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Pose Analysis and Classification in Shooting Sport Using Convolutional Neural Network and Long Short-Term Memory

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Abstract

Shooting sport requires high accuracy and speed, making training evaluation essential for athlete performance improvement. Conventional evaluation methods are often limited, thus the application of Artificial Intelligence (AI) and Computer Vision provides an effective alternative. This research aims to analyze and classify shooting sport poses using Deep Learning methods. A dataset consisting of several thousand pose images was collected from both field recordings and publicly available sources, followed by preprocessing for coordinate extraction. Convolutional Neural Network (CNN) was employed to extract coordinate data from shooting pose images, while Long Short-Term Memory (LSTM) was applied for pose classification. Experimental results demonstrated 94% accuracy, 95% Percentage of Correct Keypoints (PCK), and 4 mm Mean Per Joint Position Error (MPJPE), with training conducted at a learning rate of 0.0001 over 150 epochs on 5% test data, involving a total of 596,642 parameters. These results indicate that the proposed CNN–LSTM model provides a reliable approach for pose analysis and classification in shooting sport. The contribution of this study lies in presenting a novel dataset and framework for AI-based shooting sport evaluation, which can enhance training feedback and broaden AI applications in sports.

Keywords: Convolutional Neural Network (CNN); Long Short-Term Memory (LSTM); Pose Estimation

1. Introduction

The rapid development of Artificial Intelligence (AI), particularly in Computer Vision, has enabled significant advancements in sports science and training evaluation (Cossich et al., 2023; Wen et al., 2024; Zhang, 2022). These technologies provide coaches and athletes with quantitative insights, allowing for better decision-making and optimized training strategies (Siddesh Padala et al., 2019; Palermi et al., 2024; Yu, 2024). Deep Learning techniques such as Convolutional Neural Networks (CNN) have been widely applied in image-based analysis, supporting tasks like pose estimation, movement classification, and performance evaluation (Dindorf et al., 2023; Nguyen et al., 2021; Sowjanya et al., 2023). Traditional training evaluation relies heavily on manual observation, which is time-consuming, prone to human error, and often unavailable when athletes practice without a coach (Moreira da Silva et al., 2021; Zhao et al., 2023). In shooting sport, maintaining proper pose is a critical factor that directly influences accuracy, stability, and consistency (Vardar & Senduran, 2021). Considering that a single training session can take up to 120 minutes and involve more than 60 repetitive shooting actions, an automated and objective evaluation system is needed to reduce labor intensity while maintaining training quality.

Previous studies have applied machine learning and Deep Learning to various sports. For example, CNN combined with Blazepose achieved 80–90% accuracy in badminton movement classification (Rizki & Zuliarso, 2022). Support Vector Machine (SVM) achieved 96.87% accuracy in evaluating fitness movements (Rahmadani et al., 2022). In yoga, combining CNN with Long Short-Term Memory (LSTM) reached 99.38% accuracy in pose estimation, outperforming CNN–SVM approaches (Anand Thoutam et al., 2022) These studies demonstrate that supervised learning methods can achieve high accuracy in analyzing complex human motions. However, most existing works focus on sports with either dynamic body movements or static postures, whereas shooting sport presents unique challenges due to its repetitive yet highly precise motion characteristics.

To address this gap, this research proposes a CNN–LSTM-based framework for pose analysis and classification in shooting sport. CNN is employed to extract coordinate features from pose images, while LSTM is utilized to model temporal dependencies in pose sequences, enabling more accurate evaluation of shooting techniques. The novelty of this study lies in applying CNN–LSTM to shooting sport pose estimation, supported by a dataset collected from both field recordings and public sources. Unlike prior works in badminton, fitness, and yoga, this study focuses on shooting pose accuracy, which is critical for performance improvement but underexplored in existing literature. The objective of this study is twofold: to develop and evaluate a CNN–LSTM model for shooting pose analysis and classification, and to provide an AI-based evaluation framework that supports coaches and athletes in improving training efficiency and outcomes.

2. Research Methods

This research adopts a quantitative, exploratory, and experimental approach using the Cross Industry Standard Process for Data Mining (CRISP-DM) framework as the methodological foundation. The main research stages are outlined in Figure 1.

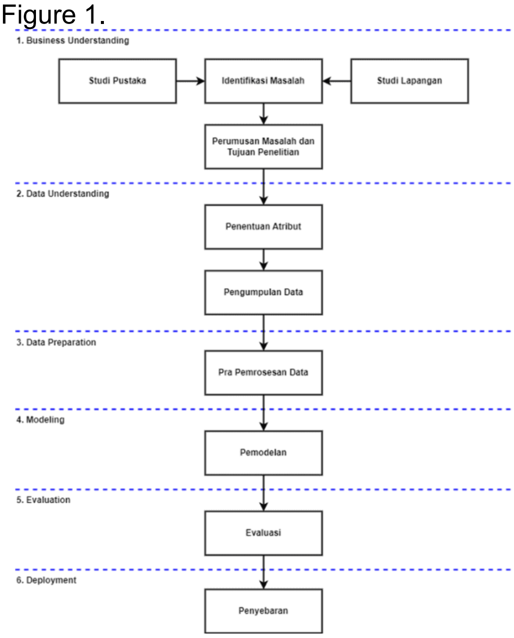


Figure 1: Steps of the Research Stage

2.1 Business Understanding

At this stage, the research focuses on shooting pose estimation using computer-detectable keypoints. The objectives include identifying research problems, defining system requirements (data, hardware, software), and formulating how CNN can recognize shooting poses. A literature review was also conducted to establish the theoretical foundation and dataset design.

2.2 Data Understanding

The dataset was obtained from both live captures at the shooting range and relevant public/private repositories. Data understanding activities consisted of collection, cleaning, visualization, and statistical analysis to ensure data validity. Keypoints of human body joints (head, neck, shoulders, elbows, wrists, pelvis, knees, and ankles) were extracted using the Mediapipe pose estimation framework. Distance and joint angle calculations followed standard geometric formulas (Equations 1–3) to quantify movement patterns.

$$distance = \sqrt{(x2 - x1)^2 + (y2 - y1)^2} \quad (1)$$

$$\theta = \arccos\left(\frac{\overrightarrow{P_{12}} \cdot \overrightarrow{P_{13}}}{|\overrightarrow{P_{12}}| \cdot |\overrightarrow{P_{13}}|}\right) \quad (2)$$

$$\theta = \arccos\left(\frac{y_1^2 - y_1 \cdot y_2}{y_1\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}}\right) \quad (3)$$

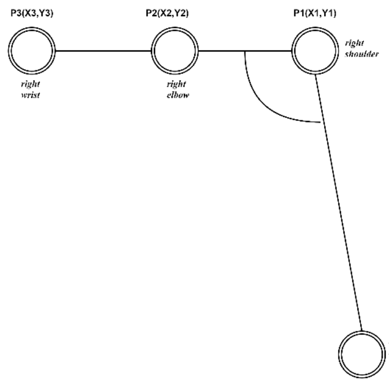


Figure 2. Body angle measurement

As shown in Figure 2, the results of the joint and body angle analysis of the shooting sports poses in this study were obtained from Equation (2) and Equation (3).

2.3 Data Preparation

In this phase, the dataset was curated and processed to ensure readiness for modeling. Key steps included media selection (photos and videos), categorization (e.g., pre-stance, stance), augmentation (cropping/trimming), merging, and transformation into numerical representations suitable for machine learning input (see Figure 3).

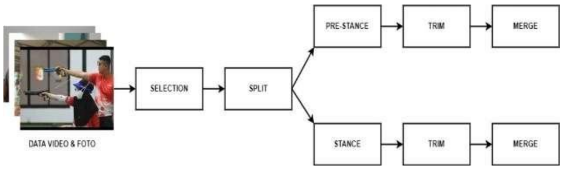


Figure 3. Data Preparation

The Data Preparation stage includes:

1. Selection: Manually choosing high-quality videos and photos.
2. Split: Sorting media into categories, such as Pre-Stance and Stance.
3. Trim: Performing data augmentation by cutting media for the next process.
4. Merge: Combining photos and videos into one file for the modeling process.

2.4 Modeling

Two modeling scenarios were developed: File Data Modeling: Pose estimation from uploaded video files using CNN for feature extraction and LSTM for temporal sequence learning (Figure 4).

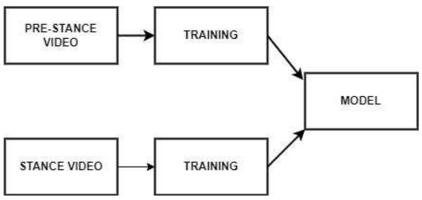


Figure 4. Video File Data Modeling Scenario

Webcam Data Modeling: Real-time pose estimation using live video input. CNN processed frames into keypoints, while LSTM analyzed them as Numpy arrays without manual annotation (Figure 5).

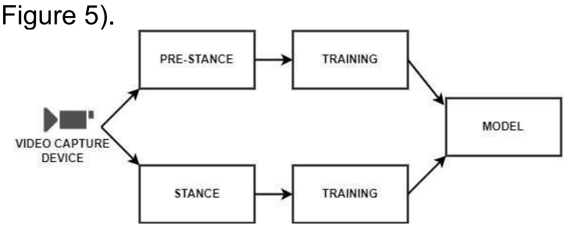


Figure 5. Video Capture Data Modeling Scenario

The integrated CNN–LSTM architecture is illustrated in Figure 6, where convolution and pooling layers extract spatial features and LSTM layers capture temporal dynamics.

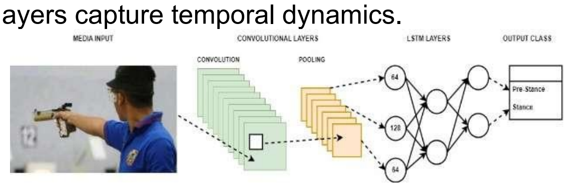


Figure 6. Diagram Arsitektur Neural Network

2.5 Evaluation

Model performance was evaluated using metrics such as Confusion Matrix, Mean Per Joint Position Error (MPJPE), and Percentage of Correct Keypoints (PCK). Evaluation included testing on both file-based and real-time datasets, followed by comparative analysis and potential model refinement.

2.6 Deployment

The final stage involved deploying the trained model into an application environment for real-world use. This included system integration, performance monitoring, user acceptance testing, and maintenance to ensure reliable operation.

3. Results and Discussion

3.1 Business Understanding

The results of field observations and literature studies show that pose estimation in shooting sports has several main purposes: helping coaches evaluate the joint angles of athletes' bodies, providing visual feedback for shooters, and translating joint angles into a computational system that can be used for pose modeling.

The developed application model is shown in Figures 7 and 8, where the processing flow of video or camera capture data is processed into pose estimation. The web interface is built using Streamlit to facilitate user interaction. The application displays pose information, joint angles, as well as performance metrics such as execution time and model accuracy. Interpretation: This stage ensures the application can be used by both coaches and athletes as a technology-based evaluation tool, so that it not only displays technical data but also serves as an easy-to-understand feedback medium.

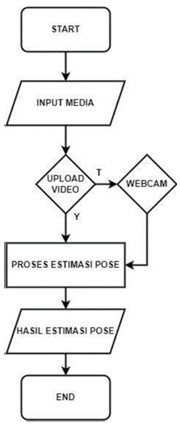


Figure 7. Flowchart of Application Model

After understanding the application model flow, an interface design schematic was created to align with the research objectives. The interface in Figure 8 shows a data selection page for pose estimation, either from an uploaded file or a video capture device like a webcam. Users can directly use the application by choosing the data type in the side menu, either uploading a file or streaming live from the webcam.

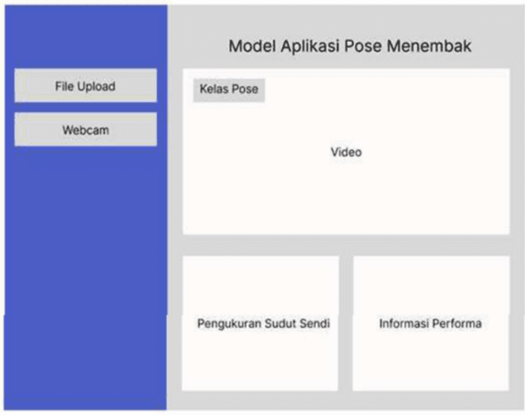


Figure 8. Application Model Interface Design

3.2 Data Understanding and Preparation

Photo and video data was collected for two main classes of poses: Pre-Stance and Stance. Data diversity was obtained from variations in angle, light intensity, and environmental conditions to make the model more robust. From the selection results, a total of 2013 data was obtained with a more dominant distribution in Stance poses. Interpretation: The imbalance in the amount of data between the Pre-Stance and Stance classes could potentially affect the accuracy of the model. However, the use of video augmentation techniques such as rotation, distortion and rescaling helped to add variety so that the model was still able to recognize patterns in general. Thus, the data collected was representative enough for the CNN-LSTM training process.

Table 1. Sample Pose Class

Pose Sampel	**Pose Class**	**Explanation**
	*Pre-Stance*	In this pose, it is indicated that you are preparing to shoot, characterized by the position of the joints that have not yet focused on the target direction.
	*Stance*	The main indication of this pose is the stance that points the gun at the target.

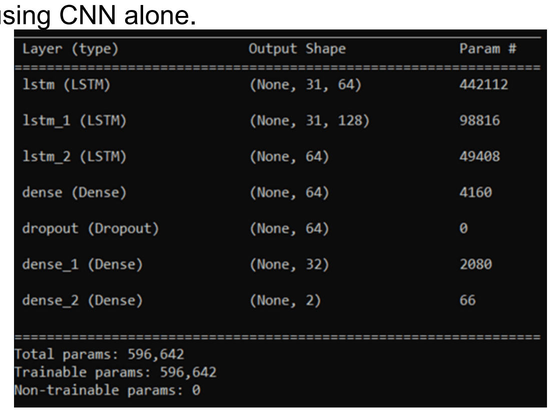
Table 1 distinguishes the two pose classes based on posture in the training pattern. Media selection photos and videos is based on visual judgment and keypoint detection to match shooting sport poses. Clear joint and skeleton visibility is crucial to ensure model accuracy and performance, allowing the dataset to include diverse, relevant poses for effective training.

Table 2. Photo Data Categories

No.	**Sub Kategori**	**Kategori**	**Sub Total**
1.	*Pre-Stance*	*Pre-Stance*	68
2.	*One Handed*	*Stance*	368
3	*Weaver*	*Stance*	1201
4	*Isosceles*	*Stance*	316
5	*Chapman*	*Stance*	60
		Total	**2013**

3.3 Modeling with CNN and LSTM

A CNN model was used to extract features from the video frame, resulting in 1662 body coordinate points, which were then processed by LSTM to recognize the temporal sequence of poses. The architecture consists of 3 LSTM layers and 3 Dense layers with a total of 596,642 parameters. Interpretation: This CNN-LSTM combination is important because CNN is strong in detecting spatial patterns (keypoints), while LSTM excels in capturing temporal patterns. Thus, the model is able to classify Pre-Stance and Stance differences more accurately than when using CNN alone.



Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 31, 64)	442112
lstm_1 (LSTM)	(None, 31, 128)	98816
lstm_2 (LSTM)	(None, 64)	49408
dense (Dense)	(None, 64)	4160
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080
dense_2 (Dense)	(None, 2)	66

Total params: 596,642
Trainable params: 596,642
Non-trainable params: 0

Figure 9. Parameters in the Training Model

3.4 Model Training and Evaluation

The model training results are not optimal, with an Epoch Loss of 0.3020 and Epoch Accuracy of 0.8793, as shown in Figure 10.

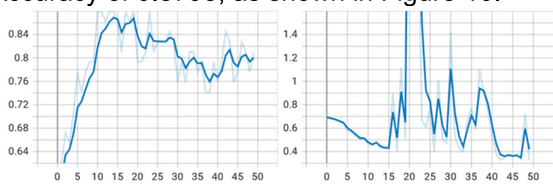


Figure 10. 50/50 Epoch Accuracy (right) and Loss (left) graphs

When the number of epochs was increased to 100, overfitting occurred, with Epoch Loss rising to 2.8423 and Epoch Accuracy dropping to 0.7241. This suggests the model was overfitting, "memorizing" the training data without generalizing well to the test data. To resolve this, adjustments in the model architecture, hyperparameters, or regularization techniques are needed. The increase in epochs did not improve accuracy and instead worsened the model's performance.

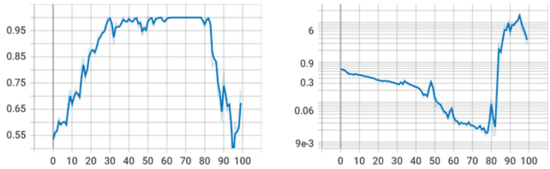


Figure 11. Graph of 100/100 Epoch Accuracy (right) and Loss (left)

After increasing the number of epochs to 150, the training results showed a slight improvement with Epoch Accuracy rising to 0.8276. However, the Epoch Loss remained high at 0.8563, indicating limited improvement in performance despite higher accuracy. The accuracy and loss curves followed similar trends, suggesting that increasing epochs did not effectively enhance the model's predictions. These results are shown in Figure 12.

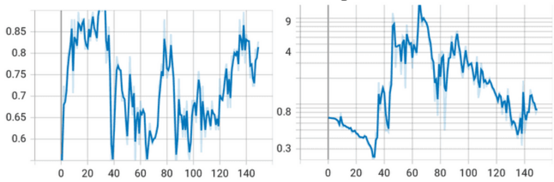


Figure 12. Graph of 150/150 Epoch Accuracy (right) and Loss (left)

In the experiment with 200 epochs, the results were unsatisfactory, with Epoch Accuracy at 0.6034 and Epoch Loss at 8.5218. This indicates that increasing the number of epochs did not lead to significant improvements. Further analysis of accuracy metrics is needed to identify the best model. The phenomenon and graphical anomalies suggest a mismatch between the training process and model performance, as shown in Figure 13.

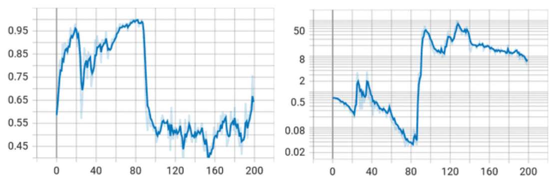


Figure 13. 200/200 Epoch Accuracy (right) and Loss (left) graphs

The evaluation results are shown in Table 3, using parameters: Learning Rate 0.0001, Threshold 0.5, 95% training data, and 5% test data. The best model for pose estimation from video files was achieved at 50 epochs.

Table 3. Category Data Photo Recapitulation Accuracy of File Model Training

Jumlah *Epoch*	**Model File**	
	Accuracy	***Loss***
50	0,8793	0,3020
100	0,7241	2,8423
150	0,8276	0,8563
200	0,6034	8,5218

The training results show the highest accuracy at 50 epochs for video file data with a value of 87.9% (loss 0.3020). However, when the number of epochs is increased to 100-200, the performance degrades due to overfitting: the model "remembers" the training data too much and thus fails to generalize to the test data. This phenomenon can be seen from the increasing loss value despite the high initial accuracy.

In contrast, in the webcam scenario, accuracy increased to 100% at 100 epochs with very low loss (0.0209). This indicates that the real-time webcam data is more varied and fits the learning pattern of the model, so the generalization is better than the video file data. Observations of the accuracy and loss curves, along with test data evaluation, offer insight into model performance for pose estimation and guide improvements like architecture tuning, hyperparameter optimization, or expanding training data. As shown in Figure 24, the model performs well with a low Epoch Loss of 0.1221 and a high Epoch Accuracy of 0.9655.

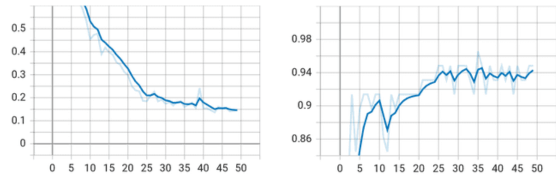


Figure 14. Webcam 50/50 Epoch Accuracy (right) and Loss (left) graphs

After increasing the number of epochs to 100 with 5% fixed test data, the training results show a very low Epoch Loss at 0.0209 and a high Epoch Accuracy at 0.9625. This indicates that increasing epochs provides a significant increase in model accuracy, as shown in Figure 15.

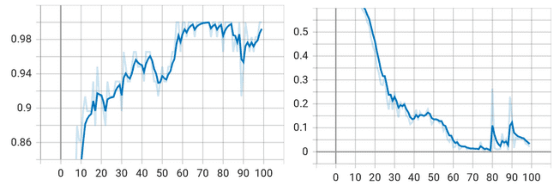


Figure 15. 200/200 Epoch Accuracy (right) and Loss (left) graphs

Based on the accuracy and loss curve analysis, the model with 100 epochs was chosen for webcam inference, as shown in Table 3.

Table 3. Recapitulation of Webcam Model Training Accuracy.

Jumlah *Epoch*	**Model *Webcam***	
	Accuracy	***Loss***
50	0,9625	0,1221
100	1,0000	0,0209
150	0,9828	0,0292
200	0,8793	0,6867

After analyzing the accuracy and loss curves, the 100-epoch model was selected for webcam inference (Table 4). The evaluation shows that this model outperforms the video-based model in accuracy and flexibility, making it more effective for building diverse datasets. Interpretation: The number of epochs has a direct effect on generalization ability. Too few epochs make the model underfitting, while too many epochs trigger overfitting. Results show that the combination of 50 epochs for file data and 100 epochs for webcam provides the best balance.

3.5 Performance Metrics (Confusion Matrix, PCK, and MPJPE)

The recapitulated results of the inference of the 1-minute video with 60 classified frames are shown in the Confusion Matrix in Table 4.

Table 4. Confusion Matrix

Aktual	**Prediksi**	
	Pre-Stance	***Stance***
Pre-Stance	56	4
Stance	2	58

With the classification data from Table 5, Accuracy, Precision, and Recall were calculated to assess the performance of the model.

1. Accuracy, Overall accuracy performance on the results of this study resulted in an accuracy of 94%.

$$Accuracy = \frac{TP+TN}{Total\ Testing\ Sample\ tested} x\ 100\% \quad (11)$$

$$Accuracy = \frac{(56+58)}{(56+4+2+58)} x\ 100\ \% = 94\ \% \quad (12)$$

Precision, Overall precision performance in the results of this study resulted in a precision of 94%.

$$Precision = \frac{TP}{TP+FP} x\ 100\% \quad (13)$$

Pre-Stance

$$Presisi = \frac{56}{(56+2)} = x\ 100\% = 96{,}55\% \quad (14)$$

Stance

$$Presisi = \frac{58}{(58+4)} = x\ 100\% = 93{,}55\% \quad (15)$$

2. Recall, Overall accuracy performance in the results of this study resulted in an accuracy of 94%.

$$Recall = \frac{TP}{TP+FN} x\ 100\% \quad (16)$$

Pre-Stance

$$Recall = \frac{56}{(56+4)} = x\ 100\% = 93{,}33\% \quad (17)$$

Stance

$$Recall = \frac{58}{(58+2)} = x\ 100\% = 96{,}67\% \quad (18)$$

Recapitulation of model performance for Pre-Stance and Stance classes as shown in Table 5.

Table 5. Recapitulation of Model Performance

Kelas Pose	**Akurasi**	**Presisi**	**Recall**
Pre-Stance	94 %	96,55 %	93,33 %
Stance	94 %	93,55 %	96,67 %

The model achieved 94% accuracy, 96.55% precision, and 93.33% recall, indicating strong pose classification performance. It was tested using unseen 1-minute videos for each class, and the predictions were evaluated to support model improvement and optimization.

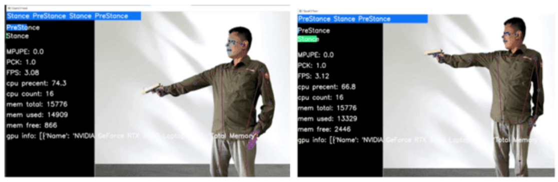


Figure 16. Pose Analysis Result with 150/150 Epoch Model

Figure 16 shows the model effectively distinguishes between Pre-Stance and Stance poses, with MPJPE of 0.0 mm and PCK of 0.96.

Table 8 shows the model performs well in pose classification, with 94% accuracy, 96.55% precision, and 93.33% recall.

Table 6. Evaluation of PCK and MPJPE

Model	Model Webcam		Model File	
Epoch	PCK	MPJPE	PCK	MPJPE
50	76 %	12,56 mm	65 %	15,57 mm
100	88 %	10,81 mm	69 %	16,81 mm
150	96 %	4,75 mm	85 %	5,48 mm
200	92 %	9,83 mm	73 %	17,83 mm

Evaluation using confusion matrix resulted in 94% accuracy, 95% average precision, and 95% average recall. Testing using PCK (Percentage of Correct Keypoints) and MPJPE (Mean Per Joint Position Error) metrics showed the best results at 150 epochs with PCK 96% and MPJPE 4.75 mm.

Interpretation: High PCK and low MPJPE values indicate that the model is not only able to classify poses well, but also accurately detect joint positions. This means that the model can provide detailed feedback to athletes regarding the suitability of poses to the shooting technique standards.

3.6 Robustness Testing (Lighting, Distance, and Speed)

Testing the model in dim and bright lighting conditions shows that the model can detect poses well at various light intensities, as shown in Table 7.

Table 7: Test Results for Lighting

Pose Class	Prediksi			
	Pre-Stance		***Stance***	
	Dim	**Bright**	**Dim**	**Bright**
Pre-Stance	Detected	Detected	-	-
Stance	-	-	Detected	Detected

Testing Distance the model at a distance of 1 meter, 2 meters, and 3 meters shows that the model can detect poses well at all these distances, as shown in table 8.

Table 8. Test Results for Distance

Kelas Pose	Prediksi					
	Pre-Stance			***Stance***		
	1 M	**2 M**	**3 M**	**1 M**	**2 M**	**3 M**
Pre-Stance	Terdeteksi	Terdeteksi	Terdeteksi	-	-	-
Stance	-	-	-	Terdeteksi	Terdeteksi	Terdeteksi

Estimation Speed, model testing with a 1-minute video, using both a file and a webcam, showed an average pose estimation speed of 20 ms per frame. Table 9 evaluates the model's efficiency for applications requiring quick responses and potential optimizations.

Table 9. Pose Estimation Speed

Kelas Pose	Model File		Model Webcam	
	1 Frame	**5 Frame**	**1 Frame**	**5 Frame**
Pre-Stance	20 ms	20 ms	20 ms	20 ms
Stance	20 ms	20 ms	20 ms	20 ms

The conclusion is that the CNN-LSTM model for shooting pose estimation achieves 94% accuracy, 95% PCK, and 4 mm MPJPE, using a Learning Rate of 0.0001, 150 Epochs, and 596,642 parameters with 5% test data.

Deployment an interface that is familiar to the user will certainly continue to be done as usage increases. The interface is shown in figure 17.

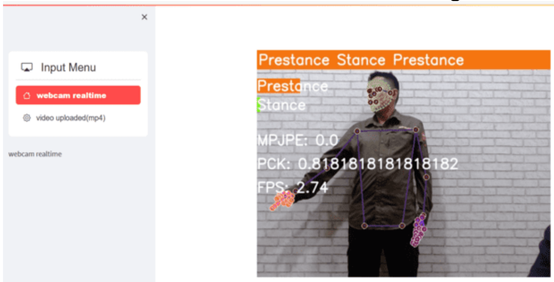


Figure 17. Application Model Interface

User Acceptance Test (UAT) The application model was tested for effectiveness, reliability, and ease of use using black-box testing. This test, involving 5 respondents, focused on validating the input and output without examining the internal workings.

Table 10. Black Box Testing

Test Class	Test Item	Testing Type	Results Obtained
Upload Video File	Upload Video Change Video	Black Box Black Box	Successfully upload and replace the video to be estimated.
Stream Video Webcam	Buka *Webcam* Change *Webcam*	Black Box Black Box	Successfully open the webcam device and change the webcam used.

3.7 Synthesis of Findings

Overall, the results of this study show that:

1. The CNN-LSTM model is effective in distinguishing Pre-Stance and Stance poses with high accuracy.
2. The generalization of the model is affected by the number of epochs; 50 epochs is suitable for file data, while 100 epochs is optimal for webcam.
3. Robustness is proven under lighting and distance variations, so the model is ready to be used in real situations.
4. Evaluation metrics (PCK & MPJPE) confirm the accuracy of the model in recognizing pose details, so the results are not just a binary classification but also provide useful technical insights for athletes and coaches.
5. Thus, the main contribution of this research is not only on technical accuracy, but also on the interpretive ability of the model to support shooting sports training through accurate and real-time pose feedback..

4. Conclusion

This research has successfully demonstrated the integration of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) for basketball shooting pose estimation, achieving an accuracy of 94%. The main scientific contribution of this work lies in combining spatial and temporal feature extraction to enhance real-time pose recognition, thereby providing a methodological advancement compared to single-model approaches. Furthermore, the study highlights the practical relevance of deep learning in sports training, where automated feedback can support athletes in improving shooting techniques. Nevertheless, several limitations must be acknowledged. The dataset was relatively limited in terms of player diversity, environmental conditions, and number of shooting variations, which may restrict the model's generalizability. In addition, the system's performance under extreme lighting or occlusion conditions remains a challenge. Addressing these constraints in future work will require the use of larger and more heterogeneous datasets, domain adaptation strategies, and optimization for lightweight deployment on mobile platforms.

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