Jurnal Teknik Informatika Vol. 19 No. 1, April 2026 (109-121)
ISSN: p-ISSN 1979-9160 (Print)| e-ISSN 2549-7901 (Online)
DOI: https://doi.org/10.15408/jti.v19i1.49778

JURNAL TEKNIK INFORMATIKA
Homepage : http://journal.uinjkt.ac.id/index.php/ti

Accuracy Evaluation of 2D MediaPipe-Based Pose Estimation for Archery Posture Detection Using N-MPJPE

Muhammad Andhika Bayu Prasetya[1*], Harits Ar Rosyid[2], M. Zainal Arifin[3]

[1,2,3] Departement of Electrical Engineering and Informatics, Faculty of Engineering, State University of Malang
[1,2,3] Jl. Cakrawala No. 5, Sumbersari, Lowokwaru District, Malang City, East Java 65145

Article:
Accepted: February 08, 2026
Revised: December 12, 2025
Issued: April 30, 2026

***Correspondence Address:**
muhammad.andhika.2305348@students.um.ac.id

ABSTRACT

Archery requires high consistency and precise body posture, where small deviations can affect stability and accuracy. Recently, 2D human pose estimation has become an effective approach for analyzing sports techniques through automatic joint detection. This study proposes a 2D pose estimation system based on the MediaPipe framework to detect eight fundamental phases of archery technique and evaluate accuracy using the Normalized Mean Per Joint Position Error (N-MPJPE) metric. The dataset consists of annotated images representing the eight phases, which serve as ground-truth references. Accuracy is measured by calculating the normalized Euclidean distance between predicted joint positions and ground-truth coordinates across all phases. Experimental results show an average N-MPJPE of 0.71, indicating low joint-position deviation after scale normalization. Compared with prior studies reporting N-MPJPE values between 0.6 and 1.2, the proposed system demonstrates competitive accuracy for real-time 2D pose estimation. These results indicate that the system can reliably capture posture variations across archery phases and provide quantitative feedback on body alignment, making it a practical tool to support athletes and coaches in improving training quality and shooting performance.

Keywords : *Archery; MediaPipe; N-MPJPE; 2D Human Pose Estimation; Computer Vision.*

1. INTRODUCTION

Archery is a sport that demands a high level of technical skill, concentration, and movement consistency. Proper body posture plays a crucial role in maintaining balance, minimizing vibration, and improving shooting accuracy throughout the shooting process. According to Mulyanti in 2024, beginner performance in archery is strongly influenced by shooting distance; therefore, training should be conducted progressively while emphasizing consistency in technique and posture [1]. This finding is reinforced by Destriani in 2024, who reported that stable posture and consistent technical execution are key factors in improving shooting accuracy, particularly for novice athletes [2]. These studies highlight that a stable and well-aligned body posture is fundamental to achieving optimal archery performance.

With advancements in computer vision and artificial intelligence, human pose estimation has been increasingly applied in various sports, including boxing, gymnastics, and football, to analyze athletes' movements and technical execution. Pose estimation provides an innovative solution for automatically and objectively analyzing body posture in real time, enabling athletes and coaches to receive immediate feedback on movement errors. Ludwig in 2021 demonstrated that pose estimation techniques can effectively support performance improvement by providing quantitative feedback on body motion patterns during training sessions [3]. Despite its growing adoption across multiple sports domains, the application of pose estimation in archery remains relatively limited, particularly for comprehensive posture analysis covering multiple shooting phases.

Several studies have explored computer vision–based analysis in archery. Lee in 2024 proposed an automated approach to analyze shooting time using pose estimation and image processing techniques, focusing primarily on the anchoring and release phases [4]. Although their method demonstrated promising results, it relied heavily on video quality and was sensitive to variations in individual athletes' postures. These limitations indicate that existing approaches have yet to provide a robust and generalizable system capable of accurately detecting full-body posture across all fundamental archery phases while maintaining real-time performance. Human pose estimation has become a fundamental problem in computer vision, serving as a key component for higher-level tasks such as motion analysis, action recognition, and sports performance evaluation. Recent surveys indicate that despite rapid advances in deep learning-based approaches, efficient and lightweight 2D pose estimation methods remain highly relevant for real-time and resource-constrained applications [5].

In the broader field of human pose estimation, various frameworks have been developed, including OpenPose, YOLO-Pose, and MediaPipe. OpenPose, introduced in 2017, was among the first frameworks capable of multi-person pose estimation, detecting up to 135 keypoints across the body, face, and hands. While OpenPose offers high accuracy and detailed keypoint representations, it requires substantial computational resources, limiting its suitability for lightweight or real-time sports training applications [6]. YOLO-Pose integrates object detection and keypoint estimation within a unified network, achieving strong performance in complex scenarios; however, its computational complexity similarly constrains its deployment in real-time or resource-limited environments [7].

In contrast, MediaPipe provides a lightweight and efficient alternative for real-time pose estimation. MediaPipe can detect 33 body keypoints with low latency and modest computational requirements, making it well suited for desktop and mobile platforms [6]. Although its accuracy may be slightly lower than OpenPose on large-scale datasets, MediaPipe demonstrates a favorable balance between accuracy, speed, and efficiency. Recent studies have also shown that hybrid approaches combining MediaPipe with YOLO-based detectors can further improve accuracy while maintaining real-time performance [7]. These characteristics make MediaPipe particularly attractive for sports training scenarios that require immediate feedback during practice sessions.

Based on these considerations, MediaPipe offers a practical balance between accuracy and real-time performance for archery training applications. However, limited research has systematically evaluated its effectiveness for archery posture analysis using quantitative accuracy metrics. Therefore, this study aims to develop a MediaPipe-based 2D pose estimation

Jurnal Teknik Informatika Vol. 19 No. 1, April 2026 (109-121)
ISSN: p-ISSN 1979-9160 (Print)| e-ISSN 2549-7901 (Online)
DOI: https://doi.org/10.15408/jti.v19i1.49778

system to detect eight fundamental phases of archery techniques and to quantitatively evaluate its accuracy using the Normalized Mean Per Joint Position Error (N-MPJPE). By focusing on scale-normalized joint error analysis, this research seeks to provide a reproducible and objective evaluation framework for pose estimation in archery, addressing an existing gap in sports-specific pose estimation studies.

The main scientific contributions of this study are summarized as follows. First, this research presents a domain-specific application of 2D human pose estimation for archery, a sport that has received relatively limited attention in pose estimation literature compared to other athletic disciplines. The proposed system is designed to detect and classify eight fundamental phases of archery techniques based on body keypoints, enabling structured posture analysis throughout the shooting process.

Second, this study introduces a quantitative evaluation of pose estimation accuracy using the Normalized Mean Per Joint Position Error (N-MPJPE). Unlike prior archery-related studies that primarily relied on timing analysis or manual joint-angle measurements, this work applies to a scale-normalized metric to objectively assess joint position prediction accuracy across different postures. This contributes to a reproducible and interpretable evaluation framework for future sports-specific pose estimation research.

Third, this research provides empirical justification for the use of MediaPipe in archery posture analysis by positioning its accuracy within the commonly reported N-MPJPE range in real-time pose estimation studies. The achieved average N-MPJPE value of 0.71 demonstrates that the proposed system attains a favorable balance between accuracy and computational efficiency, supporting its suitability for real-time sports training applications.

2. METHODS

The development of the proposed system in this study employed the PPDIOO methodology, which consists of six sequential phases: Prepare, Plan, Design, Implement, Operate, and Optimize. Each phase is defined by specific objectives and systematic procedures that guide the research process from initial preparation to final optimization. This phased structure ensures that the development and evaluation of the pose estimation system are conducted in an organized, transparent, and traceable manner, thereby minimizing inconsistencies and methodological ambiguity throughout the research lifecycle [8].

The PPDIOO methodology was selected because it provides a structured and comprehensive framework that effectively supports system-oriented research involving both implementation and quantitative evaluation. Previous studies have shown that PPDIOO is particularly effective for research that integrates system design, deployment, and performance assessment, as it allows each development stage to be explicitly documented and evaluated based on predefined technical criteria [9]. This methodology enables the researcher to systematically define system requirements, design the pose estimation architecture, implement the model, deploy it in an experimental environment, and refine its performance based on objective accuracy measurements. In the context of this study, PPDIOO is particularly suitable for pose estimation research, as it facilitates the integration of dataset preparation, pose detection using predefined reference postures, quantitative accuracy evaluation using the Normalized Mean Per Joint Position Error (N-MPJPE), and iterative optimization based on evaluation results. Unlike conventional machine learning pipelines that rely on training–testing splits, system development methodologies such as PPDIOO emphasize evaluation-driven refinement and operational validation, making them appropriate for studies that focus on inference-level accuracy and system reliability rather than model retraining [10]. Therefore, PPDIOO provides a rigorous and reproducible methodological foundation for assessing the proposed archery pose estimation system.

2.1. Plan

The Plan phase represents the initial stage of the PPDIOO methodology, in which the fundamental requirements for developing the proposed pose estimation model were systematically identified. This phase focused on conducting a needs analysis and clearly defining the research problem to ensure that the

Jurnal Teknik Informatika Vol. 19 No. 1, April 2026 (109-121)
ISSN: p-ISSN 1979-9160 (Print)| e-ISSN 2549-7901 (Online)
DOI: https://doi.org/10.15408/jti.v19i1.49778

developed system addresses practical challenges encountered in archery training. The outcomes of this phase serve as a conceptual foundation for subsequent stages and guide the overall direction of the research, particularly in terms of model design and quantitative accuracy evaluation. The main outputs of the Plan phase are described as follows:

a. Problem Identification

Archery athletes frequently experience posture-related technical errors during training sessions, particularly in hand positioning during the drawing phase. Improper hand posture at this critical stage can negatively affect shooting stability, consistency of arrow release, and overall shooting accuracy. These posture deviations are often subtle and difficult to identify through direct visual observation alone, especially in real-time training environments. This limitation highlights the need for an automated and objective posture analysis system capable of detecting joint-level deviations with sufficient precision.

b. Objectives

The primary objective of this study is to develop a two-dimensional pose estimation model capable of accurately detecting body posture across eight fundamental phases of archery movements. By extracting and analyzing body joint positions, the proposed model aims to identify posture deviations that may occur during each shooting phase. In addition, this study seeks to quantitatively evaluate the accuracy of the pose estimation results using the Normalized Mean Per Joint Position Error (N-MPJPE), enabling objective, scale-normalized, and reproducible performance assessment.

c. Scope

This research focuses on the analysis of body posture in archery athletes using two-dimensional human pose estimation techniques, with particular emphasis on key joints involved in shooting mechanics. The scope of the study is limited to posture detection and accuracy evaluation based on joint position estimation using annotated ground-truth references. Biomechanical force analysis, physiological measurements, psychological factors, and three-dimensional motion reconstruction are beyond the scope of this work.

d. Information Gathering

To support the planning process, an extensive literature review was conducted on human pose estimation frameworks, pose detection algorithms, and archery training principles. The review provided insights into commonly used pose estimation methods, quantitative accuracy metrics such as MPJPE and N-MPJPE, and best practices in sports-related computer vision research. These findings were used as references for defining system requirements, selecting the MediaPipe framework, and designing the evaluation strategy adopted in this study.

2.2. Prepare

The Prepare phase focuses on establishing the technical foundation required for developing and evaluating the proposed pose estimation system. This phase includes dataset collection, data preprocessing, and pose estimation framework selection. The primary objective of this stage is to ensure that all system requirements such as the types of poses to be detected, the structure of the ground-truth data, and the target application environment are clearly defined and aligned with the research objectives. A well-prepared dataset and an appropriate model selection are essential to achieving reliable and reproducible pose estimation accuracy [11].

In this study, archery posture data were obtained through collaboration with expert archery coaches as well as from image frames extracted from video recordings of athletes performing standardized archery shooting techniques [12]. These data sources were selected to ensure that the collected samples accurately represent correct and commonly accepted postures according to standard archery training principles. Each sample serves as a ground-truth reference for evaluating pose estimation accuracy rather than for training a learning-based model.

a. Dataset Collection

The dataset used in this research consists of annotated image samples representing eight fundamental phases of the archery shooting sequence: Stance, Nocking, Hooking, Setup, Drawing, Anchoring, Aiming, and Release. Each image corresponds to one reference posture for a specific phase and serves as ground truth for pose accuracy evaluation rather than as training data for model learning.

The dataset was obtained from archery athletes, who were photographed while performing standardized shooting techniques under supervision. A total of eight reference images were collected, with one representative image for each archery phase, captured from the same athlete to maintain posture consistency across phases. While the dataset size is limited, this design is sufficient for evaluating pose estimation accuracy at the joint level, which is the primary objective of this study rather than model generalization.

All images were captured indoors under controlled lighting conditions to minimize illumination variability and external interference. The camera was positioned at a distance of approximately 3–5 meters from the athlete, aligned at body height to ensure full-body visibility and accurate joint representation. This setup was selected to simulate a realistic training observation distance while maintaining sufficient image clarity for pose estimation.

It is important to emphasize that this study does not employ a conventional training–testing split. The MediaPipe pose estimation framework used in this research is a pre-trained model and was not retrained using the collected dataset. Instead, the dataset functions exclusively as ground-truth reference data for evaluating joint position prediction accuracy using the N-MPJPE metric. Therefore, data partitioning and sampling strategies commonly used in supervised learning are not applicable in this evaluation-oriented study.

b. Preprocessing

Data preprocessing was conducted to enhance dataset quality and ensure reliable pose estimation evaluation. This stage plays a critical role in preventing error propagation into subsequent analysis and evaluation phases, as data validation and cleaning are widely recognized as essential steps for ensuring model reliability and accuracy [13]. The preprocessing process involved verifying image clarity, body visibility, and joint coverage. Images that were blurred, poorly illuminated, or partially occluded were excluded to prevent inaccuracies in keypoint detection and joint position measurement. Furthermore, careful preprocessing is particularly important in computer vision–based systems, as inconsistencies or noise in input data can significantly affect quantitative evaluation results. Prior studies emphasize that rigorous data preparation and validation are necessary to minimize misleading outcomes caused by unverified or erroneous data, especially in scenarios where models are evaluated against reference postures rather than trained through large-scale datasets [13].

Each image was manually labeled according to its corresponding archery phase based on a predefined eight-phase shooting protocol. Accurate labeling is a fundamental prerequisite for reliable image-based analysis, as ground-truth annotations directly influence the validity of downstream evaluation metrics. Previous research highlights that manual and interactive labeling approaches provide greater control over annotation quality, particularly for complex visual structures and limited datasets where precision is critical [14]. To minimize labeling bias and human error, all labeled images were validated by an experienced archery coach, ensuring that each posture accurately represents standard and correct technical execution for its respective phase. This expert-based validation functions as a quality assurance mechanism, reinforcing annotation consistency and reducing subjective bias in the absence of multiple annotators. Such validation strategies align with data-centric approaches that prioritize dataset quality as a key determinant of system performance and evaluation credibility [13].

c. Pose Estimation Modeling

For the pose estimation component, MediaPipe was selected as the core framework due to its favorable balance between accuracy and computational efficiency in real-time applications [15]. MediaPipe provides a pre-trained two-dimensional human pose estimation model capable of detecting 33 body keypoints, including joints that are critical in archery movements such as the shoulders, elbows, wrists, hips, and knees. MediaPipe Pose has been widely adopted in recent studies due to its ability to provide reliable 2D joint localization while maintaining real-time performance on CPU-based systems. Previous research has demonstrated that MediaPipe can serve as a robust off-the-shelf pose estimation framework without additional model training, making it

Jurnal Teknik Informatika Vol. 19 No. 1, April 2026 (109-121)
ISSN: p-ISSN 1979-9160 (Print)| e-ISSN 2549-7901 (Online)
DOI: https://doi.org/10.15408/jti.v19i1.49778

suitable for practical and lightweight motion analysis applications [16].

In this study, MediaPipe was utilized as an off-the-shelf pose estimation framework without additional model training. The detected keypoints produced by MediaPipe were directly compared with ground-truth joint coordinates to evaluate pose estimation accuracy. Its ability to perform real-time pose detection with relatively low computational cost makes MediaPipe suitable for desktop-based applications and aligns with the objective of evaluating practical pose estimation accuracy for sports training scenarios.

2.3. Design

This phase focuses on designing the overall system architecture for pose detection and quantitative accuracy evaluation using the MediaPipe framework. The design stage emphasizes a clear and structured data flow, ensuring that each processing step directly supports reliable pose detection and objective performance evaluation. By defining the system architecture at this stage, the proposed system is structured to enable reproducible accuracy assessment of 2D pose estimation results in the context of archery posture analysis.

The data flow begins with dataset preparation, where preprocessed and labeled archery posture images corresponding to the eight defined phases, Stance, Nocking, Hooking, Setup, Drawing, Anchoring, Aiming, and Release are provided as system inputs. These inputs are processed by the MediaPipe pose estimation module to extract two-dimensional body keypoints. The extracted keypoints represent the predicted joint positions produced by the pose estimation framework. Subsequently, the predicted joint coordinates are compared with manually annotated ground-truth joint positions for each archery phase. The comparison is performed using the Normalized Mean Per Joint Position Error (N-MPJPE), which serves as the primary metric for evaluating pose estimation accuracy. This end-to-end design integrates pose detection and quantitative accuracy evaluation into a unified and reproducible evaluation pipeline.

a. Flowchart

The workflow of the proposed system is illustrated in Figure 1. The process begins with dataset collection, followed by a preprocessing stage that includes data cleansing and phase labeling to ensure high-quality and consistent input data.

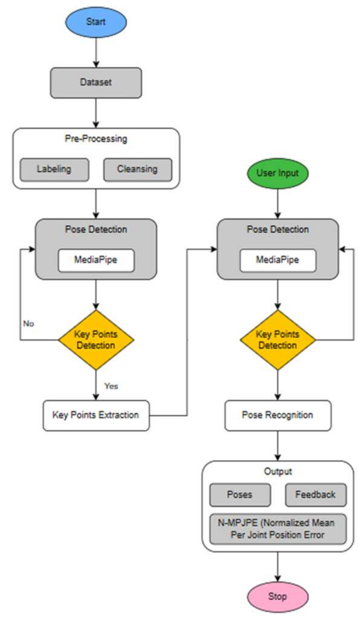

Figure 1. *Flowchart Model Design*

After preprocessing, the input images are processed by the MediaPipe pose estimation module, which detects 33 two-dimensional human body keypoints. These keypoints correspond to major body joints such as the shoulders, elbows, wrists, hips, knees, and ankles, which are essential for analyzing posture during archery movements across all shooting phases.

Following pose detection, a keypoint validation step is performed to ensure that all required joints are successfully detected. When validation is successful, the detected joint coordinates are extracted and stored as numerical data for evaluation. The extracted keypoints are then directly compared with the corresponding ground-truth joint annotations for each archery phase.

Finally, the system computes the N-MPJPE value to quantify the deviation between predicted and ground-truth joint positions after scale normalization. The output of the system consists of pose estimation accuracy results for each archery phase, providing an objective and quantitative assessment of MediaPipe-based 2D pose estimation performance in archery posture detection.

ISSN: p-ISSN 1979-9160 (Print)| e-ISSN 2549-7901 (Online)
DOI: https://doi.org/10.15408/jti.v19i1.49778

2.4. Implement

At this stage, the pose estimation system was implemented and evaluated using the labeled archery posture dataset. The implementation process involved processing preprocessed images representing the eight defined archery phases, Stance, Nocking, Hooking, Setup, Drawing, Anchoring, Aiming, and Release through the MediaPipe pose estimation framework. For each input image, MediaPipe generated two-dimensional body keypoints corresponding to major joints, which served as the predicted joint positions for evaluation. Each image in the dataset was accompanied by manually annotated joint keypoints that functioned as ground-truth references. The implementation focused on executing the pose estimation pipeline and extracting predicted joint coordinates, rather than training or updating the underlying pose estimation model. This approach ensured that the evaluation reflected the inherent pose estimation capability of the MediaPipe framework when applied to archery postures.

Following pose detection, the accuracy of the predicted keypoints was quantitatively evaluated using the Normalized Mean Per Joint Position Error (N-MPJPE) metric. N-MPJPE measures the average Euclidean distance between predicted joint positions and ground-truth annotations after scale normalization, providing a fair and consistent assessment across different postures and body proportions. The implementation phase concluded with consistent keypoint detection results across all eight archery phases and an average N-MPJPE value that indicated satisfactory pose estimation accuracy. These results demonstrate that the implemented MediaPipe-based system can reliably estimate body joint positions and support objective accuracy evaluation for archery posture analysis in a real-time training context.

2.5. Operate

In this phase, the implemented pose estimation system was deployed into a desktop-based application environment to support real-time archery posture analysis. The application integrates the MediaPipe framework to process input data in the form of images or video streams and to detect body keypoints corresponding to the eight defined archery phases: Stance, Nocking, Hooking, Setup, Drawing, Anchoring, Aiming, and Release.

The primary objective of the Operate phase was to verify that the pose estimation system could function reliably during runtime inference, producing stable and consistent keypoint detection results under various input conditions. System operation was assessed by observing the continuity of pose detection, the consistency of extracted joint coordinates, and the responsiveness of the application during real-time execution. This phase ensured that the system operated without significant latency, frame drops, or computational instability when integrated into the desktop application workflow. The detected keypoint data generated during system operation were systematically stored and structured for quantitative analysis. These operational outputs served as the input for computing the Normalized Mean Per Joint Position Error (N-MPJPE) in the subsequent evaluation and optimization phase. By using keypoint data obtained from actual system operation, the evaluation reflects realistic deployment conditions rather than controlled or offline processing scenarios.

2.6. Optimize

The Optimize phase represents the final stage of the PPDIOO methodology, in which refinements were conducted based on quantitative evaluation results obtained during system operation. In this phase, the Normalized Mean Per Joint Position Error (N-MPJPE) values calculated for each archery movement phase were analyzed to identify variations in joint position accuracy and potential sources of estimation error. Particular attention was given to phases involving more dynamic upper-body movements, where larger joint deviations were more likely to occur.

Based on this analysis, minor system-level adjustments were applied to improve detection stability and reduce overall prediction error. These optimizations focused on refining inference-related parameters, data handling consistency, and keypoint validation procedures, rather than modifying the underlying pose estimation model or introducing additional training processes. The objective of this phase was to enhance the robustness and consistency of keypoint

Jurnal Teknik Informatika Vol. 19 No. 1, April 2026 (109-121)
ISSN: p-ISSN 1979-9160 (Print)| e-ISSN 2549-7901 (Online)
DOI: https://doi.org/10.15408/jti.v19i1.49778

detection across all archery phases while preserving real-time performance characteristics. Through this optimization process, the final pose estimation system achieved more stable and reliable keypoint outputs during operation. The resulting accuracy levels were found to be consistent with pose estimation performance ranges reported in recent literature. The optimized system configuration was subsequently used as the basis for the final performance evaluation and result analysis presented in this study.

2.7. Formula Definition of N-MPJPE

To quantitatively evaluate the accuracy of the proposed pose estimation system, this study employs the Normalized Mean Per Joint Position Error (N-MPJPE) as the primary evaluation metric. N-MPJPE measures the average positional deviation between predicted joint coordinates and their corresponding ground-truth annotations while incorporating a normalization factor to compensate for differences in body scale and posture size. This scale-invariant property makes N-MPJPE particularly suitable for evaluating pose estimation performance across subjects with varying body proportions and camera perspectives [17].

The metric evaluates pose estimation accuracy by computing the normalized Euclidean distance between each predicted joint position and its corresponding ground-truth joint. Through normalization, the influence of absolute body size, posture scale, and camera distance is reduced, enabling a fair and consistent comparison of joint position accuracy across different archery movement phases. Consequently, N-MPJPE provides a robust and interpretable quantitative measure for evaluating pose estimation performance in sports motion analysis.

The formula for NMPJPE is as follows:

$$\text{N-MPJPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{\|J_i - J_i^*\|_2}{S_i} \qquad (1)$$

Where:

- N = number of key points (joints),
- J_i = predicted joint coordinates,
- J_i^* = ground-truth joint coordinates,
- S_i = scale normalization factor,
- $\|\cdot\|_2$ = Euclidean norm.

In this study, the Euclidean distance between each predicted joint and its corresponding ground-truth joint is first computed to quantify the positional error at the joint level. The resulting error is then normalized using a scale factor S, defined as a reference body distance derived from the ground-truth pose (e.g., the distance between selected key joints such as shoulder-to-hip or the maximum inter-joint distance). This normalization ensures that pose estimation accuracy is evaluated relative to body scale rather than absolute pixel distance.

The normalized errors are subsequently averaged across all detected joints to obtain the final N-MPJPE value. This averaging process ensures that each joint contributes equally to the overall accuracy assessment, resulting in a comprehensive evaluation of full body pose estimation performance.

A lower N-MPJPE value indicates that the predicted joint positions are closer to the ground-truth annotations, reflecting higher pose estimation accuracy and reduced positional deviation. Therefore, smaller N-MPJPE values signify a more precise and reliable pose estimation system, making this metric well suited for evaluating real-time 2D archery posture detection applications.

3. RESULTS AND DISCUSSION

3.1. Results

This section presents the quantitative accuracy evaluation of the proposed MediaPipe-based 2D pose estimation system using the Normalized Mean Per Joint Position Error (N-MPJPE) metric. The evaluation was conducted using eight ground-truth reference images, each representing one fundamental phase of archery motion: stance, nocking, hooking, setup, drawing, anchoring, aiming, and release. These reference samples were used to assess the inference-level accuracy of joint position prediction produced by the pre-trained MediaPipe model. This evaluation setup emphasizes reference-based accuracy assessment rather than statistical generalization, aligning with the study's objective to analyze inference-level pose estimation reliability.

The evaluation results indicate that the proposed system achieved an average N-

Jurnal Teknik Informatika Vol. 19 No. 1, April 2026 (109-121)
ISSN: p-ISSN 1979-9160 (Print)| e-ISSN 2549-7901 (Online)
DOI: https://doi.org/10.15408/jti.v19i1.49778

MPJPE value of 0.71, demonstrating a low normalized positional deviation between predicted joint coordinates and their corresponding ground-truth annotations. This result suggests that the model is capable of accurately estimating body keypoints across different archery postures after scale normalization.

Table 1. *N-MPJPE Result per Step*

Steps	N-MPJPE
Stance	0.69
Nocking	0.55
Hooking	0.65
Setup	0.68
Drawing	0.65
Anchoring	0.71
Aiming	0.63
Release	0.61

As summarized in Table 1, the N-MPJPE values range from 0.55 in the nocking phase to 0.71 in the anchoring phase. Lower error values were observed in relatively stable and well-defined phases such as nocking and stance, where body posture remains more static. In contrast, phases involving increased upper-body coordination and fine motor control, such as anchoring and drawing, produced slightly higher error values due to greater joint movement variability.

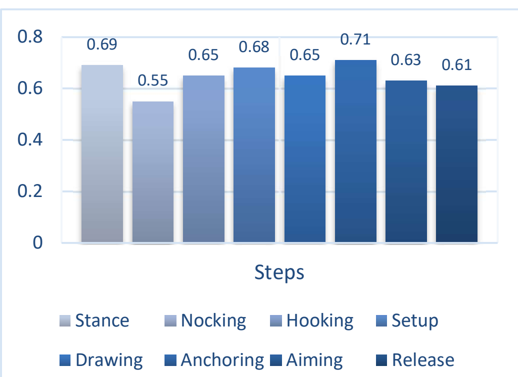

Figure 2. *N-MPJPE Result in Diagram*

Figure 2 visually reinforces the numerical trends presented in Table 1 by clearly illustrating the variation of N-MPJPE values across the eight archery phases. The bar chart highlights that the anchoring phase exhibits the highest error, while the nocking phase shows the lowest, confirming the quantitative findings in a more intuitive form. Phases such as stance and setup appear relatively stable with moderate error values, whereas phases that involve more dynamic upper-body coordination, including drawing and anchoring, display higher variability. This visual comparison makes it easier to identify which phases are more challenging for accurate pose estimation and supports the interpretation that increased joint movement complexity leads to higher estimation error. Because the MediaPipe model used in this study is pre-trained, the reported N-MPJPE values reflect pose estimation accuracy during inference, rather than performance derived from supervised model training or dataset-driven optimization. To further validate the practical correctness of the detected poses, the output results were reviewed by an experienced archery coach. The expert confirmed that the detected posture phases were consistent with standard archery techniques commonly applied in training sessions, supporting the reliability of the system outputs in real-world coaching contexts.

3.2. Discussion

The experimental results demonstrate that the proposed MediaPipe-based pose estimation system is capable of capturing archery body postures with reliable accuracy across all eight fundamental movement phases. Although there is no universally established benchmark threshold for N-MPJPE, prior pose estimation studies have reported normalized joint errors typically ranging from approximately 0.6 to 1.2, depending on dataset characteristics, normalization strategies, and model architecture. Within this comparative range, the achieved average N-MPJPE value of 0.71 places the proposed system within the favorable accuracy range for real-time 2D pose estimation applications. Several studies have demonstrated that 2D pose estimation is sufficient for evaluating movement quality and posture correctness in sports and exercise training scenarios. By analyzing joint positions and angular relationships, such systems can provide meaningful feedback without the complexity of 3D reconstruction, supporting their applicability in practical training environments [18].

The variation in N-MPJPE values across different archery phases reflects the inherent complexity of each movement. Static or semi-static phases, such as stance and nocking, tend to yield lower positional errors due to limited joint displacement. Conversely, more dynamic phases, including drawing, anchoring, and release, involve coordinated multi-joint motion, which increases prediction variability and results in slightly higher normalized errors. These findings are consistent with previous sports pose estimation studies, where dynamic actions generally exhibit higher estimation errors compared to static postures.

An important contribution of this study lies in its explicit use of N-MPJPE as a quantitative accuracy metric for archery-specific pose estimation. Unlike earlier archery-related works that focused primarily on timing analysis or manual joint-angle measurements, this research provides a scale-normalized and reproducible evaluation framework for assessing joint position accuracy. This allows for objective comparison across different poses and subjects, even when body proportions or camera distances vary. By formalizing this evaluation approach, the study also provides methodological clarity for future pose estimation research that utilizes pre-trained models without task-specific retraining.

Furthermore, the involvement of an expert archery coach in validating the detected phases strengthens the practical relevance of the system. This expert-based validation ensures that the pose estimation results correspond to technically correct archery movements rather than purely numerical alignment, reinforcing the applicability of the system as a supportive training and analysis tool.

It should be noted that this evaluation was conducted under controlled conditions using a limited number of ground-truth reference samples. As such, the reported accuracy reflects system-level pose estimation reliability during inference, rather than population-level generalization. Future studies with larger and more diverse datasets are necessary to further assess robustness across different athlete profiles and training environments.

CONCLUSION

This study presented the evaluation of a MediaPipe-based 2D pose estimation system for detecting eight fundamental phases of archery motion. Using the Normalized Mean Per Joint Position Error (N-MPJPE) as an inference-level accuracy metric, the proposed system achieved an average value of 0.71, indicating low normalized positional deviation between predicted and ground-truth joint coordinates. These results demonstrate that the system can reliably capture posture variations across different archery phases using scale-normalized joint position analysis.

When interpreted within the context of existing pose estimation literature, where normalized joint errors commonly fall within the range of approximately 0.6–1.2, the obtained N-MPJPE value confirms that the proposed MediaPipe-based approach achieves competitive accuracy for real-time 2D pose estimation. This performance highlights MediaPipe's suitability for sports motion analysis applications that require a balance between computational efficiency and reliable accuracy.

The main scientific contribution of this work lies in the clear formulation and application of N-MPJPE as a reproducible accuracy evaluation metric for archery-specific pose estimation. By focusing on quantitative, scale-normalized joint error analysis, this study establishes a reference framework for evaluating pose estimation systems in underexplored sports domains, moving beyond qualitative or timing-based assessments.

Therefore, while the reported results demonstrate reliable inference-level accuracy, further studies with larger and more diverse datasets are required to evaluate population-level robustness and long-term deployment performance.

REFERENCES

[1] C. Mulyanti *et al.*, "Differences in Archery Skill Results for Vocational School Students and Beginners Based on Shooting Distance," *Retos*, vol. 55, pp. 957–962, Aug. 2024, doi: 10.47197/retos.v55.106081.

[2] D. Destriani *et al.*, "Results of Beginner Archery Skills Among Adolescents Based on Gender Review and Shot Distance," *Retos*, vol. 56, pp. 887–894, Aug. 2024, doi: 10.47197/retos.v56.106629.

[3] K. Ludwig, S. Scherer, M. Einfalt, and R. Lienhart, "Self-Supervised Learning for Human Pose Estimation in Sports," in *2021 IEEE International Conference*

on Multimedia and Expo Workshops, ICMEW 2021, Institute of Electrical and Electronics Engineers Inc., 2021. doi: 10.1109/ICMEW53276.2021.9456000.

[4] S. Lee, J. Y. Moon, J. Kim, and E. C. Lee, "AI-Based Analysis of Archery Shooting Time from Anchoring to Release Using Pose Estimation and Computer Vision," *Appl. Sci.*, vol. 14, no. 24, Dec. 2024, doi: 10.3390/app142411838.

[5] H. Chen, R. Feng, S. Wu, H. Xu, F. Zhou, and Z. Liu, "2D Human pose estimation: a survey," *Multimed. Syst.*, vol. 29, no. 5, pp. 3115–3138, 2023, doi: 10.1007/s00530-022-01019-0.

[6] J.-L. Chung, L.-Y. Ong, and M.-C. Leow, "Comparative analysis of skeleton-based human pose estimation," *Futur. Internet*, vol. 14, no. 12, p. 380, Dec. 2022.

[7] N. Andriyanov and S. Mikhailova, "Improving Gesture Recognition Efficiency with MediaPipe and YOLO-Pose," *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.*, vol. XLVIII-2/W9-2025, pp. 13–18, 2025, doi: 10.5194/isprs-archives-XLVIII-2-W9-2025-13-2025.

[8] D. F. Al Muzaki, Tino Feri Efendi, and M. Muqorobin, "Penerapan Jaringan Hotspot Berbasis Mikrotik Menggunakan Metode PPDIO (Prepare, Plan, Design, Implement, Operate, Optimize)," *Bull. Comput. Sci. Res.*, vol. 5, no. 4 SE-, pp. 490–502, Jun. 2025, doi: 10.47065/bulletincsr.v5i4.592.

[9] M. N. Ahmadi, D. Risqiwati, and B. F. Muthohirin, "Optimalisasi Jaringan MikroTik Dengan Menggunakan Load Balancing PCC dengan Pendekatan PPDIOO," *J. Algoritm.*, vol. 22, no. 2 SE-Artikel, pp. 632–643, Nov. 2025, doi: 10.33364/algoritma/v.22-2.2878.

[10] D. Saputra, M. T. Kurniawan, and M. Fathinuddin, "Analysis of Quality of Service in Software Defined Networks Using the Opendaylight Controller with Prepare, Plan, Design, Implement, Operate, Optimize Method," *JIPI (Jurnal Ilm. Penelit. dan Pembelajaran Inform.*, vol. 10, no. 4, pp. 3396–3405, 2025.

[11] A. A. A. Fernandes, M. Koehler, N. Konstantinou, P. Pankin, N. W. Paton, and R. Sakellariou, "Data Preparation: A Technological Perspective and Review," *SN Comput. Sci.*, vol. 4, no. 4, Jul. 2023, doi: 10.1007/s42979-023-01828-8.

[12] J. Stenum, K. M. Cherry-Allen, C. O. Pyles, R. D. Reetzke, M. F. Vignos, and R. T. Roemmich, "Applications of pose estimation in human health and performance across the lifespan," Nov. 01, 2021, *MDPI*. doi: 10.3390/s21217315.

[13] P.-O. Côté, A. Nikanjam, N. Ahmed, D. Humeniuk, and F. Khomh, "Data cleaning and machine learning: a systematic literature review," *Autom. Softw. Eng.*, vol. 31, no. 2, p. 54, 2024, doi: 10.1007/s10515-024-00453-w.

[14] M. Arzt *et al.*, "LABKIT: Labeling and Segmentation Toolkit for Big Image Data," *Front. Comput. Sci.*, vol. Volume 4-2022, 2022, doi: 10.3389/fcomp.2022.777728.

[15] J. Liu, G. Huang, J. Hyyppä, J. Li, X. Gong, and X. Jiang, "A survey on location and motion tracking technologies, methodologies and applications in precision sports," *Expert Syst. Appl.*, vol. 229, p. 120492, 2023, doi: https://doi.org/10.1016/j.eswa.2023.120492.

[16] J.-W. Kim, J.-Y. Choi, E.-J. Ha, and J.-H. Choi, "Human Pose Estimation Using MediaPipe Pose and Optimization Method Based on a Humanoid Model," *Appl. Sci.*, vol. 13, no. 4, 2023, doi: 10.3390/app13042700.

[17] G. Dibenedetto, S. Sotiropoulos, M. Polignano, G. Cavallo, and P. Lops, "Comparing Human Pose Estimation through deep learning approaches: An overview," *Comput. Vis. Image Underst.*, vol. 252, p. 104297, 2025, doi: https://doi.org/10.1016/j.cviu.2025.104297.

[18] Achmad Ivan Taruna Jaya, P. Puspitaningayu, A. P. Adiwangsa, and N. Funabiki, "Two-dimensional Human Pose Estimation using Key Points' Angular Detection for Basic Strength Training," *J. Intell. Syst. Telecommun.*, vol. 1, no. 1, pp. 105–119, Dec. 2024,

doi: 10.26740/jistel.v1n1.p105-119.

[19] Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., Zhang, F., Chang, C.-L., Yong, M. G., Lee, J., Chang, W.-T., Hua, W., Georg, M., & Grundmann, M. (2019). *MediaPipe: A Framework for Building Perception Pipelines*. http://arxiv.org/abs/1906.08172

[20] Mitrović, K., & Milošević, D. (2023). Pose Estimation and Joint Angle Detection Using Mediapipe Machine Learning Solution. In N. Filipovic (Ed.), *Applied Artificial Intelligence: Medicine, Biology, Chemistry, Financial, Games, Engineering* (pp. 109–120). Springer International Publishing.

[21] Phang, J. T. S., Lim, K. H., Lease, B. A., & Chiam, D. H. (2022). Deep Learning Pose Estimation for Kinematics Measurement in Archery. *2022 International Conference on Green Energy, Computing and Sustainable Technology (GECOST)*, 298–302. https://doi.org/10.1109/GECOST55694.2022.10010619

[22] Putra, A. A. A. W., Suranata, I. W. A., & Kusumawati, A. A. I. P. (2024). Pengembangan Prototype Aplikasi MedCov Indonesia dengan Metode Human Centered Design dan Usability Testing. *Jurnal Algoritma*, *21*(2), 91–100. https://doi.org/10.33364/algoritma/v.21-2.1970

[23] Rhodin, H., Constantin, V., Katircioglu, I., Salzmann, M., & Fua, P. (2019, June). Neural Scene Decomposition for Multi-Person Motion Capture. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.

[24] SIMOES, W., REIS, L., ARAUJO, C., & MAIA JR., J. (2024). Accuracy Assessment of 2D Pose Estimation with MediaPipe for Physiotherapy Exercises. *Procedia Computer Science*, *251*, 446–453. https://doi.org/https://doi.org/10.1016/j.procs.2024.11.132

[25] Sukarno, P., & Medina, F. R. (2025). Enhancing IoT Security: Optimizing PUF Responses through Pre-Processing Techniques. *JURNAL INFOTEL*, *17*(2), 210–228. https://doi.org/10.20895/infotel.v17i2.1236

[26] Totlani, K., Dhavala, S. S., Vijayarao, S. S. K., Challagundla, Y., Roy, B., & Zhuo, E. R. (2024). Real-Time Human Pose Estimation Using Media-Pipe an Artificial Intelligence Applications in Health and Fitness. *2024 4th International Conference on Artificial Intelligence and Signal Processing (AISP)*, 1–6. https://doi.org/10.1109/AISP61711.2024.10870725

[27] Vendrame, E., Belluscio, V., Truppa, L., Rum, L., Lazich, A., Bergamini, E., & Mannini, A. (2024). Performance assessment in archery: a systematic review. In *Sports Biomechanics* (Vol. 23, Issue 12, pp. 2444–2466). Routledge. https://doi.org/10.1080/14763141.2022.2049357

[28] Wang, J., Qiu, K., Peng, H., Fu, J., & Zhu, J. (2019). AI Coach: Deep Human Pose Estimation and Analysis for Personalized Athletic Training Assistance. *Proceedings of the 27th ACM International Conference on Multimedia*, 374–382. https://doi.org/10.1145/3343031.3350910

[29] Zheng, C., Wu, W., Chen, C., Yang, T., Zhu, S., Shen, J., Kehtarnavaz, N., & Shah, M. (2023). Deep Learning-based Human Pose Estimation: A Survey. *ACM Comput. Surv.*, *56*(1). https://doi.org/10.1145/3603618

[30] Debnath, S., & Debnath, S. (2018). *Performance Evaluation by Image Processing Techniques in Archery – A Case Study*.

[31] Arif, A., Ghadi, Y. Y., Alarfaj, M., Jalal, A., Kamal, S., & Kim, D. S. (2022). Human Pose Estimation and Object Interaction for Sports Behaviour. *Computers, Materials and Continua*, *72*(1), 1–18. https://doi.org/10.32604/cmc.2022.023553

[32] Arkin, I., & Budak, M. (2021). Trunk stabilization, body balance, body perception, and quality of life in professional physically disabled and

able-bodied archers. *Sport Sciences for Health*, *17*(4), 881–889. https://doi.org/10.1007/s11332-021-00744-9

[33] Badiola-Bengoa, A., & Mendez-Zorrilla, A. (2021). A systematic review of the application of camera-based human pose estimation in the field of sport and physical exercise. In *Sensors* (Vol. 21, Issue 18). MDPI. https://doi.org/10.3390/s21185996

[34] Lin, Z., Chen, H., Rao, F., & Li, D. (2022). Application of AI Motion Capture Technology in Archery Teaching. *HBDSS 2022; 2nd International Conference on Health Big Data and Smart Sports*, 1–5.

[35] Ferraris, C., Amprimo, G., Cerfoglio, S., Vismara, L., & Cimolin, V. (2025). A Deep Dive Into MediaPipe Pose for Postural Assessment: A Comparative Investigation. *IEEE Access*, *13*, 211055–211074. https://doi.org/10.1109/ACCESS.2025.3643126

[36] Garg, S., Saxena, A., & Gupta, R. (2023). Yoga pose classification: a CNN and MediaPipe inspired deep learning approach for real-world application. *Journal of Ambient Intelligence and Humanized Computing*, *14*(12), 16551–16562. https://doi.org/10.1007/s12652-022-03910-0

[37] Ji, X., Al Tamimi, Z., Gao, X., & Piovesan, D. (2025). The Impact of Draw Weight on Archers' Posture and Injury Risk Through Motion Capture Analysis. *Applied Sciences (Switzerland)*, *15*(2). https://doi.org/10.3390/app15020879

[38] Knap, P., Hardy, P., Tamajo, A., Lim, H., & Kim, H. (2024). Improving Real-Time Omnidirectional 3D Multi-Person Human Pose Estimation with People Matching and Unsupervised 2D-3D Lifting. *2024 International Conference on Electronics, Information, and Communication (ICEIC)*, 1–4. https://doi.org/10.1109/ICEIC61013.2024.10457094

[39] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. In F. Pereira, C. J. Burges, L. Bottou, & K. Q. Weinberger (Eds.), *Advances in Neural Information Processing Systems* (Vol. 25). Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

[40] Lease, B. A., Lim, K. H., Phang, J. T. S., & Zuo, H. (2024). Deep Learning Posture Estimation for Archery Consistency Measurement. *2024 International Conference on Image Processing, Computer Vision and Machine Learning (ICICML)*, 1770–1773. https://doi.org/10.1109/ICICML63543.2024.10957898

[41] Difini, G. M., Martins, M. G., & Barbosa, J. L. V. (2021). Human Pose Estimation for Training Assistance: a Systematic Literature Review. *Proceedings of the Brazilian Symposium on Multimedia and the Web*, 189–196. https://doi.org/10.1145/3470482.3479633

[42] Elrashdi, A. S., Alferjani, S. K., Omar, R. R., & Hasan, F. M. (2024). The efficiency of using PPDIOO Methodology to Design Graduation Projects for Network Department Students. *2024 IEEE 7th International Conference on Advanced Technologies, Signal and Image Processing (ATSIP)*, *1*, 438–442. https://doi.org/10.1109/ATSIP62566.2024.10638951

[43] Fang, H.-S., Li, J., Tang, H., Xu, C., Zhu, H., Xiu, Y., Li, Y.-L., & Lu, C. (2023). AlphaPose: Whole-Body Regional Multi-Person Pose Estimation and Tracking in Real-Time. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*(6), 7157–7173. https://doi.org/10.1109/TPAMI.2022.3222784