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Angle-Based Pose Analysis for Digital Documentation and Learning Support of Ibing Penca Stances in Pencak Silat

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Abstract

Supporting independent learning of traditional martial arts presents a challenge when direct instructor guidance is unavailable. This study explores the feasibility of recognizing Ibing Penca stances using an interpretable, computer vision–based pose representation. The proposed system aims to support independent practice by identifying and classifying 62 Ibing Penca stances under controlled conditions. Image and video data were collected using an Orbbec camera and processed through a pose landmark detection pipeline. Human body landmarks were extracted using MediaPipe, which provides 33 keypoints representing major joints and body segments. Based on these landmarks, six joint angles corresponding to the right arm, left arm, right leg, left leg, right foot, and left foot were computed using three-point angle calculations. These angle features were then used in a rule-based classification framework to represent stance configurations. Experimental results indicate that the proposed angle-based representation can distinguish most stance prototypes within the constructed dataset, achieving a stance-level recognition rate of 91% (57 out of 62 stances) under controlled conditions. Rather than claiming generalizable performance, this study is positioned as an initial feasibility investigation. Future work will focus on expanding the dataset, incorporating greater movement variability, and evaluating performance under more diverse environmental and subject conditions.

Keywords: Angle, classification, ibing penca, keypoint, stance.

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1. Introduction[1]

Research to detect body movements has been conducted in various fields, including recognizing work poses (Bataineh, 2025), pencak silat poses (AMinudin et al., 2020), multi-person poses (Cao et al., 2019), etc. In the initial research conducted by (AMinudin et al., 2020), data was collected on 8 Tapak Suci pencak silat moves, and a learning tool was created using genetic algorithms and dynamic time wrapping.

In this research, an application system was developed to recognize *ibing penca* 62 stances using the angle heuristics method, which analyzes six angle values from three key points. This system is designed to assist individuals in learning independently by identifying and classifying different stances. Research on the use of computer vision in pencak silat technique recognition has been limited due to a lack of collaboration between the two fields.

Let's take a more detailed look at *pencak silat. Pencak silat* is a martial art that represents Indonesian cultural identity and has been designated by UNESCO as an Intangible Cultural Heritage. In West Java, *pencak silat* is not only categorized as a martial art (athletics) but also as an art form (aesthetic, ethical, and academic). In the context of performing arts, *pencak silat* is often referred to as *Kendang Penca* (from a musical aesthetic perspective) and *Ibing Penca* (from a dance aesthetic perspective). The focus of this article, written by Oktriyadi, Riky, and Sentosa, Gempur (Oktriyadi & Sentosa, 2023), is to describe the diversity of *tepak ciwaringinan* patterns in *pencak silat* schools in Bandung. This consideration arises from the fact that the song and *tepak* no longer appear in every *kendang penca* performance, leading to claims that it is becoming extinct. In this article, the authors use a qualitative approach based

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on Jhon W. Creswell's methodology, with data collected through observation, documentation, and interviews. After the data is obtained, it is analyzed to verify its accuracy. This article discusses the description of *pencak silat* performance art, the accompaniment music of *pencak silat* in Bandung, and the *tepak ciwaringinan* patterns in *pencak silat*. The article concludes that *pencak silat* is one of the most important aspects of performing arts in Indonesia, particularly in West Java.

Aesthetically, *Pencak Silat* generally consists of the aesthetics of the *Pencak Silat* dance form (*ibing penca*), music aesthetics (*karawitan*), and traditional clothing aesthetics. Additionally, the findings of this study reveal that there are still various *Ciwaringinan tepak* patterns that remain unknown to the public. From a scientific perspective, this study also examines the natural movements of *ibing penca*, which are performed in self-defense.

Each region has a *paguron pencak silat* that has different characteristics and styles. The differences in each *paguron pencak silat* become the identity of each *paguron*, both in terms of personal identity, social identity, and cultural identity. *Ibing pencak silat Baragbag* in *paguron sinar pusaka putra Garut* develops *ibingan* (style of motion) which has a characteristic pattern of motion and supporting components of motion. In the research conducted by Azzahra, Nabila Rizkyta et al (Azzahra et al., 2023) aims to describe the average *ibing penca* of *Garut baragbag* based on the elements of motion presentation (choreographic structure and *ibing penca* function) and its composition. The results showed that the middle *baragbag ibing penca* consists of several components, namely choreographic components including motion and function, with a fast and integrated choreographic structure, and has its own uniqueness.

Each region has a *paguron* (traditional martial arts school) of *pencak silat*, each with distinct characteristics and styles. These differences define the identity of each *paguron* in terms of personal, social, and cultural aspects.

In addition, *pencak silat* is a martial art that is beneficial for self-defense, increasing physical strength, maintaining posture and maintaining heart health. The benefits of learning *pencak silat* for Physical Fitness, such as increasing strength and flexibility, increasing cardiovascular endurance, improving posture. Mental Health can increase self-confidence, reduce stress, improve concentration and focus. Self Defense, such as improving self-defense skills, increasing alertness. Pencak Silat has noble values, such as fostering discipline, instilling respect, building character, and building a sense of brotherhood (Rustiyanti et al., 2021)(Rustiyanti et al., 2019)(Rustiyanti et al., 2020)(Rustiyanti, 2019). However, *pencak silat* training is often challenging to conduct in groups due to various factors such as crowd restrictions and pandemics. Although pencak silat is included in school curricula, sports teachers still face difficulties in teaching the movements directly. Practicing *pencak silat* alone without a coach can also lead to injuries if the movements are performed incorrectly. To address this issue, Rahmawati et al. (Rahmawati et al., 2023) developed an application system for martial arts motion recognition. The system utilizes the Convolutional Neural Network (CNN) method based on body pose detection. The body posture data is sent to the CNN for motion recognition. CNN was chosen because of its ability to automatically extract patterns and representations from inputs with high accuracy. The research achieved an accuracy rate of 77% when tested on previously unseen data. In addition, pencak silat is a martial art that provides various benefits, including self-defense, increased physical strength, posture maintenance, and heart health improvement.

2. Methods

Computer vision as a branch of computer science will be utilized in the research here. Human movement during activities can be stored as two-dimensional or three-dimensional data by considering the depth contour (Rasoulidanesh, 2022) . The data collection process can be obtained by utilizing depth sensors (Pradana & Prasetya, 2019).

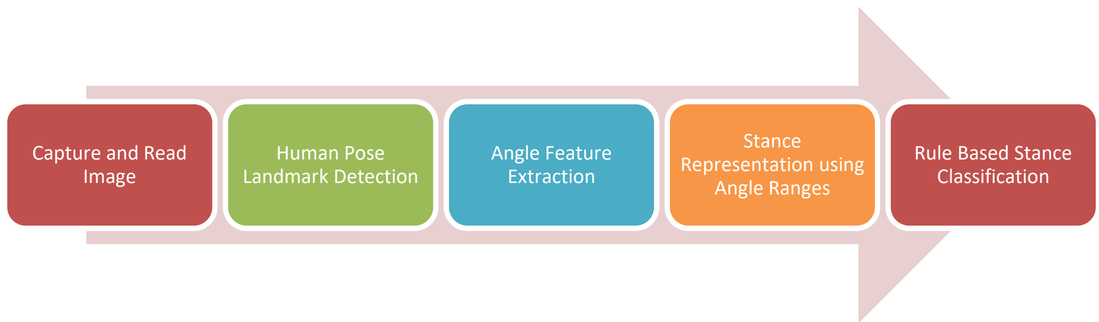


Figure 1. System diagram block

The proposed system aims to explore the feasibility of recognizing Ibing Penca stances using an interpretable, rule-based pose representation. The system consists of four main stages: (1) human pose landmark detection, (2) angle feature extraction, (3) stance representation using angle ranges, and (4) rule-based stance classification.

2.1. Capture and Read Image

The input to the system is an image or video of a person performing ibing penca moves. Image or video capture in this research uses the Orbbec Astra S camera, but can also use other cameras such as Kinect-v2 (Nguyen, 2023), and the camera output is a digital image, which can have types: black and white image, RGB color image, spectral, and thermal (Hameed et al., 2018). Furthermore, digital images will be processed to obtain meaningful information.

2.2. Dataset Description

Due to the absence of publicly available data sets for Ibing Penca, a small controlled d ata set was created for this exploratory study. The dataset consists of 62 different Ibing Penca attitudes. For each stance, two people were used in training with 5 images each taken for training, resulting in a total of 620 training images. Additional images were taken for testing with 2 of the same people in training and 1 different person in training, 5 images each in 62 stances for a total of 930 testing images.

All images were recorded using an Orbbec Astra S camera in an indoor environment with controlled lighting and a fixed camera position. The same practitioner performed all stances to ensure consistency in movement execution. This dataset design supports prototype-level evaluation but does not aim to capture inter-subject variability.

2.3. Human Pose Landmark Detection

Body Pose Estimation. Recent multi-person body pose estimation approaches can be divided into bottom-up and top-down approaches. Bottom-up approaches first detect all the keypoints of every person in images and then group them into individuals. Top-down methods first detect the bounding boxes and then predict the human body keypoints in each box. By resizing and cropping, top-down approaches normalize the poses to approximately the same scale. Therefore, they are more robust to human-level scale variance and recent state-of-the-arts are obtained by top-down approaches. However, direct usage of the top-down methods for whole-body pose estimation will encounter the problem of scale variance of different body parts (body vs face/hand). To tackle this problem a single-network top-down approach that zooms in to the hand/face regions and predicts the hand/face keypoints using higher image resolution for accurate localization (Jin et al., 2020).

Face/Hand/Foot Keypoint Localization. Previous works mostly treat the tasks of face/hand/foot keypoint localization independently and solve by different models. For facial keypoint localization, cascaded networks and multi-task learning are widely adopted. For hand keypoint estimation, most work rely on auxiliary information such as depth information or multi-view information. For foot keypoint estimation (Cao et al., 2019), proposed a generic bottom-up method. In this paper solve the tasks of face/hand/foot keypoint localization as a whole. It takes into account the inherent hierarchical structure of the full human body to solve the scale variation of different parts in the same person.

Whole-Body Pose Estimation. Whole-body pose estimation has not been well studied in the literature due to the lack of a representative benchmark. OpenPose applies multiple models (body keypoint estimator) to handle different kinds of keypoints. It first detects body and foot keypoints, and estimates the hand and face position. Then it applies extra models for face and hand pose estimation. Since OpenPose relies on multiple networks, it is hard to train and suffers from increased runtime and computational complexity. Unlike OpenPose, a single-network method as it integrates five previously separated models (human body pose estimator, hand/face detectors, and hand/face pose estimators) into a single network with shared lowlevel features. Recently, Hidalgo et al. proposes an elegant method SN for bottom-up whole-body keypoint estimation. SN is based on PAF which predicts the keypoint heatmaps for detection and part affinity maps for grouping.

Since there exist no such dataset with whole-body annotations, they used a set of different datasets and carefully designed the sampling rules to train the model. However, bottom-up approaches cannot handle scale variation problem well and would have difficulty in detecting face and hand keypoints accurately. In comparison, a top-down approach that well handles the extreme scale variance problem. Recent works also explore the task of monocular 3D whole-body capture. Romero et al. proposes a generative 3D model to express body and hands. Xiang et al. introduces a 3D deformable human model to reconstruct whole-body pose and Joo et al. presents Adam which encompasses the expressive power for body, hands, and facial expression. Their methods still rely on OpenPose to localize 2D body keypoints in images.

Human pose landmarks were extracted using MediaPipe Pose, which provides 33 two-dimensional body landmarks per frame. MediaPipe was selected due to its efficiency, robustness, and suitability for real-time applications. Only landmark coordinates relevant to limb articulation were used for subsequent analysis.

The digital image is then processed with MediaPipe, which can track the pose in real-time. MediaPipe (Putra et al., 2022) with the Blazepose module (Bazarevsky et al., 2020) is openCV software with the Python programming language. The output of MediaPipe is 33 keypoints representing the main points on the human body as can be seen in Figure 2 (Jeong & Kook, 2023). Research using MediaPipe and the OpenCV library on yoga positions has been conducted to help users practice regularly. This application helps users practice, when a physical trainer is not available (Jeong & Kook, 2023)(Patel & Lathigara, 2022) and has been used in yoga motion detection (Sunney, 2022) (Anand Thoutam et al., 2022).

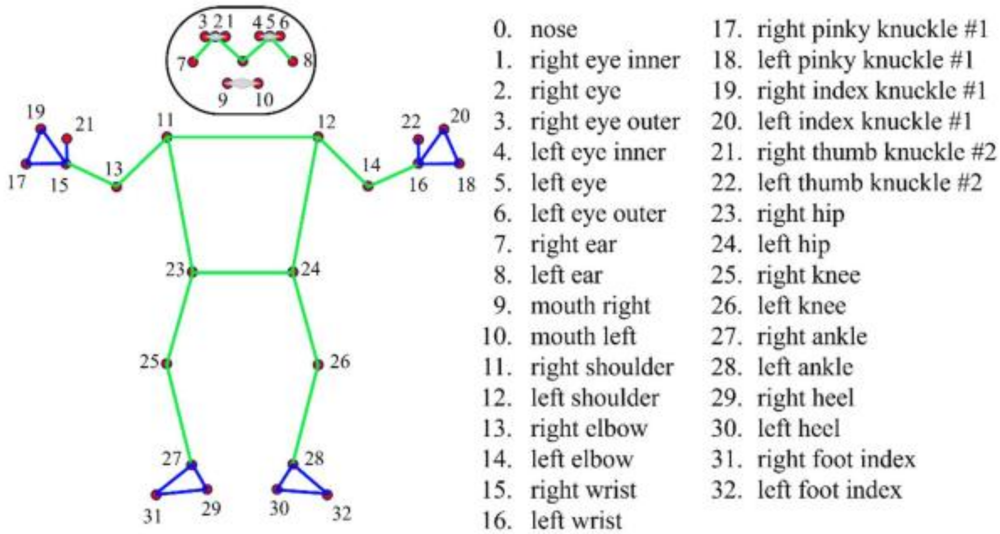


Figure 2. Pose 33 keypoints (Jeong & Kook, 2023)

2.4. Angle Feature Extraction

Next, we will find six angles from the keypoints above. Table 1 and Figure 3 shows the keypoints used to find the six angles. Six joint angles were computed to represent each stance: right arm, left arm, right leg, left leg, right foot, and left foot. Each angle was defined using three MediaPipe landmarks.

Table 1. Six Angle From Three Keypoints (Jeong & Kook, 2023)

Angle	Keypoint	Description
1	12-14-16	left_shoulder, left_elbow, left_wrist
2	11-13-15	right_shoulder, right_elbow, right_wrist
3	24-26-28	left_hip, left_knee, left_ankle
4	23-25-27	right_hip, right_knee, right_ankle
5	28-30-32	left_ankle, left_heel, left_foot_index
6	27-29-31	right_ankle, right_heel, right_foot_index

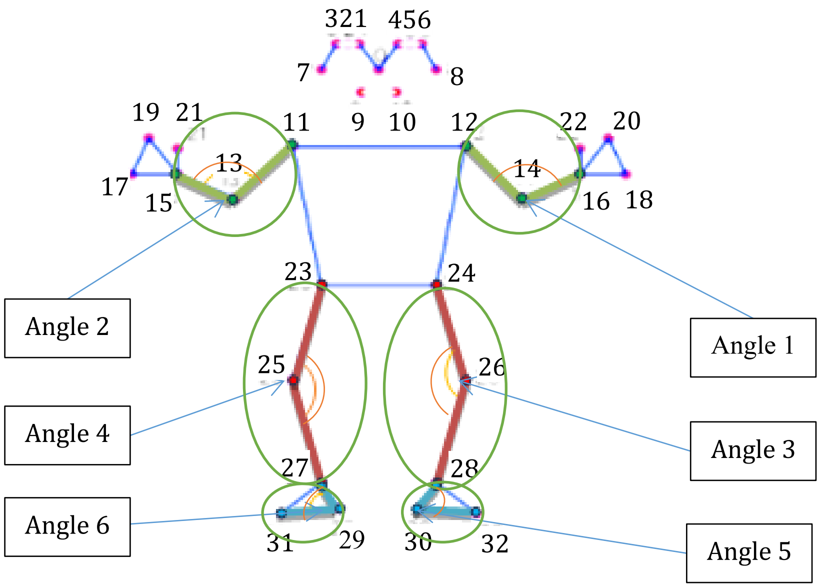


Figure 3. Six angles from each three keypoints

Human position assessment is an emerging problem in the field of computer vision that has exposed many challenges and consequences in the past, almost a global problem now (Shan et al., 2024). Human activity analysis is beneficial in many fields such as video surveillance (Elharrouss et al., 2021), biometrics (Ray et al., 2018), living assistants (Achirei et al., 2022), home health monitoring (Bibbò & Vellasco, 2023), remote monitoring (Yang & Hsu, 2012), etc. With our fast-paced lives today, people usually prefer to exercise at home but feel the need for an instructor to evaluate their exercise form. Since these resources are not always available, human pose detection can be used to build a self-service exercise system that allows people to learn and practice exercises comfortably on their own.

This project builds the foundation for building such a system by discussing various machine learning and deep learning methods to accurately classify yoga positions in real time (Chaudhary et al., 2023). Using the system, the user is given the option to select the position he/she wants to practice. The user's position is detected and the angular differences of various joints of the body are calculated. Based on these angular differences, audio and text feedback is given to the user so that he can correct his pose. With the audio and text feedback, it is as if there is a live interaction session with the instructor.

The method used: yoga poses are taken through a camera with the openCV application in the form of images, then the image is detected using the Blazepose modeler from mediapipe, 33 keypoints are determined, segmentation, classification and detection are carried out. The pose detection results are displayed textually and audibly using SpVoice which is a TTS (Text to Speech) engine (Tawar et al., 2022).

This research discusses a realtime approach to detect 2D poses of multiple people in an image. The method used is to use a nonparametric representation called Part Affinity Fields (PAF) to associate body parts with individuals in the image (Jessika et al., 2019). The system has high accuracy and realtime performance, independent of the number of people in the image. Through this research, it was found that PAF enhancement alone, without body part location enhancement, can improve the performance and accuracy of the system. In addition, this research also presented the first combined body and foot keypoint detector (Jessika et al., 2019), based on an annotated foot dataset. This detector has successfully reduced the inference time and maintained the accuracy of each of its individual components. This research also resulted in the release of OpenPose, the first open-source realtime system for multi-person 2D pose detection (Zhang et al., 2023), including body, foot, hand, and face keypoints (Cao et al., 2019), (Cao et al., 2017).

2.5. Stance Representation using Angle Ranges

For each stance, the minimum and maximum values of each angle were computed from the training samples, forming a six-dimensional angle interval representation. This representation provides an interpretable description of each stance's pose configuration.

2.6. Rule-Based Classification

During testing, extracted angles were compared against the stored angle intervals for each stance. A stance was considered correctly recognized if all six angles fell within the corresponding interval that correspond to the angle range during training. In cases where multiple stances satisfied this condition, the sample was marked as ambiguous and assigned to the closest matching stance based on aggregate deviation.

2.7. Evaluation

Evaluation was conducted at the stance level using held-out images captured under the same conditions as the training data. Recognition accuracy was defined as the percentage of stances correctly identified. This evaluation reflects feasibility under controlled conditions and does not imply generalizable performance.

3. Results

This section presents the experimental results obtained from the proposed angle-based stance recognition system for ibing penca. The evaluation focuses on stance-level recognition performance under controlled acquisition conditions.

3.1. Experimental Setup

The system was evaluated using a dataset consisting of 62 standardized ibing penca stances. Each stance was represented by reference angular configurations derived from pose landmark detection using MediaPipe. All data were captured using a single depth-sensing camera under consistent environmental conditions, including fixed camera position, lighting, and background.

The evaluation was conducted at the stance level, where each test sample corresponded to a complete static posture representing one ibing penca stance. Recognition was considered correct if the extracted angular features matched the reference configuration of the intended stance according to the predefined angle comparison rules described in the Methodology section.

The research here is classified into 62 stances, namely: *1) Hormat sebagai pembuka persembahan kepada Tuhan dan penonton, 2) Idiom gerak hormat, 3) Rengkuh kuda-kuda kiri, 4) Idiom gerak kuda-kuda, 5) Langkah serong tangkis handap, 6) Keneme Langkah serong tangkis handap, 7) Lengkah sajajar pasang tungkup, 8) Keneme Lengkah sajajar pasang tungkup, 9) Langkah soja maju katuhu sambut kenca, 10) Keneme Langkah soja maju katuhu sambut kenca, 11) Sajajar siku katuhu, 12) Keneme Sajajar siku katuhu, 13) Gesoh soja katuhu kepeng katuhu, 14) Soja katuhu pepeuh katuhu, 15) Keneme Soja katuhu pepeuh katuhu, 16) Langkah sajajar tangkis dua, 17) Keneme Langkah sajajar tangkis dua, 18) Soja kenca rungkup, 19) Keneme Soja kenca rungkup, 20) Soja kenca dengkul kenca, 21) Keneme Soja kenca dengkul kenca, 22) Luncat pasang gantung, 23) Keneme Luncat pasang gantung, 24) Deku katuhu rawel, 25) Deku katuhu giles kenca, 26) Keneme Deku katuhu giles kenca, 27) Siku katuhu serong, 28) Keneme Siku katuhu serong, 29) Soja katuhu kebut kenca, 30) Soja katuhu bandul katuhu, 31) Keneme Soja katuhu bandul katuhu, 32) Lengkah silang kebut, 33) Keneme Lengkah silang kebut, 34) Langkah serong kenca tukang siku katuhu, 35) Keneme Langkah serong kenca tukang siku katuhu, 36) Muter rogok katuhu ajeg, 37) Keneme Muter rogok katuhu ajeg, 38) Langkah serong katuhu tukang giles deukem, 39) Keneme Langkah serong katuhu tukang giles deukem, 40) Gesoh katuhu silang tangkis gigir kenca, 41) Tajong katuhu, 42) Keneme Tajong katuhu, 43) Langkah soja kenca pepeuh katuhu, 44) Keneme Langkah soja kenca pepeuh katuhu, 45) Gesoh kenca silang besot kenca, 46) Keneme Gesoh kenca silang besot kenca, 47) Ambreg, 48) Keneme Ambreg, 49) Pasang nyumput sajajar, 50) Keneme Pasang nyumput sajajar, 51) Deku katuhu tendet katuhu, 52) Keneme Deku katuhu tendet katuhu, 53) Sapu katuhu, 54) Tangkis maju soja katuhu, 55) Soja katuhu tonjok, 56) Keneme Soja katuhu tonjok, 57) Soja katuhu angkis katuhu gigir, 58) Soja katuhu catok katuhu, 59) Keneme Soja katuhu catok katuhu, 60) Malik soja kenca Balang katuhu kenca, 61) Malik soja katuhu giles kenca, 62) Sajajar malik gigir tendet katuhu*. The 62 stances with their names and visuals can be seen in Table 2.

Table 2. The 62 stances *ibing penca*

Photo pose						
1	2	3	4	5	6	7
						
Hormat sebagai pembuka persembahan kepada Tuhan dan penonton	*Idiom gerak hormat*	*Rengkuh kuda-kuda kiri*	*Idiom gerak kuda-kuda*	*Langkah serong tangkis handap*	*Keneme Langkah serong tangkis handap.*	*Lengkah sajajar pasang tungkup*
8	9	10	11	12	13	14
						
Keneme Lengkah sajajar pasang tungkup	*Langkah soja maju katuhu sambut kenca.*	*Keneme Langkah soja maju katuhu sambut kenca*	*Sajajar siku katuhu*	*Keneme Sajajar siku katuhu*	*Gesoh soja katuhu kepeng katuhu*	*Soja katuhu pepeuh katuhu.*
15	16	17	18	19	20	21
						
Keneme Soja katuhu pepeuh katuhu	*Langkah sajajar tangkis dua.*	*Keneme Langkah sajajar tangkis dua*	*Soja kenca rungkup*	*Keneme Soja kenca rungkup*	*Soja kenca dengkul kenca.*	*Keneme Soja kenca dengkul kenca*
22	23	24	25	26	27	28
						
Luncat pasang gantung	*Keneme Luncat pasang gantung*	*Deku katuhu rawel*	*Deku katuhu giles kenca*	*Keneme Deku katuhu giles kenca*	*Siku katuhu serong*	*Keneme Siku katuhu serong*
29	30	31	32	33	34	35

						
Soja katuhu kebut kenca	*Soja katuhu bandul katuhu*	*Keneme Soja katuhu bandul katuhu*	*Lengkah silang kebut*	*Keneme Lengkah silang kebut*	*Langkah serong kenca tukang siku katuhu*	*Keneme Langkah serong kenca tukang siku katuhu*
36	37	38	39	40	41	42
						
Muter rogok katuhu ajeg	*Keneme Muter rogok katuhu ajeg*	*Langkah serong katuhu tukang giles deukem*	*Keneme Langkah serong katuhu tukang giles deukem*	*Gesoh katuhu silang tangkis gigir kenca*	*Tajong katuhu*	*Keneme Tajong katuhu*
43	44	45	46	47	48	49
						
Langkah soja kenca pepeuh katuhu	*Keneme Langkah soja kenca pepeuh katuhu*	*Gesoh kenca silang besot kenca*	*Keneme Gesoh kenca silang besot kenca*	*Ambreg*	*Keneme Ambreg*	*Pasang nyumput sajajar*
50	51	52	53	54	55	56
						
Keneme Pasang nyumput sajajar	*Deku katuhu tendet katuhu*	*Keneme Deku katuhu tendet katuhu*	*Sapu katuhu*	*Tangkis maju soja katuhu*	*Soja katuhu tonjok.*	*Keneme Soja katuhu tonjok*

57	58	59	60	61	62
					
Tsoja katuhu angkis katuhu gigir	*Soja katuhu catok katuhu*	*Keneme Soja katuhu catok katuhu*	*Malik soja kenca Balang katuhu kenca*	*Malik soja katuhu giles kenca.*	*Sajajar malik gigir tendet katuhu.*

3.2. Result Skeleton Detection

Figure 4 shows an example of the results of testing the detection of the Hormat position as an opening gesture to God and the audience. In training, the system was given five photos for each position (the training data taken from two people with 5 images each taken for training, resulting in a total of 620 training images. Additional images were taken for testing with two of the same people in training and one different person in training, five images each in 62 stances for a total of 930 testing images), and angles 1 to 6 were detected for each photo. The values for angles 1 to 6 ranged from 0 to 180 degrees.

(a) (b) (c)

Figure 4. The *Hormat* stance as an opening offering to God and the audience (a) photo (b) angle calculation (c) keypoint results

3.3. Angle Range from Training

The value range of angle 1 to angle 6 ranges from training can be seen in Figure 5 (a) to (f). The calculation result the range of angle 1 can be seen in Figure 5, the calculation result of angle 2 can be seen in Figure 6, the calculation result of angle 3 can be seen in Figure 7, the calculation result of angle 4 can be seen in Figure 8, the calculation result of angle 5 can be seen in Figure 9, the calculation result of angle 6 can be seen in Figure 10. This angle range shows that when performing a certain stance movement, the angle formed from the movement ranges between the red-colored line from the minimum angle to the maximum angle. Classification decisions are based on Figure 5 to Figure 10. Each *Ibing Penca* Stances follows the minimum to maximum value range for angles 1 to angle 6. If the value range does not match then it is taken from the closest value range.

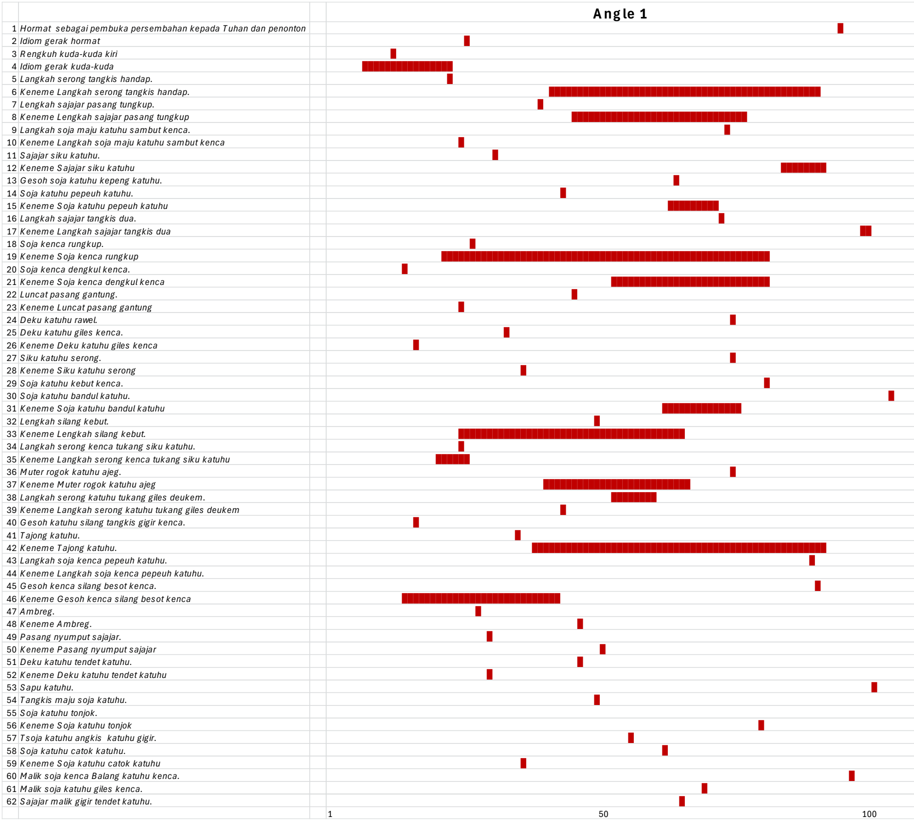


Figure 5. calculation result the range of angle 1

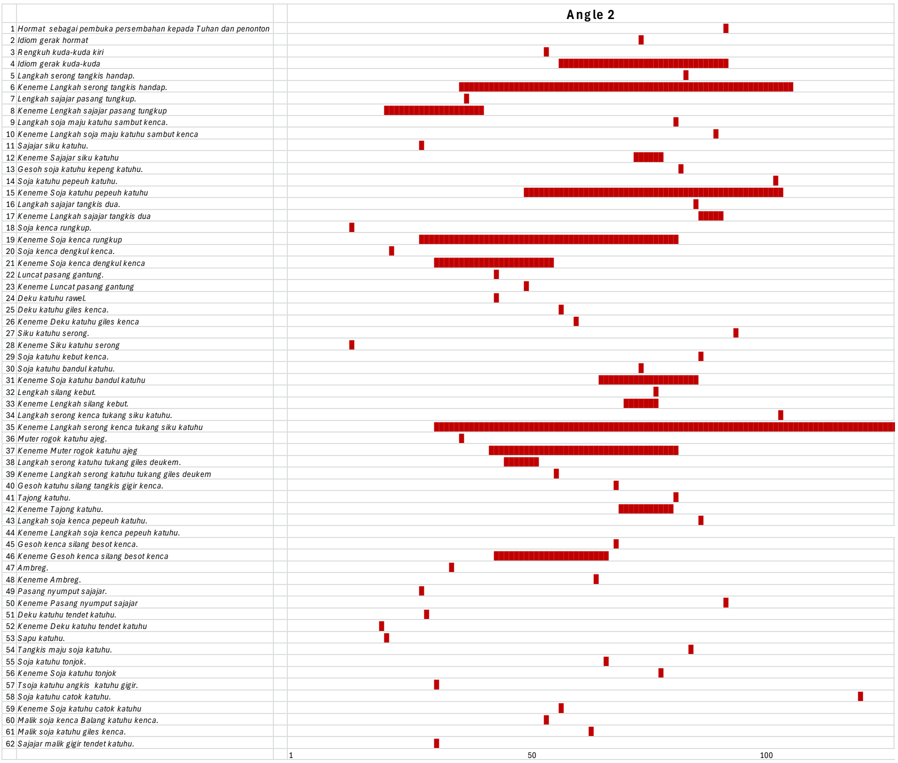


Figure 6. calculation result of angle 2

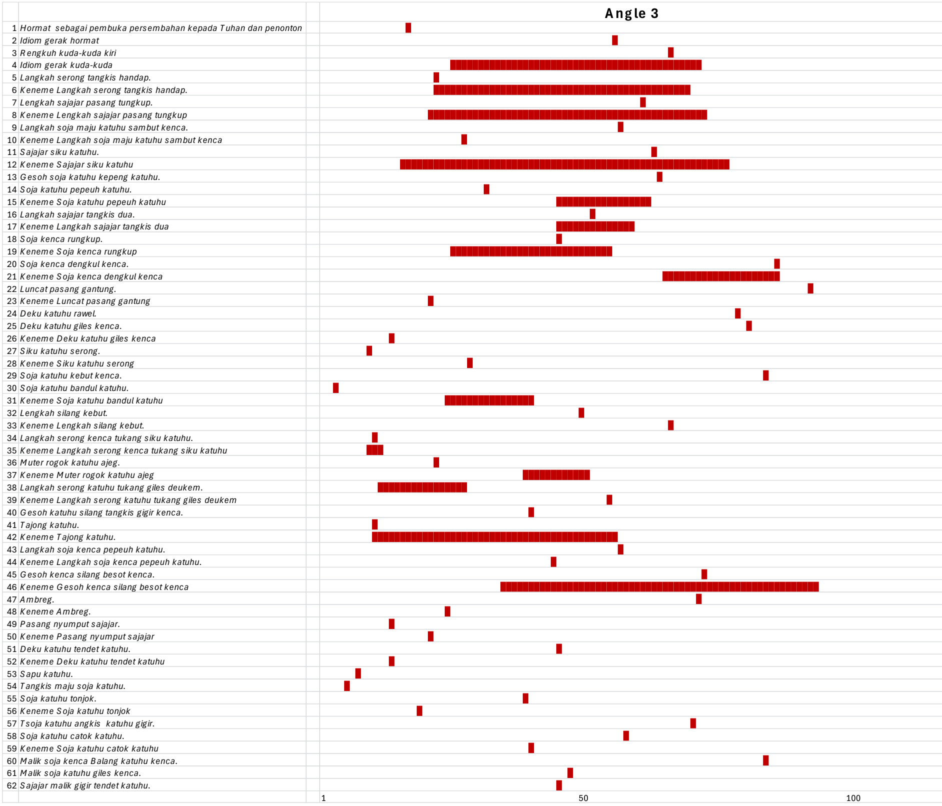


Figure 7. calculation result of angle 3

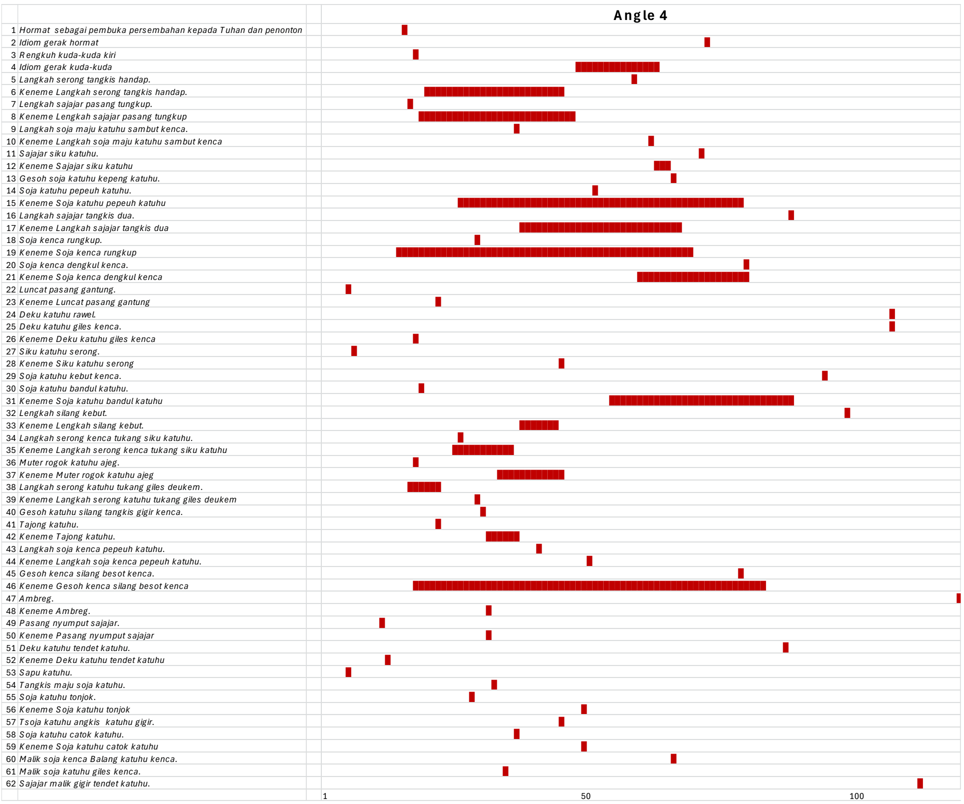


Figure 8. calculation result of angle 4

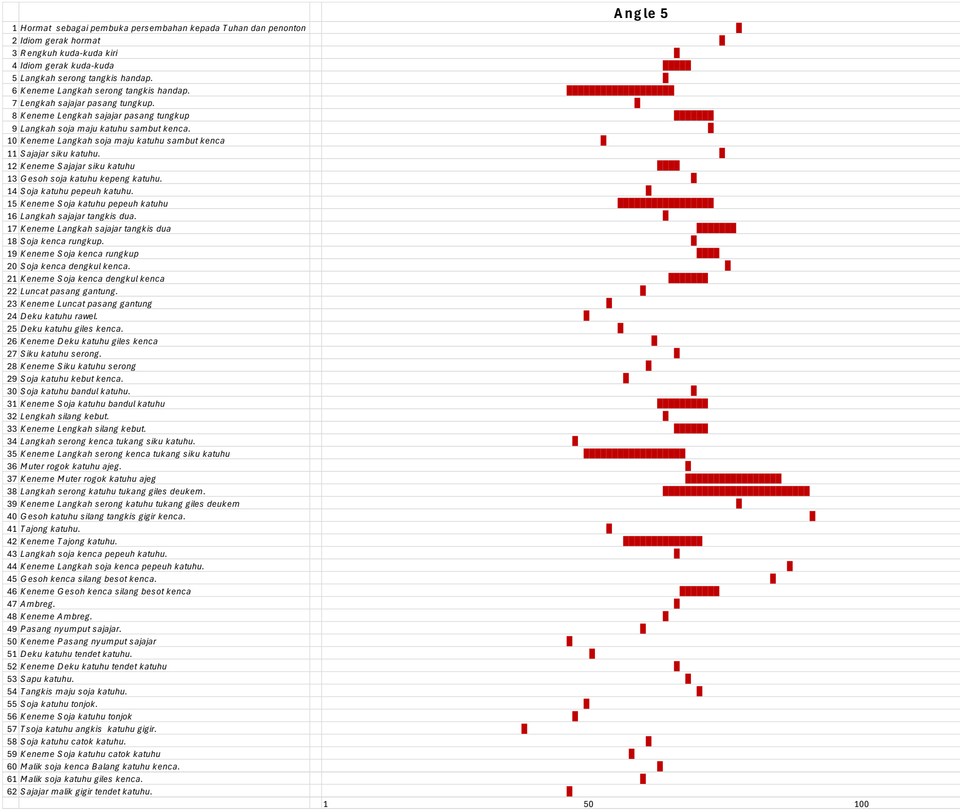


Figure 9. calculation result of angle 5

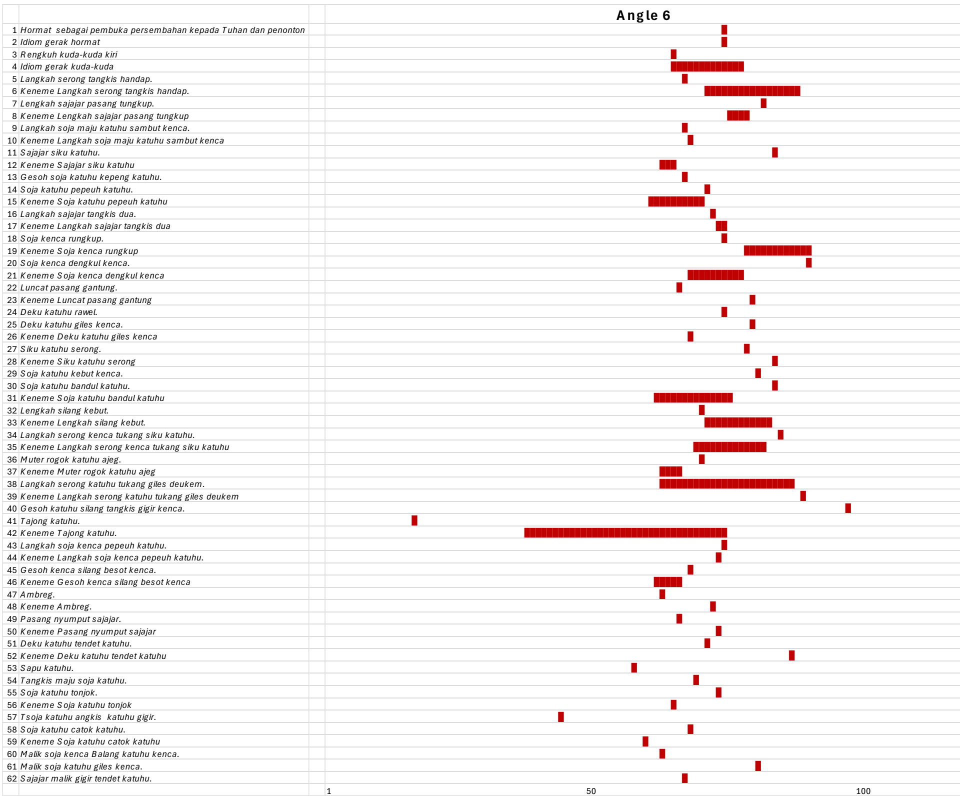


Figure 10. calculation result of angle 6

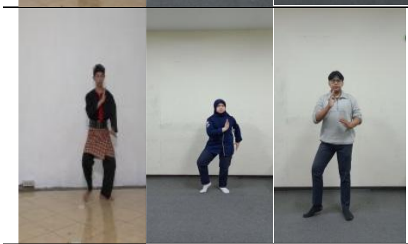
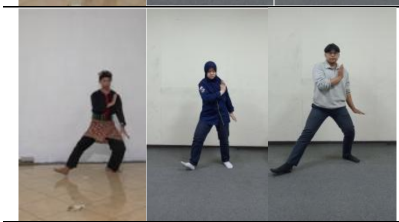
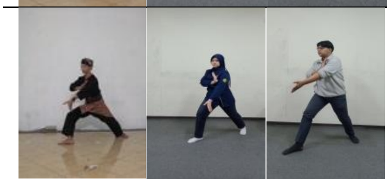
3.4. Testing Result

In the testing process, the system is given input photos of each stance without label on the type of stance entered and the system detects 6 angles, then the system classifies the type of stance based on the range of angle values from training. The sample classification of testing can be seen on Table 3.

The test was conducted with three individuals of varying body types, heights, weights, and genders. The camera was positioned so that the entire body was captured from head to toe, ensuring that the movements of the moves were captured. This application can be used in two ways: real-time or non-real-time. If the test is not real-time, the resulting photo or video can be saved to a file and retrieved from the application by entering the file name to be analyzed. The file can be either a photo or a video. A limitation of the video recording is the speed of the computer used. The experiment used a low-speed laptop, which often caused the classification process to lag behind the actual movement.

Application users can determine whether their moves are correct or incorrect by viewing the name of the move displayed as assessed by the application. If the movement and the name displayed match, the move is correct. If not, the move is incorrect.

Table 3. Classification of Testing Result

Input Photo	**Angle**						**Classification**
	1	**2**	**3**	**4**	**5**	**6**	
	92	89	17	16	75	72	Respect as an opening offering to God and the audience
	26	72	54	70	72	72	Gesture of respect
	13	53	64	18	64	63	Hold on to the left reins
	81	23	57	22	65	171	Sideways step with low block
	54	35	39	43	59	68	Keneme Sideways step, low block

Input Photo	Angle						Classification
	1	2	3	4	5	6	
	39	37	59	17	57	79	Step in line, pair up

3.5. Stance Recognition Performance

Based on the experimental evaluation, the proposed system successfully recognized 57 out of 62 ibing penca stances, corresponding to a stance-level recognition rate of 91%. Five stances were incorrectly classified, resulting in a misclassification rate of 9%.

The misclassified stances were identified as stance numbers 37, 42, 48, 50, and 61. Notably, three of these stances (48, 50, and 61) were consistently misclassified as stance number 6. This indicates a systematic overlap in angular configurations rather than random classification errors.

3.6. Error Distribution

The observed misclassifications suggest that certain ibing penca stances share similar geometric configurations when represented using the selected six angular features. In particular, stances with comparable limb orientations but differing in finer-grained body alignment or stylistic expression were more likely to be confused.

No recognition failures were caused by pose detection errors or missing keypoints, indicating that MediaPipe provided stable landmark extraction under the experimental conditions.

4. Discussion

From the experiments conducted to recognize the penca ibing stance 91%. successfully recognized the input stance, and this is very helpful for application users to learn independently. While 9%. of errors occur because the angle of motion is the same as the angle of motion of another stance so that the application recognizes a different stance. This is because the position of the hands and feet are similar.

There are 5 stances that failed to be detected, 1) should be stance no 42 *Keneme Tajong katuhu* detected as stance no 19 *Keneme Langkah soja maju katuhu sambut kenca*, 2) should be stance no 37 *Keneme Muter rogok katuhu ajeg* detected as stance no 15 *Keneme Soja katuhu pepeuh katuhu*, 3) should be stance no 48 *Keneme Ambreg* detected as stance no 6 *Keneme Langkah serong tangkis handap*, 4) should be stance no 50 *Keneme Pasang nyumput sajajar* detected as stance no 6 *Keneme Langkah serong tangkis handap*, 5) should be stance no 61 *Malik soja katuhu giles kenca* detected as stance no 6 *Keneme Langkah serong tangkis handap* shown in Table 3. This happens because in stance 37 and stance 15 the range of angle 1 to angle 6 overlaps, as well as for stance no 48 and stance no 6, stance 42 and 19, stance no 50 and stance no 6, stance no 61 and stance no 6 so that the reading results are wrong.

5. Conclusion

The conclusion of this research is the successful utilization of keypoints from the use of Mediapipe as one of the efforts to classify 62 Ibing Penca stances by utilizing 6 angles (angle heuristics) and programs made using the Python programming language. The results of the 62 stance recognition classification program with the success rate of stance recognition using the calculation of 6 angles (angle heuristics): as much as 91% (ie 57 stances), with an error rate of 9% (ie 5 stances) due to the angle values (angle heuristics) whose numbers are the same between one stance and another stance.

This study presents a feasibility investigation into the use of computer vision–based pose analysis for recognizing standardized ibing penca stances as part of an effort to support independent learning of traditional Indonesian martial arts. By leveraging MediaPipe-based pose landmark detection and an interpretable angle-based representation, the proposed system demonstrates that a subset of ibing penca stances can be distinguished using a small number of geometrically meaningful features.

Experimental results obtained under controlled acquisition conditions show that 57 out of 62 stances were correctly recognized, indicating that joint-angle relationships capture essential structural characteristics of many ibing penca postures. At the same time, systematic misclassifications among several closely related stances reveal inherent limitations of low-dimensional, handcrafted feature representations when applied to culturally nuanced and stylistically rich movement forms.

Rather than proposing a general-purpose stance recognition solution, this work should be viewed as a proof of concept that highlights both the potential and constraints of angle-based pose descriptors for traditional martial arts analysis. The findings suggest that while such representations offer transparency, computational efficiency, and ease of implementation, they are insufficient to fully discriminate between stances with subtle postural variations.

Several limitations of this study must be acknowledged. The dataset size was limited, the evaluation was conducted under controlled conditions using a single camera setup, the camera used for training can be a handphone camera or a standard computer camera, and temporal movement dynamics in this study have not been used. Additionally, inter-individual variability in body proportions, flexibility, and performance style was not systematically examined. These factors restrict the generalizability of the reported results and indicate the need for more comprehensive validation.

Future research should therefore focus on expanding the dataset across diverse practitioners and environments, incorporating additional spatial and temporal features, and exploring hybrid approaches that combine interpretable geometric features with lightweight learning-based classifiers. From an application perspective, integrating real-time feedback mechanisms and evaluating usability in authentic learning contexts would further clarify the system's practical value.

In conclusion, this study contributes an initial, interpretable framework for stance recognition in ibing penca and provides empirical insights that can inform subsequent developments at the intersection of computer vision, martial arts pedagogy, and cultural heritage preservation.

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