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HUMAN POSE DETECTION IN SPORTS ACTION ANALYSIS: THE IMPACT OF INPUT IMAGE SIZE AND LIGHTING CONDITIONS ON THE ACCURACY OF JOINT POINT DETECTION.

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Abstract. Human Pose Estimation (HPE) is one of the important areas of computer vision, which serves to identify the joints of the human body based on image and video data. This technology is of great importance in the field of sports for analyzing athletes' movements, assessing exercise techniques, and preventing injuries. In this study, the influence of input image size, lighting conditions, and model architecture on the accuracy of joint point detection in the process of analyzing sports movements was studied. The results obtained will serve to improve the efficiency of human pose detection systems and expand the possibilities of their application in sports analysis.

The performance of the YOLOv8n-pose, HRNet, and OpenPose models was evaluated under different image sizes (256×256, 384×384, and 640×640) and lighting conditions (normal, low, and high), and the analysis was performed based on the PCK (Percentage of Correct Keypoints), OKS (Object Keypoint Similarity), AUC (Area Under Curve), and NME (Normalized Mean Error) metrics.

The results showed that increasing the image size leads to an improvement in the accuracy of joint point detection. At 640×640 resolution, the accuracy increased and the NME values decreased. The lighting conditions also had a significant impact on the model performance, with the most stable results observed under normal lighting conditions.

The experimental results showed that the HRNet model demonstrated high accuracy results, the OpenPose model performed stably, and the YOLOv8n-pose model was an effective solution for real-time systems. The results confirm the importance of choosing optimal image parameters in HPE systems.

Keywords*:* *Human pose detection, articulation points, Human Pose Estimation, HRNet, OpenPose, YOLOv8n-pose, image size, lighting conditions, computer vision.*

I. INTRODUCTION

In recent years, automatic analysis of human motion has become one of the most relevant scientific directions in the field of computer vision. In particular, HPE technology allows modeling motion by determining the spatial location and joint points of the human body. HPE is aimed at identifying the main points of the human skeleton from an image or video stream, achieving high accuracy and real-time efficiency using modern algorithms based on deep learning [1].

HPE serves to identify anatomically important points of the human body. These points are usually represented by two-dimensional (x, y) coordinates and a reliability index. Based on the points, a model of the human skeleton is formed, and this model is of great importance in the processes of analyzing movement dynamics, assessing posture, and classifying movements.

Joint points are important centers of movement of the human body. These points are the main supporting elements of the skeletal model and are used in the process of HPE and movement analysis [2]. The skeletal model is not a complete representation of the biological skeleton, but a set of main joint centers sufficient for movement analysis.

The main and most complex stage of the HPE system is the process of determining the joints. This process involves determining the main joints of the human body from an image or video frame and calculating their coordinates. The accuracy of the joints and their stability over time are one of the main factors determining the overall efficiency of the HPE system [3]. Studies have shown that errors in the location of the skeleton points directly affect the accuracy of the kinematic parameters calculated in subsequent stages. In particular, even small spatial displacements can lead to significant deviations in calculating the angle between vectors.

A number of studies have been conducted on skeleton-based HPE systems, in which the main focus is on the accuracy and stability of determining the joints.

In [4], the OpenPose model is one of the first effective systems for bottom-up joint detection in multi-person scenes. This model generates probability maps and vector fields for each joint and then builds a skeletal structure based on them. Although this approach shows stable results in multi-person images, it is computationally expensive and suffers from reduced accuracy in the presence of mutual occlusion and small objects.

In [1], the HRNet (High-Resolution Network) architecture is based on maintaining high spatial accuracy. Unlike traditional networks, HRNet stores high-dimensional feature maps in parallel throughout the network and integrates multi-dimensional information. This approach is particularly effective in detecting small joint segments and reducing local spatial drift. As a result, HRNet achieves high accuracy on benchmark datasets such as COCO and MPII.

In recent years, single-stage approaches designed to work in real time have also been widely developed. In particular, pose models based on YOLO are based on the principle of simultaneous object detection and joint coordinate regression [3]. This approach increases computational efficiency and is convenient for real-time systems. However, in some cases, a decrease in spatial accuracy can be observed in the price of high speed.

Although the architecture and overall accuracy of these models have been widely studied, the combined effects of input image size, confidence limit, and lighting conditions on the quality of joint point detection in real environments have not been systematically analyzed.

In this work, the performance of YOLOv8n-pose, HRNet, and OpenPose models with different architectures in real video conditions is analyzed, and the effects of input image size, recognition confidence limit, and lighting conditions on the accuracy of joint point detection are comprehensively evaluated. The scientific novelty of this study lies in the systematic analysis of the combined effects of these key parameters in real-world environments.

II. LITERATURE REVIEW

In recent years, deep learning-based methods have been widely developed in the field of HPE. The proposed models in this direction aim to increase the accuracy and speed of human body joint detection.

The first effective approaches in the field of HPE were developed based on convolutional neural networks (CNN), which are based on the detection of joint points not directly as coordinates, but through probability maps [5]. CNN structures learn features from the image and create a joint heatmap, which is then used to detect joint points. In many HPE models, regression of probability maps is adopted as the main criterion [6]. In this method, each joint point is represented as a 2D Gaussian heatmap. The point with the highest value in the heatmap indicates the approximate location of the joint. [7] The study emphasizes that models based on CNN and recurrent neural network architectures (RNN) are among the most widely used approaches in 2D HPE. However, it has been noted that these models have certain limitations in providing stable and high-accuracy results in environments with complex scene conditions, mutual occlusion, and noisy backgrounds.

In recent years, new architectures have been developed to further improve the accuracy of node detection and reduce spatial information loss. In particular, the HRNet (High-Resolution Network) model proposed in [8,18] is based on the principle of preserving high-dimensional feature maps at all stages of the network. This approach serves to improve the local accuracy of node detection and provides high efficiency in detecting small segments.

In [9,19], the OpenPose model was developed based on a bottom-up approach, which first detects all the joint points in the image, and then combines them into a skeletal structure using Part Affinity Fields technology. This model is characterized by its effective performance in scenes with many people. However, the high computational complexity and increased demand for hardware resources are noted as the main limitations of OpenPose.

[10] The study compared the performance of the AlphaPose and BlazePose models in HPE with OpenPose. The studies noted that these models work based on a top-down approach, that is, first human objects are detected in the image, and then the joint points are predicted separately for each detected person. While the AlphaPose model is characterized by high accuracy in processing biomechanical data, the BlazePose model is characterized by its lightweight architecture and the ability to work in real time on mobile devices. At the same time, BlazePose is a key component of the MediaPipe Pose system and is capable of detecting 33 2D joint points. However, both models are characterized by a decrease in accuracy in complex scene conditions, lighting changes, and mutual occlusion.

In research, lightweight models designed for real-time operation have also been widely developed. In particular, the YOLOv8-pose model is based on the principle of simultaneous object detection and joint coordinate regression, which provides high computational speed [11,20]. This model is convenient for use in mobile devices and real-time monitoring systems. However, in some cases, especially when detecting small joint points, a decrease in spatial accuracy can be observed.

Although the architecture, accuracy, and computational efficiency of HPE models have been studied in existing studies, the problems that arise when using these models in real-world environments have not yet been fully resolved. In particular, complex scene conditions, mutual occlusion, background noise, and changes in illumination levels significantly affect the accuracy of joint point detection.

In most studies, models are evaluated based on standard benchmark datasets. However, such evaluations do not fully reflect factors such as lighting irregularities, camera noise, and image degradation that occur in real video environments. As a result, models that perform well in laboratory conditions may not perform well in practical environments [12]. Also, most of the existing works have not systematically analyzed the combined effects of input image size, detection confidence limit, and lighting conditions on the quality of vertex detection.

In addition, the problem of trade-off between accuracy and computational speed remains relevant among modern models. While high-accuracy architectures require large computational resources, models adapted to real-time systems are sometimes characterized by reduced spatial accuracy [13]. Determining the optimal point of this trade-off is important for practical systems.

This study aims to systematically evaluate the performance of HPE models with different architectures in real-world video environments, taking into account these existing limitations. The study analyzes the impact of input image size, confidence limits, and lighting conditions on the quality of vertex detection. As a result, practical recommendations are developed for selecting optimal parameters for real-time monitoring systems.

Analysis of existing studies shows that the performance of modern HPE models is directly related to their architectural structure. In particular, the HRNet model has an advantage in detecting small and complex joint segments, as it maintains high spatial accuracy throughout the network. The OpenPose model, on the other hand, shows stable results in multi-person scenes due to its bottom-up approach, but is characterized by high computational complexity. While models based on a top-down approach, such as AlphaPose and BlazePose, provide high accuracy for individual objects, errors in the object detection stage can negatively affect the overall result. Although the YOLOv8-pose model is characterized by real-time performance, in some cases a decrease in spatial accuracy is observed. Therefore, the trade-off between accuracy and computational speed between different models remains an important research issue.

III. METHODS

A. *Experimental data*

In this study, a single video recording was used to analyze human movement. The selected video contained the same scene conditions and movement sequence, allowing for a consistent and controlled assessment of the effects of these parameters. The video consists of 62 consecutive frames, each frame containing a single human subject.

The parameters of the video recording used in the study are as follows: video size 1280×720 pixels, frame rate 30 FPS. The total duration of the video is 2 seconds. In order to determine the effect of lighting conditions on the performance of the model, the video was analyzed in three different lighting modes: normal, low, and high. This approach allowed us to assess the impact of environmental factors, in particular, light intensity, on the quality of detecting human body joints.

B. *Joint point detection model*

In this study, three models, YOLOv8n-pose, HRNet, and OpenPose, which are widely used in modern HPE, were used to detect human body joints. These models belong to different architectural approaches, and their operating principle and computational complexity differ. This allows us to compare their stability under different conditions. YOLOv8n-pose is a single-stage detection architecture, a neural network designed to work in real time. HRNet preserves high-resolution features throughout the network. The model combines features through a multi-dimensional parallel structure and detects joints based on a heatmap. OpenPose is a bottom-up model that uses the Part Affinity Fields (PAF) technique.

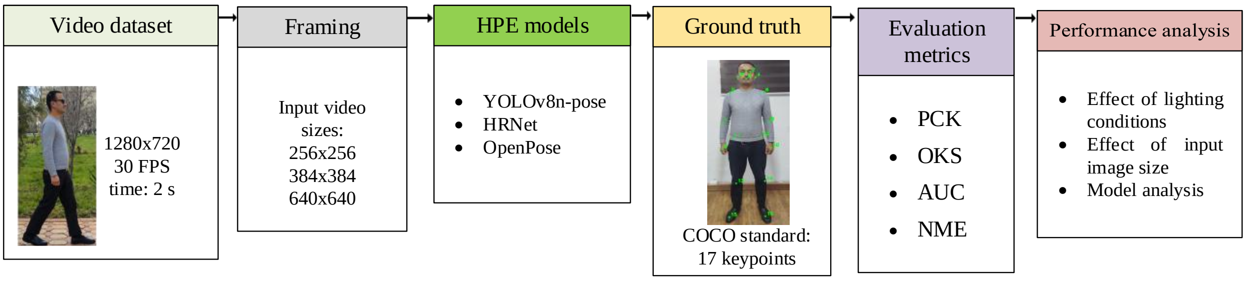

Figure I. Process architecture for evaluating HPE models under different conditions.

The model first detects all joints in the image, and then combines them according to the skeletal structure. In the study, all models were adapted to the 17-joint structure based on the COCO standard.

In HPE systems, each joint point is formally represented in a two-dimensional coordinate system as follows:

$$P_i = (x_i, y_i, c_i) \tag{1}$$

where $i \in \{1, 2, ..., 17\}$ – joint index;

x_i, y_i – coordinates in the image plane;

$c_i \in [0,1]$ – level of confidence in detection.

To filter out incorrectly identified points, a minimum confidence limit τ is applied:

$$c_i > \tau \tag{2}$$

If $c_i \le \tau$, this point is excluded from the analysis.

The experiments were performed on a computer with an Intel Core i7-2600 processor. Graphical calculations were performed using an Intel HD Graphics video adapter using the Python 3.10 programming environment and related libraries. The calculation results were obtained under conditions of limited hardware resources.

C. *Experimental parameters.*

To evaluate the factors affecting the quality of joint point detection, three main parameters were selected: input image size, confidence limit, and lighting conditions. The experiment was tested on images with sizes of 256×256, 384×384, and 640×640. The confidence $\tau \in [0.3 - 0.7]$ interval was chosen and defined based on values commonly used in applied research. This interval was chosen to encompass low, medium, and high levels of confidence.

In this study, the ground truth (GT) data of the human body was generated using special marking tools based on the COCO standard and was checked several times to reduce errors. This GT data was compared with the junction points identified by the models and used as the main criteria in calculating the evaluation metrics.

D. Evaluation metrics.

In this study, OKS, PCK, NME, and AUC metrics were used to evaluate the accuracy of human body joint point detection models.

Normalized Mean Error (NME)

The NME metric represents the average distance between the model-defined node points and the GT points in a normalized form [14]. This metric is defined as:

$$NME = \frac{1}{N}\sum_{i=1}^{N}\frac{d_i}{s} \qquad (3)$$

were:

d_i – the error distance of the i-th joint point;

s – normalization coefficient (body size);

N – number of joints.

Percentage of Correct Keypoints (PCK)

The PCK metric represents the total percentage of keypoints identified with an error smaller than a specified threshold [15]:

$$PCK = \frac{1}{N}\sum_{i=1}^{N} I(d_i < \alpha s) \qquad (4)$$

were:

α – accuracy threshold;

$I(\cdot)$ – indicator function.

OKS (Object Keypoint Similarity)

The OKS metric is based on the COCO standard and evaluates the similarity of keypoints [16]:

$$OKS = \frac{1}{N}\sum_{i=1}^{N}\exp\left(-\frac{d_i^{\,2}}{2s^2 k_i^{\,2}}\right) \qquad (5)$$

were:

k_i – the complexity coefficient of the i-th point.

The accuracy increases as the OKS value approaches 1.

Area Under Curve (AUC)

The AUC metric represents the area under the PCK curve and evaluates the overall performance of the model [17]:

$$AUC = \int_0^1 PCK(\alpha)\,d\alpha \qquad (6)$$

A large AUC value indicates that the model performs stably under different conditions.

A total of 27 calculations were performed in the experiment. During each calculation, video frames were processed and the accuracy of the articulation points was evaluated based on the OKS, PCK, NME, and AUC metrics.

IV. RESULTS

In this study, the impact of input image size, illumination conditions, and selected model architecture on the quality of human body joint point detection was comprehensively analyzed. During the evaluation process, the performance of the models was calculated and analyzed based on the NME, PCK, OKS, and AUC metrics (Table I).

Table I. Performance of HPE models under various test conditions.

YOLOv8n-pose			**HRNet**			**OpenPose**			**Evaluation metrics**	
Low	Normal	High	Low	Normal	High	Low	Normal	High	Size	Metrics
0.63	0.79	0.76	0.78	0.83	0.8	0.75	0.81	0.77	256	**PCK**
0.68	0.84	0.81	0.84	0.885	0.86	0.81	0.865	0.83	384	

0.73	0.88	0.85	0.88	0.92	0.895	0.85	0.9	0.87	640	
0.56	0.63	0.59	0.64	0.7	0.66	0.6	0.66	0.62	256	
0.61	0.68	0.64	0.71	0.77	0.73	0.66	0.72	0.68	384	**OKS**
0.66	0.73	0.69	0.76	0.82	0.78	0.71	0.76	0.73	640	
0.71	0.771	0.74	0.763	0.814	0.783	0.732	0.792	0.752	256	
0.76	0.821	0.79	0.824	0.871	0.844	0.792	0.848	0.812	384	**AUC**
0.801	0.862	0.831	0.866	0.908	0.881	0.833	0.883	0.853	640	
0.062	0.05	0.056	0.054	0.042	0.05	0.058	0.046	0.054	256	
0.053	0.041	0.047	0.045	0.033	0.041	0.049	0.037	0.045	384	**NME**
0.046	0.034	0.04	0.038	0.027	0.034	0.042	0.031	0.038	640	

According to the experimental results, it was observed that increasing the input image size led to an increase in the accuracy indicators for all models. While the PCK and OKS values were relatively low at 256×256 resolution, the maximum values were achieved at 640×640 resolution (Figure II). This is explained by the better preservation of spatial information about human body segments in high-resolution images.

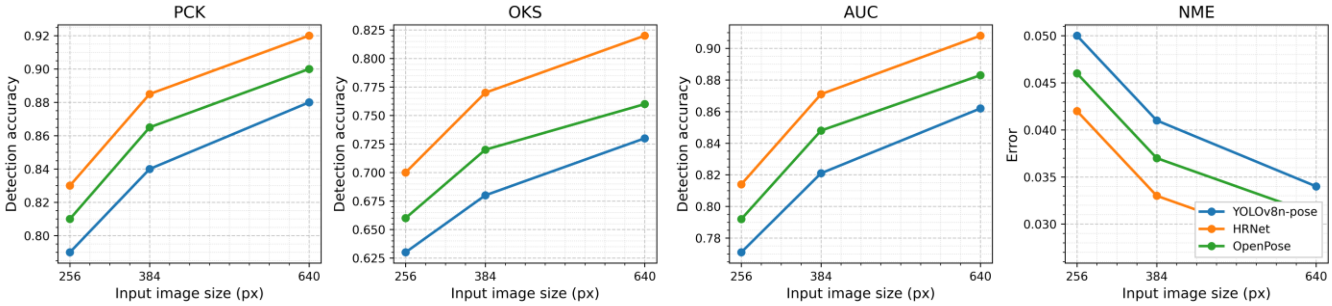

Figure II. Performance of HPE models at different input image sizes.

For the YOLOv8n-pose model, the PCK value increased from 0.790 to 0.880 under normal lighting conditions, while the NME value decreased from 0.050 to 0.034. Both HRNet and OpenPose models showed improved accuracy with increasing image size. The superior performance of the HRNet model is due to the high-resolution feature maps stored throughout the network in its architecture.

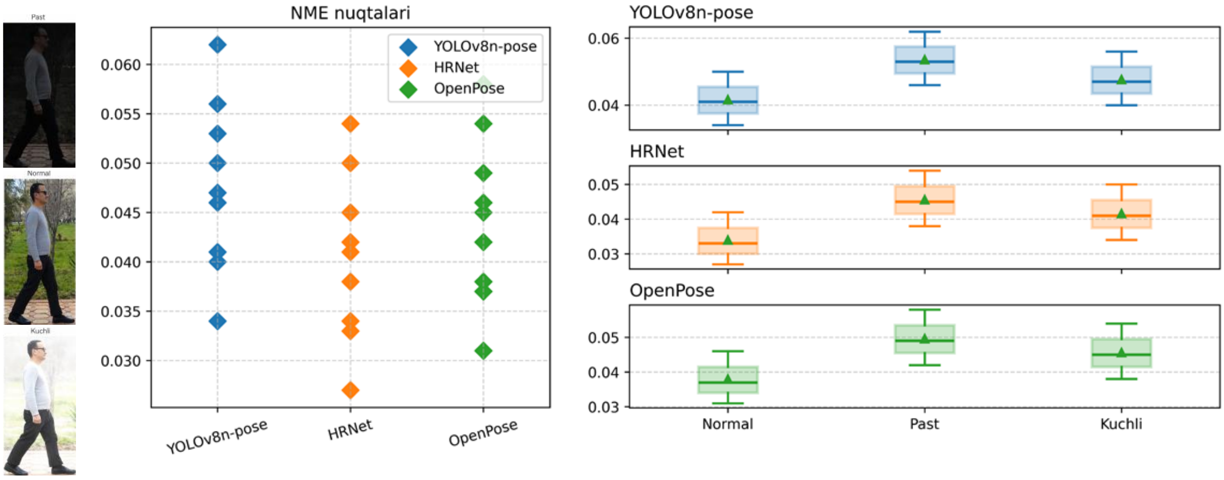

Figure III. Error distribution of models under different lighting conditions.

According to the results of Figure III, the lighting conditions had a significant impact on the performance of the models. While the highest accuracy results were recorded under normal lighting conditions, a decrease in PCK and OKS values was observed under low lighting conditions. This is explained by the decrease in image brightness and the increase in noise level. Under strong lighting conditions, excessive brightness led to the loss of spatial features in some joint segments.

Comparative analysis between the models showed that the HRNet model has the highest accuracy. Under normal lighting and a resolution of 640×640, the HRNet model achieved PCK=0.920 and OKS=0.820. While the OpenPose model demonstrated stable results, the YOLOv8n-pose model was evaluated as an effective solution for real-time systems due to its lightweight architecture and high computational speed.

V. CONCLUSION

In this study, the effects of input image size, illumination conditions, and model architecture on the accuracy of joint point detection in HPE systems were systematically studied. As part of the study, the performance of the YOLOv8n-pose, HRNet, and OpenPose models in a real video environment was analyzed based on the PCK, OKS, AUC, and NME evaluation metrics. These analyses are also important in sports action analysis and automatic monitoring of exercise performance. The results showed that increasing the input image size leads to a significant improvement in the accuracy of joint point detection for all models. In particular, the PCK, OKS, and AUC indicators reached maximum values in 640×640 images, and a decrease in the NME error rate was observed. This is characterized by better preservation of information about human body segments in images with high spatial resolution. Such accuracy is important for analyzing athletes' movements, assessing exercise techniques, and studying sports biomechanics.

The experimental results also confirmed that lighting conditions are an important factor in the HPE process. While all models demonstrated the highest accuracy results under normal lighting conditions, a decrease in image intensity and an increase in noise levels led to a decrease in accuracy under low lighting conditions. In strong lighting conditions, some spatial points were lost due to excessive brightness.

The results of the comparative analysis between the models showed the superiority of the HRNet model in terms of accuracy. This model demonstrated the highest PCK and OKS values and the lowest NME values under all test conditions. While the OpenPose model demonstrated stable performance, the YOLOv8n-pose model was evaluated as an effective solution for real-time monitoring systems due to its lightweight architecture and high computing speed. This allows for real-time monitoring of sports training processes and rapid analysis of athletes' movements.

Overall, the results of the study show that the correct selection of input image size and lighting conditions is essential for achieving optimal performance in HPE systems. These results expand the possibilities of effective use of HPE technologies in sports analysis of movements, assessment of athlete technique, automation of training processes and study of sports biomechanics. In the future, our research plans to expand our research in the direction of deep analysis of sports movements and automatic monitoring of athlete performance, as well as assessment of temporal stability in complex scene conditions, crowded environments and video sequences.

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