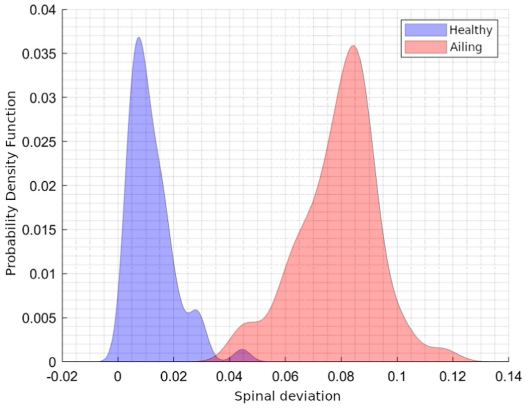

Fig. 7. Probability density function for $\Delta\phi_{sp}$ deviation.

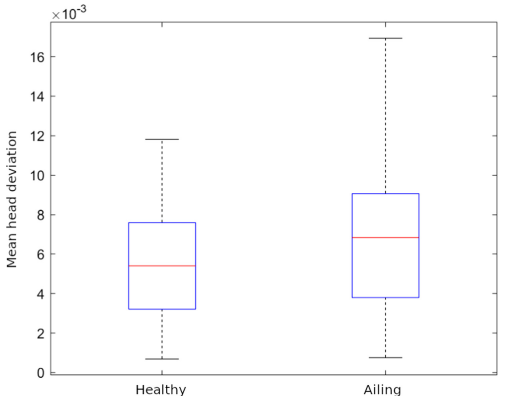

Fig. 8. Overall mean $\Delta\phi_h$ deviation.

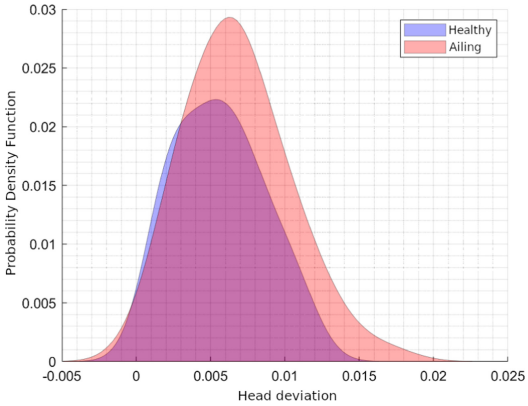

Fig. 9. Probability density function for $\Delta\phi_h$ deviation.

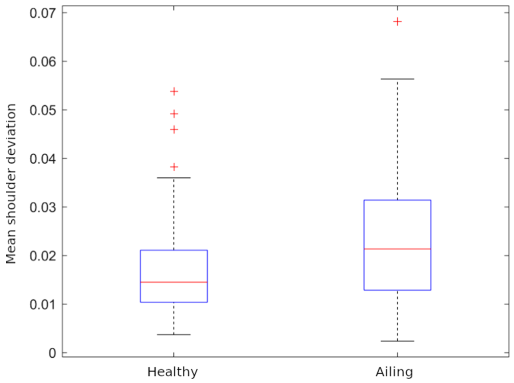

Fig. 10. Overall mean $\Delta\phi_{sh}$ deviation.

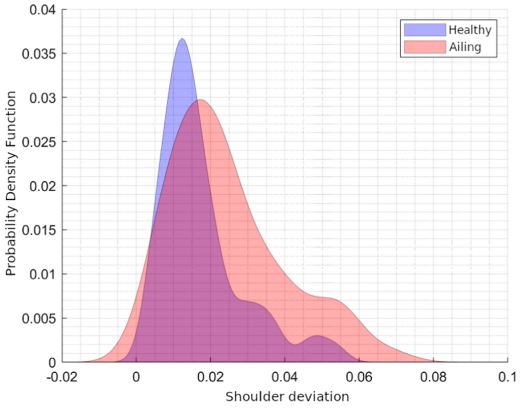

Fig. 11. Probability density function for $\Delta\phi_{sh}$ deviation.

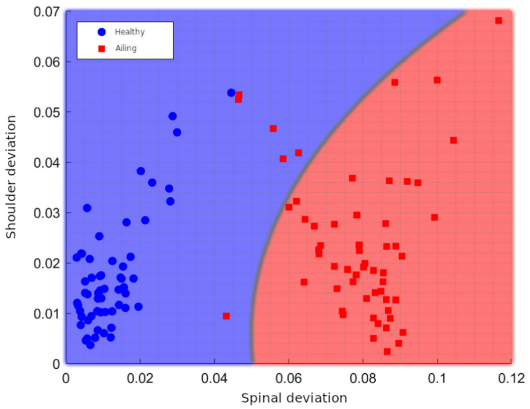

Fig. 12. $\Delta\phi_{sh}$ and $\Delta\phi_{sp}$ deviation correlation between normal and abnormal exercise.

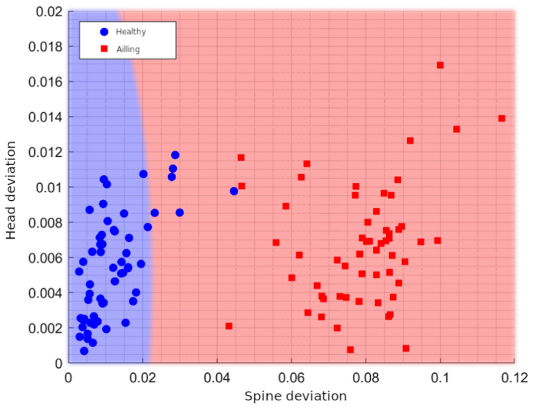

Fig. 13. $\Delta\phi_h$ and $\Delta\phi_{sp}$ deviation correlation between normal and abnormal exercise.

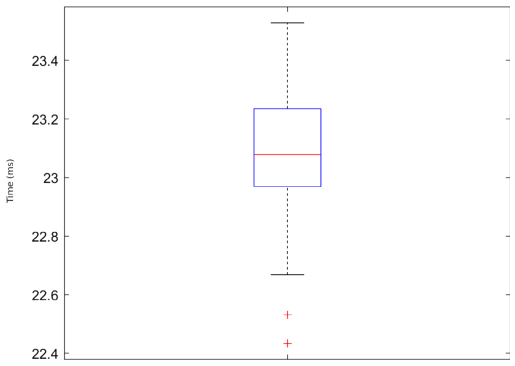

Fig. 14. Average time it took for processing of a single video frame.

5 Conclusions

We have proposed a deep heuristic neural network for, which is capable of estimating and classifying human pose in addition to providing angle of deviation from nominal exercise parameters. Experimental results have shown that the biggest indicator of the posture abnormalities were spinal heuristics accounting for 95% of all abnormalities. Furthermore, the given approach uses *BlazePose* model as its backbone neural network giving it 23-ms response times, which makes it suitable for the use in real-time systems. The results obtained confirm the fact that the proposed method is valuable and can be applied to determine the quality of patients' movement, to monitor the course of rehabilitation and to evaluate its effectiveness.

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